CovenantAI - New Insights into Covenant Violations*

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Abstract

This paper investigates how lenders adjust covenants during renegotiations and explores how these adjustments differ across outcomes such as amendments, waivers, and technical defaults. Using CovenantAI, an advanced AI-powered tool based on a Generative AI approach, we extract a comprehensive, time-series dataset of covenant violations and thresholds from SEC filings, enhancing accuracy compared to traditional methods. Our analysis reveals that renegotiation outcomes vary significantly in severity, shaping creditor interventions. Amendments before violations involve minimal adjustments, reflecting creditor leniency, while technical defaults and amendments with violations result in substantial recalibrations, such as stricter leverage and liquidity requirements. We validate our findings against prior literature and document cyclical patterns in covenant violations, including a decline over the past two decades and a sharp increase during the COVID-19 pandemic. By comparing likelihood and threshold adjustments, we demonstrate a dual mechanism of creditor behavior, balancing proactive flexibility with reactive oversight to manage borrower risk.

JEL classification: G21, G32, G34

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

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1 Introduction

Prior research has established the pivotal role of covenants, and covenant violations in particular, in both corporate and macro-finance contexts.[1] Interestingly, however, this literature relies on two methods to identify covenant violations, either using reported data on financial covenants in Dealscan (e.g., Chava & Roberts, 2008) or using text searches on regulatory Securities and Exchange Commission (SEC) filings (e.g., Nini et al., 2012).[2] Both approaches have shortcomings. While the thresholds of covenants frequently change until the loan matures making it difficult to identify covenant violations using the originally reported thresholds in Dealscan, a text-search approach on SEC filings has limitations, for example, because of the complex language structure in regulatory filings. Importantly, both approaches overlook the nuanced adjustments and creditor interventions tied to different loan renegotiation outcomes, which is a key innovation of our analysis.

"CovenantAI" is an advanced AI-powered tool that offers several key advantages for academic research. It generates a comprehensive, time-series dataset of covenant violations covering all SEC filings, providing a more up-to-date and inclusive analysis compared to traditional methods.[3] Unlike keyword-based approaches, CovenantAI interprets the context within regulatory filings, enhancing accuracy and consistency in identifying covenant violations. Additionally, it can exploit complex language structures to identify nuanced situations, such as pre- and post-violation loan amendments and waivers. Its adaptability and scalability allow it to easily incorporate new data and adjust to changes in financial reporting standards, making it a highly flexible tool for ongoing research.

Our initial contribution is methodological, as we present CovenantAI, a tool that enables researchers to extract quarterly information on covenant violations for nearly all U.S. firms directly from their 10K and 10Q SEC filings. The model is calibrated using over 580,000 filings, identified through the CIK numbers of the full range of Compustat firms. We apply a

[1] The effects of covenant violations on firm-level outcomes are documented in, for example, Chava and Roberts (2008); Roberts and Sufi (2009b); Nini et al. (2012); Freudenberg et al. (2017); Chodorow-Reich and Falato (2022); 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; Greenwald et al., 2019).

[2] A few other papers use confidential SNC data from the Federal Reserve Bank (e.g., Chodorow-Reich & Falato, 2022; Haque & Kleymenova, 2023).

[3] Chava et al. (2019) highlight that difficulty in data collection is an important factor impeding research on debt contracts and covenants.

small set of filters (described in detail in Section 2.1). Our final dataset comprises 11,432 U.S. publicly listed non-financial firms over the 1996 to 2022 period.

A manual inspection of SEC filings reveals that loan renegotiation outcomes are more complex than previously recognized in the literature. These outcomes include amendments without covenant violations, amendments following violations, combinations of amendments and waivers (where lenders temporarily waive covenant compliance), pure waivers, and technical defaults (where a covenant violation occurs without an amendment or waiver within two quarters). These distinct outcomes reflect varying levels of severity that must be carefully accounted for in the analysis. We train a Large Language Model (LLM) to classify our data into these categories as detailed in Subsection 2.2.

We then compare covenant violations obtained from CovenantAI to those in other methods. Building on methodologies from prior studies (e.g., Nini et al. (2012), Griffin, Nini, and Smith (2024), and Roberts and Sufi (2009a)), we compute annual violation rates as the ratio of firms in violation to the total number of firms each year. Our analysis reveals that while annual violation rates from CovenantAI closely mirror those from Griffin ($\rho = 0.95$) and Nini ($\rho = 0.78$ up to 2009), and show a moderate correlation with the quarterly data of Roberts ($\rho = 0.83$ until 2010), differences emerge when the data are disaggregated to a quarterly level. Here, the correlations drop substantially ($\rho = 0.43$ with Roberts and $\rho = 0.47$ with Nini), indicating that small timing discrepancies are smoothed out in annual aggregates.

To further examine these identification differences, we analyze a random sample of 102 firm-quarters where CovenantAI's labeling of covenant violations deviates from that of the other approaches. Using confusion matrices to compare a binary classification of violation versus no violation, our results show that CovenantAI achieves a superior accuracy of 79.41%, outperforming both manually adjusted and simple keyword-based methods. In contrast, the approach by Roberts (2009) delivers only 45.10% accuracy. Moreover and despite a manual adjustment on top of the keywords-based approach, Nini et al. (2012) only find 66.2% of the covenant violations identified in CovenantAI. Roberts and Sufi (2009a) only identify 27.8% of these violations. In other words, this comparison not only highlights the shortcomings of keyword-based approaches but also underscores the advantages of using a large language model to accurately identify covenant violations in SEC filings.

We validate CovenantAI using the same data source as most papers (10K or 10Q filings) and revisit the main economic results from prior research. To do that, we drop all loan amendments that occur without covenant violations. We then follow traditional empirical approaches in this literature such as Roberts and Sufi (2009a) and Nini et al. (2012) to test different economic relationships as to the implications of covenant violations for firm outcomes found in this literature. These can be broadly separated into four categories, i.e., the effects of covenant violations on investment and employment, financial policies, operational and financial performance as well as on firms' access to credit. We also add proxies that have not been used in this literature thus far but gained importance, for example, during the COVID-19 period such as the reliance on cash holdings in overall liquidity management of firms or the usage of credit lines. As expected, firms rely more on cash after covenant violations (*e.g.*, expecting somewhat lower access to credit) as well as have lower credit line usage rates (*e.g.*, as lenders restrict access to credit lines after violations). All other results, similarities, and differences with the literature are discussed in Subsection 3.3.

We document also several interesting time-series patterns. As expected, our covenant violations exhibit cyclical behavior increasing during economic stress periods. Importantly, we find a decline in covenant violations over the last two decades (consistent with Griffin et al. (2024)), which are driven mainly by a decline in loan amendments (rather than technical defaults). These patterns also vary across rating classes. While amendments of firms that are investment-grade (IG) rated are almost stable over time, they mainly decrease in the sample of non-investment-grade (Non-IG) rated firms and, to some extent, among unrated firms. Most striking, however, is the jump in covenant violations during the COVID-19 pandemic, which is entirely driven by loan amendments. Interestingly, amendments spike similarly for IG and Non-IG-rated firms.

Interestingly, we identify loan amendments without covenant violations specifically for IG-rated firms, a pattern that remains remarkably consistent over time. Waivers or amendments after covenant violations are rare in these cases. The surge in amendments during the COVID-19 pandemic is also primarily attributed to these amendments. We observe a decrease in violations primarily among Non-IG firms, evident in loan amendments as well as waivers. Interestingly, the COVID-19 pandemic saw an increase in both amendments without or following covenant

violations. This trend, however, was not evident among unrated firms.

We then turn to a thorough investigation of the consequences of covenant violations in Section 4. We focus on firms that obtain loan amendments vis-a-vis firms that remain in technical default after covenant violations. In a first step, we analyze the determinants as to why firms obtain an amendment. Following earlier approaches such as Chen and Wei (1993) or Acharya et al. (2020), we find strong evidence that firm risk is key driver of this decision, i.e., firms that have lower bankruptcy risk are more likely to obtain amendments. We use different specifications as well as proxies for risk to show this finding is robust.

We know from our validation exercise as well as prior literature that borrowers change their behavior after covenant violations (*e.g.*, decrease debt levels, increase cash, reduce shareholder payouts, or have less access to credit). It is a testable hypothesis that these adjustments is a function of loan renegotiation outcomes following covenant violations. For example, a borrower who secures an amendment before a violation occurs might be in a better position to renegotiate with its lenders compared to a firm that has just violated a covenant. Consistently, we find that firms securing amendments exhibit a smaller decrease in assets, maintain less cash, and display a lower likelihood of default. These effects are more pronounced for firms that might be more financially constrained, such as unrated or Non-IG-rated firms.

We finally investigate how lenders adjust covenants during renegotiations and how these adjustments differ across outcomes such as amendments, waivers, and technical defaults. By leveraging a Generative AI approach with a Large Language Model (GPT-4O Mini), we extract detailed information on covenant inclusion and threshold changes from a large corpus of SEC filings. The analysis focuses on understanding how the likelihood of covenant inclusion and the recalibration of financial thresholds evolve before and after renegotiation events.

Our findings show that the severity of renegotiation outcomes plays a central role in shaping creditor behavior. Amendments before violations, as the least severe outcome, involve minimal changes to covenant inclusion or thresholds, reflecting temporary creditor leniency. In contrast, technical defaults and amendments with violations are associated with significant recalibrations, including stricter leverage and liquidity requirements, signaling heightened creditor attention to borrower risk. By comparing the likelihood and threshold adjustments, our results highlights a dual mechanism of creditor intervention: proactive measures in less severe cases

and aggressive oversight in response to greater financial distress. These insights offer a nuanced understanding of how covenant renegotiations balance borrower flexibility with creditor discipline.

Literature review. The primary innovation of this paper lies in introducing a novel methodology for identifying covenant violations. Therefore, this literature review focuses on comparing "CovenantAI" with existing approaches used in previous research on covenant violations. In the first step, we compile a list of the most widely-cited papers on loan covenant violations over the 1993 to 2023 period and summarize this literature in Table 1. Most important for our purposes is the "Focus" of the paper, the "Time Period" analyzed, the "Data Source" used to identify covenant violations, and whether the respective paper used a machine-learning algorithm ("ML"). We note a number of intriguing findings.

We first document that most of this literature focuses on financial and real adjustments of firms as a consequence of covenant violations. For simplicity, we categorize these adjustments into four groups: (1) Investment & Employment; (2) Financial Policies; (3) Operational & Financial Performance; and (4) Access to Credit.[4] We also observe that most existing studies have limited their focus to relatively short time periods, often concluding either before the 2008-2009 global financial crisis or before 2011.[5] In contrast, CovenantAI generates a comprehensive time series of covenant violations, spanning the entire duration for which regulatory filings are available. This not only ensures a more up-to-date analysis but also encompasses all companies filing with the SEC. In other words, while short time spans and (quasi) random sampling in previous research might reveal significant economic relationships, our method's broader cross-section can enhance the robustness of certain tests, enable new economic analyses, or reveal potential shifts in these relationships over time.

All papers use either SEC filings (10-K or 10-Q), Dealscan, or confidential data from the Shared National Credit Programme (SNC) as data sources to identify covenant violations. Ignoring for a moment studies using SNC data due to limited access to researchers, we observe that around 80% of the remaining papers use SEC filings and about 20% use Dealscan to

[4] Naturally, these categories do not capture all of this literature. For example, other papers focus on CEO turnover (e.g., Ozelge & Saunders, 2012; Nini et al., 2012), accounting changes prior to violations (Sweeney, 1994; Dichev & Skinner, 2002), violation or the probability to waive a violation (Chen & Wei, 1993; Beneish & Press, 1993; Demerjian & Owens, 2016).

[5] Notable exceptions are more recent papers by Dyreng et al. (2022); Griffin et al. (2024); Haque and Kleymenova (2023).

identify covenant violations. Importantly, all papers rely on very few approaches. Authors of papers using Dealscan data use the Chava and Roberts (2008) approach to identify covenant violations, authors of papers using SEC data use either the Roberts and Sufi (2009a) or the Nini et al. (2012) approach, and, frequently, simply the data readily provided by these authors. None of these papers use a machine-learning algorithm, which is at the heart of this paper.

The paper is structured as follows. The next section outlines the data and methodology, including time-series characteristics of our new measures. We then compare the advantages of CovenantAI with other approaches, such as textual analysis, and empirically validate our measure. In Section 4, we examine the consequences of covenant violations, followed by an analysis of lenders' responses during renegotiations in Section 5. Finally, Section 6 concludes.

2 CovenantAI - A Machine Learning Approach

2.1 Data Sources

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

2.1.1 Company and loan data

We utilize the Compustat database to select US companies for our study, focusing on the period from 1996 to 2022. Our criteria included companies with assets over USD 10 million, excluding those with missing or negative key financial metrics like total assets and sales. We limited our analysis to non-financial firms, omitting those with SIC codes 6000-6999. Firms without a CIK identifier were also excluded. Our final dataset includes 377,653 firm-quarter observations from 11,432 US non-financial companies.

We obtain quarterly information about the usage of credit lines of U.S. publicly listed from from the Capital IQ database. Compustat/CRSP and Capital IQ can be merged using the GVKEY-CIK identifier. Credit rating information is sourced from S&P. Our information contains the long-term issuer ratings as well as the rating data and unique company ID, and we transform the rating into a numerical scale.[6] Overall, 77.6% of our sample firms are unrated,

[6] We report the industry classification as well as the numerical mapping of the S&P Credit Ratings in Online Appendix A. If a company has a rating number 26 or 27, it means that it is rated as "D" or in a selective

6.0% are investment-grade (IG) rated, and 16.4% are non-investment-grade (Non-IG) rated.

We use loan data at the deal and facility level from Refinitiv Dealscan. We extend the Chava and Roberts (2008) Dealscan-Compustat link to 2022. From our 11,430 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).[7] Dealscan provides us with terms *at origination* of the loan including spread, amount, lenders but also initial covenants.

2.1.2 SEC filings

This section outlines our method for processing regulatory filings. Companies issue 10K reports annually at fiscal year-end, and 10Q reports for the first three quarters. If a firm reports only three quarters, its 10K includes the fourth quarter data. We combined 10K and quarterly filings to ensure continuity in our dataset. Covenant violations appear in both annual and quarterly reports. Additionally, 8K reports, issued for specific events like bankruptcy or CEO changes, provide further relevant data for shareholder analysis.

In total, we extract 132,591 10K, 451,826 10Q, and 1,285,768 8K reports over the 1996 to 2022 period from the SEC Edgar database.[8] As we describe further below in this paper and in contrast to other machine learning models, we do not need to further clean these reports as our model interprets the context of complete sentences. We develop a data frame capturing paragraphs with the term "covenant," including 700 characters surrounding it to gather relevant information for our model. The source files varied in format, with newer ones in HTML and older ones in txt. We rechecked HTML-based paragraphs to confirm adherence to the 700-character limit, as the model cannot process beyond this. To optimize paragraph labeling by our algorithm, we applied a filter to our dataset. This filter highlights paragraphs containing specific word combinations that suggest possible covenant violations and amendments.[9] To verify the accuracy, we randomly sampled a subset of our data, checking for correctly identified potential

default (SD). In our empirical tests, we match our companies to the LoPucki bankruptcy database. Both approaches, however, identify similar corporate defaults.

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

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

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

violations and amendments. After this process, we have 1,081,905 paragraphs remaining for labeling by the algorithm.

2.2 Alogrithm

In this section, we develop our new machine learning (ML) algorithm to identify covenant violations, which we call "CovenantAI" (a detailed technical discussion is relegated to Sections B and C of the Online Appendix). We then compare our approach to those used in prior literature on covenant violations. Finally, we replicate the main results from this literature using our measure and highlight differences and similarities.

A manual inspection of the SEC filings suggest that loan renegotiation outcomes are more complex than previous literature suggests. There are loan amendments without covenant violations, amendments after covenant violations, a combination of amendments and waivers (i.e., a situation in which a lender temporarily waives the compliance with a covenant), pure waivers or technical defaults (i.e., a situation after a covenant violation that does not lead to an amendment or waiver in the two quarters following a violation).[10]

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

Step 1-Labeling. To train our classification algorithm, we define a ground truth comprising firms identified as *Amendment w/o Violation*, *Amendment w/ Violation*, *Amendment and Waiver*, *Waiver* and *Technical Default*. This serves as the classification labels. We selected 4,184 firm-quarter observations mentioning "covenant" in their 10K and 10Q reports. The sample was constructed partly randomly and partly by targeting instances where "violation" appeared in the text to enrich the dataset with potential covenant violations. With 2,000 truly randomly sampled observations, which were only used in the test and validation sets, while the training set consisted of a more balanced dataset

Our manual labeling process categorizes firm quarters into six groups: 'no violation' (label 0), 'amendment without violation' (label 1), 'waiver' (label 2), 'amendment and waiver' (label 3), 'amendment after violation' (label 4) and 'technical default' (label 5). No violation is

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

assigned where there is no evidence of a covenant breach. An amendment with violation label indicates a loan modification to rectify a violation, and technical default is used when no amendment or waiver is present in the following two quarters. Section B of the Online Appendix provides examples from SEC filings for these categories.

In our sample, there are 519 (12.71%) instances of technical defaults, 198 (4.85%) of amendments with violation, 238 (5.83%) of waivers, and 519 (12.71%) of amendments without violation. This prevalence stems from our sampling method, aimed at balancing the dataset for model training and validation.[11]

Step 2-Classification. We divide the labeled sentences into three datasets: training (70%), testing (15%), and validation (15%)[12]. These datasets include varying distributions of technical default, waiver, amendment with violation, amendment without violation and no-violation observations and are employed to calibrate and assess the model's performance.

For our analysis, we use the MPNET Sentence Transformer, a type of advanced language model. In simpler terms, this model takes complete sentences and transforms them into a format it can understand, like converting sentences into numerical code. It is particularly adept at recognizing and differentiating various types of data, such as distinguishing between different classes in our dataset, by focusing on the unique features of each class. What makes it special is its ability to learn from both similarities and differences in these categories, helping it make more accurate classifications. This technique is key to teaching the model to correctly identify and classify different types of data we are studying (such as technical default, amendments or no violations). A key advantage of CovenantAI is its ability to understand complex language structures. We exploit this to look in more detail into our loan amendments. However, several consequences of violations might be feasible. For example, a violation may be waived, in which case there is no explicit consequence for the borrower, and the credit contract preserves its original terms and conditions. A waiver may last only for a limited period of time. Also, waivers tend to be given after a covenant violation has occurred, whereas amendments might be granted prior to the occurrence of a violation. We can thus classify amendments either directly associated with and following a violation or outside of a covenant violation. Finally, a borrower might obtain a waiver first, but eventually is required to amend some of the loan terms

[11] However, this sample is not fully representative of the five categories; a random sample from our full dataset indicates a mean technical default rate of about 3.7%, reflecting a more accurate distribution.
[12] We tested the model for various combinations of test, training and validation data sizes.

after the waiver period has expired. These variations hold significant economic implications, as they embody scenarios of varying severity for companies. For instance, companies proactively negotiating amendments prior to any covenant violation are potentially in a more advantageous position. They have prepared ahead and may even secure more favorable terms than previously. Conversely, firms that breach covenants and subsequently negotiate amendments might face stricter terms during these negotiations.

Our machine learning model's performance is illustrated in Figure 1, using two types of data: test (628 observations) and validation (628 observations). In these matrices, we compare the model's predictions (horizontal axis) with the actual data (vertical axis). The model showed a high accuracy rate: about 92.17% for the test data and 90.95% for the validation data. Specifically, it correctly identified nearly 87% of violations, 93% of all amendments with violation, 89% of the waivers, 89% of all amendments without violations and 84% of non-violations in the test data.[13]

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 180 days, we do not count the observation as a violation, as it contains information about a previous violation that has already been reported (and recognized as such by our model). We apply the same machine learning algorithm to the 8K filings to validate our results. 8Ks give us real-time information because they need to be filed within four days after the event. In cases where a Technical Default is succeeded by an Amendment with Violation, an Amendment with Violation/Waiver, or a Waiver within the subsequent two quarters, it is not classified as a Technical Default.

Applying our algorithm using these criteria, we obtain 19,048 (3.36%) loan amendments without violation, 7,336 (1.26%) amendments after a violation, 7,536 waiver (1.33%) and 5,475

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

(0.97%) observations with firms in technical default for all firm quarters. The number of firm quarters in which we find a "new" technical default is 2,850 (0.50%), a "new" waiver is 4,425 (0.78%), a "new" amendment with violation is 3,844 (0.68%) and in which we find a "new" amendment without violation is 9,499 (1.68%).[14]

Time-series of covenant violations. Figure 2 shows the time series of covenant violations from our ML approach over the 1996 to 2022 period. Panel A shows the number of covenant violations 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 violations resulting in technical defaults and amendments. The amendment variable contains all amendments without violation, amendments with violations and waivers.

Panel A shows a cyclicality of covenant violations during periods of economic downturns and recessions.[15] For example, violations spike during the 2001-2003 period and the burst of the dotcom bubble. They also spiked during the global financial crisis (2008-09), albeit at a lower level compared to the 2001-2003 period. During the 2014-2016 oil crisis, we also observe an increase in covenant violations. Most strikingly, however, is the increase in covenant violations reported during the COVID-19 pandemic. Violations rose to about 14% (to levels seen during the global financial crisis). Overall, we observe a significant decline in covenant violations over the last twenty years consistent with the results in Griffin et al. (2024).

Panel B shows that this decline is mainly driven by violations that result in loan amendments, which exhibit the same time-series pattern as covenant violations. Interestingly, covenant violations only rarely result in technical default. In the early 2000s, technical defaults were the outcome of about 15% of violations, but also they have been declining since then. Towards the end of our sample period, less than 5% of covenant violations end in technical default.

In a next step, we split our firms into three rating categories, *IG-rated*, *Non-IG-rated* and *Unrated* and plot loan amendments and technical defaults by rating category in Figure 3. Panel A shows the time series for the subsample if *IG*-rated, Panel (B) of *Non-IG*-rated and Panel (C) of *Unrated* firms. As expected (given the high quality of IG-rated firms), we do not observe a high percentage of IG-rated firms that remain in technical default. This percentage is higher

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

[15] We also plot covenant violations over time together with time-series of both credit rating downgrades as well as corporate defaults and document a consistent cyclicality. These figures are reported in Online Appendix D.

among Non-IG and unrated firms. It is well below 10% during the 2001-2003 period and declines thereafter almost towards zero at the end of our sample period.

More interestingly is the time-series of loan amendments by rating categories as the patterns vary substantially between these groups. We observe a secular decline in amendments (and, therefore, in covenant violations) among Non-IG and unrated firms. The decline is somewhat more pronounced among Non-IG firms. Amendments increase to almost 30% in early 2000 and then decline to about 10% in 2022. Both time series exhibit a similar cyclical pattern that we have seen in the time series of covenant violations in Figure 2b. Amendments among IG-rated firms, however, were relatively constant, around 8% among IG-rated firms over the last two decades, and did not show the same cyclicality during periods of economic stress.

Figure 4 plots the time-series of amendments w/o violation, amendments w/ violations, and waivers over time and by rating class. Panel A shows these time series for IG-rated firms. Evidently, a large part of the amendments of IG-rated firms are not because of covenant violations but before violations occur. Consistent with our summary statistics, amendments after violations and waivers were infrequent over the last two decades. Interestingly, the significant increase in amendments during the COVID-19 period, which we previously noted, is entirely attributable to amendments without covenant violations. This aligns with anecdotal evidence and statements from practitioners suggesting that these firms proactively renegotiated their debt agreements with lenders to preempt a covenant violation.

Panel B shows the time series for Non-IG-rated firms. This panel clearly illustrates that the overall reduction in covenant violations, previously discussed, is predominantly attributed to Non-IG-rated firms. This trend is noticeable in both amendments and waivers over time. Additionally, there is a notable cyclical pattern in the amendments, with an increase both before and after covenant violations, particularly during times of economic turmoil. Remarkably, during the COVID-19 period, there was a significant rise in amendments without violations, along with an increase in amendments following covenant violations and, to a lesser extent, waivers.

Panel C presents the time-series data for unrated firms. Consistent with the trend observed in IG-rated firms, amendments without violations have remained relatively steady over the past two decades. There is an absence of a distinct cyclical pattern, along with only a marginal

increase during the COVID-19 period, especially when compared to IG or Non-IG firms. Post-violation, there is a noticeable reduction in the number of amendments and waivers. The overall level, as corroborated by summary statistics, is generally higher than that of Non-IG rated firms, consistent with existing research highlighting the financial constraints faced by unrated firms. Notably, there was no significant rise in either amendments or waivers during the COVID-19 period.

3 CovenantAI vs. Other Approaches

In this subsection, we first contrast our methodology with previous research on covenant violations. Specifically, we want to highlight the contribution of an AI-based algorithm for our understanding of the economic implications of covenant violations.

3.1 Comparing covenant violation rates

In a next step, as papers in this literature rely only on a few measures to identify covenant violations, we compare our covenant violations to those identified in these approaches. To do this, we follow (Nini et al., 2012) and (Griffin et al., 2024) and calculate annual violation rates as the number of firms who violate covenants in any given year divided by the total number of firms in this year.

Figure 5 shows the violation rates of the different approaches. The violation rates of Roberts and Sufi (2009a) and Nini et al. (2012) are available from the respective authors on a quarterly basis. For the Griffin et al. (2024) we use the annual data provided in Appendix Table I in Griffin et al. (2024). We compare these violation rates to those identified by CovenantAI.

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

However, different methods (Griffin et al. (2024), Nini et al. (2012), CovenantAI) often line up once you aggregate to the yearly level—any small timing differences within a year might get washed out in an annual statistic. Hence, we expect to see high correlations in Panel A of Table 2. Moreover, annual violation rates might be substantially larger as the nominator increases with each quarter while the denominator (the total number of firms) might stay constant. As a next step, we thus compute quarterly violation rates and compare them across the different approaches. We report these correlations in Panel B of Table 2.

Indeed, comparing the quarterly correlations of covenant violation rates, we find much lower correlations. For example, the correlation of violation rates from CovenantAI with those from Roberts and Sufi (2009a) are $\rho = 0.43$ and with those from Nini et al. (2012) are $\rho = 0.47$. We do not include the correlation with the Griffin et al. (2024) violation rates, because covenant violations are not available on a firm-quarter level.

3.2 Comparing CovenantAI to alternative approaches

What explains the lower correlations in the firm quarter observations, particularly between CovenantAI (based on a LLM) and Griffin et al. (2024) (based on textual analysis), and what are the key differences between both approaches? We highlight three important differences between these models and their potential impact on our analysis (and applicability in other economic contexts). Firstly, CovenantAI interprets the *context* of the various regulatory filings, while their method is a *keywords-based* approach. The latter requires a "stemming" of the text, i.e., the removal of so-called "stopwords" such as "not"; for CovenantAI, these stopwords are an important part of the context.[16] For example, the filing could state that the firm "did not violate" a covenant, which would misinterpreted in a text-based approach and might result in a large number of false negatives. That is, CovenantAI provides improved accuracy and consistency in the identification of covenant violations as the algorithm can detect patterns and nuances in the context of the filings. To the extent that the keywords-based approach relies on manual classifications, the consistent application of criteria of CovenantAI also reduces human error and bias.

[16] Our model can thus also process and analyze vast amounts of text data much faster than manual text analysis. The time and labor required for data processing is substantially lower, offering a more efficient approach for large datasets. In other words, CovenantAI is easily scalable and can accommodate increasing amounts of data.

Secondly, CovenantAI is capable of handling complex language structures as they occur in regulatory filings, and we can exploit these complexities to better understand their economic implications. For example, we can go beyond a simple classification of firms that violate or do not violate covenants and investigate how these violations are eventually resolved. Do firms obtain a waiver of the covenant violations over a specific period? Are the contracts amended? Do firms amend contracts outside of covenant violations? And, do firms remain in technical default? These are all different outcomes with likely different severity in terms of the economic impact on the firms themselves. CovenantAI can be trained to understand the complexity of regulatory filings and differentiate between these important outcomes.

Thirdly, in contrast to methods relying on keyword searches, CovenantAI exhibits greater adaptability. This system can be retrained with new datasets, allowing it to adjust to developments such as shifts in financial reporting standards or regulatory changes. However, it is important to note that training these models generally incurs higher costs than employing basic keyword-based methods. Regular updates and modifications to the system even entail additional expenses. Consequently, there is a need to carefully weigh these costs against the potential economic advantages offered by utilizing CovenantAI.

To compare the performances of the three models and emphasize the identification differences, we take a random sample of 102 firm quarters where the labeling of CovenantAI disagrees with the labeling of either of the Nini et al. (2012) or the Roberts and Sufi (2009a) approach. Therefore, the confusion matrices are not representative of the overall performance of the respective model and only give us an indication how the models perform when we apply them to more complicated paragraphs. To make the labeling comparable to the other approaches, we simply divide the firm quarters into *Violation* and *No Violation*. The *Violation* is assigned with 1 if the firm either obtained a waiver, an amendment with violation or was in a technical default. The *Violation* is assigned with 0 if the firm was not in violation or obtained an amendment without violation. Panel A shows the confusion matrix of CovenantAI, which outperforms the other approaches with an accuracy of 79.41%. Panel B shows the confusion matrix of the Nini et al. (2012) data, being constructed by additional manual adjustments on top of a simple keyword search. Panel C shows the performance on a simple keyword based approach build on the approach by Nini et al. (2012). It simply searches for the keywords *waiv*, *viol*, *in default*,

modif, *not in compliance* within seven lines surrounding the word covenant. In the Appendix Table 11 we show examples of paragraphs where CovenantAI does not agree with the labeling of the keyword based approach. It highlights the shortcomings of keyword based approaches and the advantages of using a large language model in the task of identifying covenant violations in SEC filings. The Roberts and Sufi (2009a), using Dealscan data, performs the worst in identifying covenant violations with an accuracy of 45.10%.

3.3 Validation exercise

To investigate these differences in more detail and show similarities and differences, we can use CovenantAI on the same data sources used in prior papers. In this subsection, we employ the covenant violations generated by CovenantAI over the 1996 to 2022 period and revisit the most prominent economic messages from the previous literature. Table 3 provides summary statistics of our sample consisting of 11,530 non-financial U.S. companies over the 1996 to 2022 period. All quarterly variables are annualized. All variables are defined in the Appendix A.

3.3.1 Methodology

We investigate the impact of covenant violations on investment and employment, financial policies, access to credit, as well as operational and financial performance using a "quasi-regression discontinuity design" (RDD) that is common in the literature (Roberts & Sufi, 2009a; Nini et al., 2012). This design is particularly useful in the context of covenant violations: (1) there is a sharp cutoff for comparison as firms either violate (treatment group) or not violate a covenant (control group); (2) we can control for unobserved heterogeneity between violating and non-violating firms using a first-difference specification; (3) we can control for confounding variables that are related to the likelihood of a covenant violation to isolate the effect of the violation itself on the firm's outcomes; (4) we can identify a causal effect related to covenant violations, separate from the trajectory a firm was already on due to its fundamentals; and (5) there is some flexibility in modeling as to how firm performance changes over time using higher-order controls and controlling for both current and lagged variables.

We estimate the following regression model using OLS:

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

The dependent variable $y_{i,t+4} - y_{i,t}$ is the change in our proxies for (1) Investment & Employment; (2) Financial Policies; (3) Operational & Financial Performance and (4) Access to Credit over the four quarters following a covenant violation. $Violation_{i,t}$ is an indicator variable that is one if firm i has a covenant violation in quarter t. We do not differentiate by renegotiation outcome and drop all amendments that occur without covenant violations.

$X_{i,t}$ is a vector of covenant control variables (operating cash flow scaled by assets, leverage ratio, the ratio of interest expense to assets, the ratio of net worth to assets, the current ratio, and the market-to-book ratio). We also add industry (γ_j) and quarter (δ_t) fixed effects. All regressions include higher-order covenant control variables, as well as the four-quarter lag of these variables. We also include a four-quarter lag of our covenant violation dummy $Violations_{i,t-4}$. Standard errors are clustered at the firm level.

3.3.2 Results

Investment & Employment. We first investigate the implications of covenant violations on investment and employment of firms using five different proxies. There are: (1) Δ *Ln(Assets)*; (2) Δ *Ln(PPE)*; (3) $\Delta Capex/Assets$; (4) $\Delta CashAqu/Assets$; and (5) *Emp Growth*.

Panel A of Table 4 shows the results. Consistent with prior literature, firms reduce assets (-8.1%) and PPE (-8.8%) in the fourth quarter after a covenant violation. The point estimates, however, more than double compared to Nini et al. (2012).[17] We find a significant reduction in $\Delta Capex/Assets$ (-0.4%), an effect similar in economic magnitude compared to earlier literature but that was insignificant before. Maybe our tests, including a larger number of firms and events, have more power (column 3). In contrast to prior literature, however, we do not find a significant effect on $\Delta CashAqu/Assets$ (column 4), which is also substantially lower in terms of economic magnitudes. Firms do not report employment on a quarterly basis. We thus perform our investigation on the effect of violations on employment at the annual level (column 5) and

[17] We provide a similar analysis in Appendix Table 12, in which we include amendments without violations. The economic magnitudes are closer to the results in prior literature suggesting that these papers likely capture loan renegotiations that do not follow a covenant violation.

find a 8.3% reduction in employment following a violation. This effect is only significant at the 10% level and, in economic magnitudes, somewhat smaller compared to Falato and Liang (2016).

Financial Policies. We then investigate the implications of covenant violations on financial policies of firms using six different proxies. There are: (1) Δ *Net Debt Issuance/Assets)*; (2) Δ *Ln(Debt)*; (3) Δ *Cash/Assets)*; (4) Δ *Ln(Shareholder Payout)*; (5) Δ *Cash Ratio* (which is the ratio of cash over cash and undrawn credit lines; and (6) Δ *Usage* (which is the change in the ratio of drawn credit line volume and total credit lines outstanding).[18]

Panel B shows that firms do not reduce NDI over average assets after a covenant violation, in contrast to earlier literature. This is likely due to the more strikingly increase in total assets as reported earlier, as total debt is considerably lower after violations. The economic magnitude is again larger as, for example, in Nini et al. (2012). The effect on cash over average assets (an increase of about 0.4%) is almost identical. Firms also reduce shareholder payouts by about 2.8%, which is similar in magnitude compared to before but was insignificant in prior literature. We add two measures related to firm cash holdings in the spirit of Sufi (2009) and Acharya et al. (2020), even though they have not been used in the context of covenant violations. These are the *Cash Ratio*, which describes how much cash a firm holds relative to the total amount of liquidity it can access via cash or unused credit lines, as well as the *Usage* of credit lines. The results are reported in columns (5) and (6), respectively. While the cash ratio remains stable, credit line usage declines by about 2.3%. In other words, credit lines become less important in overall liquidity management of firms after covenant violations.

Operational & Financial Performance. We then investigate the financial and operating performance of firms using six proxies, there are: (1) Δ *Operating Cash Flow/Assets* which are operating cash flows over average assets; (2) Δ *Ln(Sales)*; (3) Δ *Ln(Cost)*, the difference between sales and operating cash flows; (4) *Downgrade* (i.e., an indicator that is one if the firm is downgraded in the four quarters after a violation); and (5) $Default$ (i.e., an indicator that is one if the firm defaults in the four quarters after a violation).

The results are reported in Panel C. We do not find statistical or economically meaningful evidence that operating cash flows increase following a covenant violation. Nini et al. (2012) reported a 1.2% increase, about a third of our point estimate. We investigate the two components

[18] We obtain information about drawn and undrawn credit lines from Capital IQ.

of operating cash flow, sales, and costs, and find that violations both reduce sales (-3.8%) and, importantly, costs (-6.2%), and the results that are statistically and economically significant.

To add to our analysis of the implications of covenant violations on financial performance of firms, we include possible rating downgrades as well as corporate bankruptcy (either Chapter 11 or Chapter 7) as dependent variables. Column (5) investigates credit rating downgrades (*Downgrade*), and we thus focus on rated firms only. We do not find evidence that credit rating agencies reduce firm rating after violations. However, we find that the likelihood that a firm declares bankruptcy (*Default*) is about 2.5% higher after a covenant violation relative to non-violating firms.

Access to Credit. How do covenant violations impact firm access to credit? To investigate this, we follow earlier literature (e.g., Chodorow-Reich & Falato, 2022) and use the Refinitiv Dealscan database to construct loan market measures. We first match Dealscan with our covenant violation dataset using the Chava and Roberts (2008) linking table (extended to June 2022) and create three new (dependent) variables: (1) the change in the loan spread over the eight quarters following a violation ($\Delta Spread$), (2) the change in the natural logarithm of the loan amount ($\Delta Ln(LoanAmount)$), and (3) an indicator that is one if the loan amount of a firm is reduced in the eight quarters following a violation relative to the loan before the violation (*Credit Access Reduction*).

The results are reported in Panel D of Table 4. Columns (1) to (3) focus on term loans, and columns (4) to (6) on credit lines issuances. All regressions include 2-digit industry fixed effects to account for possible changes in loan demand at the industry level, as well as quarterly fixed effects (intensive margin).[19]

The findings indicate a contraction in credit availability to firms subsequent to covenant violations. We observe lower loan amounts, and a higher probability of loan amount reductions in the subsample of credit lines, but no effect on term loans.

Loans might represent refinancings of existing loans rather than being entirely new issuances. Utilizing the "Refinancing" indicator from Dealscan, we categorize the sample into refinanced and non-refinanced loans. Subsequently, we apply the same regression analysis to the subsample of credit lines and show the results in Panel E. The analysis predominantly shows a higher

[19] We run the same specifications using firm instead of industry fixed effects to control for loan demand at the firm level. The results remain qualitatively similar. The table is reported in the Online Appendix Section D.

occurrence of loan refinancings. Notably, the significant results stem exclusively from refinanced loans, as the coefficients in the non-refinanced loan subset are both economically negligible and statistically non-significant.[20] Overall, they are consistent with prior literature such as Chodorow-Reich and Falato (2022).

4 Consequences of Covenant Violations

One advantage of CovenantAI is that we can train the model to identify whether covenant violations are resolved, e.g., through amendments, or whether firms remain in technical default over a specific period of time. In this section, we investigate the determinants that lenders and borrowers agree on an amendment to cure a covenant breach and whether financial and real adjustments of firms are different for these firms relative to those that remain in technical default.

4.1 Descriptive evidence

Table 5 shows summary statistics at the firm level. Overall, we have 288 firms that remain in technical default and 4,088 firms that obtain amendments after a covenant violation. As expected, firms in technical default are usually smaller, more leveraged, and unrated. Among rated borrowers, they also have a worse credit rating.

4.2 Determinants of loan amendments

As of now, we look at the combined group of amendments and technical default. Within the group of amendments, however, we can differentiate between a scenario in which lenders waive a violation for a specific period of time without making any changes to the loan agreement or a situation in which material terms of the loan are changed (such as interest rate, maturity or loan amount). The literature as to how covenant breaches are cured is also sparse. Nonetheless, few papers have further inquired about the use of waivers (such as Chen and Wei (1993) or Acharya et al. (2020)), and we can use some of their insights.

[20] In our final analysis step, we divide the refinanced loan dataset into two subcategories: credit lines and term loans. Consistent with our expectations, the main results are observed in the refinancings of credit lines. Although the term loan sample exhibits coefficients of a comparable magnitude, they lack statistical significance. We do not report the results for brevity.

Empirical model. Chen and Wei (1993) argue that the likelihood of borrower default is a key determinant of the decision to waive a violation. They use a balance-sheet based approach to measure the probability of default. As our sample includes only publicly listed firms, we use a market-driven approach and the "Distance to Default" as our preferred measure of bankruptcy (DD).[21]

We estimate the following model via OLS:

$$Pr(Amendment)_{i,t} = \alpha + \beta \times DD_{i,t} + \theta \times X_{i,t} + \gamma_j + \delta_t + \varepsilon_{i,t} \tag{2}$$

$DD_{i,t}$ is the distance-to-default of firm i in quarter t. $X_{i,t}$ is a vector of control variables that likely affects the amendment decision (asset size, 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). In some specifications, we add indicator variables for different rating categories, i.e., IG if a company is investment-grade rated, $Non-IG$ if a company is non-investment-grade rated, and $Unrated$ (if a firm is not rated). We also add industry (γ_j) and quarter (δ_t) fixed effects. Standard errors are clustered at the firm and quarter level.

Results. Panel A of Table 6 shows the results. Column (1) only includes DD and the coefficient suggests that a higher distance to default (i.e., lower default risk) increases the likelihood that lenders amend a loan contract following a violation. We include year and quarter fixed effects in column (2) the coefficient of DD does not change much. In column (3) we add important determinants of borrower risk (those that lenders usually write covenants on). The economic impact of DD declines substantially as our control variables account for default risk. Specifically, firms higher *Operating Income/Assets*, lower *Leverage Ratio* and more liquidity (i.e., a higher *Current Ratio*) are more likely to obtain amendments. We add four-quarter-lags for all our control variables as well as higher order controls in column (4). We also add rating categories differentiating between *IG*, *Non-IG* and unrated firms, with *Unrated* being the omitted group. Both IG and Non-IG-rated firms have a 4% higher likelihood of

[21] We implement the "naive distance to default" approach described in Bharath and Shumway (2008) and start with an estimate of σ_E using the previous year's daily returns. From this σ_D is approximated as $\sigma_D = 0.05 + 0.25(\sigma_E)$. We next calculate a value of $\sigma_V = \sigma_E[E/(D+E)] + \sigma_D[D/(D+E)]$. μ is taken to be the stock return over the previous year. The implied distance-to-default over the next one-year horizon from this procedure is then calculated as $DD = (ln((E+D)/D) + \left(\mu_V - 0.5\sigma_V^2\right) / (\sigma_V)$, where DD is the "*Distance to Default*".

obtaining an amendment vis-a-vis unrated firms. The coefficients of *DD* and other borrower default risk proxies remain largely unchanged, suggesting that our rating categories measure borrower opaqueness rather than default risk and more transparent firms are more likely to obtain amendments. Finally, we add firm size measured as the natural logarithm of firm assets (*Ln(Assets)*). Acharya et al. (2020) suggest that larger firms are more likely to obtain waiver following covenant violations. Consistently, we find that larger firms are more likely to obtain a loan amendment. Interestingly, the coefficients on our rating proxies become almost zero (consistent with those being a proxy for borrower transparency). The economic magnitude of DD also somewhat declines while the coefficients of *Operating Income/Assets* and *Current Ratio* remain remarkably stable across all specifications. Overall, borrower risk and transparency appear to be key determinants of lenders to amend loans.

4.3 Amendments and firm adjustments following violations

In line with existing research, Subsection 3.3 of this paper details significant changes in corporate policies subsequent to covenant violations. This section investigates the significance of the resolution methods of these covenants, examining the impact of either amendments or the continuance of firms in technical default on these policy adjustments.

Descriptive analysis. We first investigate this graphically in Figure 7 using a selected set of outcome variables such as leverage ratio, PPE, debt, credit line usage, operating performance and sales. Across all these outcome variables, we observe different adjustments after renegotiations as a function of the respective outcome. While firms that obtain loan amendments without a covenant violation show only very small changes around the event, firms that remain in technical default or amend after a violation show significant reductions in, for example, debt, leverage or credit line usage. Overall, these graphs highlight the importance of renegotiations outcomes on firm performance and policies.

Empirical approach. We focus on the sample of firms that have violated a covenant and select a few outcome variables from our analysis in Table 4.[22] There are: (1) Δ *Ln(Assets)*, (2) Δ *Ln(PPE)*, (3) Δ Ln(*Shareholder Payout)*, (4) *Cash Ratio*, (5) Δ *Ln(Cost)*, and (6) $Default$.

[22] The remaining outcome variables are reported in Online Appendix D.

We estimate the following regression model using OLS:

$$y_{i,t+4} - y_{i,t} = \alpha + \beta \times Amendment_{i,t} + \theta \times X_{i,t} + \gamma_j + \delta_t + \varepsilon_{i,t} \tag{3}$$

where $X_{i,t}$ are all variables from column (5) in Table 6 which determine the likelihood that a loan is amended.

Results. Panel B of Table 6 shows the the effects of amendments subsequent to covenant violations on firm performance, accounting for multiple determinants influencing the probability of a borrower securing an amendment. The findings indicate that firms acquiring an amendment post-covenant violation tend to exhibit a smaller decrease in assets and PPE, maintain lower cash reserves, implement fewer cost reductions, and display a reduced likelihood of default. This is particularly evident in comparison to firms that continue to be in technical default, at least in the two quarters following a violation.

It is important to note that the regression specification controls for all variables that are shown in column (5) in Table 6 to predict amendments (following earlier literature, e.g., Acharya et al. (2020)). In other words, even controlling for the financial factors leading to an amendment, an amendment has an independently large and statistically significant effect on real outcomes of firms.

4.4 Amendment vs. covenant violation waiver

Descriptive Results. Panel A of Table 7 shows the summary statistics of our outcome categories. This involves computing the yearly average statistic, followed by the calculation of the mean across all years for both the entire sample and the various rating categories. Evidently, *Amendment w/o Violation* is the largest group. In the full sample, on average, 7.6% of firm-quarter observations within a year are amendments before covenant violations occur. 3.15% of the observations were amendments that followed covenant violations, 3.46% waivers following violations, and about 2.19% were technical defaults. Amendments w/o violations are highest for Non-IG-rated firms (12.56%), followed by unrated (7.60%) and IG-rated (6.90%) firms. As expected, amendments or waivers after covenant violations, as well as technical defaults, are negligible in the sample of IG-rated firms. These are more likely among Non-IG and, in particular, unrated firms, consistent with our earlier result that both credit risk and

transparency drive amendment decisions.

Regression results. To assess the economic implications of different consequences of covenant violation on firms, we run the same model specification as for Panel A of Table 6. We also focus on the sample of firms that have violated a covenant and select the same outcome variables: (1) Δ *Ln(Assets)*, (2) Δ *Ln(PPE)*, (3) Δ Ln(*Shareholder Payout)*, (4) *Cash Ratio*, (5) Δ *Ln(Cost)*, and (6) $Default$.[23]

The results (Table 7) are consistent with our hypothesis that different violation outcomes represent also scenarios of varying severity for companies. Columns (1) and (2) indicate that the smaller decrease in assets and PPE is within the set of firms that secure amendments before the violation occurs. For firms that obtain amendments or waivers post-violation, there is no differential effect compared to those that remain in technical default. As before, there is no difference as to the reduction in shareholder payouts (column 3), but we also do not find statistically significant differences in terms of cash holdings (column 4). Firms that renegotiate amendments before default implement fewer cost reductions and exhibit a lower likelihood to default compared to violating firms.

5 How Do Lenders Respond during Loan Renegotiations?

How do lenders adjust covenants during covenant renegotiations and how does this differ for amemdments, technical default or waiver? We use a Large Language Model (LLM) in this section to extract information about covenants and covenant thresholds from SEC filings. We then investigate changes in the use of covenants and respective thresholds around renegotiation outcomes.

5.1 Extracting Covenant Thresholds Using a Generative AI Approach

To identify covenant thresholds within a large corpus of exhibits, we employ a Generative AI methodology leveraging GPT-4O Mini, a large language model. Our methodology includes

[23] The remaining outcome variables are reported in Section D of the Online Appendix

metadata extraction, filtering, retrieval of relevant content, and data cleaning to ensure precise and scalable extraction of covenant-related information.

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

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

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

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

In the final step, we consolidate and clean the extracted data to ensure consistency. We standardize ratios for comparability across filings and map effective dates carefully. When effective dates are not explicitly mentioned, we infer the report date of the exhibit as the effective date, relying on contextual cues. This step ensures the data is accurate and ready for subsequent analysis.[24]

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

5.2 Covenant adjustments during renegotiations

5.2.1 Summary statistics

The summary statistics in Panel A of Table 7 provide an overview of key financial covenants and their prevalence across firms subject to covenant agreements. The data is extracted at the firm-quarter level from SEC filings and then aggregated to the firm level. The leverage ratio is the most commonly applied metric, observed in 72.49% of firms, followed by the fixed charge coverage ratio (44.42%) and the interest coverage ratio (41.99%). These ratios emphasize the focus of lenders on assessing firms' solvency and ability to service debt, underscoring their centrality in monitoring firm financial health. In contrast, liquidity-based metrics such as the current ratio and quick ratio are less frequently included, appearing in only 8.34 and 4.43% of firms, respectively. This indicates that while liquidity is considered, creditors prioritize long-term debt management and financial stability over short-term liquidity in covenant design.

The data also reveal substantial variation in the financial ratios across firms, as reflected in relatively wide inter-quartile ranges and standard deviations, particularly for the leverage and debt-to-cashflow ratios. These differences highlight the diverse financial profiles of firms subject to covenant agreements. Overall, the widespread inclusion of leverage and coverage ratios suggests that creditors primarily target solvency and debt-servicing capacity, while liquidity measures play a more limited role in covenant structures.

5.2.2 Covenant adjustments during renegotiations

Likelihood. Panel A of Table 8 analyzes changes in the likelihood of including specific financial covenants before and after renegotiation outcomes. The results indicate a clear escalation in creditor intervention as the severity of outcomes increases, moving from waivers to technical defaults and amendments with violations. Waivers, the least severe outcome, show minimal changes. For instance, the quick ratio increases slightly post-event (0.01, $p < 0.05$), while the current ratio declines marginally (-0.02, $p < 0.01$). These small adjustments reflect creditors' reluctance to impose significant changes, consistent with waivers being used to address temporary financial strains without fundamentally altering the contract structure.

For technical defaults, creditors impose more significant changes to covenant inclusion. A notable decline in the current ratio (-0.03, $p < 0.001$) and a slight increase in the quick ratio

(0.01, $p < 0.05$) highlight efforts to balance liquidity constraints while maintaining operational flexibility. Amendments without violations exhibit modest but meaningful changes, such as an increase in the debt-to-cashflow ratio (0.01, $p < 0.001$), indicating preemptive creditor actions to tighten oversight and reduce the likelihood of future breaches. In amendments with violations, the most severe outcome, we observe the most significant adjustments, including a notable decline in the current ratio (-0.02, $p < 0.001$) and an increase in the leverage ratio (0.05, $p < 0.001$). These results underscore creditors' heightened risk aversion and stricter control when borrowers fail to meet their obligations, reflecting the escalating severity of renegotiation outcomes.

Thresholds. Panel B of Table 8 shifts focus from likelihood to changes in covenant thresholds, offering a more granular view of how financial targets are recalibrated post-event. As with likelihood, adjustments to thresholds align with the severity of renegotiation outcomes. Waivers show minimal changes, consistent with their less severe nature. For instance, the interest coverage ratio declines slightly (-0.18, $p < 0.01$), while the number of covenants increases modestly (0.04, $p < 0.05$). This reflects creditors' preference for temporary accommodations with limited recalibration of financial targets.

Technical defaults, however, involve more substantial threshold adjustments. The current ratio threshold increases significantly (0.13, $p < 0.001$), signaling stricter liquidity requirements, while the debt-to-cashflow ratio threshold decreases sharply (-0.30, $p < 0.001$), indicating tighter leverage constraints. These recalibrations reflect creditors' efforts to manage financial risks more rigorously after a default. Amendments without violations show moderate changes, such as a slight increase in the debt-to-cashflow ratio (0.07, $p < 0.01$) and leverage ratio (0.03, $p < 0.05$), balancing creditor control with borrower flexibility. For amendments with violations, the most severe adjustments occur, including a significant increase in the debt-to-cashflow ratio (0.15, $p < 0.01$) and a notable reduction in the debt service coverage ratio (-0.11, $p < 0.001$). These stringent adjustments indicate creditors' heightened risk management to address borrower instability.

Comparison. Panels A and B of Table 8 provide complementary insights into how creditor interventions vary with the severity of renegotiation outcomes. The likelihood analysis in Panel A highlights the frequency and context of covenant inclusion, with minor changes for waivers

and substantial shifts for technical defaults and amendments with violations. It provides a broad picture of how renegotiation events align with creditors' perceived risk, showing escalating oversight as outcomes become more severe. For instance, waivers involve minimal inclusion changes, while amendments with violations reflect significant increases in the inclusion of stricter covenants, such as leverage and liquidity ratios.

The threshold analysis in Panel B complements this by revealing how creditors recalibrate financial targets post-event. While waivers exhibit negligible threshold changes, technical defaults and amendments with violations show significant adjustments to liquidity and leverage thresholds. This recalibration underscores creditors' intent to tighten financial conditions and prevent further breaches. For example, the increased current ratio threshold after technical defaults highlights creditors' focus on improving liquidity buffers, while the stricter leverage thresholds in amendments with violations signal heightened risk aversion.

Together, the two analyses reveal a consistent pattern: less severe outcomes, such as waivers, involve minimal likelihood changes and limited threshold adjustments, reflecting leniency from creditors. In contrast, severe outcomes like technical defaults or amendments with violations feature both stricter covenant inclusion and substantial threshold recalibrations, indicating aggressive risk mitigation. This dual perspective illustrates the dynamic relationship between financial performance and creditor oversight, with the severity of outcomes driving the extent of creditor intervention.

6 Conclusion

This paper introduces CovenantAI, an advanced AI-powered tool that significantly enhances the identification and analysis of covenant violations in SEC filings. By leveraging a Generative AI approach, CovenantAI surpasses traditional methods by providing a comprehensive time-series dataset of covenant violations, offering detailed insights into renegotiation outcomes such as amendments, waivers, and technical defaults. Crucially, the tool distinguishes between amendments occurring before and after covenant violations, enabling a more nuanced understanding of creditor interventions during loan renegotiations.

Our findings reveal that the severity of renegotiation outcomes is a key determinant of creditor behavior. Amendments before violations reflect minimal changes to covenant inclusion or

thresholds, highlighting temporary leniency by creditors toward financially stable borrowers. In contrast, technical defaults and amendments following violations are associated with significant recalibrations, including stricter leverage and liquidity requirements, signaling heightened creditor attention to borrower risk. These differences underscore the dual mechanism of creditor intervention: proactive adjustments in less severe cases and aggressive oversight for borrowers in financial distress.

In addition to methodological advancements, this paper provides novel evidence on the time-series behavior of covenant violations. We observe cyclical patterns in violation rates, with spikes during economic downturns, such as the COVID-19 pandemic, and a long-term decline driven by reductions in loan amendments among Non-Investment-Grade firms. Importantly, the rise in amendments without violations among Investment-Grade firms reflects a shift toward proactive risk management and negotiation strategies that mitigate the need for formal breaches.

Overall, this study highlights the critical role of covenants in creditor-borrower relationships and the value of CovenantAI in enabling granular and scalable analyses of covenant violations. By providing deeper insights into the dynamics of renegotiation outcomes, our work contributes to a more comprehensive understanding of how covenants shape firm behavior and creditor interventions.

There are interesting directions for future research to explore. The COVID-19 period is an interesting laboratory as it provides a quasi-exogenous shock to firm credit risk. Preliminary examination of our data regarding the impact of covenant violations during this period indicates that lenders were willing to suspend profitability-based covenants and grant a temporary relief. Notably, in approximately one-third of these instances, a "new" liquidity covenant was introduced, mandating firms to maintain an average of USD 235 million in additional cash reserves. This aligns with the observed substantial rise in cash holdings among Compustat-listed companies at that time. We have previously observed a significant clustering of covenant activity prior to the pandemic. This raises the question: Did lenders alter their contract-writing practices post-COVID-19 to permanently incorporate liquidity covenants, or is this merely a transient adjustment, with firms and lenders reverting to pre-pandemic norms?

Additionally, our attention centers on the loan market in the United States. Exploring the

possibility of comparable patterns in the evolution of loan markets and the implementation of covenants in loan agreements in other regions, such as Europe, presents an intriguing avenue for further investigation. This area offers significant potential for future research.

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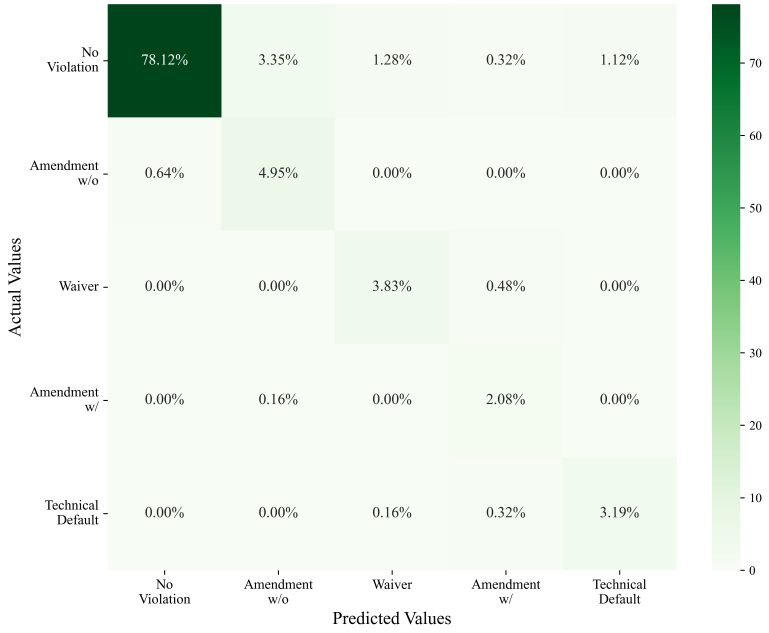
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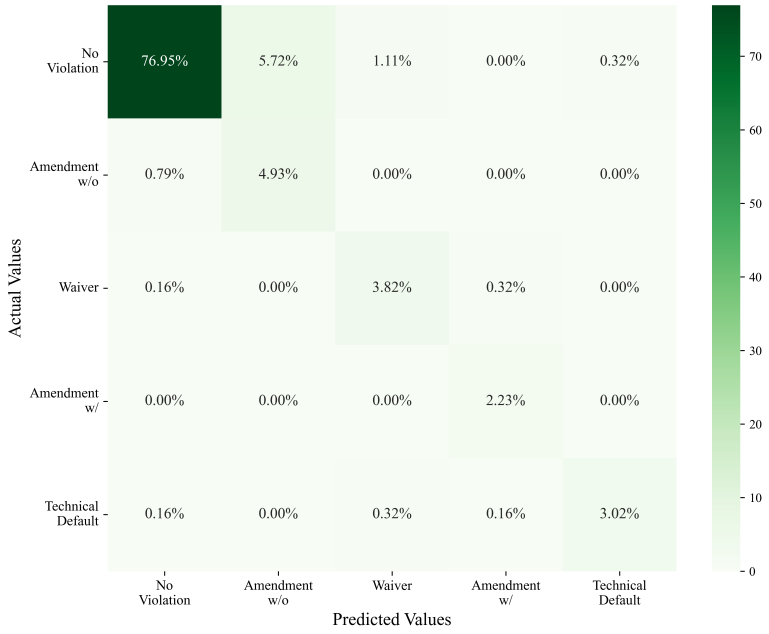
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Figures and Tables

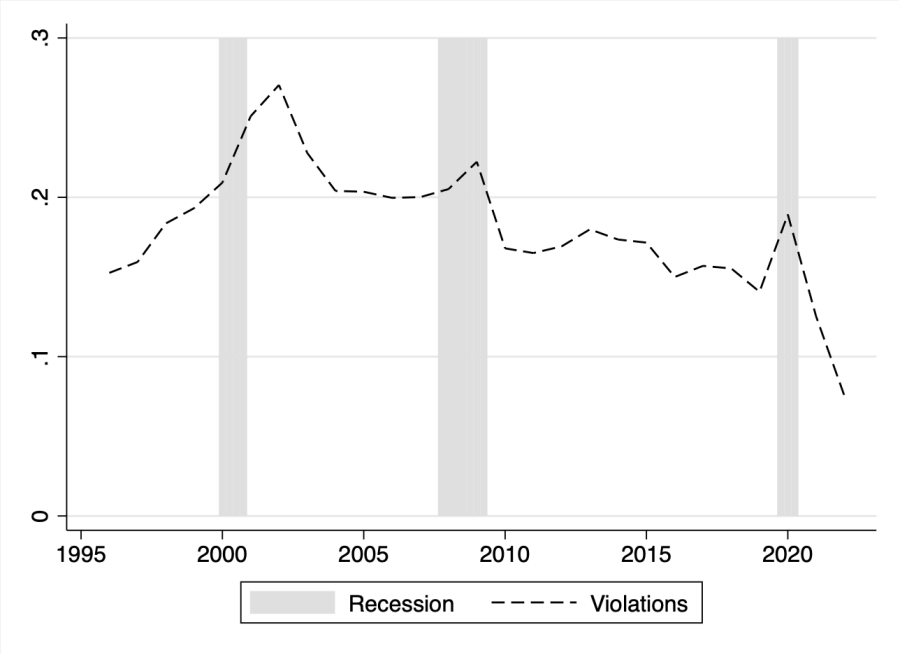


(a) Confusion matrix of the Test Data

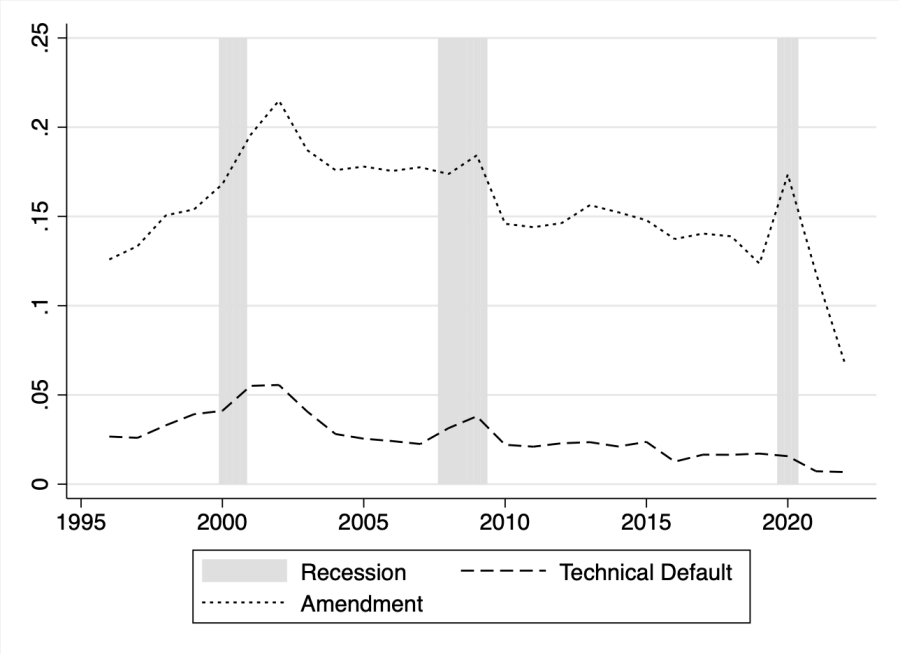


(b) Confusion matrix of the Validation Data

Figure 1: **Confusion matrix 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.

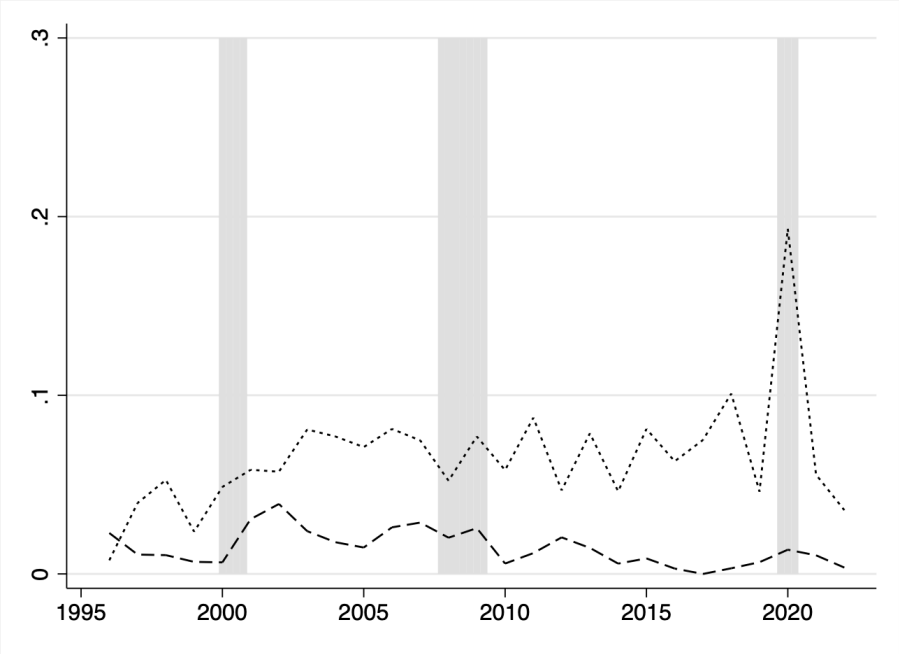


(a) Covenant Violations

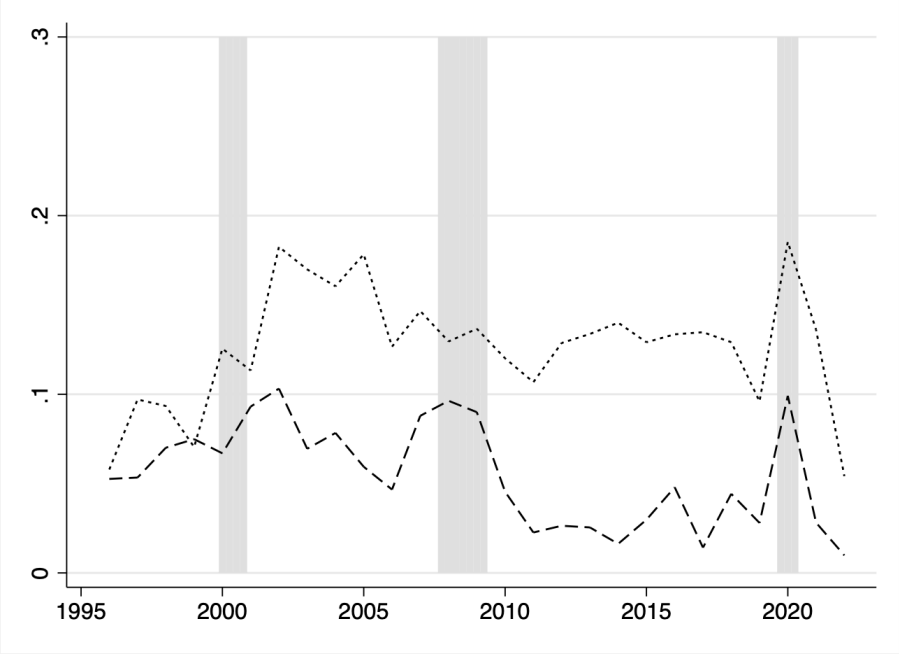


(b) Technical defaults and loan amendments

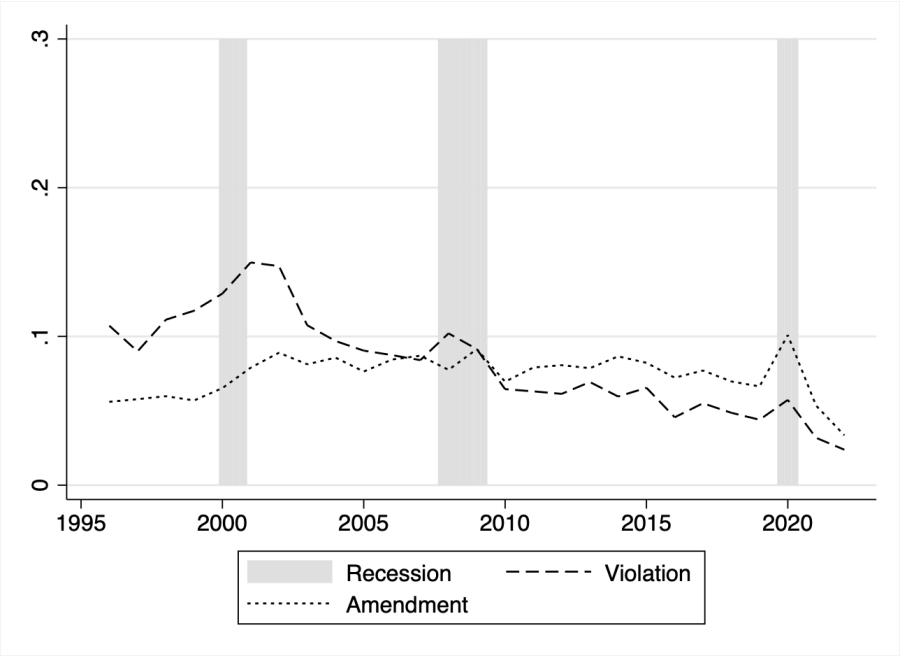
Figure 2: **Covenant Violation Distribution**
This figure plots the annual share of technical defaults and loan amendments for the full sample of U.S. publicly listed, non-financial firms. The shaded areas represent the NBER recession periods (Panel A). Panel B plots the combined share of technical defaults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



(a) IG rated firms

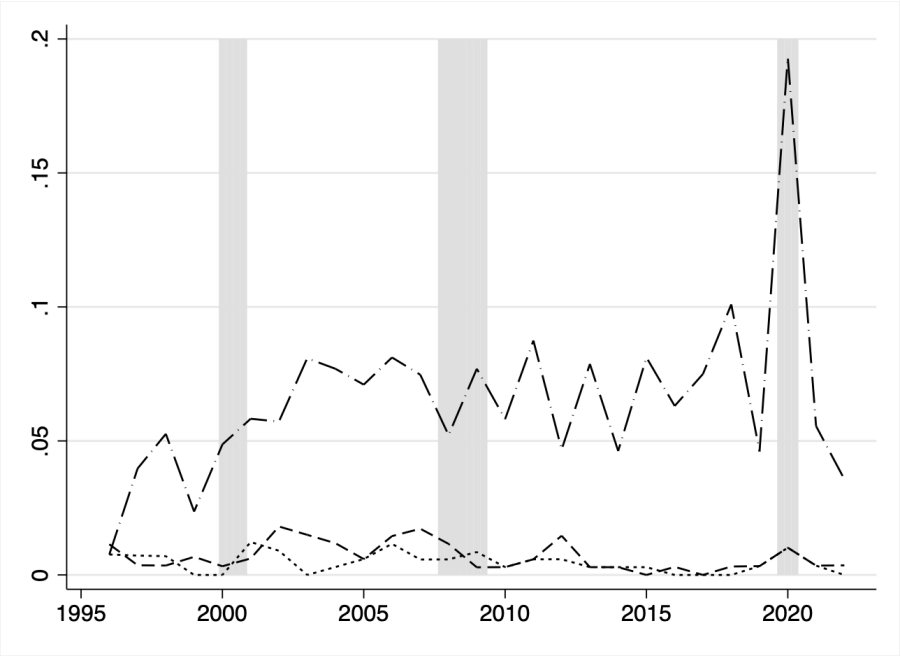


(b) Non-IG rated firms

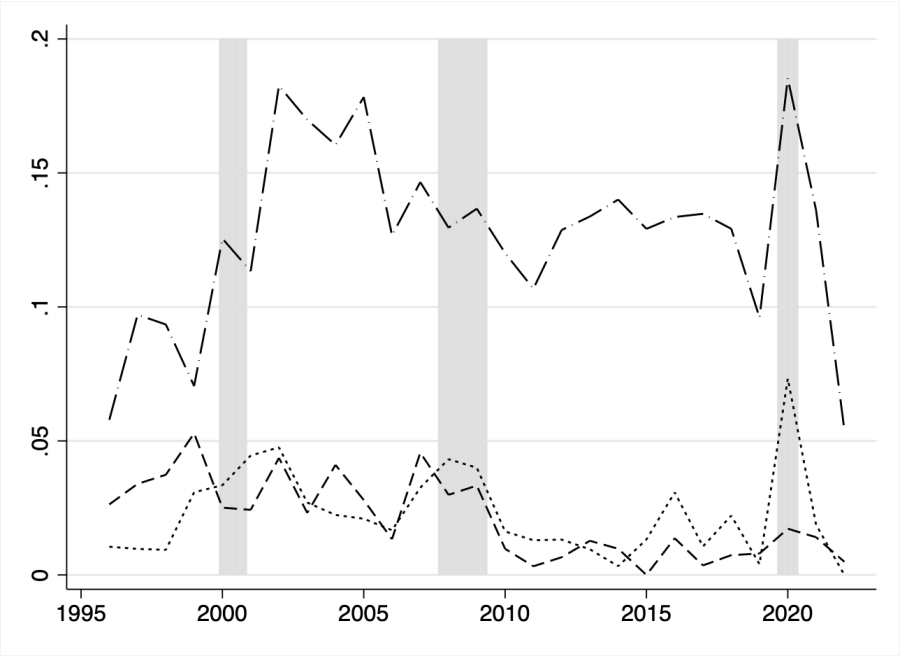


(c) Unrated firms

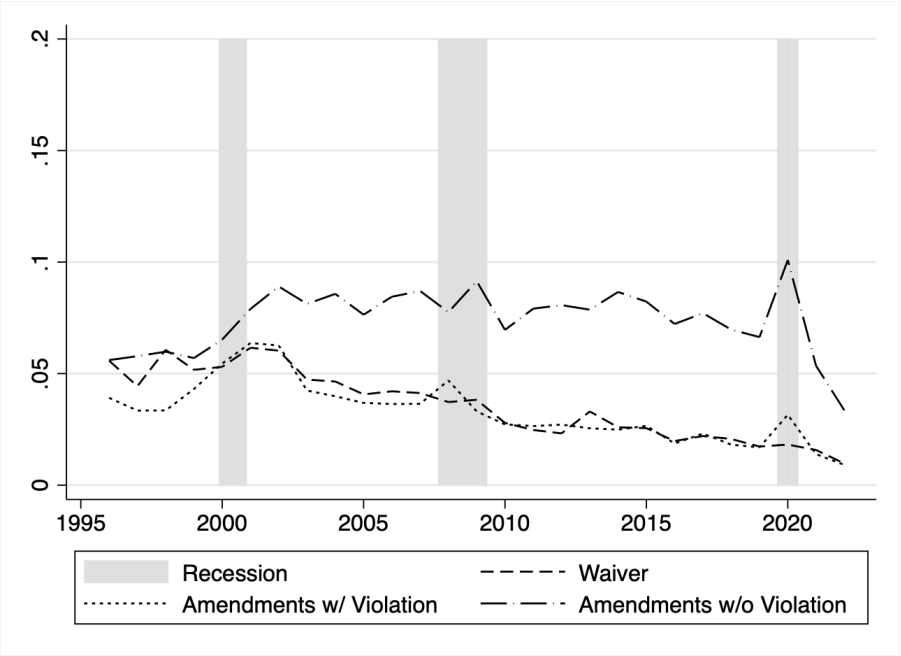
Figure 3: **Technical defaults and Loan Amendments by credit rating**
This figure plots the annual share of technical defaults and loan amendments within their credit rating. The shaded areas represent the NBER recession periods. The right side plots the combined share of technical defaults and amendments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



(a) IG rated firms



(b) Non-IG rated firms



(c) Unrated firms

Figure 4: **Consequences of Covenant Violations by Credit Rating**
This figure plots the time-series of *Amendments w/o Violation*, *Amendments w/ Violation* and *Waiver* over the 1996 to 2022 period for different rating classes, IG, Non-IG and unrated firms.

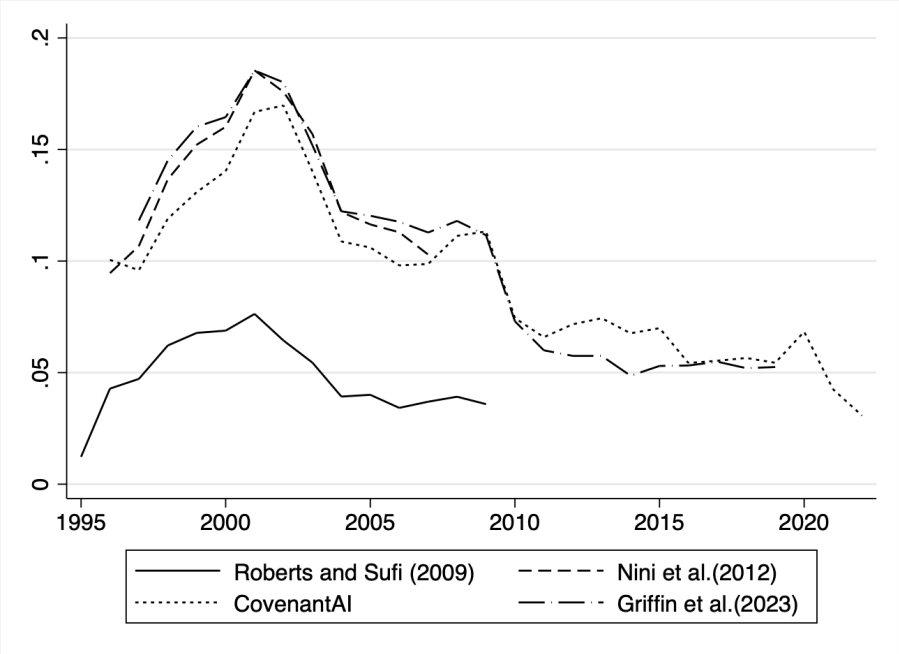
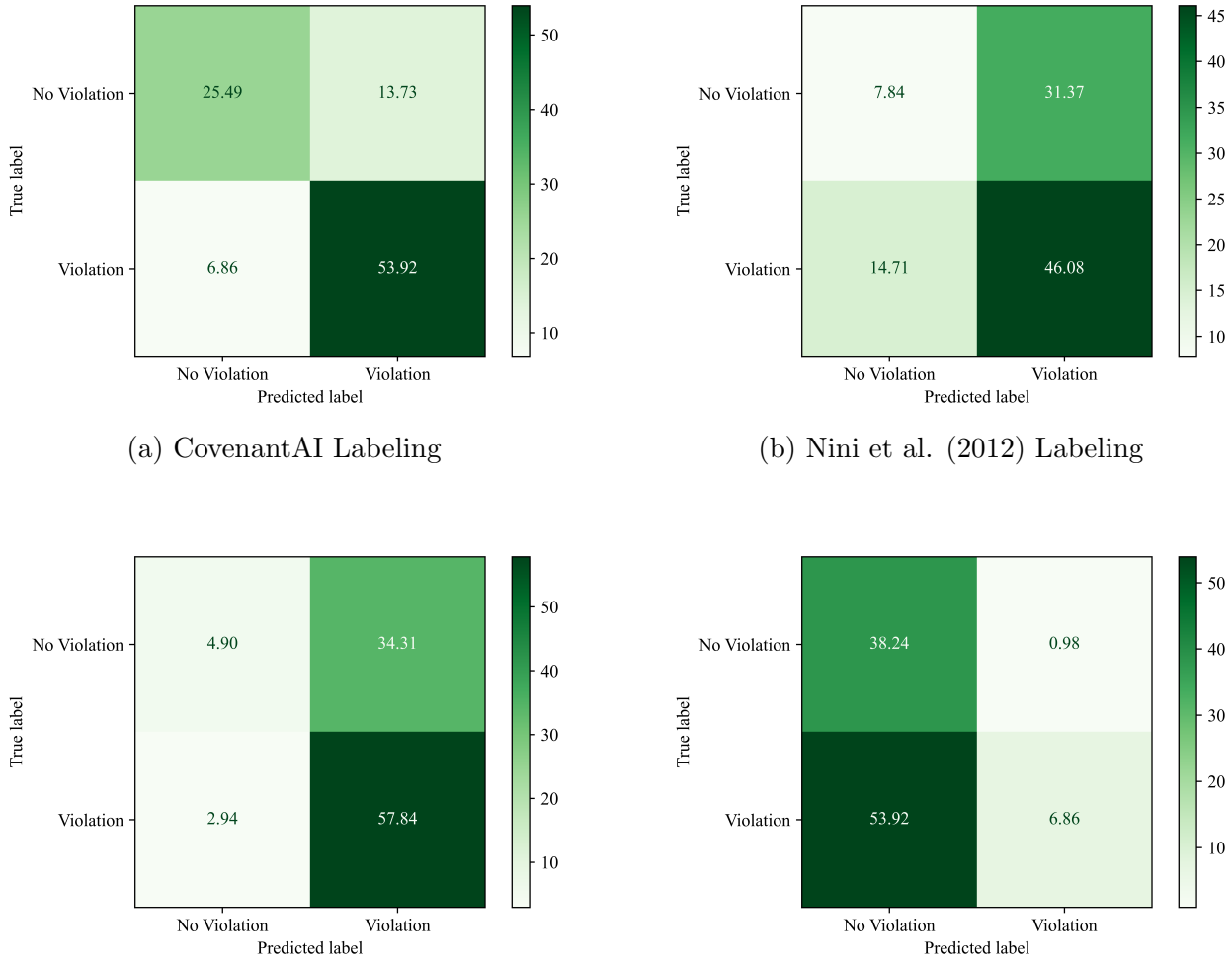


Figure 5: **Comparison of Covenant Violation Rates**
This figure shows covenant violation rates of different approaches used in the literature. The data for the time-series of Roberts and Sufi (2009a) and Griffin et al. (2024) are from Appendix I in Griffin et al. (2024). The data for Nini et al. (2012) are from their Appendix. "CovenantAI" are violations obtained from our model.



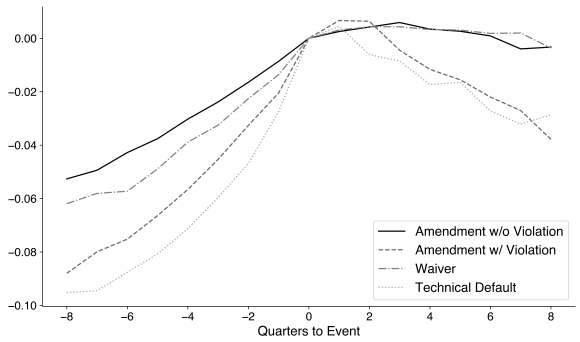
(a) CovenantAI Labeling

(b) Nini et al. (2012) Labeling

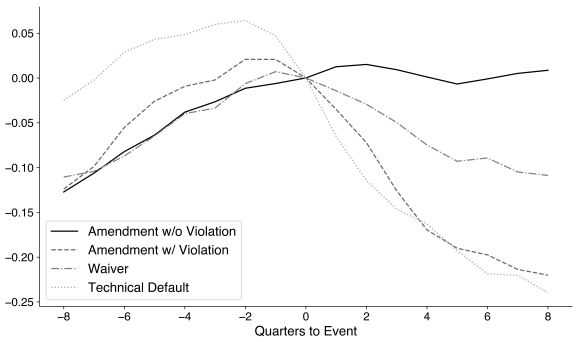
(c) Keyword Approach Labeling

(d) Roberts and Sufi (2009) Labeling

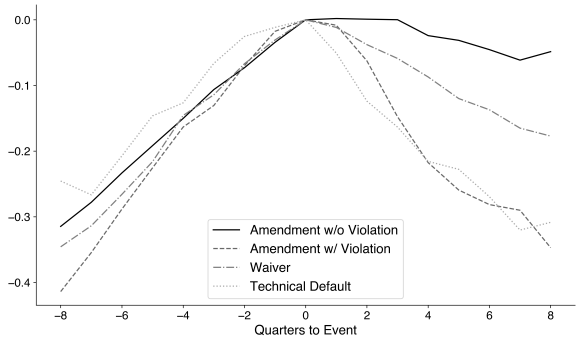
Figure 6: **Confusion Matrices of the Different Approaches.**
This figure plots the confusion matrices of the different approaches for two categories *No Violation* and *Violation*. The true value is displayed on the vertical axis, and the value predicted by the respective model is on the horizontal axis. Panel A shows the performance of CovenantAI, where we created the "Violation" class by adding up *Waiver*, *Amendment w/ Violation* and *Technical Default* cases. Panel B shows the performance of the labeling by Nini et al. (2012) and Panel C the replication of the approach by Nini et al. (2012) without manual adjustments. Panel D plots the performance of the Roberts and Sufi (2009a) using the Dealscan data. The confusion matrices are constructed based on a random dataset of 102 firm quarters, where CovenantAI didn't agree with either of the approaches and it is therefore not representative for the full sample.



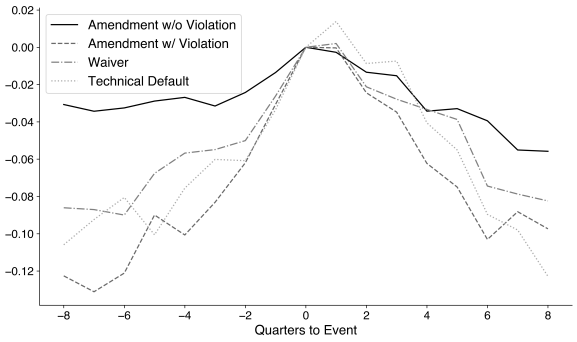
(a) Leverage Ratio



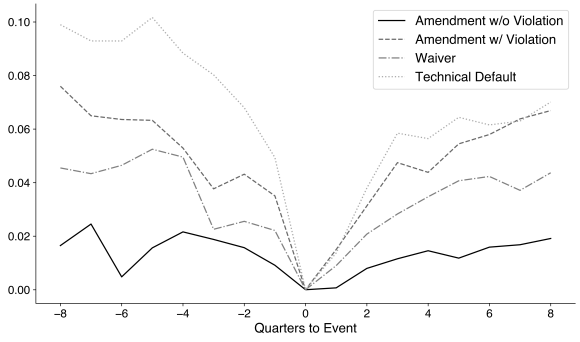
(b) LN(PPE)



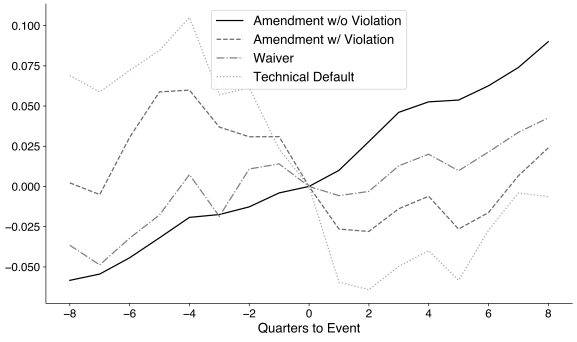
(c) Ln(Debt)



(d) CL Usage



(e) Operating Income/Assets



(f) Ln(Sales)

Figure 7: **Change in Ratios for Violation and Amendment Categories**
This figure plots the pre and post event performance as a change to the time of the event (t = 0) of the leverage ratio (a), the Ln(PPE) (b), the Ln(Debt) (c), the usage of credit lines (d), the operating income/ assets (e) and the Ln(Sales) (f) for the five violation and amendment categories.

Table 1: **Prior Research**

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

Authors	Title	Journal	Focus	Time period	Data Source	ML/AI
Denis and Wang (2014)	Debt Covenant Renegotiations and Creditor Control Rights	JFE	Impact of violations on CapEx restrictions, Debt/EBITDA restrictions, CapEx and Leverage	1996-2005	10-K / 10-Q	No
Roberts (2015)	The role of dynamic renegotiation and asymmetric information in financial contracting	JFE	Frequency of renegotiations; changes in contract terms (amount, pricing, maturity, covenant structure)	1991-2011	10-K	No
Demerjian and Owens (2016)	Measuring the probability of financial covenant violation in private debt contracts	JAE	Measuring covenant violation probability	1987-2004	Dealscan and Tearsheets	No
Falato and Liang (2016)	Do Creditor Rights Increase Employment Risk? Evidence from Loan Covenants	JF	Employment	1994-2010	Dealscan	No
Chava, Nanda, and Xiao (2017)	Lending to Innovative Firms	RCFS	Innovation	1987-2011	Dealscan	No
Freudenberg et al. (2017)	Covenant Violations and Dynamic Loan Contracting	JCF	Dynamic effect of violations on contract terms and covenant structure	1996-2010	10-K / 10-Q	No
Gu, Mao, and Tian (2017)	Banks' Interventions and Firms' Innovation: Evidence from Debt Covenant Violations	JLE	Innovation	1996-2008	10-K / 10-Q	No
Balsam, Gu, and Mao (2018)	Creditor Influence and CEO Compensation: Evidence from Debt Covenant Violations	AR	Innovation	1997-2008	10-K / 10-Q	No
Acharya et al. (2020)	Bank lines of credit as contingent liquidity: Covenant violations and their implications	JFI	Credit line contract terms	2002-2011	10-K	No
Ersahin et al. (2021)	Creditor control rights and resource allocation within firms	JFE	Within firm resource allocation and restructuring outcomes	1996-2009	10-K / 10-Q	No
Bird, Ertan, Karolyi, and Ruchti (2022)	Lender Forbearance	JFQA	Determinants of violation; Contract enforcement (fees and renegotiations)	1996-2008	10-K / 10-Q	No
Chodorow-Reich and Falato (2022)	The Loan Covenant Channel: How Bank Health Transmits to the Real Economy	JF	Credit reduction upon covenant violation; real effects	2006-2011	Shared National Credit (SNC) program	No

Authors	Title	Journal	Focus	Time period	Data Source	ML/AI
Dyreng et al. (2022)	Measurement Error when Estimating Covenant Violations	WP	Measurement error when calculating slack using commerical data bases	2000-2016	10-K / 10-Q	No
Griffin et al. (2024)	Losing Control? The Two-Decade Decline in Loan Covenant Violations	JF	Ex-ante covenant design	1997-2019	10-K	No
Haque and Kleymenova (2023)	Private Equity and Debt Contract Enforcement: Evidence from Covenant Violations	WP	Access to credit for PE vs non-PE owned firms	2012-2021	Shared National Credit (SNC) program	No

Table 2: **Correlation Matrix Different Approaches**

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

Panel A: Correlation Matrix Yearly Violation Rates

	Roberts and Sufi (2009a)	Nini et al. (2012)	**CovenantAI**	Griffin et al. (2024)
Roberts and Sufi (2009a)	1.0000	0.7817	0.8305	0.9450
Nini et al. (2012)	0.7817	1.0000	0.7646	0.8300
CovenantAI	0.8305	0.7646	1.0000	0.9732
Griffin et al. (2024)	0.9450	0.8300	0.9732	1.0000

Panel B: Correlation Matrix Firm Quarter Observations

	Roberts and Sufi (2009a)	Nini et al. (2012)	CovenantAI
Roberts and Sufi (2009a)	1	0.4743	0.4292
Nini et al. (2012)	0.4743	1	0.6812
CovenantAI	0.4292	0.6812	1

Table 3: **Summary Statistics**

This table provides summary statistics of important firm characteristics. All absolute values are given in USD millions. All variables are defined in the Appendix (Table 10).

Summary Statistics					
	Mean	p25	Median	p75	SD
Amendment	0.47	0.00	0.00	1.00	0.50
Amendment w/o Violation	0.30	0.00	0.00	1.00	0.46
Violation	0.35	0.00	0.00	1.00	0.48
Technical Default	0.16	0.00	0.00	0.00	0.37
Control Variables					
Operating Income/ Assets	-0.10	-0.11	0.07	0.14	2.77
Leverage Ratio	0.25	0.06	0.21	0.38	0.23
Interest Expenses/ Assets	0.03	0.01	0.02	0.03	0.03
NWA/ Assets	0.46	0.30	0.49	0.69	0.31
Current Ratio	3.63	1.40	2.28	4.11	3.93
MTB	2.37	1.22	1.72	2.77	1.88
Dependend Variables					
Ln(Assets)	5.35	3.94	5.16	6.55	1.85
Ln(PPE)	3.31	1.56	3.15	5.02	2.52
CapEx/ Assets	0.06	0.02	0.04	0.07	0.07
CashAqui/ Assets	0.03	0.00	0.01	0.04	0.07
Employees	7.75	0.11	0.66	3.96	40.25
NDI/ Assets	0.46	-0.00	0.00	0.02	28.83
Ln(Debt)	3.33	1.42	3.27	5.31	2.69
Cash/ Assets	0.25	0.04	0.13	0.39	0.26
Ln(Payout)	0.65	0.00	0.09	0.71	1.19
Cash Ratio	0.50	0.26	0.50	0.74	0.28
Usage	0.29	0.05	0.22	0.47	0.27
Operating Income/ Assets	-0.10	-0.11	0.07	0.14	2.77
Ln(Sales)	3.52	2.13	3.57	5.02	2.24
Ln(Costs)	3.59	2.29	3.45	4.81	1.92
Downgrade	0.21	0.00	0.00	0.00	0.41
Default	0.03	0.00	0.00	0.00	0.17
Spread	196.85	137.50	198.12	250.00	84.57
Ln(Loan Amount)	4.71	3.73	4.83	5.73	1.42
Observations	11,530				

Table 4: **Firm Adjustments to Covenant Violations**

This table relates covenant violations to financial and real adjustments of firms and the access to credit. The unit of observation is the firm-quarter level t. The sample period is 1996 to 2022. $Violation$ is an indicator variable that is one if a firm i violates a covenant in quarter t. Panel A relates covenant violations to firm adjustments in investment and employment over a period of four quarters $(t+4)$ after a covenant violation. Ln(Δ Assets) is the natural logarithm of the change in total assets (column 1), Ln(Δ PPE) is the natural logarithm of the change in property, plant and equipment (column 2), $\Delta\frac{CapEx}{Assets}$ is the change in capital expenditures over assets (column 3), $\Delta\frac{CashAcq}{Assets}$ is the change in cash acquisitions over assets (column 4), $\Delta Employment$ is defined as employment growth (column 5). Panel B relates covenant violations to firm adjustments in financial policies over a period of four quarters $(t+4)$ after a covenant violation. $\Delta\frac{NDI}{Assets}$ is the change in net debt issuances over total assets (column 1), $Ln(\Delta Debt)$ is the natural logarithm of the change in total debt (column 2), $\Delta\frac{Cash}{Assets}$ is the change of cash over average assets (column 3), $\Delta Ln(Payout)$ the change in the natural logarithm of shareholder payouts (column 4), $\Delta CashRatio$ is the change in firm's cash over the sum of the undrawn credit lines and cash (column 5), and $\Delta Usage$ is the change in the drawn amount of credit lines over the total balance of credit lines outstanding (column 6). Panel C relates covenant violations to firm adjustments in operational and financial performance over a period of four quarters $(t+4)$ after a covenant violation. $\Delta\frac{OpIncome}{Assets}$ is the change in operating income over Assets (column 1), $Ln(\Delta Sales)$ is the natural logarithm of the change in sales (column 2), $Ln(\Delta Cost)$ is the natural logarithm of operating costs (column 3), $\Delta\frac{EBIT}{Assets}$ is change in EBIT over assets (column 4), $Downgrade$ is an indicator that is one if the firm was downgraded during this period (column 5), and $Default$ is an indicator that is one if the company filed for Chapter 7 or Chapter 11 during this period (column 6). Panel D relates covenant violations to access to credit separately for term loans and credit lines. As proxies for access to credit and dependent variables we use $\Delta Spread$, which is the change in the loan spread compared to the previous loan (columns (1) and (4)), Δ Ln(Loan Amount), which is the natural logarithm of the change in the loan amount compared to the previous loan (column (2) and (5)), and *Credit Access Reduction* (columns (3) and (6)), an indicator that is one of the loan amount is lower compared to the previous loan. The changes are always calculated based on new loans issued in the eight quarters following a covenant violation. The regression results are reported separately for term loans and credit lines. Panel E relates covenant violations to access to credit separately for loans that are refinancing previously issued loans (*Refinancing*) as well as newly issued loans (*Non-Refinancing*) for credit line loans. The dependent variables are the same as in Panel A. All regressions include the following firm characteristics as control variables that are frequently used as covenants in loan contracts (*Covenant Controls*): the ratio of operating income over average assets, leverage ratio, the ratio of net worth over assets, the market-to-book-ratio, the ratio of interest expenses and average assets, and the current ratio. Each specification includes a four-quarter lag of the covenant violation variable ($Violation_{t-4}$), four-quarter lags of *Covenant Controls*, and higher order terms of *Covenant Controls*. Each specification includes industry and quarter fixed effects (calendar and fiscal quarter) and we cluster standard errors at the firm and the reporting quarter level. $\Delta Employment$ and $\Delta\frac{EBIT}{Assets}$ are only available annually; we use industry fixed effects, and cluster standard errors at the industry level. Standard errors are reported in parentheses ($^{*}\ p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$).

Panel A: Investment & Employment

	(1) Δ Ln(Assets)	(2) Δ Ln(PPE)	(3) $\Delta\frac{CapEx}{Assets}$	(4) $\Delta\frac{CashAcq}{Asset}$	(5) Empl Growth
Violation	-0.081***	-0.088***	-0.004**	-0.002	-0.083*
	(-12.841)	(-9.847)	(-2.314)	(-0.575)	(-1.743)
Industry FE	Yes	Yes	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes	Yes	No
Calendar Quarter FE	Yes	Yes	Yes	Yes	No
Year FE	No	No	No	No	Yes
R^2	0.124	0.091	0.011	0.013	0.064
N	201,532	199,826	198,302	191,096	21,708
$Violation_{t-4}$	Yes	Yes	Yes	Yes	Yes
Covenant Controls	Yes	Yes	Yes	Yes	Yes
Higher Order Controls	Yes	Yes	Yes	Yes	Yes
Lagged Covenant Controls	Yes	Yes	Yes	Yes	Yes

Panel B: Financial Policies

	(1) $\Delta\frac{NDI}{Assets}$	(2) Δ Ln(Debt)	(3) $\Delta\frac{Cash}{Asset}$	(4) Δ Ln(Payout)	(5) Δ Cash Ratio	(6) Δ Usage
Violation	-0.007	-0.110***	0.004**	-0.028**	0.003	-0.023***
	(-0.337)	(-6.550)	(2.426)	(-2.161)	(0.473)	(-2.675)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.008	0.062	0.064	0.030	0.044	0.047
N	198,277	169,407	201,489	177,354	76,874	70,537
$Violation_{t-4}$	Yes	Yes	Yes	Yes	Yes	Yes
Covenant Controls	Yes	Yes	Yes	Yes	Yes	Yes
Higher Order Controls	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Covenant Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Operational and Financial Performance

	(1) $\Delta \frac{OperatingIncome}{Assets}$	(2) Δ Ln(Sales)	(3) Δ Ln(Cost)	(4) $Downgrade_{t+4}$	(5) $Default_{t+4}$
Violation	0.035*	-0.038***	-0.062***	-0.010	0.025***
	(1.981)	(-4.351)	(-8.065)	(-0.542)	(7.052)
Industry FE	Yes	Yes	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	No	No	No	No
R^2	0.399	0.047	0.071	0.071	0.111
N	197,072	193,723	197,424	19,476	227,808
$Violation_{t-4}$	Yes	Yes	Yes	Yes	Yes
Covenant Controls	Yes	Yes	Yes	Yes	Yes
Higher Order Controls	Yes	Yes	Yes	Yes	Yes
Lagged Covenant Controls	Yes	Yes	Yes	Yes	Yes

Panel D: Term Loan vs. Credit Line

	Term Loan			Credit Line		
	(1) $\Delta Spread$	(2) Ln(Δ Loan)	(3) Credit Access	(4) $\Delta Spread$	(5) Ln(Δ Loan)	(6) Credit Access
Violation	37.273	-0.102	-0.048	13.149	-0.169***	0.119***
	(1.502)	(-0.677)	(-0.691)	(1.366)	(-2.968)	(3.525)
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.123	0.080	0.080	0.173	0.052	0.061
N	4,204	4,204	4,204	9,851	11,026	11,026
Covenant Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel E: Refinancing vs. Non Refinancing (Credit Lines)

	Refinancing			Non Refinancing		
	(1) $\Delta Spread$	(2) Ln(Δ Loan)	(3) Credit Access	(4) $\Delta Spread$	(5) Ln(Δ Loan)	(6) Credit Access
Violation	18.631*	-0.178**	0.124***	-13.283	-0.154	0.115
	(1.840)	(-2.341)	(2.908)	(-0.858)	(-0.829)	(1.538)
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.193	0.066	0.069	0.163	0.145	0.143
N	8,526	8,526	8,526	2,495	2,495	2,495
Covenant Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: **Summary Statistics- Technical Defaults vs. Amendments**

This table provides summary statistics for firms that remain in technical default within two quarters following a covenant violation (Panel A) and those firms that obtain an amendment (Panel B). All variables are defined in Appendix A.

Panel A: Firms in Technical Default					
	Mean	p25	Median	p75	SD
Control Variables					
Operating Income/ Assets	-0.05	-0.12	0.06	0.12	0.36
Leverage Ratio	0.34	0.14	0.30	0.49	0.25
Interest Expenses/ Assets	0.04	0.01	0.03	0.06	0.04
NWA/ Assets	0.34	0.17	0.39	0.59	0.34
Current Ratio	2.48	1.19	1.84	3.02	2.05
MTB	2.13	1.18	1.57	2.47	1.64
Dependend Variables					
Ln(Assets)	5.11	3.65	4.89	6.35	1.87
Ln(PPE)	3.36	1.55	3.21	4.94	2.39
CapEx/ Assets	0.07	0.02	0.04	0.08	0.10
CashAqui/ Assets	0.03	0.00	0.01	0.05	0.08
Employees	5.78	0.16	0.84	4.27	14.42
NDI/ Assets	0.02	-0.00	0.01	0.02	0.11
Ln(Debt)	3.46	1.73	3.26	5.21	2.42
Cash/ Assets	0.17	0.04	0.11	0.26	0.18
Ln(Payout)	0.52	0.00	0.06	0.53	1.01
Cash Ratio	0.48	0.24	0.48	0.71	0.27
Usage	0.32	0.09	0.25	0.51	0.27
Operating Income/ Assets	-0.05	-0.12	0.06	0.12	0.36
Ln(Sales)	3.43	1.95	3.35	4.86	2.04
Ln(Costs)	3.52	2.15	3.38	4.73	1.77
Downgrade	0.18	0.00	0.00	0.00	0.39
Default	0.09	0.00	0.00	0.00	0.29
Spread	220.15	162.50	212.50	275.00	84.69
Ln(Loan Amount)	4.58	3.58	4.68	5.53	1.39
Observations	571				

Table B: Firms with Amendments					
	Mean	p25	Median	p75	SD
Control Variables					
Operating Income/ Assets	-0.01	-0.02	0.08	0.13	0.49
Leverage Ratio	0.29	0.12	0.26	0.41	0.21
Interest Expenses/ Assets	0.03	0.01	0.02	0.04	0.03
NWA/ Assets	0.41	0.27	0.44	0.59	0.27
Current Ratio	2.46	1.31	1.98	2.96	1.82
MTB	1.91	1.14	1.48	2.20	1.30
Dependend Variables					
Ln(Assets)	5.26	3.91	5.14	6.37	1.71
Ln(PPE)	3.47	1.81	3.42	5.02	2.25
CapEx/ Assets	0.06	0.02	0.04	0.07	0.07
CashAqui/ Assets	0.03	0.00	0.01	0.04	0.06
Employees	7.17	0.20	1.15	5.15	24.44
NDI/ Assets	0.10	-0.00	0.01	0.02	3.55
Ln(Debt)	3.51	1.90	3.45	5.14	2.30
Cash/ Assets	0.16	0.04	0.09	0.22	0.17
Ln(Payout)	0.54	0.00	0.11	0.62	0.93
Cash Ratio	0.48	0.25	0.48	0.70	0.27
Usage	0.33	0.11	0.29	0.52	0.26
Operating Income/ Assets	-0.01	-0.02	0.08	0.13	0.49
Ln(Sales)	3.75	2.48	3.76	4.93	1.83
Ln(Costs)	3.78	2.54	3.70	4.82	1.65
Downgrade	0.27	0.00	0.00	1.00	0.44
Default	0.05	0.00	0.00	0.00	0.22
Spread	211.03	155.28	203.66	256.25	77.00
Ln(Loan Amount)	4.46	3.59	4.50	5.39	1.31
Observations	2,191				

Table 6: **Determinants of Loan Amendments**

Panel A relates firm characteristics to the likelihood that a firm obtains an amendment after a covenant violation. *Amendment* is an indicator that is one if the covenant violation was amended and 0 if the firm remained in technical default. Column (1) includes the distance to default measure (*DD*) described in Bharath and Shumway (2008) without controls or fixed effects. Column (2) includes industry and quarter-fixed effects. In column (3), we add the following firm characteristics: *Operating Income/Assets* is the ratio of operating income and average assets, *Leverage Ratio* is the debt-equity ratio, *Interest Expenses/Assets* is the ratio of interest expenses over average assets, *NWA/Assets* is the ratio of net worth over assets, *Current Ratio* is the ratio of current assets over current liabilities, *MTB* is the market-to-book-ratio. Column (4) additionally includes lagged control variables (4 lags), higher order controls, and the rating categories (*IG* and *Non-IG*) with unrated firms being the omitted group. Column (5) adds *Ln(Assets)*, the natural logarithm of total assets, as additional firm characteristics.
Panel B relates the decision to amend a covenant violation to financial and real adjustments of firms. The unit of observations is the firm-quarter level and we condition the sample on firms that have violated a covenant. Panel A relates amendments to firm adjustments over a period of four quarters (t + 4) after a covenant violation. $Amendment_{i,t}$ is an indicator variable that is one if the firm obtained an amendment after a covenant violation and zero if it remained in technical default in the two quarters after the violation. Firm outcome variables are $\Delta Ln(Assets)$ in column (1), $\Delta Ln(PPE)$ in column (2), $\Delta Ln(Shareholder\ Payout)$ in column (3), $\Delta Ln(Cash\ Ratio)$ in column (4), $\Delta Ln(Operating\ Costs)$ in column (5) and *Default* is an indicator that is one if the company filed for Chapter 7 or Chapter 11 during this period (column 6). The regressions include the control variables shown in column (5) of Panel A Table 6 (only in period t). We include the first two digits of the standard industry classification and quarter fixed effects and cluster standard errors at the firm and quarter level. Standard errors are reported in parentheses ($^{*}\ p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$).

Panel A: Amendment Likelihood

	(1) Pr(Amendment)	(2) Pr(Amendment)	(3) Pr(Amendment)	(4) Pr(Amendment)	(5) Pr(Amendment)
DD	0.018***	0.015	0.007	0.008	0.007
	(4.496)	(.)	(1.217)	(1.382)	(1.154)
IG				-0.109	-0.118
				(-1.250)	(-1.382)
Non-IG				-0.091	-0.097
				(-1.508)	(-1.606)
Ln(Assets)					0.004
					(0.667)
Operating Income/ Assets			0.154***	0.157***	0.153***
			(5.829)	(6.031)	(5.618)
Leverage Ratio			-0.227***	-0.229***	-0.232***
			(-3.634)	(-3.671)	(-3.755)
Interest Expenses/ Assets			-0.259	-0.258	-0.232
			(-0.488)	(-0.486)	(-0.436)
NWA/ Assets			-0.076	-0.086*	-0.083
			(-1.477)	(-1.664)	(-1.586)
Current Ratio			0.011	0.011	0.011
			(1.158)	(1.197)	(1.215)
MTB			0.012	0.011	0.011
			(1.166)	(1.067)	(1.111)
Firm Quarter FE	No	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes
Calendar Quarter FE	No	Yes	Yes	Yes	Yes
R^2	0.007	0.069	0.110	0.111	0.111
N	4,301	4,297	3,158	3,158	3,158
Higher Order Controls	No	No	No	Yes	Yes
Lagged Covenant Controls	No	No	No	Yes	Yes

Panel B: Amendments and firm adjustments

	(1) Δ Ln(Assets)	(2) Δ Ln(PPE)	(3) Δ Ln(Payout)	(4) Δ Cash Ratio	(5) Δ Ln(Cost)	(6) $Default_{t+4}$
Amendment after Violation	0.041***	0.054***	0.016	-0.005	0.048***	-0.029***
	(3.473)	(2.869)	(0.814)	(-0.349)	(3.325)	(-4.668)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.134	0.150	0.144	0.190	0.186	0.190
N	6,832	6,807	5,793	2,015	6,554	8,237
Operating Income Controls	Yes	Yes	Yes	Yes	Yes	Yes
Leverage Ratio Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: **Covenant Violations - Amendments vs. Waivers**

This table relates the decision to amend a covenant violation to financial and real adjustments of firms based on a further breakdown of loan amendments. The unit of observations is the firm-quarter level and we condition the sample on firms that have violated a covenant or obtained an amendment. Panel A shows the distributions of Amendments without Violations (*Amendment w/o Violation*), Amendments with Violations (*Amendment w/ Violation*), *Waiver* and *Technical Defaults* for the full sample (1) and for the Rating categories (2-4). *Amendment w/o Violation* is an indicator variable that is one if the firm obtained an amendment without being in violation of a covenant and *Amendment w/ Violation* is an indicator variable that is one if the firm obtained an amendment in combination with a covenant violation. *Waiver* is an indicator variable that is one if the firm obtained a waiver, what also implies that they had covenant violation and *Technical Defaults* is an indicator variable that is one if the firm obtained no amendment or waiver in combination with a covenant violation.
Panel B relates *Technical Defaults* to firm adjustments over a period of four quarters after the violation. *Technical Default (0/1)* is an indicator variable that is one if the violation was not resolved by an amendment or waiver and zero if the firm obtained a waiver or an amendment following the violation. Firm outcome variables are $\Delta Ln(Assets)$ in column (1), $\Delta Ln(PPE)$ in column (2), $\Delta Ln(Shareholder\ Payout)$ in column (3), $\Delta Ln(Cash\ Ratio)$ in column (4), $\Delta Ln(Operating\ Costs)$ in column (5) and *Default* is an indicator that is one if the company filed for Chapter 7 or Chapter 11 during this period (column 6).
Panel C relates *Amendment w/o Violation*, *Amendment w/ Violation*, *Waiver* and *Technical Defaults* to firm adjustments over a period of four quarters (t + 4) after a covenant violation. We use the same firm outcome variables as in Panel B. We include the first two digits of the standard industry classification and quarter fixed effects and cluster standard errors at the firm and quarter level. Standard errors are reported in parentheses ($^{*}\ p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$).

Panel A: Sample Distribution (in %)

	(1) Full Sample	(2) IG	(3) Non-IG	(4) Unrated
Amendment *w/o* Violation	7.60	6.90	12.56	7.60
Amendment *w/* Violation	3.15	0.54	2.15	3.16
Waiver	3.46	0.74	1.96	3.46
Technical Default	2.19	0.42	1.37	2.20

Panel B: Firms in Technical Default

	(1) Δ Ln(Assets)	(2) Δ Ln(PPE)	(3) Δ Ln(Payout)	(4) Δ Cash Ratio	(5) Δ Ln(Cost)	(6) $Default_{t+4}$
Technical Default (0/1)	-0.056***	-0.061***	-0.016	-0.003	-0.056***	0.029***
	(-4.097)	(-3.247)	(-0.906)	(-0.218)	(-3.181)	(4.033)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.176	0.159	0.079	0.125	0.148	0.171
N	11,216	11,187	9,754	4,360	10,891	13,111
Covenant Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Operational and Financial Performance

	(1) Δ Ln(Assets)	(2) Δ Ln(PPE)	(3) Δ Ln(Payout)	(4) Δ Cash Ratio	(5) Δ Ln(Cost)	(6) $Default_{t+4}$
Amendment *w/o* Violation	0.085***	0.091***	0.023	0.002	0.071***	-0.031***
	(5.701)	(4.830)	(0.992)	(0.110)	(3.612)	(-4.146)
Amendment *w/* Violation	0.015	0.021	0.002	0.011	0.025	-0.021**
	(0.990)	(0.908)	(0.087)	(0.756)	(1.416)	(-2.438)
Waiver	0.041***	0.045**	0.017	-0.002	0.057***	-0.032***
	(2.727)	(2.145)	(0.824)	(-0.143)	(2.996)	(-4.567)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.181	0.162	0.079	0.125	0.149	0.171
N	11,216	11,187	9,754	4,360	10,891	13,111
Covenant Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: **Summary Statistics**

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

Panel A: Summary Statistics

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

Panel B: Covenant Definitions

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

Table 9: **Covenants Pre and Post Event**

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

Panel A: Likelihood of including Covenants

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

Panel B: Covenant Thresholds

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

A Appendix

Variable Definition

Table 10: Compustat Variables used for quarterly financial data

Panel A: Compustat & Capital IQ

Variable Names	Variables	Compustat Variables/ Capital IQ
Assets	Total assets	= atq
$\overline{Assets}$	Average assets	= (Total assets$_t$ + Total assets$_{t-1}$) /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		
Operating Income/ Assets	Operating income scaled by average assets	= oibdpq / Average assets
Leverage Ratio	Leverage ratio	= Total debt / Total assets
Interest Expenses/ Asset	Interest expense scaled by average assets	= xintq / Average assets
NWA/ Assets	Net worth to assets ratio	= seqq / Total assets
Current Ratio	Current ratio	= actq / lctq
MTB	Market-to-book-ratio	= Market value / Total assets
Dependent Variables		
Δ Ln(Assets)	Change in Ln(assets)	= Ln(Total assets$_{t+4}$)-Ln(Total assets$_t$)
Δ Ln(PPE)	Change in Ln(PPE)	= Ln(PPE$_{t+4}$)-Ln(PPE$_t$)
$\Delta\frac{CapEx}{Assets}$	Capital expenditures scaled by average assets	= Capital expenditures / Average assets
$\Delta\frac{CashAcq}{Assets}$	Cash acquisitions scaled by average assets	= Cash acquisitions / Average assets
Empl Growth	Relative change of employees	= (emp$_t$- emp$_{t-1}$) / emp$_{t-1}$
$\Delta\frac{NDI}{Assets}$	Net debt issuance scaled by average assets	= (Total debt$_t$ – Total debt$_{t-1}$) / Average assets$_t$
Δ Ln(Debt)	Change in Ln(total debt)	= Ln(total debt$_{t+4}$)-Ln(total debt$_t$)
$\Delta\frac{Cash}{Assets}$	Cash scaled by assets	= cheq /Total assets
Δ Ln(Payout)	Change in Ln(shareholder payout)	= Ln(shareholder payout$_{t+4}$)-Ln(shareholder payout$_t$)
$\Delta\frac{OpIncome}{Assets}$	Change Operating cash flow by average assets	= (OpIncome/Assets$_{t+4}$) - (OpIncome/Assets$_t$)
Δ Ln(Sales)	Change in Ln(sales)	= Ln(Sales$_{t+4}$)-Ln(Sale$_t$)
Δ Ln(Cost)	Change in Ln(Operating Costs)	= Ln(Operating Costs$_{t+4}$)-Ln(Operating Costs$_t$)
Δ Cash Ratio	Total assets	= cheq/ (undrawn_balance + cheq)
Δ Usage	change in usage	= usage$_{t+4}$-usage$_t$

Panel B: Dealscan

Variable Names	Variables	Dealscan
Term Loan	1/0	loantype "TermLoan"
Credit Line	1/0	loantype "Revolver"
Δ Spread	Change in spread (in bps)	= $AISD_{i+1} - AISD_i$
Δ Ln(Loan Amount)	Change in LoanAmount	= Ln(facilityamt$_{i+1}$) - Ln(facilityamt$_i$)

Table 11: **Examples for Labeling Disagreement**

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

(1) **Link**	(2) **Reporting Date**	(3) **Nini**	(4) **CovenantAI**	(5) **Paragraph**	(6) **Keywords**
1060801/000095014903001934/f92308e10vq.htm	30.06.2003	0	1	The credit facility was amended on March 25, 2003 and again on July 18, 2003, as a result of non-compliance with the financial covenants of the facility.	
1086939/000095013102001978/d10q.txt	31.03.02	1	0	We amended our credit agreement on February 5, 2002 to include additional covenants. We will be in default if our cash expenditures incurred in connection with the Plan (including, without limitation, the costs of structuring and negotiating the divestiture transactions, terminating employees and closing facilities), exceeds by $10 million the sum of EBITDA from the discontinued management services operations plus the cash proceeds from these transactions. As of March 31, 2002, we were in compliance with all our credit agreement covenants [...]	in deafault
701345/000119312504040367/d10k.htm	31.12.03	1	0	Effective March 12, 2004, US Airways obtained covenant relief for the measurement periods beginning June 30, 2004 through December 31, 2005. If the Company is unable to meet these financial covenants, as amended, the Company would be in default under the ATSB Loan and the Stabilization Board would have the right to accelerate the ATSB Loan and exercise other remedies against the Company.	in default
912241/000119312505051263/d10k.htm	31.12.04	1	0	We maintain a $17.5 million working capital revolving line of credit facility with Foothill Capital Corporation. We have not drawn on this credit facility, but any borrowing will also increase our indebtedness and the related risks we currently face. We may not be in compliance with quarterly financial covenants to be able to borrow under this credit facility should it be deemed necessary.	not in compliance
930735/000110465903005515/j8935$_1$0k.htm	21.12.02	1	0	If we fail to comply with these covenants, and if our lenders do not agree to waive the covenants, then we would be in default under our debt agreements. If we are in default under our debt agreements, our lenders can request immediate repayment of all outstanding principal balances. We would not have sufficient liquidity to repay our indebtedness under these circumstances without substantial asset sales, and if we were unable to refinance our borrowings at that time, we would need to seek protection from our creditors	waiv, in default
931948/000103570404000120/d12924e10vk.htm	31.12.03	1	0	Events of default in the credit facility include: (1) a cross-default to other indebtedness of the company [...] (5) any breach or modification of any of the sales contracts. The company anticipates it will refinance the credit facility during 2004. The company is in compliance with its debt covenants at December 31, 2003.	modif

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

Table 12: **Covenant Violations - Financial and Real Adjustments**

This table relates covenant violations to financial and real adjustments of firms. The unit of observation is the firm-quarter level t. The sample period is 1996 to 2022. $Violation$ is an indicator variable that is one if a firm i violates a covenant in quarter t. Panel A relates covenant violations to firm adjustments in investment and employment over a period of four quarters $(t+4)$ after a covenant violation. Ln(Δ Assets) is the natural logarithm of the change in total assets (column 1), Ln(Δ PPE) is the natural logarithm of the change in property, plant and equipment (column 2), $\Delta\frac{CapEx}{Assets}$ is the change in capital expenditures over assets (column 3), $\Delta\frac{CashAcq}{Assets}$ is the change in cash acquisitions over assets (column 4), $\Delta Employment$ is defined as employment growth (column 5). Panel B relates covenant violations to firm adjustments in financial policies over a period of four quarters $(t+4)$ after a covenant violation. $\Delta\frac{NDI}{Assets}$ is the change in net debt issuances over total assets (column 1), $Ln(\Delta Debt)$ is the natural logarithm of the change in total debt (column 2), $\Delta\frac{Cash}{Assets}$ is the change of cash over average assets (column 3), $\Delta Ln(Payout)$ the change in the natural logarithm of shareholder payouts (column 4), $\Delta CashRatio$ is the change in firm's cash over the sum of the undrawn credit lines and cash (column 5), and $\Delta Usage$ is the change in the drawn amount of credit lines over the total balance of credit lines outstanding (column 6). Panel C relates covenant violations to firm adjustments in operational and financial performance over a period of four quarters $(t+4)$ after a covenant violation. $\Delta\frac{OpIncome}{Assets}$ is the change in operating income over Assets (column 1), $Ln(\Delta Sales)$ is the natural logarithm of the change in sales (column 2), $Ln(\Delta Cost)$ is the natural logarithm of operating costs (column 3), $\Delta\frac{EBIT}{Assets}$ is change in EBIT over assets (column 4), $Downgrade$ is an indicator that is one if the firm was downgraded during this period (column 5), and $Default$ is an indicator that is one if the company filed for Chapter 7 or Chapter 11 during this period (column 6). All regressions include the following firm characteristics as control variables that are frequently used as covenants in loan contracts (*Covenant Controls*): the ratio of operating income over average assets, leverage ratio, the ratio of net worth over assets, the market-to-book-ratio, the ratio of interest expenses and average assets, and the current ratio. Each specification includes a four-quarter lag of the covenant violation variable ($Violation_{t-4}$), four-quarter lags of *Covenant Controls*, and higher order terms of *Covenant Controls*. Each specification includes industry and quarter fixed effects (calendar and fiscal quarter) and we cluster standard errors at the firm and the reporting quarter level. $\Delta Employment$ and $\Delta\frac{EBIT}{Assets}$ are only available annually; we use industry fixed effects, and cluster standard errors at the industry level. Standard errors are reported in parentheses (* $p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$).

Panel A: Investment & Employment

	(1) Δ Ln(Assets)	(2) Δ Ln(PPE)	(3) $\Delta\frac{CapEx}{Assets}$	(4) $\Delta\frac{CashAcq}{Asset}$	(5) Empl Growth
Violation	-0.046***	-0.051***	-0.004***	-0.002	-0.264**
	(-11.253)	(-9.228)	(-2.992)	(-1.058)	(-2.051)
Industry FE	Yes	Yes	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes	Yes	No
Calendar Quarter FE	Yes	Yes	Yes	Yes	No
Year FE	No	No	No	No	Yes
R^2	0.123	0.091	0.011	0.013	0.027
N	201,532	199,826	198,302	191,096	24,451
$Violation_{t-4}$	Yes	Yes	Yes	Yes	Yes
Covenant Controls	Yes	Yes	Yes	Yes	Yes
Higher Order Controls	Yes	Yes	Yes	Yes	Yes
Lagged Covenant Controls	Yes	Yes	Yes	Yes	Yes

Panel B: Financial Policies

	(1) $\Delta\frac{NDI}{Assets}$	(2) Δ Ln(Debt)	(3) $\Delta\frac{Cash}{Asset}$	(4) Δ Ln(Payout)	(5) Δ Cash Ratio	(6) Δ Usage
Violation	0.004	-0.048***	0.002*	-0.033***	-0.000	-0.016**
	(0.245)	(-4.254)	(1.955)	(-2.698)	(-0.011)	(-2.310)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.008	0.061	0.064	0.030	0.044	0.047
N	198,277	169,407	201,489	177,354	76,874	70,537
$Violation_{t-4}$	Yes	Yes	Yes	Yes	Yes	Yes
Covenant Controls	Yes	Yes	Yes	Yes	Yes	Yes
Higher Order Controls	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Covenant Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Operational and Financial Performance

	(1) $\Delta \frac{OperatingIncome}{Assets}$	(2) Δ Ln(Sales)	(3) Δ Ln(Cost)	(4) $Downgrade_{t+4}$	(5) $Default_{t+4}$
Violation	0.024**	-0.013**	-0.028***	-0.015*	0.017***
	(2.346)	(-2.169)	(-5.652)	(-1.735)	(7.285)
Industry FE	Yes	Yes	Yes	Yes	Yes
Firm Quarter FE	Yes	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	No	No	No	No
R^2	0.399	0.047	0.071	0.071	0.112
N	197,072	193,723	197,424	19,476	227,808
$Violation_{t-4}$	Yes	Yes	Yes	Yes	Yes
Covenant Controls	Yes	Yes	Yes	Yes	Yes
Higher Order Controls	Yes	Yes	Yes	Yes	Yes
Lagged Covenant Controls	Yes	Yes	Yes	Yes	Yes