CovenantAI - New Insights into Covenant Violations*

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Abstract

This paper introduces CovenantAI, a novel artificial intelligence (AI)-powered tool that tracks SEC-reported covenant violations with improved accuracy over existing text-search methods, covering data from 1996 to 2022. It accurately identifies amendments, waivers, and technical defaults, providing a detailed timeline of covenant breaches. We use a "quasi" regression discontinuity approach to analyze the effects of these violations on key firm outcomes such as investments, employment, or credit access, revealing complex patterns and pronounced effects during economic downturns such as the COVID-19 pandemic. The changing loan market, resembling bond markets with the rise of CLOs and secondary trades, has decreased covenant reliance and violations among non-investment grade firms.

JEL classification: G21, G32, G34

Keywords: Covenant violations, Loan amendments, Waiver, Big data, Large language models, 10K/Q, Leveraged loans, COVID-19

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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. In this paper, we introduce the first artificial intelligence (AI) - powered covenant monitoring tool (called "CovenantAI") that not only deals with these limitations but can exploit the complexity of the language in regulatory filings. That is, we can flexibly adjust CovenantAI to identify the consequences of violations, i.e., amendments borrowers obtain before violations, amendments or waivers as a consequence of violations, or whether the firm remains in technical default.[3] Arguably, all of these consequences are associated with scenarios of varying economic severity for firms. To the best of our knowledge, this is the first paper that integrates an AI-powered tool into this research area, offering new insights into the economic implications of covenant violations.

Our first contribution is methodological in nature. We introduce CovenantAI, a tool that allows researchers to obtain quarterly information on covenant violations for virtually all U.S. firms directly from their 10K and 10Q filings with the SEC. To calibrate our model, we obtain more than 580,000 10K and 10Q filings using the CIK identifier of the universe of Compustat firms. We apply a small set of filters (described in detail in Section 2). Our final dataset comprises 11,432 U.S. publicly listed non-financial firms over the 1996 to 2022 period. Initially, we differentiate between loan amendments and technical default as incidences of covenant vio-

[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.

lations on the one hand and non-violating firms on the other hand and use a Large Language Model (LLM) to classify our data into these groups. We describe our approach in detail in Subsection 3.1. Overall, CovenantAI improves the accuracy of, for example, text-search approaches such as in Nini et al. (2012) and others by as much as 20 percentage points.

We then map our approach to the prior literature on covenant violations (which we summarize in Table 1 below) and highlight the focus of these papers, the time-period that is analyzed, the data that has been used to identify covenant violations as well as the analytical approach. While we document several interesting findings, a key insight suggests that 20% of all papers (that do not use confidential data) use the Dealscan approach to identify covenant violations, i.e., a comparison of the "at-origination" covenant threshold with quarterly Compustat data.[4] 80% use SEC filings and the approaches initiated by Roberts and Sufi (2009a) and Nini et al. (2012). Interestingly, all studies use the exact same approach, or they even obtain the covenant violation data from these authors. This also explains that most existing studies have limited their focus to relatively brief periods, often concluding before the 2008-2009 global financial crisis (GFC) or before 2011.[5] While we find that the correlation between the covenant violation rates from CovenantAI and text-search approaches such as in Griffin et al. (2023) is about 80%, the correlation with the approaches in Chava and Roberts (2008) and Roberts and Sufi (2009a) is small and statistically insignificant.

There are several advantages associated with the AI-powered approach that we develop in this paper that are important for academic research. First, 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 comprises all companies filing with the SEC. 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. Second and in contrast to keyword-based approaches, CovenantAI interprets the context from regulatory filings and provides improved accuracy and

[4] For example, Chodorow-Reich and Falato (2022) and Haque and Kleymenova (2023) use confidential data from the Shared National Credit Program (SNC), which is governed by an interagency agreement among the Board of Governors of the Federal Reserve System, the Federal Deposit Insurance Corporation, and the Office of the Comptroller of the Currency.

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

consistency in the identification of covenant violations as the algorithm can detect patterns and nuances in the context of the filings. Third, CovenantAI can be trained to exploit the complex language structure and, for example, identify situations in which firms amend loans before/after a violation occurs or whether lenders grant waivers and for how long. Fourth, CovenantAI exhibits greater adaptability compared to models relying on keyword searches. It can easily be scaled by adding more regulatory filings over time, but can also adjust to changes in financial reporting standards or regulatory changes.

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 use a "quasi" regression discontinuity design approach following Roberts and Sufi (2009a) and Nini et al. (2012) and select one model to test different relationships found in prior 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. (2023)), 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.

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 and transparency are key drivers of this decision, i.e., firms that have lower bankruptcy risk and are more transparent are more likely to obtain amendments. We use different specifications as well as proxies for risk and transparency 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 are a function of how covenant violations are resolved. 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 already highlighted CovenantAI's proficiency in handling complex language, which we utilize to examine loan amendments in depth. Until now, we have classified firms as either amending loans or remaining in technical default post-violation. Yet, outcomes like waivers, which temporarily maintain original contract terms without penalties, are possible. Notably, waivers usually follow violations, whereas amendments can occur before. This allows us to categorize amendments as either violation-related or independent. Additionally, firms might initially receive waivers, later leading to mandatory loan term adjustments post-waiver. This differentiation is economically significant. Proactively negotiating amendments before violations can place companies in a stronger position, possibly gaining better terms. In contrast, firms amending post-violation may confront tougher negotiation conditions.

We thus train CovenantAI to differentiate between these outcomes (i.e., amendment before or after covenant violations, waiver, or technical default), which we describe in Subsection 4.4. Our findings reveal several notable trends. Specifically, IG firms typically secure loan amendments prior to any covenant violation, a pattern that remains remarkably consistent over time. Waivers are rare in these cases. The surge in amendments during the COVID-19 pandemic is primarily attributed to pre-violation amendments. We observe a decrease in violations primarily among Non-IG firms, evident in both pre- and post-violation amendments, as well as waivers. Interestingly, the COVID-19 pandemic saw an increase in both pre-and post-violation amendments. However, this trend was not evident among unrated firms. The overall data from our descriptive and empirical analyses supports the interpretation that amending loan agreements before a violation occurs is generally the least severe consequence for a firm.

The decrease in covenant violations among non-investment grade firms, particularly in relation to amendments and waivers, is a central focus of our investigation in Section 5. Post-GFC, approximately 86% of loans from these firms have been held by institutional investors. Notably, almost 96% of this portion is accounted for by Collateralized Loan Obligations (CLOs) along with mutual or hedge funds. Concurrently, the trading volume in the secondary loan market has nearly tripled. This growth has shaped the leveraged loan market to increasingly resemble the high-yield bond market. The latter is predominantly characterized by bonds with negative covenants as opposed to financial ones, primarily to sidestep the complexities of creditor coordination in the event of covenant breaches (see, for example, Chava, Kumar, and Warga (2010) or Bräuning, Ivashina, and Ozdagli (2022)).

Therefore, we can hypothesize that the decrease in covenant violations is linked to the evolution of the institutional loan market. To examine this, we utilize various indicators to represent shifts in investor demand focusing on the largest investors such as CLOs, secondary loan market liquidity, and contract complexity or weakness. These proxies are: (1) CLO issuances, (2) CLO outstanding, (3) secondary loan market trading volume, (4) time-on-market, (5) percentage of covenant-lite loans, and (6) carve-outs on negative covenants. In summary, all our tests suggest that the declining trend in covenant violations correlates strongly with the development of the institutional loan market.

We also find that the covenant structure at loan origination potentially explains the decline in covenant-violations as there is a declining trend to include financial covenants. We observe an increase in covenant-lite contracts as well as a decreasing number of covenants in loan contracts. Moreover, if financial covenants are included, they are (almost exclusively) so-called "performance-based" covenants (Christensen & Nikolaev, 2012) and include usually a firm's EBITDA. Similar to carve-outs associated with negative covenants (Ivashina & Vallee, 2022), carve-outs are also common among profitability-based covenants, effectively weakening the position of creditors. Overall, as the loan market increasingly mirrors the structure of bond markets, influenced by developments such as the growth of CLOs and the expansion of secondary loan market trading, there has been a notable decrease in the reliance on covenants and the incidence of covenant violations among non-investment grade companies.

Our time-series analysis revealed a significant rise in covenant breaches during the COVID-19 pandemic. Notably, there is an uptick in amendments preceding violations in investment-grade rated firms, a trend that is nearly undetected in firms without ratings. Prior research suggests that banks play a key role as liquidity providers and offer credit to firms to avoid financial distress during bad times (Kashyap, Rajan, and Stein (2002); Gatev and Strahan (2006)) but that riskier and more opaque firms might have problems in accessing liquidity when risks materialize (Petersen and Rajan (1994); Berger and Udell (1995)). In the final Section 6 of this paper, our attention centers on covenant breaches and adjustments during the first and second quarter of 2020. The occurrence of covenant amendments before violations provides insight into potential segmentation within the loan market, particularly during times of financial stress. This segmentation may favor larger firms over smaller ones, as lenders have the discretion to choose with which firms they negotiate early. Our findings indicate that larger firms are more likely to secure amendments prior to covenant violations during the COVID period, which may help them in obtaining financing during financial distress periods. Conversely, smaller firms appear to have more limited access to credit and fewer opportunities for credit commitments, as suggested by our earlier results. These results align with those presented by Chodorow-Reich et al. (2022), who identify varying levels of access to credit line commitments between large and small firms during this period.

2 Data Sources

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

2.1 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. Computstat/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, 6.0% 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.

2.2 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

[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 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.

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

3 CovenantAI

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.

3.1 Identifying covenant violations

We provide a brief overview of the new ML algorithm in this subsection 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 having either violated or not violated a covenant. This serves as the classification label. We selected 4,000 firm-quarter observations mentioning "covenant" in their

[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".

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.

Our manual labeling process categorizes firm quarters into three groups: 'no violation' (label 0), 'loan amendment' (label 1), and 'technical default' (label 2). No violation is assigned where there is no evidence of a covenant breach. An amendment label indicates a loan modification to prevent or rectify a violation, and technical default is used when no amendment 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 692 instances of technical defaults and 606 amendments, are about 17.34% and 15.18% of the dataset, respectively. This prevalence stems from our sampling method, aimed at balancing the dataset for model training and validation.[10]

Step 2-Classification. We divide the labeled sentences into three datasets: training (68%), testing (22%), and validation (10%). These datasets include varying distributions of technical default, amendment, 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).

Our machine learning model's performance is illustrated in Figure 1, using two types of data: test (898 observations) and validation (400 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 94.79% for the test data and 94% for the validation data. Specifically,

[10] However, this sample is not fully representative of violation rates; a random sample from our full dataset indicates a mean violation rate of about 2.5%, reflecting a more accurate distribution.

it correctly identified nearly 90.85% of violations and 97.15% of non-violations in the test data.[11]

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. We further classify all covenant violations as amendments if they are followed by an amendment in the two quarters after the violation has been first reported. Applying our algorithm using these criteria, we obtain 27,742 (7.31%) loan amendments and 4,354 (1.15%) observations with firms in technical default for all firm quarters. The number of firm quarters in which we find a "new" technical default is 1,735 (0.46%), and in which we find a "new" amendment is 11,664 (3.07%).[12]

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.

Panel A shows a cyclicality of covenant violations during periods of economic downturns and recessions.[13] 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

[11] 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.

[12] A technical default or amendment is "new" if the firm did not violate a covenant in the previous two quarters.

[13] 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.

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. (2023).

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 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.

3.2 Comparison with prior literature

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.

Mapping to the existing literature. 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.

Firstly, most of this literature focuses on financial and real adjustments of firms that violate covenants. For simplicity, we categorize these adjustments into four groups for our empirical tests in Subsection 3.3: (1) Investment & Employment; (2) Financial Policies; (3) Operational & Financial Performance; and (4) Access to Credit.[14]

Secondly, we observe that most existing studies have limited their focus to relatively brief periods, often concluding before the 2008-2009 global financial crisis or before 2011.[15] 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.

Thirdly, 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 identify covenant violations. Importantly, reading through the data and methodology sections of these papers, it becomes obvious that 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.

Finally, none of these papers use a machine-learning algorithm, which is at the heart of this

[14] 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).

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

paper. We compare the advantages of this approach vis-a-vis other approaches (such as textual analysis) further below in this subsection.

Comparing covenant violation rates. In a next step, as all papers use only a few measures, we compare our covenant violation rates to those identified in these approaches. We build on Appendix Table I in Griffin et al. (2023), add our violation rates and then add the violation rates from SNC data as reported in Haque and Kleymenova (2023). We then plot all violation rates together in Figure 4. The Roberts and Sufi (2009a) time-series ends in 2011, while the violation rates from Haque and Kleymenova (2023) start in 2012. The violation rates from Chava and Roberts (2008) have been imputed by Griffin et al. (2023) until 2019. The shaded areas are NBER recession periods. While we do not have the full time series for all measures, some interesting patterns emerge.

First, there is a level-difference between all other measures and ours. Our violation rates are usually higher compared to all other approaches followed by Griffin et al. (2023) (which is an extension of the Nini et al. (2012) approach and for which a longer time-series is available). Interestingly, our violation rates are most comparable to the ones reported in the SNC data. While Chodorow-Reich and Falato (2022) report average violation rates in 2006-2007 of 25% and of 34% in 2009-2010 using SNC data, Haque and Kleymenova (2023) - using the same database - report violation rates from 12% to 22.5% over the 2012 to 2022 period. It appears as if the level difference between our violation rates and those obtained from similar SEC data is, if anything, increasing over time. However, all measures show a declining trend in covenant violation rates.

Secondly, our metric exhibits greater variability and cyclicality over time. Notably, there are more distinct spikes during periods of recession defined by the NBER, as well as throughout the 2014-2016 oil crisis. Moreover, our metric effectively highlights the significant rise in covenant violations during the COVID-19 recession, a trend which is less pronounced in the SNC data. One potential explanation for this could be our metric's enhanced sensitivity to loan amendments, which seemed to be a prevalent practice during this period to avoid covenant breaches. Another perspective, as suggested by Chodorow-Reich et al. (2022), is the preferential treatment of larger firms by lenders, especially in terms of credit access. This bias might be reflected in our sample, where a higher proportion of loan amendments among publicly listed firms aligns with the trend favoring larger corporations. We explore this hypotheses in Section 6 below in this paper.

Finally, we examine the correlation between these metrics and find that our measure aligns closely with the findings of Griffin et al. (2023) ($\rho = 0.8$), both pre and post the global financial crisis. However, the correlation with the approaches in Chava and Roberts (2008) and Roberts and Sufi (2009a) is not statistically significant.

Comparing CovenantAI to alternative approaches. What explains the difference in violation rates, particularly between CovenantAI (a LLM) and the Griffin et al. (2023) 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.

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

[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.

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.

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 2 provides summary statistics of our sample consisting of 11,432 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:

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

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. $X_{i,t}$ 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 3 shows the results. Consistent with prior literature, firms reduce assets (-3.8%) and PPE (-3.8%) in the fourth quarter after a covenant violation. The point estimate related to changes total assets in column (1) almost doubles compared to Nini et al. (2012) while the coefficient in column (2) is almost identical. 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 find a 2.5% reduction in employment following a violation. This effect is only significant at the 10% level and, in economic magnitudes, only a quarter of the effect shown in 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).[17]

Panel B shows that firms reduce NDI over average assets by about 2.3% after a covenant violation, which is similar in magnitude compared to earlier literature. Interestingly, while total debt is considerably reduced after a violation, the magnitude is roughly half of what has been shown, for example, in Nini et al. (2012). The effect on cash over average assets (an increase of about 0.5%) is almost identical. Firms also reduce shareholder payouts by about 4%, which is similar in magnitude compared to before but was insignificant in prior literature. We observe also a statistically significant reduction in payout. 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. We find that the cash ratio increases by about 1.6%, while credit line usage declines by about 2%. In other words, while lenders might reduce available credit lines to violating firms, these need, as a response as well as to secure future liquidity needs, increase the amount of cash they hold relative to available liquidity.

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. We investigate the two components of operating cash flow, sales,

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

and costs, and find that violations both reduce sales (-3.7%) and costs (-2%), results that are statistically significant. However, sales declines are larger than estimated before, and cost reductions are smaller. That is, on balance, this does not lead to a meaningful increase in operating cash flows.

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 1.2% 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 markets 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 firms 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 A of Table 4. Columns (1) to (3) focus on term loans, and columns (4) to (8) 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).[18]

The findings indicate a contraction in credit availability to firms subsequent to covenant violations. We observe heightened loan spreads, lower loan amounts, and a higher probability of loan amount reductions across both credit line and term loan samples. The magnitudes of these coefficients are similar, yet they exhibit greater statistical significance within the credit line sample. This increased significance is likely attributed to the larger volume of observations

[18] 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.

in the credit line sample, enhancing the robustness of these tests.

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 aggregated dataset of credit lines and term loans and show the results in Panel B. The analysis predominantly shows a higher 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.[19] 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, are more leveraged and unrated. Among rated borrowers, they also have a worse credit rating.

4.2 Determinants of loan amendments

As of now, our model can distinguish between amendment and technical default. Within the group of amendments, however, we cannot differentiate between a scenario, in which lenders

[19] 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.

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 their insights.

Empirical model. Chen and Wei (1993) argue that the likelihood of borrower default is a key determinant on 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).[20]

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 time 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. 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,

[20] 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 years 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*".

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 both a 4% higher likelihood of 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.

We focus on the sample of firms that have violated a covenant and select a few outcome variables from our analysis in Table 3.[21] 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*. 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

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

loan is amended.

Results. Table 7 shows the results. Panel A presents 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.

In Panel B, our analysis focuses on the varying impacts across different credit ratings, incorporating interaction terms of $Amendment_{i,t}$ with the three specified rating categories. Predominantly, these effects are influenced by firms that are either unrated or hold non-investment grade ratings. For instance, unrated firms, which typically face challenges in securing credit, exhibit a lesser reduction in assets and PPE, while also markedly decreasing shareholder payouts. In a similar vein, Non-IG-rated firms maintain lower cash reserves, undertake lesser cost reductions, and show a lower probability of default when they secure loan amendments, as opposed to firms that are in technical default.

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 Amendments vs. covenant violation waiver

As we described in Subsection 3.2 above, 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. In our classification so far, firms either obtain an amendment or remain in technical default. 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 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.

Methodology. We train CovenantAI to differentiate between these outcome categories: (1) *No Violation*, (2) *Amendment w/o Violation*, (3)*Amendment w/ Violation*, (4)*Amendment w/ Violation & Waiver*, (5) *Waiver*, (6) *Technical Default*.[22] Using the paragraphs that we classified as amendments before, we take a random sample of 1,100 paragraphs and split them into sub-categories. We then classify paragraphs as *Amendment w/o Violation* if they report an amendment without mentioning a prior covenant violation. *Amendment w/ Violation* and *Amendment w/ Violation & Waiver* are cases where the amendment was reported directly in combination with a violation or a waiver. We classify paragraphs as *Waiver* that report a waiver without mentioning a covenant amendment. We provide examples for each subcategory in Online Appendix B. Armed with these labels, we train our model and apply it to the whole database of amendments.

The relabeled amendment data contain: (1) 5,323 (3.44%) *No Violation*, 86,174 (55.72%) *Amendments w/o Violation*, 31,328 (20.26%) *Waiver*, 27,072 (17.50%) *Amendments w/ Violation/ Waiver*, 4,062 (2.63%) *Amendments w/ Violation* and 685 (0.44%) *Technical Default* observations.[23] The accuracy matrix of the model (Online Appendix C) shows that the model performs very well in classifying our data.[24]

[22] Going forward, we combine categories (3) and (4) as they have similar economic meaning.

[23] We also use the model to reclassify some cases as *No Violation* or *Technical Default*.

[24] We revise the approach for processing values predicted by the model, considering them only if the time gap between the extracted text and the reporting date was less than 180 days. To compile firm-quarter observations, we use a specific hierarchy for aggregating paragraphs, as follows: Technical Default takes precedence over Amendment with Violation, which in turn is prioritized over Amendment with Violation/Waiver, followed by Waiver, then Amendment without Violation, and finally, No Violation. 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.

Descriptive results. Panel A of Table 8 shows 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, 8.8% of firm-quarter observations within a year are amendments before covenant violations occur. 4.04% of the observations were amendments that followed covenant violations, 3.77% waivers following violations, and about 2.81% were technical defaults. Amendments w/o violations are highest for Non-IG-rated firms (13.34%), followed by unrated (7.39%) and IG-rated (6%) 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.

Figure 5 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.

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 7. 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) $Default$.[25]

The results (Table 8) 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 Decline of Covenant Violations among Non-IG Firms

This section focuses on the decline in covenant violations among non-investment grade firms, particularly regarding amendments and waivers, post-GFC. Around 86% of their loans are now held by institutional investors, mainly Collateralized Loan Obligations and mutual or hedge funds, constituting nearly 96% of this segment. Additionally, the secondary loan market's trading volume has almost tripled, making the leveraged loan market increasingly resemble

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

the high-yield bond market, which favors negative over financial covenants to ease creditor coordination in cae of covenant breaches (see, for example, Chava et al. (2010) or Bräuning et al. (2022)).

Prior studies indicate that the syndicated loan market's growth is driven by institutional investor demand, leading to contract designs aimed at minimizing creditor coordination costs (e.g., Shivdasani & Wang, 2011; Ivashina & Sun, 2011; Ivashina & Vallee, 2022). We hypothesize that the noticeable reduction in covenant violations, particularly in Non-IG firms post-GFC, is linked to these market changes, effectively lowering creditor coordination costs. This hypothesis underpins our analysis in this subsection.

5.1 Institutional loan market and covenant violations

In order to analyze the correlation between the trend of covenant violations in Non-IG firms and the growth of the institutional loan market, we construct six proxies derived from existing literature, which serve as credible indicators of this market's development. There are: (1) CLO issuances, (2) CLO outstanding, (3) secondary loan market trading volume, (4) time-on-market, (5) percentage of covenant-lite loans, and (6) carve-outs on negative covenants.[26] We discuss each of these proxies in turn below. Our time-period ends before the start of the COVID-19 pandemic.

Panel A of Figure 6 depicts a comparison between annual covenant violations, as sourced from CovenantAI, and annualized Collateralized Loan Obligation (CLO) issuances. CLO issuances are sourced from Pitchbook Leveraged Commentary and Data (LCD) and measure the annual issuances of CLOs in the U.S. in billion dollars. Prior research identified CLO issuances as an important proxy for institutional loan demand (e.g., Shivdasani & Wang, 2011). We observe a distinct negative correlation between these two time series ($\rho = -0.58$, $p < 0.001$). The decline in covenant violations appears to coincide with an increase in CLO issuances.

In Panel B, we use *CLO Outstanding* as our measure for the institutional loan market. *CLO Outstanding* represents the total dollar value of all CLOs currently existing in the market, regardless of when they were issued. This is a cumulative measure and reflects the total market size of CLOs and can indicate the level of investor involvement and exposure to CLOs over

[26] We thank Victoria Ivashina and Boris Vallee for providing the aggregate carve-out data (Ivashina & Vallee, 2022).

time. Unlike issuance volume, which is about new market activity, the outstanding volume is about the market's existing scale. In contrast to *CLO Issuances*, *CLO Outstanding* reflects the longer-term market situation and cumulative exposure, which might even make it a better proxy for the institutional loan market. Consistently, the correlation between loan amendments and outstanding CLO volume is even stronger with $\rho = -0.8$ ($p < 0.001$).

In Panel C, we use the secondary loan market *Trading Volume* as a proxy for the institutional loan market, which is defined as the annual nominal outstanding loan volume (in USD billion) in any given year that is traded in secondary loan market (and covered by the Loan Syndication and Trading Association). We obtain this data from Pitchbook Leveraged Commentary and Data (LCD). We observe a strong negative correlation between these two time series ($\rho = -0.63$, $p < 0.001$). Again, an increase in institutional lending appears to coincide with a decline in covenant violations.

We use Time-to-Market (*TOM*) as fourth proxy and plot both time-series in Panel D. TOM is measured as the average time between syndication launch date and completion date for new institutional loan tranches issued in the primary market in any given year (Ivashina & Sun, 2011). A shorter TOM can thus be interpreted as higher institutional loan demand. As expected, we find a strong positive association between loan amendments and TOM ($\rho = 0.74$, $p < 0.001$).

In Panel E, we use the percentage of covenant-lite (*% Cov-Lite*) as proxy for covenant weakness (Becker & Ivashina, 2016). As we describe in Subsection 5.2 below, we measure *% Cov-Lite* as those loans explicitly labeled as such in Dealscan or that have no financial covenants. An increase in *% Cov-Lite* suggests a further weakening of creditors and a lower likelihood that loans might get violated or amended. Consistently, we find a strong negative correlation between amendments and *% Cov-Lite* ($\rho = -0.82$, $p < 0.001$).

Finally, we use the number of carve-outs associated with the restrictions on liens as a final proxy for contractual weakness (Ivashina & Vallee, 2022) in Panel F.[27] Our time-series of carve-outs spans the 2006 to 2016 period. An increase in *Carve-Outs Liens* also suggests a further weakening of creditors and a lower likelihood that loans might get violated or are amended. Consistently, we find a strong negative correlation between amendments and *Carve-Outs Liens*

[27] So-called "Restrictions on Liens Negative Covenant" clauses for credit agreements are used to prohibit the borrower and loan parties from incurring encumbrances on their assets, with exceptions for carve-outs and baskets.

($\rho = -0.37$, $p < 0.001$).[28], [29]

5.2 Evolution of covenants in loan agreements

Our previous results suggest the decline covenant violations over the last two decades was particularly driven by Non-IG rated firms and coincides with development of the institutional loan market. In this section, we focus on the evolution of covenants that are included in the original loan agreement and document changes in the number as well as the composition of covenants.

Number of covenants. We start with the number of covenants that are included in the Refinitive Dealscan data. We merge our sample firms from CovenantAI to the Dealscan database. Overall, we can match 43% of firms to Dealscan, leaving 23,922 of loans in the merged sample. Figure 7 shows the annual percentage of loans characterized as *Covenant-Lite* - those explicitly labeled as such in the "Marketsegment" field of the Dealscan database or possessing no financial covenants - alongside loans containing *1 Covenant*, *2 Covenants*, or more than two (> *2 Covenants*). We observe a trend that, consistent with the observed decrease in covenant violations, indicates a declining prevalence of covenants in loan contracts over time. For example, while more than 40% of loan contracts contained more than 2 covenants in 2000, less than 3% of loans do in 2022. Similarly, about 30% of loans were covenant-lite in 2000, which increased to about 60% in 2022.

Performance-based vs. capital-based covenants. We follow Christensen and Nikolaev (2012) and divide the covenants in our sample if *"performance-based"* and *"capital-based"* covenants as follows:

[28] We also use carve-outs on indebtness and the sum of carve-outs on liens and indebtness as alternative measures (unreported). The correlations with amendments and these measures are $\rho = -0.14$ and $\rho = -0.28$, respectively.

[29] While our graphical evidence already convincingly shows that covenant violations decline with the growth in the institutional loan market, we provide a simple empirical strategy to support this claim. For brevity, we do not report results here. We estimate the following regression via OLS: $y_t = \alpha + \beta \times X_t + \theta \times Post + \gamma \times X_t \times Post + \delta \times y_{t-2} + \varepsilon_t$, where y_t is the amendment share, X_t is our institutional loan market proxy ((1) CLO issuances, (2) CLO outstanding, (3) secondary loan market trading volume, (4) time-on-market, (5) percent of covenant-lite contracts, or (6) number of carve-out related to restrictions on liens). *Post* is an indicator variable that is equal to one in the period after 2008. y_{t-2} is the two quarter lagged dependent variable. We do not have good control variables that determine the percentage of loan amendments in the time-series. Including the lagged dependent variable, we implicitly account for (unobserved) explanatory determinants of loan amendments at the aggregate level. Overall, our empirical results support the graphical evidence that (particularly after 2008) the amendment share highly correlates with the development of the institutional loan market.

- *Performance-based covenants*: *Debt-to-EBITDA, Fixed-charge Coverage, Interest Coverage, Debt Service Coverage, Senior Debt-to-EBITDA, EBITDA, Cash Interest Coverage*

- *Capital-based covenants*: *Tangible Net Worth, Leverage Ratio, Debt-to-Tangible Net Worth, Current Ratio, Quick Ratio, Debt-to-Equity, Senior Leverage, Loan-to-Value, Capex*

Figure 8 illustrates the annual percentage of loans featuring both performance-based and capital-based covenants from 2000 to 2020. Panel A specifically examines IG-rated firms. Over the past two decades, performance-based covenants have consistently been a component of loan contracts. This trend shows a gradual increase, rising from approximately 80% in 2000 to 90% by 2020. Notably, there has been a decreasing trend in the use of capital-based covenants in loan contracts. In 2000, around 60% of these contracts included capital-based covenants, but this figure dropped to below 20% by 2020.

Panel B presents similar trends for Non-IG-rated firms, though the patterns are more pronounced compared to IG-rated firms. For instance, performance-based covenants were present in over 90% of loans by 2020, nearly universal in contracts during that year. In contrast, capital-based covenants were initially more prevalent in Non-IG firms compared to IG-rated ones in the early 2000s, with a noticeable increase during the recessionary period of 2001-2003. However, this trend sharply reversed following the global financial crisis (2008-2009), leading to a scenario where only about 10% of loan contracts included a capital-based covenant by 2020.

Covenant composition. The preceding discussion highlights a reduction in the number of covenants incorporated into loan contracts, with a notable shift towards the near-exclusive use of performance-based covenants, especially among Non-IG-rated firms. As a last step, we investigate the composition of these covenants to determine whether lenders employ a diverse range of covenants or have gradually converged towards a limited set typically employed in loan agreements.

We offer an in-depth review of all covenants in the Online Appendix (Section E), including the annual frequency of their inclusion in contracts from 2000 to 2020. At the start of our sample period, it was common for lenders to utilize an average of more than 10 distinct types of covenants.[30]

[30] These are (in declining importance): Debt-to-EBITDA, Interest Coverage, Fixed-charge Coverage, Capex, Tangible Net Worth, Leverage Ratio, Senior Debt-to-EBITDA, Debt Service Coverage, Debt-to-Tangible Net Worth, Current Ratio

Table 9 only includes covenants that appeared in over 10% of all loan contracts during the last five years of our sample period (2016-2020), detailing their annual occurrence for both IG and Non-IG-rated firms. Remarkably, only five covenants remain significant in loan agreements. The *Debt-to-EBITDA* ratio emerges as the most prevalent, featuring in about 85% of contracts for both firm types, followed by *Interest Coverage*, which is particularly important in loans to Non-IG firms, appearing in about 50% of these loans (versus around 35% in IG-rated loans). Other widely used covenants include *Fixed-charge Coverage*, *Senior Debt-to-EBITDA* (more common among nNn-IG firms), and *Leverage Ratio* (more common among IG firms). Notably, these covenants have also seen a decline in importance over time. Aligning with our earlier discussion, it is clear that all covenants included in loans to Non-IG firms are profitability-based.

Covenant trends, composition and the decline in violations. Let us assess where we stand. This section presents various time-series trends, such as the increase in covenant-lite loans, the overall reduction in the number of covenants, and the shift towards using exclusively profitability-based covenants. All these patterns cohesively suggest that the decrease in covenant violations is likely driven by investors or creditors and a reduction in coordination costs, aligning with the hypothesis we initially proposed at the start of this section.

A substantial increase in covenant-lite contracts, as well as fewer covenants, naturally leads to a decline in covenant violations, as do the possibilities of carve-outs. We have shown this in the context of the carve-outs on liens as in Ivashina and Vallee (2022), but the focus on profitability-based covenants in loan contracts has a similar effect. For example, carve-outs in the form of add-backs to EBITDA make covenant violation less likely, reducing possibly costly renegotiations with creditors. Overall, our evidence suggests that as the loan market increasingly mirrors the structure of bond markets, influenced by developments such as the growth of CLOs and the expansion of secondary loan market trading, there has been a notable decrease in the reliance on covenants and the incidence of covenant violations among non-investment grade companies.

6 Amendments during the COVID-19 Pandemic

We document the striking increase in covenant violations and amendments in Subsection 4.4 above in this paper. Specifically, we observe an increase in amendments before violations among IG-rated firms, an effect almost unnoticed among unrated firms. Kashyap et al. (2002) and Gatev and Strahan (2006) argue that banks play a key role as liquidity providers and offer credit to firms to avoid financial distress during bad times. However, some firms (those that are arguably riskier and more opqaque) might have problems in accessing liquidity when risks materialize (Petersen and Rajan (1994); Berger and Udell (1995)). Chodorow-Reich et al. (2022) document this empirically during the COVID-19 pandemic and show that small firms were unable to access bank committed credit lines while large firms could. They attribute this to lender discretion rather than a lack of liquidity demand by small firms.

In the final section of this paper, we focus on covenant violations and amendments during the Q1 2020 to Q2 2020 period. Covenant amendments prior to violation offer a window into possible segmentation of the loan market in favor of large vs. small firms during stress periods as lender can exercise discretion with whom to negotiate early.

Descriptive statistics. Panel A of Table 10 provides summary statistics about loan amendments before violations. The left panel sorts firms by rating categories (*IG*, *Non-IG* and *Unrated*). 90.2% of possible covenant violations of IG-rated firms during the Q1 2020 to Q2 2020 period were amended before a violation occurred. This percentage drop to 65.83% (57.66%) for Non-IG and unrated firms. The right-hand panels shows amendments before violations for firms across the firm-size distribution. We create size quartiles where *Size 1* represents the smallest firms with total assets in the range from USD 10 million to USD 141 million. *Size 4* are the largest firms with total assets between USD 3.5 and USD 874 billion.

Terms of loans to large firms are more likely to be renegotiated before a violation occurs (77.48%). The likelihood halves for small firms, in which case only 37.55% of loan are amended before violation (all other violations either result in post-violation amendments, waivers or technical defaults).

Empirical model. To assess this empirical, we investigate the likelihood that a firm obtains an amendment before a violation over the post-GFC, i.e., 2010 to 2022 period (both before, during and after the COVID-19 shock). We do not test the likelihood against any other violation consequence but rather against the control group of non-violating firms. We estimate the following model via OLS:

$$
\begin{aligned}
Pr(Violation/Amendment)_{i,t} = \alpha + \beta_1 \times Covid + \beta_2 \times Exposure_i \\
+ \nu \times Rating_i + \theta \times X_i + \gamma_j + \delta_t + \varepsilon_{i,t}
\end{aligned}
\tag{4}
$$

where *Covid* is an indicator equal to one if the violation or amendment happened in the Q1 or Q2 2020 period. $Exposure_i$ is an indicator that is one if the firm is in the bottom quartile of the firm-specific year-on-year sales decline between Q2 2019 and Q2 2020. In some specifications, we add indicator variables for different rating categories ($Rating_i$). $X_{i,t}$ is a vector of control variables that likelihood to violate or not violate a covenant (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).[31] We also add industry (γ_j) and year (δ_t) fixed effects. Standard errors are clustered at the firm and quarter level.

Results. Panel B reports the results. Consistent with our earlier results, column (1) and (2) show that the likelihood that a firm violates a covenant (obtains an amendment) is 2.8% (2.7%) higher during the COVID-19 pandemic compared to before or after, highlighting that the increase in violations and amendments is transient. The dependent variable in columns (3) to (6) is *Pr(Amendment w/o)*, i.e., the likelihood that a borrower negotiates an amendment before a violation occurs. Again, the likelihood is higher during COVID-19 (column (3)) and increases if firms have higher exposure to the pandemic (column (4)). Interestingly, column (5) shows that IG firms have a lower likelihood compared to Non-IG and unrated firms to obtain an amendment outside of the COVID-19 period, but this reversed during COVID-19. During this period, both IG and (to a lesser extent) Non-IG firms were able to secured amendments early. In column (6), we interact our key variables with *Exposure* and find that those IG and Non-IG firms that had large exposure to COVID-19 (measured as the realized decline in sales as described above) were even more likely to renegotiate before a covenant violation occurs.

We now shift our focus to exploring whether smaller firms are less likely to secure amendments prior to the occurrence of violations; our preliminary findings have hinted at this pos-

[31] All results are unaffected if we include higher order controls as well as four-quarter lagged controls.

sibility. We report these results in Panel C. Instead of our rating categories, we use the size quartiles defined above. Column (1) indicates that, on average, larger firms do not have a higher propensity to arrange amendments prior to covenant violations. The findings suggest a U-shaped relationship between the likelihood of securing amendments and firm size. In column (2), we incorporate the variable *Exposure*, and in column (3), we examine the interaction between size categories and the *Covid* factor. Notably, aligning with our Panel B findings, during the COVID-19 period, larger firms exhibited a greater tendency to negotiate early amendments in contrast to smaller firms. Further, when we examine the interaction of our coefficients with *Exposure*, it becomes evident that for larger firms, this propensity to secure early amendments even increases when they are more significantly impacted by the COVID-19 pandemic, as shown in column (4).

Our findings align with those presented by Chodorow-Reich et al. (2022), who observed varying levels of access to credit line commitments between large and small firms. We demonstrate that larger firms have a higher propensity to obtain amendments before covenant breaches, potentially helping them in securing financing during periods of financial stress. Small firms, on the other hand, likely face less access to credit and fewer credit commitments as our earlier results suggest.

7 Conclusion

This paper introduces CovenantAI, a novel artificial intelligence (AI)-powered tool that allows researchers to obtain quarterly information on covenant violations for virtually all U.S. firms directly from their 10K and 10Q filings with the Securities and Exchange Commission (SEC). It accurately identifies amendments (before and after covenant violations), waivers, and technical defaults, thereby providing a detailed timeline of covenant breaches over the 1996 to 2022 period and how they are resolved. We use a "quasi" regression discontinuity approach that is common in this literature to validate our data and analyze the effects of these violations on key firm outcomes such as investments, employment, as well as firms' access to credit. Evidently, violations negatively affect firms as they, for example, have less access to credit, need to hold more cash and loose access to bank credit lines commitments compared to non-violating firms.

We also document interesting time-series patterns, notably a decrease in covenant violations among Non-IG (but not IG) rated firms. As the (leveraged) loan market for Non-IG firms increasingly mirrors the structure of bond markets, influenced by developments such as the growth of Collateralized Loan Obligations (CLOs) and the expansion of secondary loan market trading, there has been a notable decrease in the reliance on covenants and the incidence of covenant violations among non-investment grade companies. We also document a temporary spike in violations during the COVID-19 pandemic and show that particularly IG-rated as well as large firms obtain amendments before they violate covenants.

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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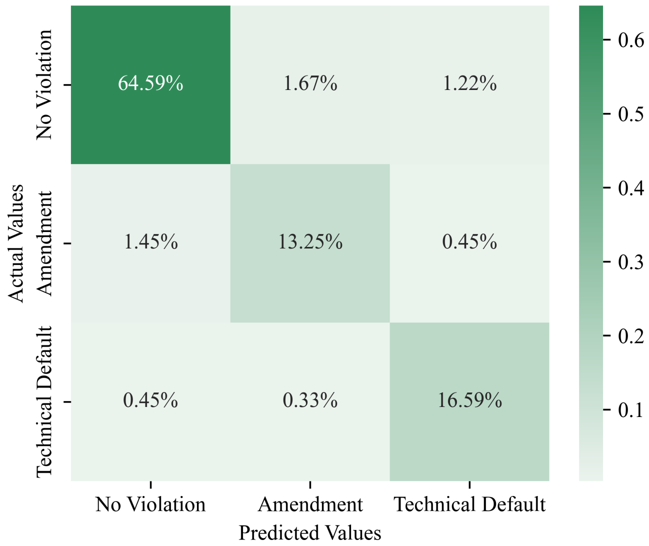
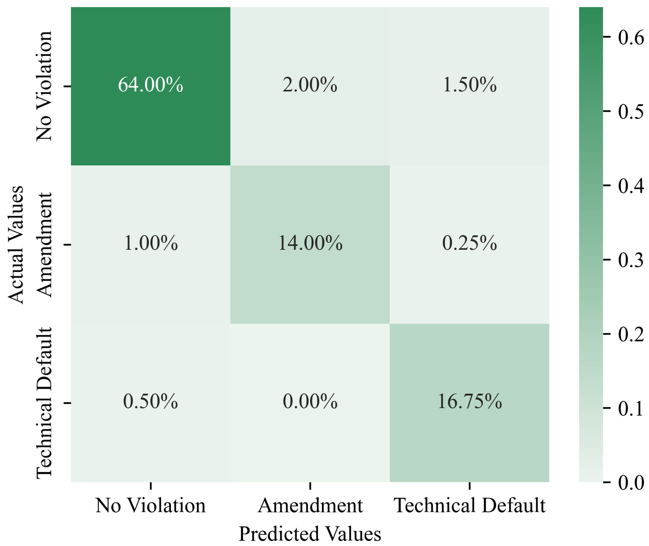
Figures and Tables

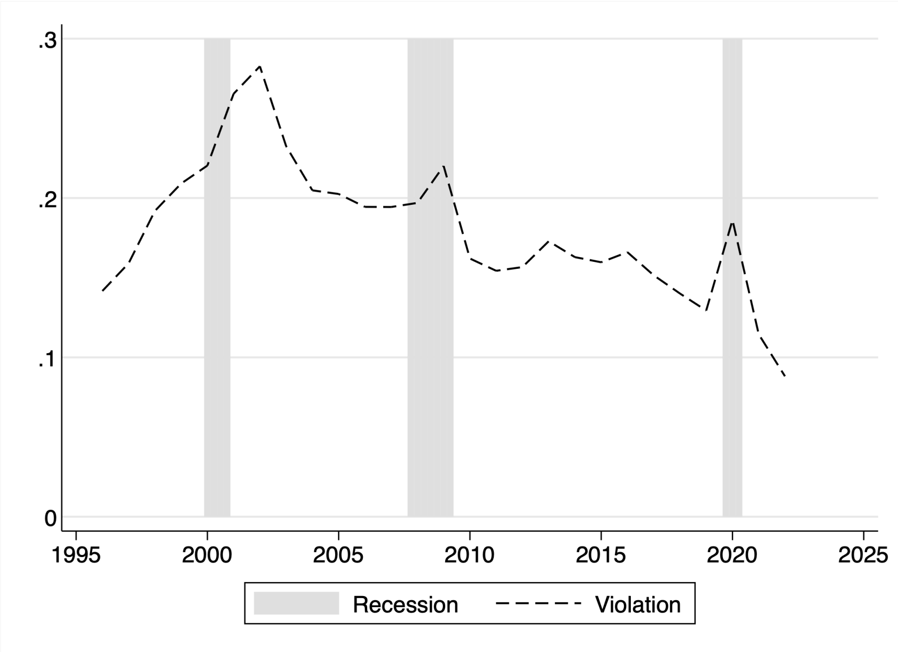


(a) Confusion matrix of the Test Data

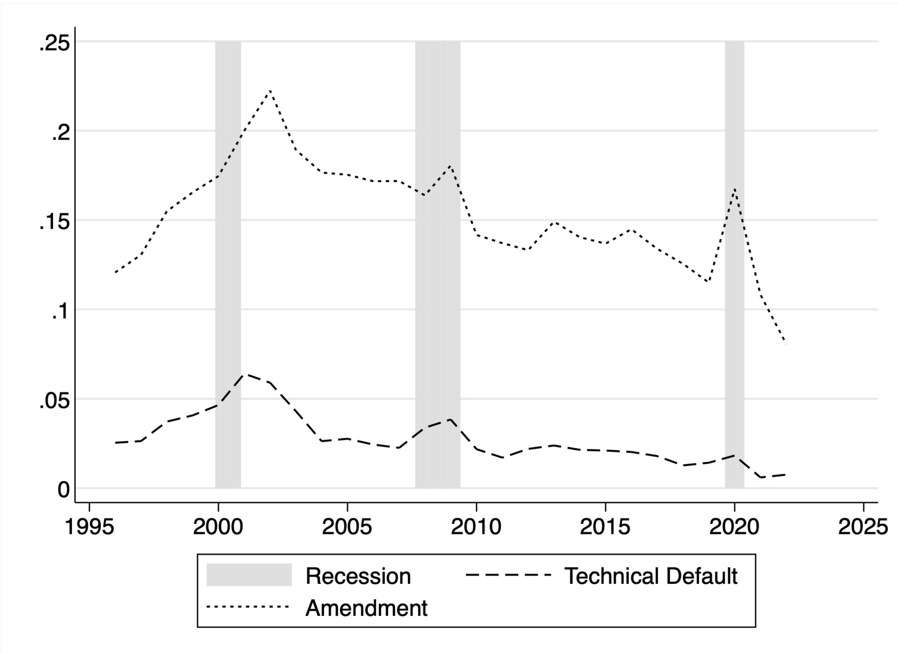


(b) Confusion matrix of the Validation Data

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.

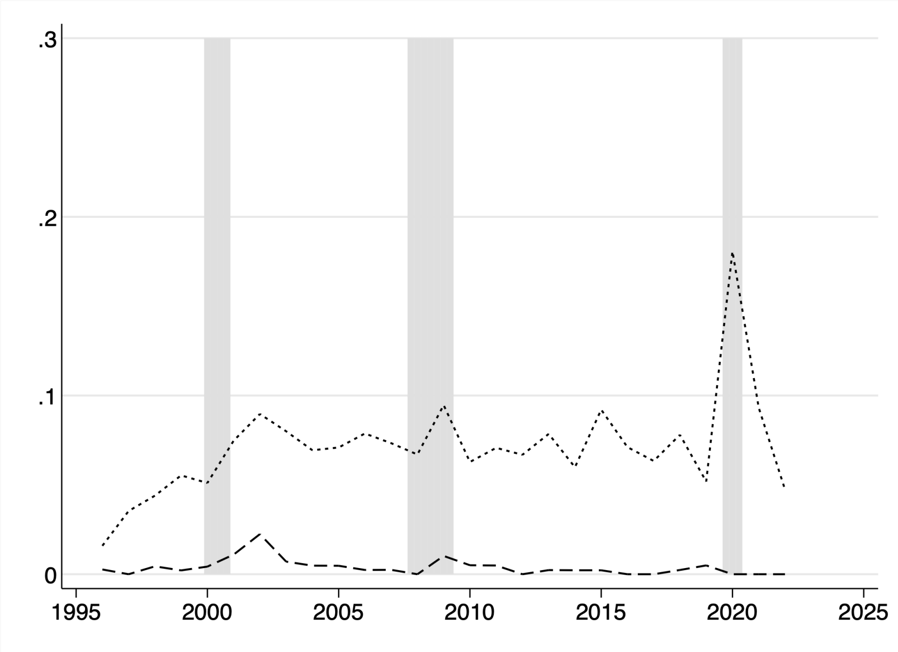


(a) Covenant Violations

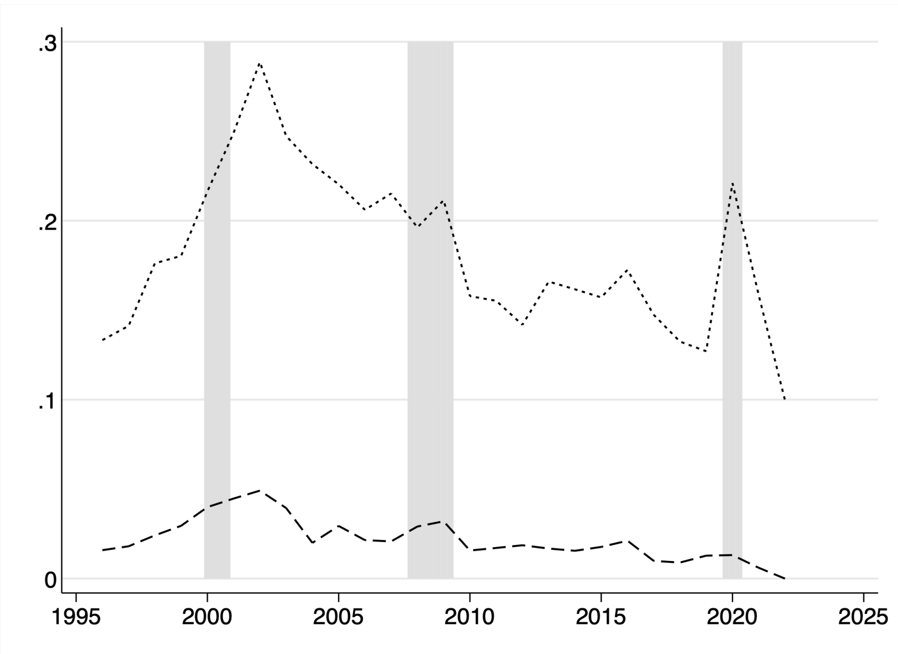


(b) Technical defaults and loan amendments

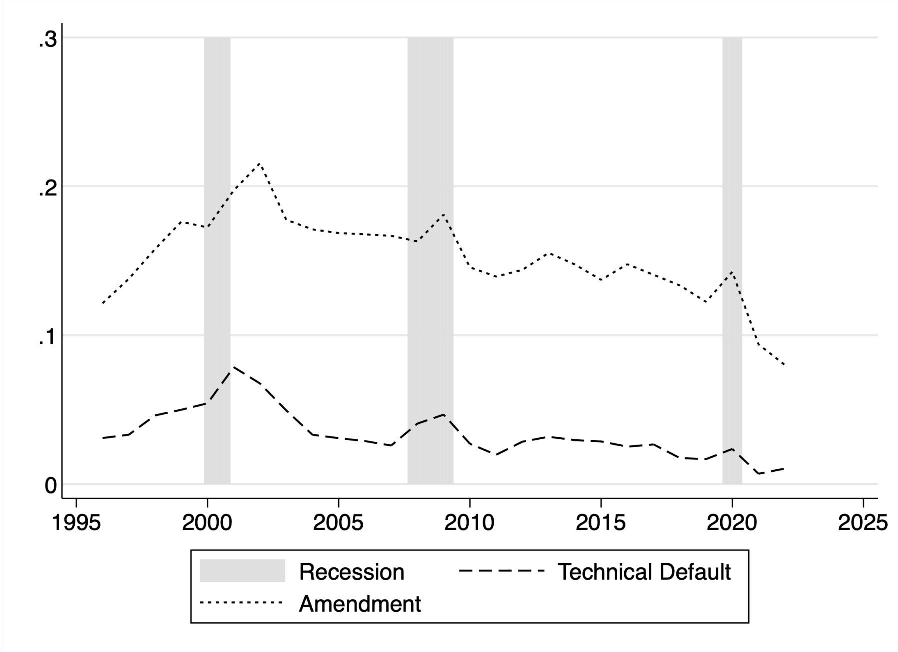
Figure 2: **Covenant Violation Distribution**
This figure plots the annual share of technical defaults and loan amendments for the full sample of U.S. publicly listed, non-financial firms. The shaded areas represent the NBER recession periods (Panel A). Panel B plots the combined share of technical defaults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

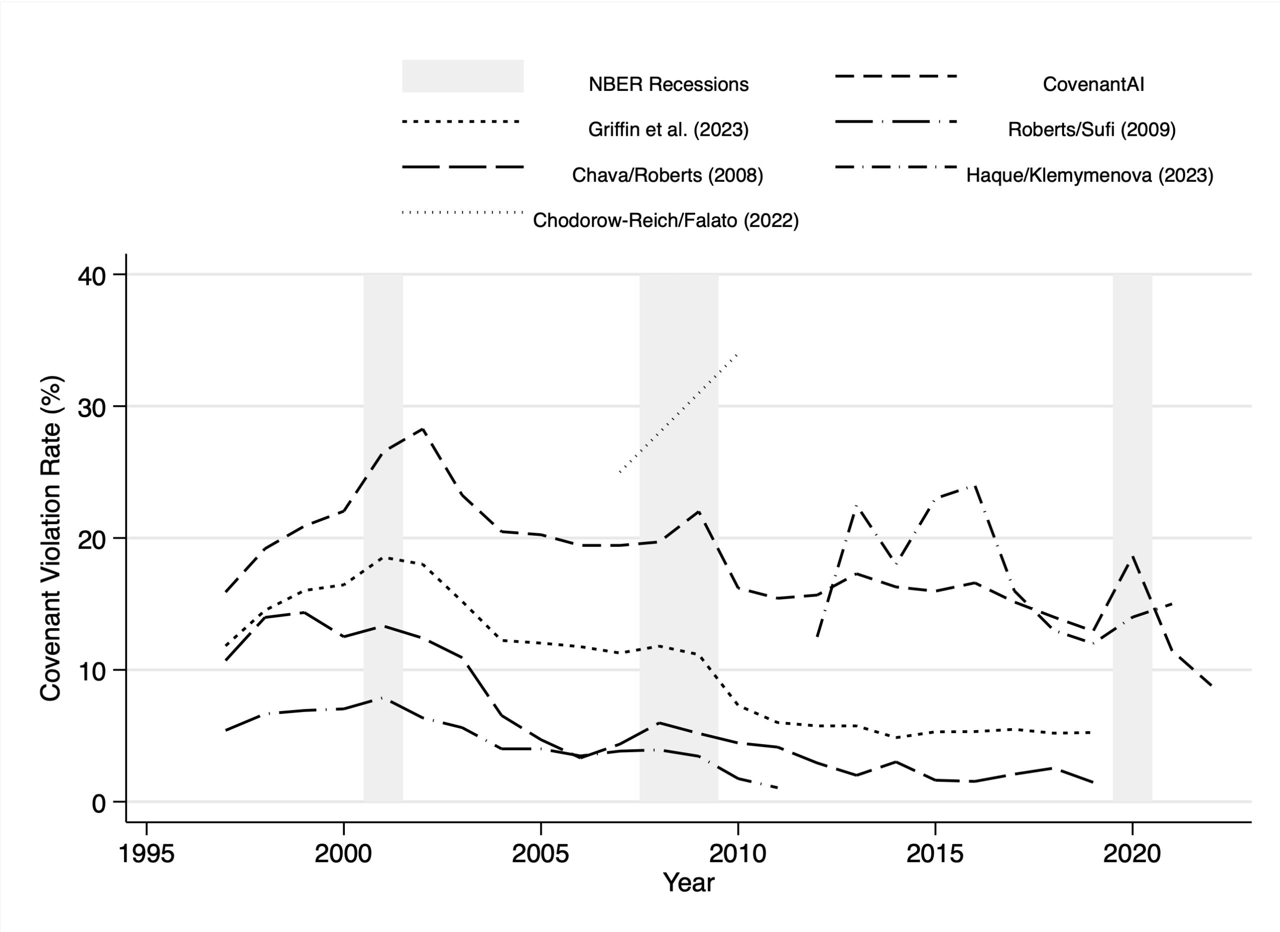
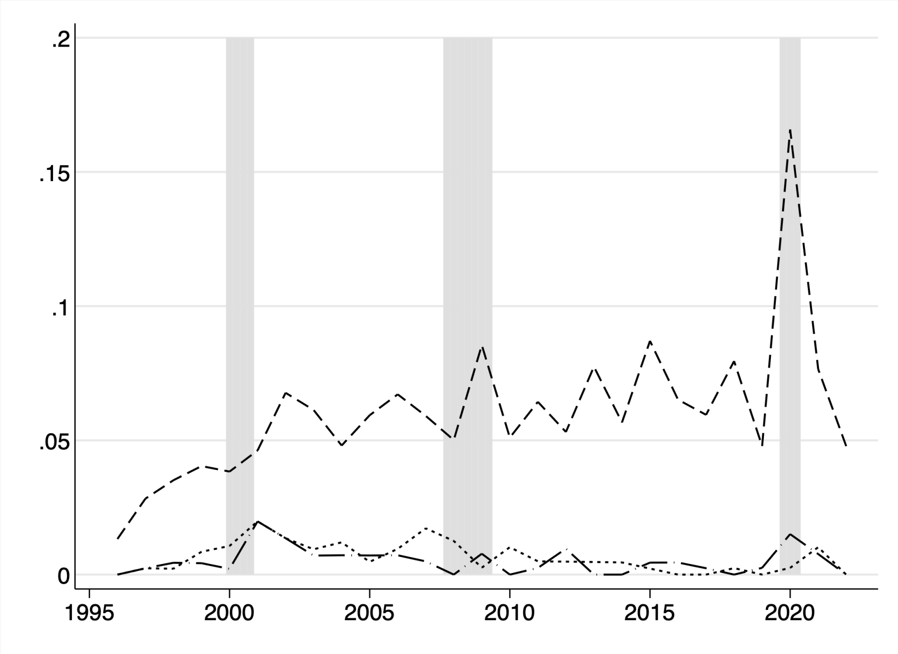
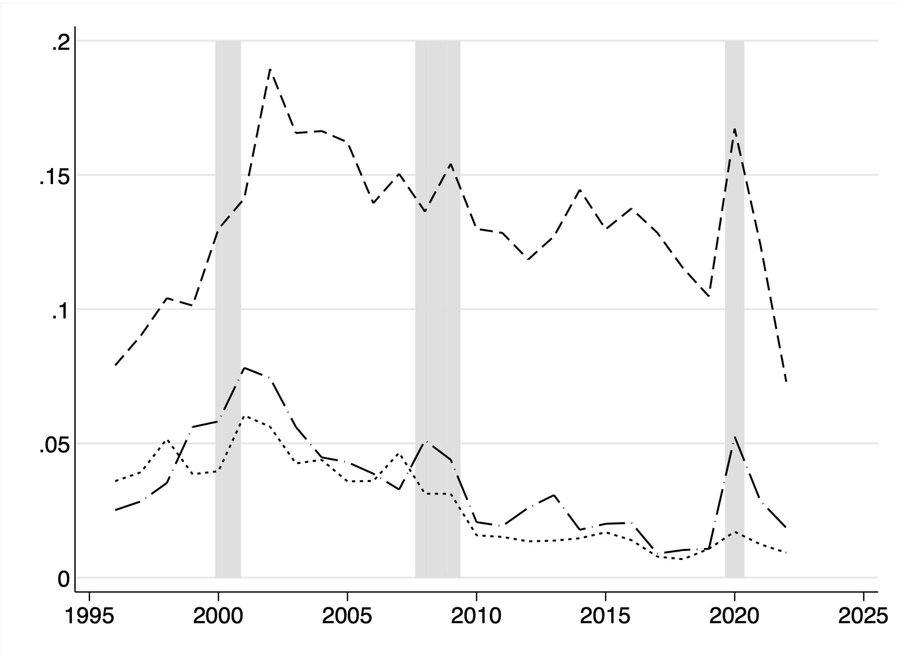


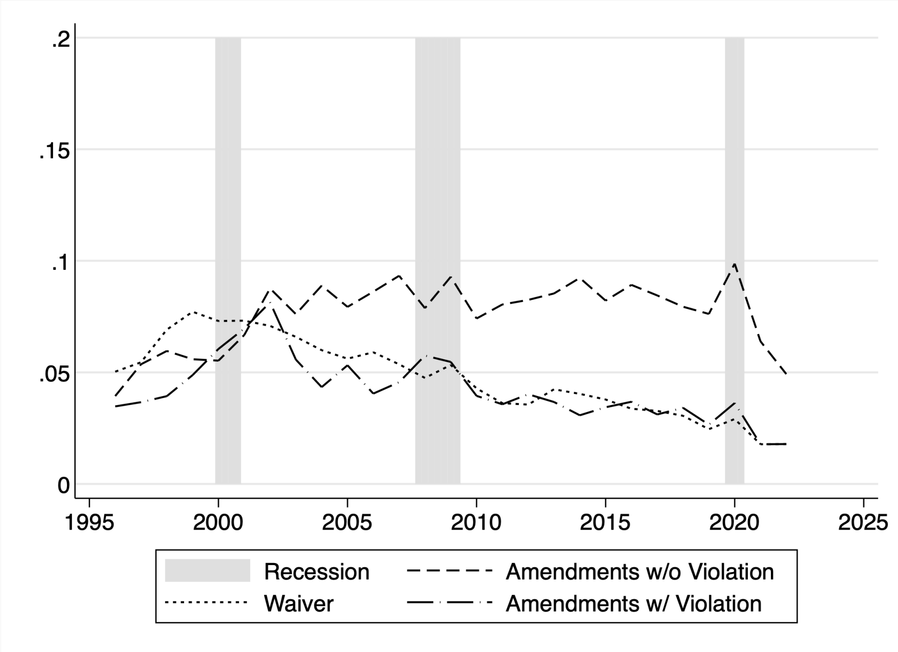
Figure 4: **Comparison of Covenant Violation Rates**
This figure shows covenant violation rates of different approaches used in the literature. The data for the time-series of Chava and Roberts (2008), Roberts and Sufi (2009a) and Griffin et al. (2023) are from Appendix I in Griffin et al. (2023).Chodorow-Reich and Falato (2022) report two data points for 2006-2007 and 2009-2010 in Table 1. The time-series data in the study by Haque and Kleymenova (2023) is derived from Figure 1 in their paper, where the average violation rates of firms owned by private equity and those not owned by private equity are used. Both of these studies obtain their covenant violation data from SNC. "CovenantAI" are violations obtained from our model.



(a) IG rated firms

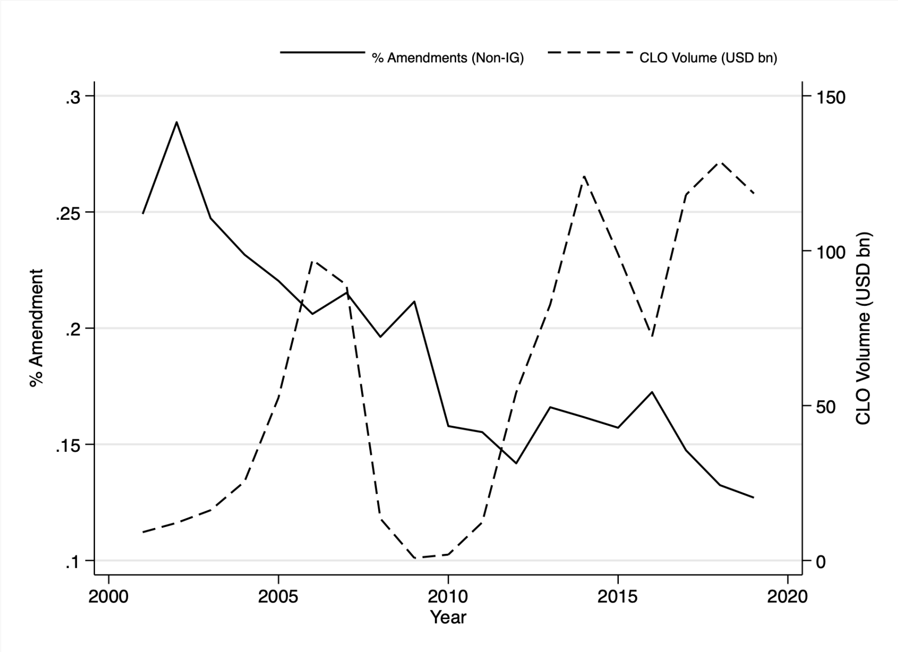


(b) Non-IG rated firms

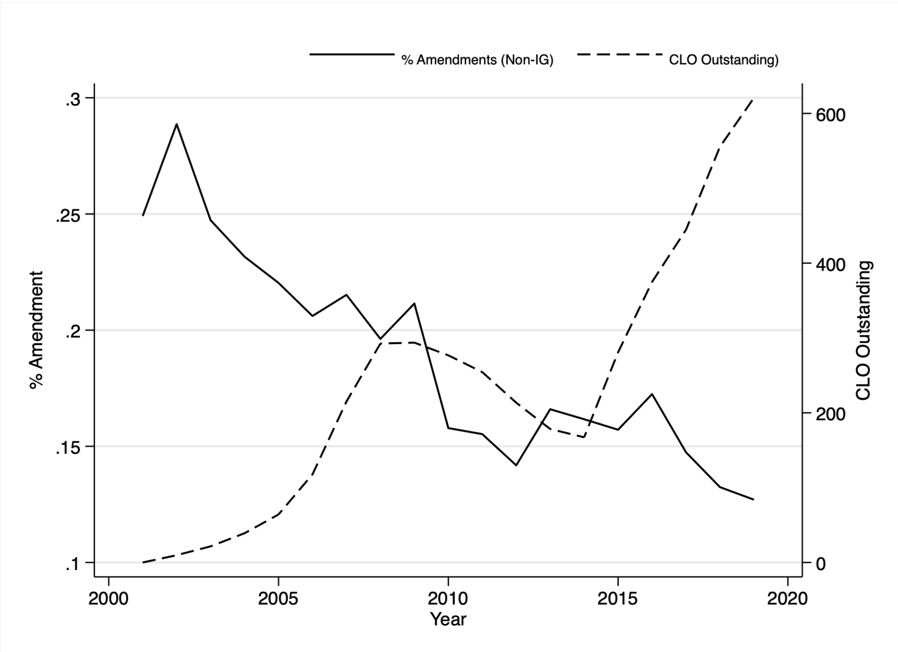


(c) Unrated firms

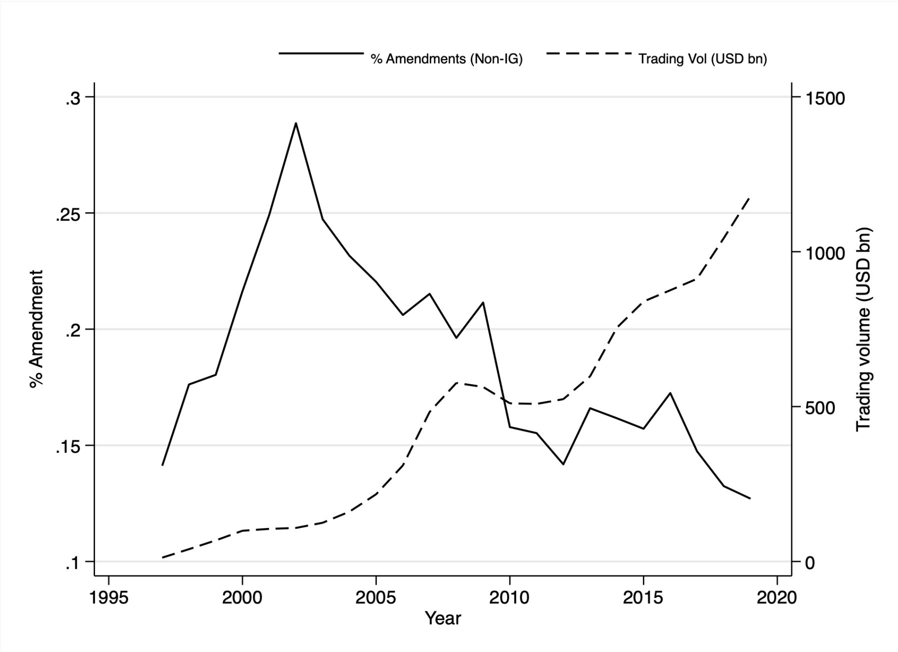
Figure 5: **Consequences of Covenant Violations by Credit Rating**
This figure plots the time-series of *Amendments w/o Violation*, *Amendments w/ Violation* and *Waiver* over the 1996 to 2022 period for different rating classes, IG, Non-IG and unrated firms.



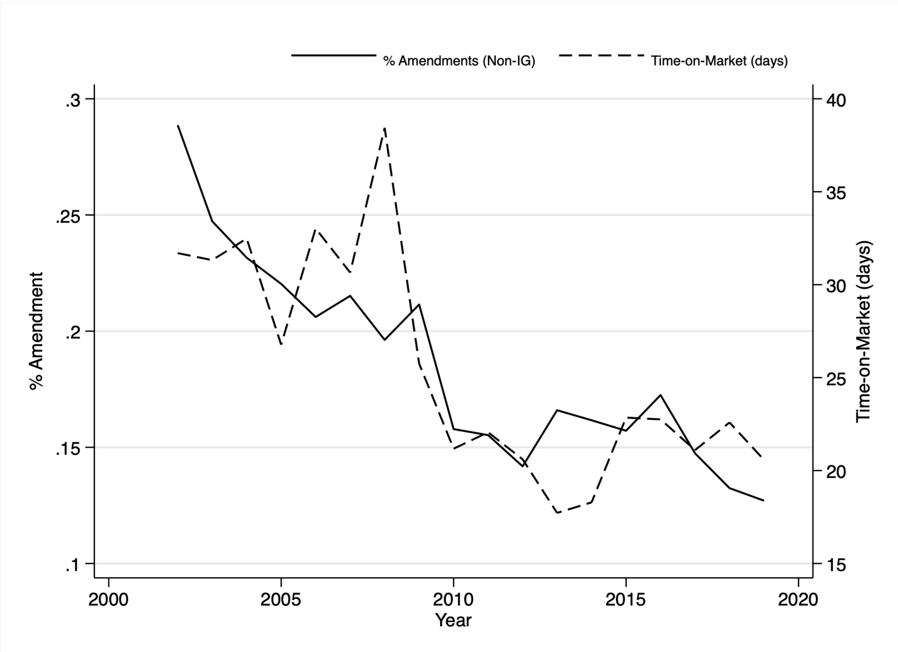
(a) Non-IG Amendments and CLO Issuance



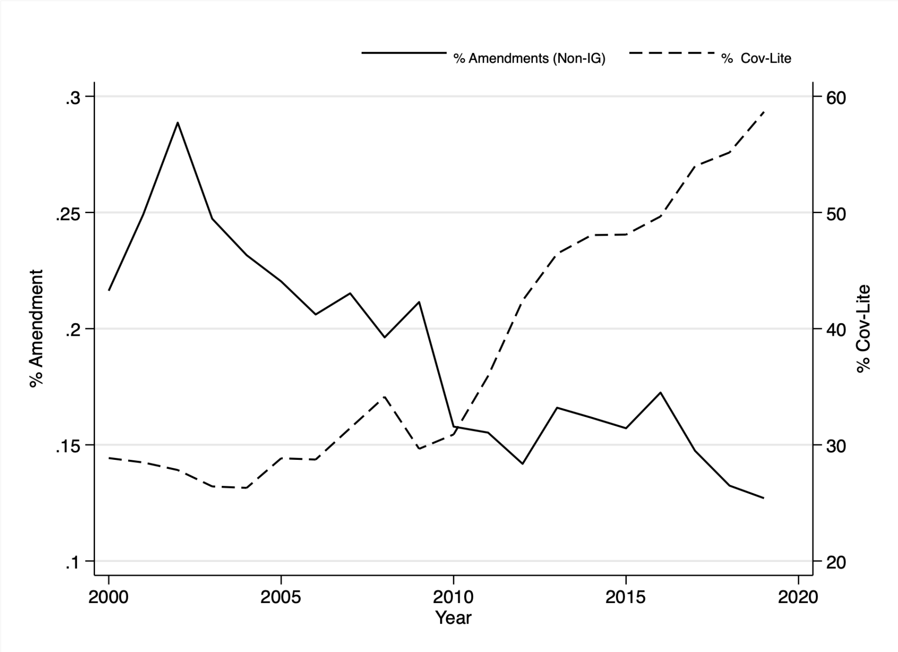
(b) Non-IG Amendments and CLO Outstanding



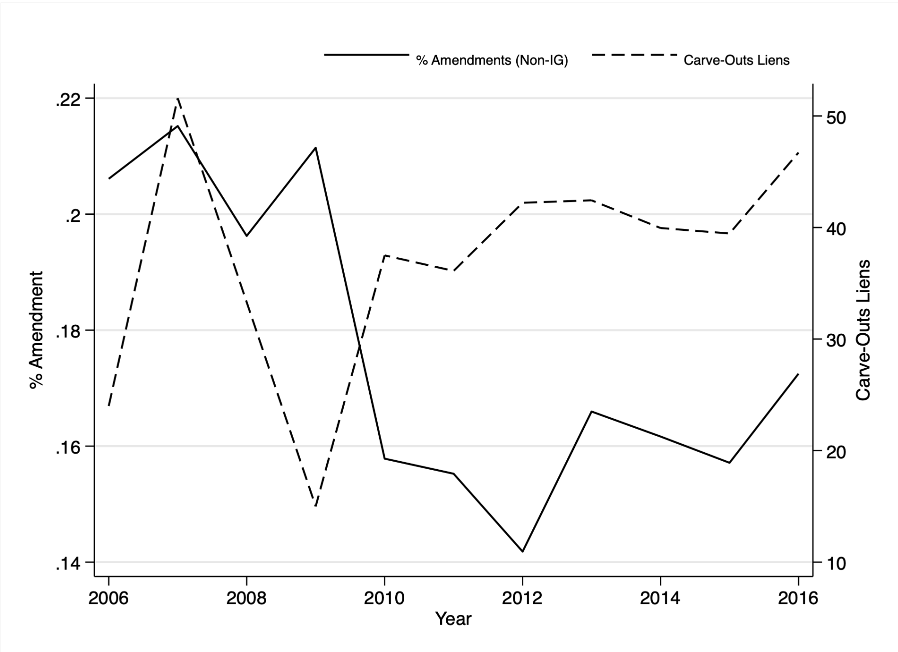
(c) Non-IG Amendments and Trading Volume



(d) Non-IG Amendments and Time-on-Market



(e) Non-IG Amendments and Covenant Lite



(f) Non-IG Amendments and Carveouts Liens

Figure 6: **Non-IG Amendments and Institutional Demand**
This figure plots the percentage of loan amendments within a year over time together with four measures from the institutional loan market. These are: (1) *CLO Issuance* (Panel A), which is the annual CLO issuance volume; (2) *CLO outstanding* (Panel B), which is calculated as the sum of U.S. CLOs issued over the previous six years; (3) *Trading Volume* (in USD billion, Panel C), which is the volume of syndicated loans traded in the secondary loan market; (4) *Time-on-Market* (Panel D), which is defined as the average time in days between syndication launch date (start of the book building process) for loan tranches marketed to institutional investors and the date at which the borrower gains access to funds (completion date); (5) *% Cov-Lite* (the percentage of covenant-lite contracts relative to all issuances in a year in Panel D); and (6) *Carve-Outs Liens* (which are carve-outs related to the restrictions on liens negative covenant in Panel E.

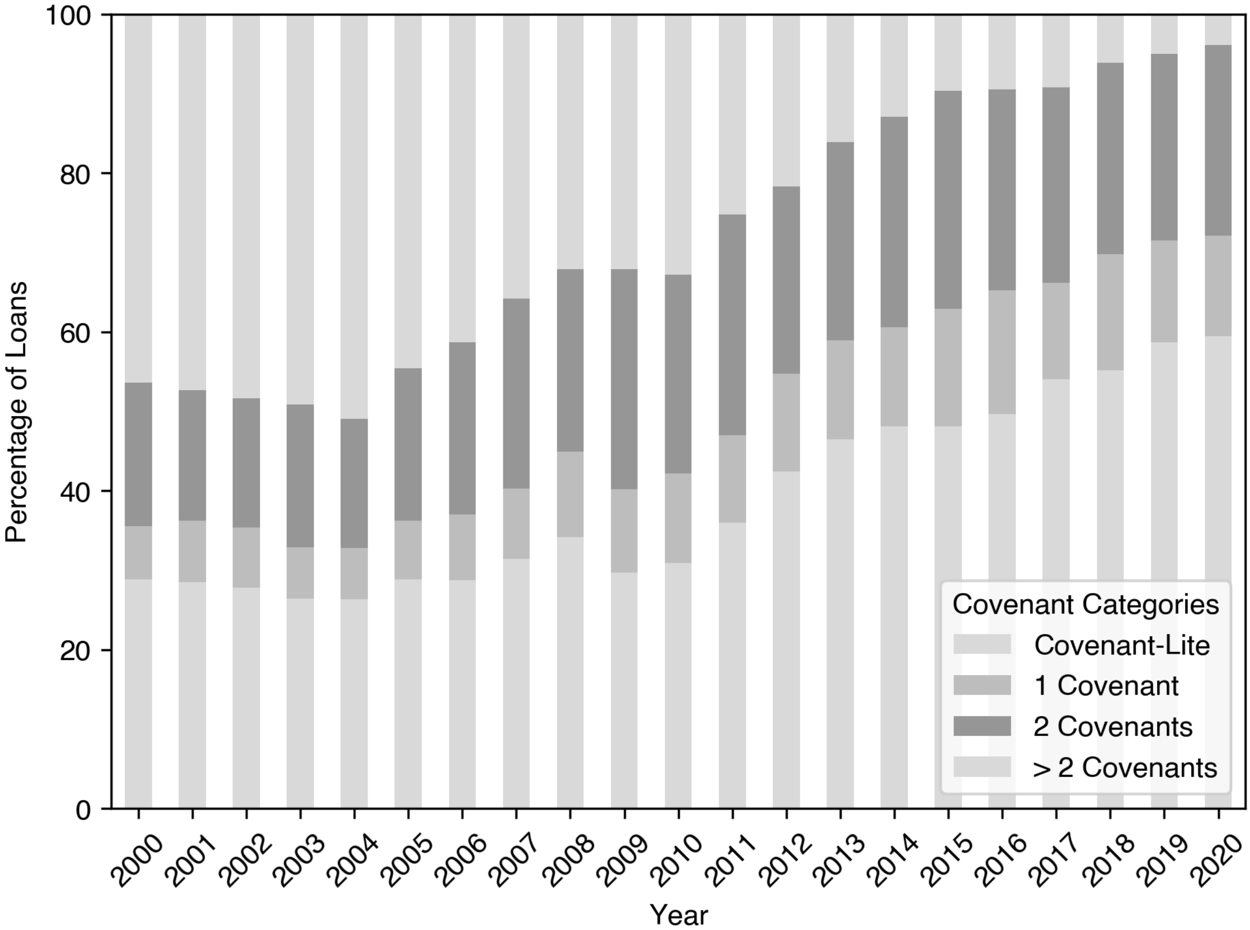
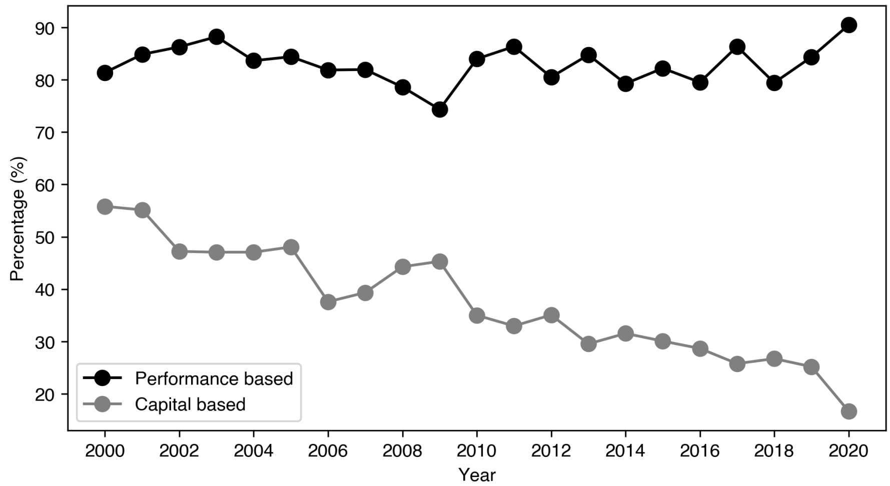
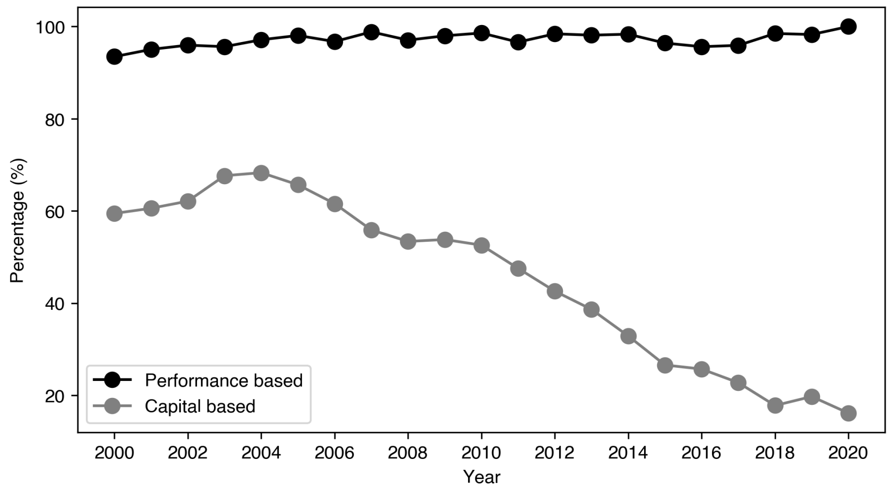


Figure 7: **Number of Covenants**
This figure plots the percentage of loans according to their number of financial covenants annually over the 2000 to 2020 period. *Covenant-Lite* are those loans classified as covenant-lite by the "Marketsegment" field in Refinitiv Dealscan (following the classification in Berlin et al. (2020) or loans without financial covenants. The other categories are one covenant (*1 Covenant*), two covenants (*2 Covenants*) and more than two covenants (*>2 Covenants*).



(a) IG-Rated Firms



(b) Non-IG-Rated Firms

Figure 8: **Performance based vs. Capital based Covenants**
This figure plots the percentage of loans containing performance-based and capital-based covenants for IG-rated (Panel A) and non-IG-rated firms (Panel B) annually over the 2000 to 2020 period. We classified the following covenants as performance-based covenants following Christensen and Nikolaev (2012): *Debt-to-EBITDA, Fixed-charge Coverage, Interest Coverage, Debt Service Coverage, Senior Debt-to-EBITDA, EBITDA, Cash Interest Coverage*. The capital-based covenants consist of the following ratios: *Tangible Net Worth, Leverage Ratio, Debt-to-Tangible Net Worth, Current Ratio, Quick Ratio, Debt-to-Equity, Senior Leverage, Loan-to-Value, Capex.*

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. (2023)	Losing Control? The Two-Decade Decline in Loan Covenant Violations	WP	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: **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 11).

Panel A: Summary Statistics					
	Mean	Median	Min	Max	SD
Violation	0.47	0.00	0.00	1.00	0.50
Amendment	0.45	0.00	0.00	1.00	0.50
Technical Default	0.12	0.00	0.00	1.00	0.33
Control Variables					
Operating Income/ Assets	-0.03	0.07	-17.17	1.92	0.34
Leverage Ratio	0.26	0.20	0.00	8.64	0.27
Interest Expenses/ Assets	0.03	0.02	-0.01	2.47	0.06
NWA/ Assets	0.47	0.50	-9.88	1.03	0.36
Current Ratio	3.08	2.26	0.24	9.91	2.38
MTB	2.23	1.67	0.74	12.75	1.64
Dependent Variables					
Ln(Assets)	5.36	5.15	2.30	13.08	1.84
Ln(PPE)	3.30	3.14	-6.91	11.89	2.52
CapEx/ Assets	0.06	0.04	-0.63	1.50	0.08
CashAqui/ Assets	0.03	0.01	-0.74	5.31	0.09
Employees	2.94	0.38	0.00	387.36	12.02
NDI/ Assets	0.04	0.01	-0.88	3.03	0.13
Ln(Debt)	3.33	3.28	-6.91	12.32	2.70
Cash/ Assets	0.25	0.13	0.00	1.00	0.27
Ln(Payout)	0.64	0.08	-1.24	8.35	1.18
Cash Ratio	0.50	0.50	0.00	1.00	0.28
Usage	0.29	0.22	0.00	1.00	0.27
Operating Income/ Assets	-0.03	0.07	-17.17	1.92	0.34
Ln(Sales)	3.51	3.57	-6.91	11.34	2.29
Ln(Cost)	3.59	3.44	-5.12	11.25	1.91
Downgrade	3.00	4.00	0.00	4.00	1.72
Default	0.02	0.00	0.00	1.00	0.13
Spread	203.65	200.00	35.00	450.00	89.76
Ln(Loan Amount)	4.50	4.59	-1.77	8.68	1.42
Observations	11,432				

Table 3: **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) $\Delta \frac{CashAcq}{Assets}$	(5) Empl Growth
Violation	-0.038***	-0.038**	-0.004***	0.001	-0.025*
	(0.002)	(0.009)	(0.001)	(0.001)	(0.014)
Observations	197,885	196,775	194,375	212,402	11,816
R^2	0.121	0.100	0.009	0.017	0.030
FE	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry
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) $\Delta \frac{Cash}{Assets}$	(4) Δ Ln(Payout)	(5) Δ Cash Ratio	(6) Δ Usage
Violation	-0.023***	-0.054**	0.005*	-0.037**	0.016**	-0.020**
	(0.004)	(0.011)	(0.002)	(0.009)	(0.004)	(0.005)
Observations	194,403	167,915	197,844	174,309	75,875	70,065
R^2	0.037	0.057	0.040	0.029	0.024	0.045
FE	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter
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) $\Delta \frac{OpIncome}{Assets}$	(2) Δ Ln(Sales)	(3) Δ Ln(Cost)	(4) Downgrade	(5) Default
Violation	0.002	-0.037***	-0.020**	-0.001	0.012***
	(0.003)	(0.004)	(0.005)	(0.007)	(0.001)
Observations	193,415	191,982	193,923	90,374	220,489
R^2	0.041	0.063	0.100	0.106	0.034
FE	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter
Violation$_{t-4}$	YES	YES	YES	YES	YES
Covenant Controls	YES	YES	YES	YES	YES
Higher Order Controls	YES	YES	YES	YES	YES
Lagged Covenant Controls	YES	YES	YES	YES	YES

Table 4: **Covenant Violations - Access to Credit**

This table relates covenant violations to firm access to credit. The unit of observation is the firm-quarter level t. The sample period is 1996 to 2020. $Violation_{it}$ is an indicator variable that is one if a firm i violates a covenant in quarter t. Loan data is sourced from Refinitiv Dealscan and mapped to Compustat and SEC filings using the (Chava & Roberts, 2008) linking table (updated to June 2020). Loan information on the facility level is collapsed at the firm-quarter-loan type-refinancing level. Panel A 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 B 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*). 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 $Violation$, four-quarter lags of *Covenant Controls*, and higher order terms of *Covenant Controls*. Each specification includes industry (two-digit SIC codes) and quarter fixed effects and we cluster standard errors at the firm and the quarter level. Standard errors are reported in parentheses (* $p < 0.10$, **$p < 0.05$, ***$p < 0.01$).

Panel A: Term Loan vs. Credit Line

	Term Loan			Credit Line		
	(1) Δ Spread	(2) Δ Ln(Loan Amount)	(3) Credit Access Reduction	(4) Δ Spread	(5) Δ Ln(Loan Amount)	(6) Credit Access Reduction
Violation	4.222	-0.065*	0.035**	7.664***	-0.060***	0.036***
	(6.051)	(0.038)	(0.017)	(2.272)	(0.020)	(0.011)
Observations	3,688	3,688	4,706	9,503	9,503	10,495
R^2	0.120	0.090	0.105	0.176	0.050	0.069
FE	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter
Covenant Controls	YES	YES	YES	YES	YES	YES

Panel B: Refinancing vs. Non Refinancing

	Refinancing			Non Refinancing		
	(1) Δ Spread	(2) Δ Ln(Loan Amount)	(3) Credit Access Reduction	(4) Δ Spread	(5) Δ Ln(Loan Amount)	(6) Credit Access Reduction
Violation	7.767***	-0.061***	0.024**	4.816	0.045	0.010
	(2.629)	(0.017)	(0.011)	(7.070)	(0.073)	(0.020)
Observations	6,704	6,704	8,014	1,764	1,764	2,592
R^2	0.220	0.072	0.078	0.184	0.125	0.112
FE	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter
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	Median	Min	Max	SD
Control Variables					
Operating Income/Assets	-0.04	0.02	-0.91	1.92	0.25
Leverage Ratio	0.33	0.29	0.00	2.24	0.28
Interest Expenses/Assets	0.04	0.03	0.00	0.43	0.05
NWA/Assets	0.36	0.40	-2.27	0.91	0.37
Current Ratio	2.39	1.72	0.24	9.26	1.89
MTB	1.94	1.57	0.74	12.56	1.26
Dependent Variables					
Ln(Assets)	4.68	4.36	2.39	12.17	1.66
Ln(PPE)	2.72	2.43	-2.95	10.75	2.16
CapEx/Assets	0.07	0.04	-0.63	0.96	0.13
CashAqui/Assets	0.03	0.00	-0.14	0.80	0.08
Employees	1.97	0.37	0.01	31.67	4.77
NDI/Assets	0.06	0.02	-0.27	1.00	0.16
Ln(Debt)	2.99	2.83	-3.01	10.79	2.21
Cash/Assets	0.19	0.12	0.00	0.97	0.19
Ln(Payout)	0.30	0.01	-0.00	6.59	0.84
Cash Ratio	0.54	0.58	0.00	0.99	0.28
Usage	0.37	0.29	0.00	1.00	0.30
Operating Income/Assets	-0.04	0.02	-0.91	1.92	0.25
Ln(Sales)	2.93	2.81	-2.72	10.49	1.87
Ln(Cost)	3.06	2.83	-0.41	10.36	1.64
Downgrade	3.38	4.00	0.00	4.00	1.44
Default	0.02	0.00	0.00	1.00	0.16
Spread	225.27	222.92	75.00	450.00	83.43
Ln(Loan Amount)	4.02	3.71	0.36	8.56	1.54
Observations	283				

Panel B: Firms with Amendments

	Mean	Median	Min	Max	SD
Control Variables					
Operating Income/Assets	0.04	0.10	-17.17	0.64	0.34
Leverage Ratio	0.30	0.27	0.00	2.37	0.22
Interest Expenses/Assets	0.03	0.02	-0.01	0.75	0.03
NWA/Assets	0.41	0.44	-3.27	0.95	0.28
Current Ratio	2.38	1.98	0.24	9.91	1.53
MTB	1.89	1.52	0.74	12.75	1.17
Dependent Variables					
Ln(Assets)	5.80	5.68	2.35	12.41	1.81
Ln(PPE)	4.02	3.95	-3.67	11.21	2.35
CapEx/Assets	0.06	0.04	-0.01	0.83	0.07
CashAqui/Assets	0.04	0.02	-0.33	1.04	0.07
Employees	4.68	0.84	0.00	265.55	13.59
NDI/Assets	0.04	0.02	-0.67	1.22	0.09
Ln(Debt)	4.09	4.11	-4.61	11.83	2.43
Cash/Assets	0.16	0.08	0.00	0.97	0.18
Ln(Payout)	0.84	0.24	-0.67	7.90	1.25
Cash Ratio	0.45	0.45	0.00	1.00	0.27
Usage	0.29	0.23	0.00	1.00	0.25
Operating Income/Assets	0.04	0.10	-17.17	0.64	0.34
Ln(Sales)	4.22	4.25	-3.61	10.53	1.94
Ln(Cost)	4.21	4.10	-1.49	10.39	1.73
Downgrade	2.52	4.00	0.00	4.00	1.92
Default	0.03	0.00	0.00	1.00	0.16
Spread	207.51	200.00	35.00	450.00	84.01
Ln(Loan Amount)	4.56	4.67	-0.73	8.68	1.35
Observations	3,985				

Table 6: **Determinants of Loan Amendments**

This table 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. We include industry times quarter fixed effects. Standard errors are clustered at the firm and quarter level and are reported in parentheses (* $p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$).

	(1) Pr(Amendment)	(2) Pr(Amendment)	(3) Pr(Amendment)	(4) Pr(Amendment)	(5) Pr(Amendment)
DD	0.020***	0.018***	0.011***	0.009***	0.006**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
IG				0.043**	-0.008
				(0.017)	(0.020)
Non-IG				0.042***	0.013
				(0.013)	(0.013)
Ln (Asset)					0.019***
					(0.004)
Operating Income/Assets			0.171***	0.181***	0.171***
			(0.025)	(0.040)	(0.039)
Leverage Ratio			-0.083*	-0.017	-0.031
			(0.046)	(0.093)	(0.092)
Interest Expenses/Assets			-0.093	-0.107	0.075
			(0.379)	(0.530)	(0.534)
NWA/Assets			-0.037	0.076	0.085
			(0.037)	(0.078)	(0.078)
Current Ratio			0.014***	0.037***	0.037***
			(0.004)	(0.010)	(0.010)
MTB			0.000	-0.013	-0.007
			(0.003)	(0.011)	(0.011)
Observations	7,061	7,045	5,402	4,765	4,765
R^2	0.027	0.099	0.130	0.153	0.156
FE	NO	Industry Quarter	Industry Quarter	Industry Quarter	Industry Quarter
Higher Order Control	NO	NO	NO	YES	YES
Lagged Controls	NO	NO	NO	YES	YES

Table 7: **Loan Amendments - Financial and Real Adjustments**

This table 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 Δ*Ln(Assets)* in column (1), Δ*Ln(PPE)* in column (2), Δ*Ln(Shareholder Payout)* in column (3), Δ*Ln(Cash Ratio)* in column (4), Δ*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 B shows the regression results using the same dependent variables but interacting $Amendment_{i,t}$ with rating categories. *IG* is an indicator that is one if the firm has an investment-grade rating. *Non-IG* is an indicator that is one if the firm has a non-investment-grade rating. *Unrated* is an indicator variable that is one if the firm is unrated. The regressions include the control variables shown in column (5) of 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: Amendments and firm adjustments

	(1) Ln(Δ Assets)	(2) Ln(Δ PPE)	(3) Ln(Δ Shareholder Payout)	(4) Cash Ratio	(5) Ln(Δ Cost)	(6) Default
Amendment	0.039***	0.054***	-0.027	-0.036**	0.061***	-0.047***
	(0.015)	(0.018)	(0.038)	(0.017)	(0.020)	(0.012)
Observations	4,953	4,950	4,361	2,273	4,826	5,430
R^2	0.176	0.154	0.075	0.100	0.169	0.123
FE	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter
Covenant Controls	YES	YES	YES	YES	YES	YES

Panel B: Amendments and credit ratings

	(1) Ln(Δ Assets)	(2) Ln(Δ PPE)	(3) Ln(Δ Shareholder Payout)	(4) Cash Ratio	(5) Ln(Δ Cost)	(6) Default
IG x Amendment	0.057	0.012	0.344	-0.052*	0.064	-0.043
	(0.037)	(0.035)	(0.219)	(0.027)	(0.078)	(0.050)
Non-IG x Amendment	0.007	0.008	0.020	-0.083***	0.132***	-0.139***
	(0.039)	(0.046)	(0.109)	(0.028)	(0.046)	(0.039)
Unrated x Amendment	0.044***	0.070***	-0.082**	-0.007	0.031	-0.012
	(0.016)	(0.020)	(0.033)	(0.024)	(0.021)	(0.009)
Observations	4,953	4,950	4,361	2,273	4,826	5,430
R^2	0.180	0.158	0.077	0.103	0.171	0.140
FE	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter
Covenant Controls	YES	YES	YES	YES	YES	YES

Table 8: **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 *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. Firm outcome variables are Δ*Ln(Assets)* in column (1), Δ*Ln(PPE)* in column (2), Δ*Ln(Shareholder Payout)* in column (3), Δ*Ln(Cash Ratio)* in column (4), Δ*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 B shows the regression results. 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

	(1) Full	(2) IG	(3) Non-IG	(4) Unrated
Amendment w/o Violation	8.80%	6.00%	13.34%	7.39%
Amendment w/ Violation	4.04%	0.65%	3.01%	5.02%
Waiver	3.77%	0.47%	3.72%	4.34%
Technical Default	2.81%	0.36%	2.46%	3.37%

Panel B: Operational and Financial Performance

	(1) Δ Ln(Assets)	(2) Δ Ln(PPE)	(3) Δ Ln(Shareholder Payout)	(4) Cash Ratio	(5) Δ Ln(Cost)	(6) Default
Amendment w/o Violation	0.050***	0.050***	0.004	-0.004	0.055***	-0.038***
	(0.013)	(0.016)	(0.033)	(0.018)	(0.015)	(0.010)
Amendment w/ Violation	0.013	0.020	0.002	-0.007	0.043**	-0.034***
	(0.015)	(0.020)	(0.035)	(0.018)	(0.017)	(0.010)
Waiver	0.014	0.031	0.050	-0.016	0.037**	-0.032***
	(0.016)	(0.020)	(0.039)	(0.018)	(0.017)	(0.009)
Observations	5,914	5,911	5,185	2,621	5,756	6,541
R^2	0.191	0.157	0.074	0.075	0.174	0.122
FE	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter	Industry, Quarter
Covenant Controls	YES	YES	YES	YES	YES	YES

Table 9: **Evolution of Covenants in Loan Agreements**

This table provides the most important covenant ratios for Non-IG-Rated and IG-Rated firms, measured by the average occurrence in more than 10% of the loan contracts between 2016 and 2020. The values represent the frequency of each covenant in the overall loan contracts and are expressed as a percentage. *Debt-to-EBITDA* is debt over EBITDA. *Fixed-charge Coverage* is the sum of EBIT and fixed charges before taxes and the sum of fixed charges before taxes and interest. *Interest Coverage* is the ratio of EBIT over interest expense, and the *Senior Debt-to-EBITDA* is calculated by the ratio of Senior Debt over EBITDA. *Leverage Ratio* is defined as Debt over Equity. We classified the following covenants as performance-based covenants following (Christensen & Nikolaev, 2012): *Debt-to-EBITDA, Fixed-charge Coverage, Interest Coverage, Debt Service Coverage, Senior Debt-to-EBITDA, EBITDA, Cash Interest Coverage.* The capital-based covenants consist of the following ratios: *Tangible Net Worth, Leverage Ratio, Debt-to-Tangible Net Worth, Current Ratio, Quick Ratio, Debt-to-Equity, Senior Leverage, Loan-to-Value, Capex.*

	Non-IG-Rated				IG-Rated		
Year	Debt-to-EBITDA	Fixed-charge Coverage	Interest Coverage	Senior Debt-to-EBITDA	Debt-to-EBITDA	Interest Coverage	Leverage Ratio
2000	70.96	49.31	56.01	18.21	52.71	53.49	37.21
2001	71.43	55.05	54.67	16.38	49.73	47.57	35.68
2002	73.85	51.92	51.54	17.31	51.78	51.78	35.03
2003	77.64	55.09	52.55	20.73	52.35	50.00	33.53
2004	79.09	60.20	53.46	24.96	54.25	58.17	28.10
2005	76.76	57.22	50.70	25.18	53.25	55.84	37.01
2006	73.07	49.40	48.37	22.81	55.70	58.39	26.85
2007	78.81	40.85	51.64	21.00	61.48	48.36	29.51
2008	79.32	42.62	49.58	21.10	52.67	49.62	32.06
2009	78.35	42.19	48.44	17.63	56.41	45.30	35.04
2010	76.87	40.65	52.57	17.29	66.00	53.00	25.00
2011	77.14	30.91	55.58	16.10	61.36	55.68	20.45
2012	76.97	37.54	49.84	10.73	62.34	49.35	25.97
2013	80.06	25.86	53.27	11.21	71.43	51.43	21.90
2014	77.07	25.69	50.28	12.43	64.86	50.45	26.13
2015	78.51	25.37	47.16	8.96	67.48	44.79	25.15
2016	76.23	25.68	44.26	11.48	67.25	50.29	25.15
2017	77.55	27.41	45.19	18.37	67.42	46.97	23.48
2018	80.72	25.30	42.77	18.07	69.18	34.93	23.97
2019	81.31	20.42	46.71	14.19	72.79	40.13	18.37
2020	83.87	19.35	50.00	12.90	85.71	35.71	16.67
Covenant Type	Performance	Performance	Performance	Performance	Performance	Performance	Capital

Table 10: **Loan Amendments during COVID**

This table relates credit ratings as well as firms size to the likelihood to amend loans before violation occurs during the covid period relative to before (our sample period is 2010-2022). Panel A shows summary statistics of our rating classes (*IG*, *Non-IG*, and *Unrated*). *Amendment w/o (%)* is the percentage of possible violations that have been renegotiated before a violation occurred. Size 1 - Size 4 are size quartiles. Panel B relates credit ratings to the likelihood to violate covenants or amend loans before violation occurs during the COVID period. *Pr(Violation)* is an indicator that is one if the firm violates a covenant (this comprises all incidences including amendments, waivers and technical defaults), our dependent variable in column (1). *Pr(Amendment)* is an indicator that is one if the firms obtains an amendment (relative to non-violating firms) and our dependent variable in column (2). Pr(Amendment w/o) is an indicator variable equal to one if the firms obtains an amendment before a covenant violation occurs (relative to non-violating firms) and our dependent variable in columns (3) to (6). *Covid* is an indicator equal to one if the violation or amendment happened in the Q1 or Q2 2020 period. *Exposure* is an indicator that is one if the firm is in the bottom quartile of the firm-specific year-on-year sales decline between Q2 2019 and Q2 2020. Panel C relates firm size quartiles to the likelihood to violate covenants or amend loans before violation occurs during the COVID period. Pr(Amendment w/o) is an indicator variable equal to one if the firms obtains an amendment before a covenant violation occurs (relative to non-violating firms) and is our dependent variable in columns (1) to (4). 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. We include industry and year fixed effects. Standard errors are clustered at the firm and quarter level and are reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: Summary Statistics by Rating and Firm Size

Rating	Amendments w/o (%)	**Size**	Amendments w/o (%)
		Size 1 (10m - 141m)	37.55%
IG	90.20%	**Size 2 (142m - 779m)**	60.74%
Non-IG	65.83%	**Size 3 (780m - 3,454m)**	73.02%
Unrated	57.66%	**Size 4 (3,455m - 873,729m)**	77.48%

Panel B: Covid and Rating Category

	(1) Pr(Violation)	(2) Pr(Amendment)	(3) Pr(Amendment w/o)	(4) Pr(Amendment w/o)	(5) Pr(Amendment w/o)	(6) Pr(Amendment w/o)
Covid	0.028***	0.027***	0.018***	0.018***	0.008**	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
IG			-0.003*	-0.003*	-0.004***	-0.003
			(0.002)	(0.002)	(0.002)	(0.002)
Non-IG			0.002*	0.002*	0.001	0.001
			(0.001)	(0.001)	(0.001)	(0.001)
Exposure				0.005***	0.005***	0.004*
				(0.002)	(0.002)	(0.002)
IG x Covid					0.042***	0.031***
					(0.011)	(0.011)
Non-IG x Covid					0.018**	0.006
					(0.007)	(0.007)
IG x Covid x Exposure						0.092**
						(0.036)
Non-IG x Covid x Exposure						0.055***
						(0.017)
Unrated x Covid x Exposure						0.020**
						(0.010)
Observations	122,254	121,908	120,434	120,434	120,434	120,434
R^2	0.016	0.014	0.011	0.011	0.011	0.012
FE	Industry, Year	Industry, Year	Industry, Year	Industry, Year	Industry, Year	Industry, Year
Covenant Controls	YES	YES	YES	YES	YES	YES

Panel C: Covid and Size

	(1) Pr(Amendment w/o)	(2) Pr(Amendment w/o)	(3) Pr(Amendment w/o)	(4) Pr(Amendment w/o)
Covid	0.018***	0.018***	0.039***	0.027***
	(0.004)	(0.004)	(0.007)	(0.007)
Size 1	-0.002	-0.002	-0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)
Size 2	0.005***	0.005***	0.006***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)
Size 3	0.003**	0.003**	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.002)
Exposure		0.005***	0.005***	0.005*
		(0.002)	(0.002)	(0.003)
Size 1 x Covid			-0.043***	-0.032***
			(0.008)	(0.008)
Size 2 x Covid			-0.027***	-0.022**
			(0.009)	(0.009)
Size 3 x Covid			-0.020**	-0.020**
			(0.009)	(0.009)
Size 1 x Covid x Exposure				0.005
				(0.011)
Size 2 x Covid x Exposure				0.039**
				(0.020)
Size 3 x Covid x Exposure				0.050***
				(0.018)
Size 4 x Covid x Exposure				0.057***
				(0.020)
Observations	120,434	120,434	120,434	120,434
R^2	0.011	0.011	0.012	0.012
FE	Industry, Year	Industry, Year	Industry, Year	Industry, Year
Covenant Controls	YES	YES	YES	YES

A Appendix

Variable Definition

Table 11: 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$_i$)