Covenant Strictness Measures

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Covenants are crucial components of loan agreements, designed to protect lenders by imposing various restrictions and obligations on borrowers. Despite extensive empirical research on covenant strictness, a universally accepted measure of covenant strictness remains elusive. Existing metrics tend to include only a limited selection of covenants from the comprehensive contract. This study utilizes loan-level credit risk data to evaluate and rank the effectiveness of several widely used covenant strictness measures. Credit risk at the loan level is assessed through two primary methods: the difference between issue ratings and issuer ratings, and the loan credit spread while controlling for fixed effects at the firm level. This approach allows for a more nuanced comparison and provides insights into which measures most accurately reflect covenant strictness and its impact on credit risk. The findings aim to contribute to a better understanding of covenant effectiveness, offering potential improvements for future loan contract structuring and risk assessment practices.

Keywords: covenant strictness, loan contracts, credit risk, syndicated loans, Covenant Intensity Index, credit spreads, loan ratings

INTRODUCTION

Covenants are an important topic in loan contracting. In general, covenants are restrictions that lenders put on borrowers in a loan contract to reduce the risk of the loan, while lenders sacrifice financial flexibility in return for a large amount of capital. In general, by using covenants, lenders are able to transfer control of the assets during covenant violation. As a result, if the covenants in loan contract are aggregately stricter, the borrower is more likely to have a covenant violation. A loan contract with a stricter set of covenants is considered a stricter contract. Therefore, it is very important to understand and measure covenant strictness to facilitate a wide range of research based on loan strictness. The importance and demand of measuring covenant strictness becomes increasingly relevant.

Recently research on banking, accounting and financial intermediation has proposed several different types of covenant strictness measures. These measures reflect different important areas of covenant strictness. In this paper, I examine the effectiveness of these covenant measures and how well they perform in measuring the loan risk using syndicated loan ratings and loan spreads. There exist three major categories of strictness measures.

The first category involves a simple count of covenants included in a loan agreement. This measure is straightforward and easy to calculate, but it often fails to capture the true risk associated with covenant strictness as it does not account for the specific nature or severity of the covenants (Christensen & Nikolaev, 2012; Drucker & Puri, 2009). The second category assesses the stringency of individual covenants, evaluating how strict or lenient each covenant is in terms of financial metrics or performance thresholds. While this approach provides a more nuanced view, it can be subjective and inconsistent across different loan agreements (Bradley & Roberts, 2015; Demiroglu & James, 2010). The third category, which I argue is the most comprehensive, measures the probability of covenant violation. This approach considers not only the presence and stringency of covenants, but also the likelihood that a borrower will breach these covenants based on their financial health and performance metrics (Murfin, 2012; Demerjian & Owens, 2016).

I construct and compare three covenants' strictness measures using both credit ratings and credit spread as benchmarks. The goal is to test whether these measures accurately reflect the overall risk of loans. Credit ratings, provided by rating agencies, offer a qualitative assessment of credit risk, while credit spreads provide a market-based quantitative measure of risk (Agarwal, Amromin, Ben-David, Chomsisengphet, & Evanoff, 2014; Berkovec & Goodman, 1996). By comparing covenant strictness measures against these benchmarks, I aim to determine their effectiveness in predicting loan risk.

The results suggest that the strictness measure using the probability of covenant violation best explains loan risk. This measure provides a more accurate reflection of the overall risk because it integrates the likelihood of covenant breaches, which directly impact the borrower's financial stability and, consequently, the loan's risk profile (Murfin, 2012; Demerjian & Owens, 2016). In contrast, a simple or arbitrary count of covenants fails to capture this complexity and does not correlate well with loan risk (Bradley & Roberts, 2015). Similarly, while assessing individual covenant stringency can offer insights, it lacks the predictive power of the probability measure due to its subjectivity and potential inconsistency (Christensen & Nikolaev, 2012).

However, the probability of covenant violation is not without limitations. One significant drawback is the reliance on historical data and financial forecasts, which can be uncertain and subject to change. Additionally, this measure may not fully capture the dynamic interactions between different covenants and their cumulative impact on loan risk. There is also the challenge of accurately estimating the likelihood of violation, which requires sophisticated modeling and continuous monitoring of the borrower's financial performance (Capozza & Thompson, 2006; Campbell & Cocco, 2015). There are certainly more areas to explore without limiting the strictness solely to the likelihood of violation. Future research could investigate the interplay between different covenants and their combined effect on loan risk, considering factors such as the borrower's industry, economic conditions, and market trends (Levitin & Wachter, 2013; Foote, Gerardi, & Willen, 2008). Additionally, incorporating qualitative assessments from loan officers and financial experts could enhance the understanding of covenant strictness and its implications for loan risk. By broadening the scope of analysis and integrating multiple dimensions of covenant strictness, we can develop more robust measures that better reflect the complexities of loan agreements and their associated risks.

To be more specific, firstly, if a loan contract has more covenants, limiting more of the borrower's financial flexibility, such a contract is considered stricter as it essentially gives the lender more potential control. Simply put, a contract with two covenants should be stricter than another contract with a single covenant. For example, a loan with both interest coverage ratio covenant and dividend restriction covenant is stricter than a loan with only interest coverage ratio covenant. The Covenant Intensity Index (CII) by Bradley and Roberts (2015) captures this idea. Although CII incorporates collateral information and puts more weight on non-financial covenants. In another example, Christensen and Nikolaev (2012) use covenant counts as strictness measures relating to borrower restrictions through performance versus capital covenants.

Secondly, specifically for financial covenants, covenant strictness should also reflect how close the initial financial ratios are to the thresholds set in the covenants, also known as initial financial slacks. A covenant is stricter if the slack is small, which means a small distance between the negotiated minimum or maximum level and the existing accounting numbers of the borrower. An obvious limitation of this measure is that only the slack of a single covenant can be measured at a time. Therefore, this measure fails to capture the effect of other covenants coexisting in the contract. Often, the measure restricts the sample to having to have the specific covenant in the contract therefore generating a nonrandom subsample which may be biased based on the covenant being used. For example, Drucker and Puri (2009) use net worth covenant slack alone as the covenant strictness measure; and Demiroglu and James (2010) measure covenant strictness based on the tightness of current ratio slack and debt to EBITDA ratio slack.

Thirdly, Murfin (2012) created a covenant strictness measure based on the probability of financial covenant violation, a more comprehensive measure focusing on the likelihood of violating the set of financial covenants existing in the contract. Murfin included 10 financial ratios and calculated the joint probability of covenants. Demerjian and Owens (2016) expanded his method to a larger scale by incorporating 15 financial covenants available in the Dealscan database and also minimized measurement errors by standardizing covenant definitions. The idea of the probability of covenant violation incorporates both the number of covenants and the slack. In addition, this measure takes into account the scale of the slack and the correlation between different covenants existing in the same contract. However, this measure, like any measures involving slack, only looks at financial covenants, while the effect of non-financial covenants is yet to be measured.

Recent authors have generally used either Murfin’s 2012 measures for covenant strictness (Darmouni 2020) or used Demerjian and Owen’s 2016 measures (Imbierowicz and Streitz 2024). Many of the latter also cite Murfin for inspiration, but the vast majority fall into one of these two camps. Some scholars have created their own measures in order to tackle specific questions, but there is still no one standardized measure for covenant strictness.

Generally speaking, if a covenant strictness measure correctly captures the overall strictness of a loan contract, it should also capture the riskiness of the loan. That is, if a contract is stricter, it should be less risky. And a good covenant strictness measure should reflect that. Therefore, in order to test the performance of the strictness measure, I propose three variables that measure loan risk.

First, credit ratings are a direct variable that measures credit risk. I use the difference between the loan rating and the borrower rating as a measure of the loan risk. This difference is therefore free of firm level variation and should be determined solely by loan characteristics. Therefore, the rating difference works as one accurate benchmark for the covenant strictness measure.

Second, credit spread measures the credit risk of loans and the issuing borrowers, while CDS spread measures the credit risk of the borrower. As a result, the difference between loan credit spread and CDS spread measures the credit risk specific to the loan, therefore making it another good benchmark for the covenant strictness measure. A larger difference between the spreads indicates a higher loan risk. Accordingly, an accurate covenant strictness measure should capture the variation in this difference.

Third, while the CDS spreads are not available, another way of identifying the variations of loan-level risk is by looking at the credit spread of multiple loans within the same firm, where I no longer need to control for firm level variation as the loans are from the same issuers. Therefore, with a sample size large enough and with enough issuers with multiple loans, I use credit spread directly as a benchmark for the covenant strictness measure.

Besides the covenant strictness measure from each of the three categories, I construct another measure by simply adding up the total number of covenants as a reference. Then I test these strictness measures against the different measures for credit risk while controlling for loan characteristics.

There are three major types of covenants: affirmative covenants, negative covenants and financial covenants. Affirmative covenants state the actions borrowers must take while the loan is outstanding. For example, these covenants often require a borrower to pay the lender interest and fees, provide audited financial statements, maintain insurance, and pay taxes. Affirmative covenants are bare minimum requirements and exist in virtually all loan contracts, so most loan databases do not report them separately. Consequently, they are not included in this study as they do not differ across different loans.

Negative covenants restrict a borrower’s actions in a particular way; for example, they might restrict the type and the amount of acquisitions, new issues, and asset sales. They may also require mandatory prepayments, such as using the proceeds of a debt issue, asset sale, or equity issue to prepay the loan. In this paper, I refer to negative covenants as non-financial covenants. Financial covenants, traditionally known as maintenance covenants, are often more restrictive than non-financial covenants. They require borrowers to maintain stipulated levels of a financial ratio or value, such as minimum interest coverage ratio and minimum net worth. If the borrower fails this test, it is then in technical default.

The remainder of the paper is structured as follows. Next section provides information about data, variables, and summary statistics. The section after introduces different empirical setups and presents the results and explanations. Last section concludes.

DATA, VARIABLES AND SUMMARY STATISTICS

In this paper, I gather the characteristics of syndicated loans issued between 1995 and 2012 from the LPC Dealscan database. I record covenants, collateral, maturity, loan type, loan size, starting and ending dates, and one-digit SIC industry code. Next, I calculated the total number of covenants and used it as one simple measure of covenant strictness.

I then follow the specifications of Bradley and Roberts (2015) to construct the Covenant Intensity Index (CII). The value of CII index ranges from 0 to 6. It weighs non-financial covenants more than financial covenants. Having one, two or three of equity issuance sweep, debt issuance sweep or asset sales sweep adds one, two or three points to CII. Having the divined restriction adds one point. If the total number of financial covenants is equal or more than two, CII gains another point. Having collateral also adds one point. Therefore, out of the total possible six points, four points are from non-financial covenants, while only one point is on financial covenants. While collateral also accounts as one point for CII, it is technically not part of the covenants.

Covenant violation probability is calculated according to Demerjian and Owens (2016), where they follow the specifications of Murfin (2012). Starting with one covenant, the probability of covenant violation is a function of initial covenant slack and the volatility of the financial value of this covenant. Now if there are two covenants, besides slack and volatility, we also need to consider the correlation between the two covenants. If the correlation is lower, then the probability of violation is higher as those two covenants are more likely to be independently violated. If there are N covenants, the probability that at least one covenant is violated is determined by N, the slack on each covenant, the volatility of each financial value defined by each covenant, and the correlations between the N financial values. With Monte Carlo simulation, the financial values of next quarter are simulated for 1000 times and the number of violations from the simulation divided by 1000 is exactly the probability of covenant violation. This probability of violation is readily available and provided by Demerjian and Owens (2016).

Now that I have these three covenant strictness measures (total number of covenants, CII, probability of violation), I test them against Moody's credit ratings. As stated in the introduction, I take the difference between loan ratings and firm ratings, thereby effectively eliminating most firm-level characteristics. Furthermore, while existing empirical research primarily examines credit spreads (loan price), I instead focus on credit ratings, a direct measure of credit risk. Whereas credit spreads contain firm characteristics, the rating difference is free of variations at the firm level.

Most firms that obtain ratings for their syndicated loans are also rated at the firm level. A firm rating is a rating of the senior unsecured debt and debt-like obligations of the firm in general. It is not linked to a specific debt contract. In contrast, rating agencies rate loans based on the existing firm ratings but incorporate specific risks for the particular loan being rated. Since loan ratings include both firm-level and loan-level characteristics, I disentangle these two risks by subtracting the firm rating from the loan rating, thereby eliminating most firm-level variation. I keep the difference as a measure of credit risk specific to a loan. This procedure allows me to explain the variation of this difference using loan characteristics.

I use Moody's syndicated loan ratings at origination from 1995 to 2012, a period when the majority of syndicated loans were rated. In this dataset, each loan has a Moody's unique identifier and a firm level identifier. In order to match loan ratings with firm ratings, I manually collect firm ratings using firm identifiers and match the firm ratings with the closest rating date to the loan ratings.

Moody’s database maintains three types of firm level ratings. The most commonly used rating that measures the firm’s credit risk is the long-term issuer rating, which rates firm’s long term senior unsecured debt and debt-like obligations. However, not every firm has a long-term issuer rating. For these firms, I use the long-term unsecured rating if it is available. This rating measures the same credit risk as the long-term issuer rating. If neither of the above-mentioned firm ratings is available, I use the long-term corporate family rating as a proxy for the issuer rating. The long-term corporate family rating is the long-term rating that reflects the relative likelihood of a default on a corporate family’s debt and debt like obligations and the expected financial loss suffered in the event of default. To justify the use of this proxy, I compare the long-term corporate family rating with the long-term issuer rating of the firms where both ratings are available. More than 90% of such firms have identical issuer and corporate family ratings. For the remaining 10% of firms, the rating difference is less than one notch. Nevertheless, as a robustness check, the empirical results are similar when I exclude loans using corporate family ratings.

Next, I match the firm rating to the loan rating by date. I first look for firm rating updates up to 365 days before the loan is rated. If an updated firm rating within this range cannot be found, then the search range is extended to up to 60 days after the loan was issued, since a recent update of the firm rating immediately following the loan issue is likely a more accurate measure of the firm’s condition at the time the loan was rated. If a firm rating does not fall into this time window, it does not appear in the sample. I test several different window sizes including 180 days before and 30 days after, 90 days before and 15 days after, and only ratings before the loan issue. The results are robust across different specifications. This procedure generates 7355 unique loans with both loan ratings and firm ratings from 1995 to 2012.

Afterwards, I gathered the characteristics of syndicated loans issued between 1995 and 2012 from the LPC Dealscan database. I record covenants, collateral, maturity, loan type, loan size, starting and ending date, and one-digit SIC industry code. Dealscan uses a unique identifier, FacilityID, for each issue at the loan level. Since there are no common identifiers of loans between Dealscan and Moody’s, I match the loans in two steps starting at the firm level. If a firm is publicly traded and has a ticker in both datasets, the firm is matched using the ticker. If a firm does not have a ticker, then I match it by the firm name manually, checking name changes and subsidiaries. Once both datasets are matched on the firm level, I identify each loan using the starting date, ending date, and loan type. This procedure yields a sample of 3,597 loans with both ratings and loan characteristics.

As the data for probability of covenant violation is readily available, merging it with Moody’s rating data yields 1,167 observations. Table 1 shows the summary statistics.

TABLE 1
SUMMARY STATISTICS: CREDIT RATING DIFFERENCE

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Firm Rating Score	1,167	8.612	2.532	2	18
Loan Rating Score	1,167	9.737	2.016	4	18
Rating Difference	1,167	1.125	1.216	-2	6
CII	1,167	4.263	1.870	0	6
Total # of Covenants	1,167	5.659	2.773	1	12
Probability of Violation	1,167	0.380	0.418	0	1
Secured	1,167	0.817	0.386	0	1
Size	1,167	6.407	1.092	3.219	9.989
Maturity	1,167	61.26	18.58	3	144
Term Loan	1,167	0.460	0.499	0	1

Another benchmark I use to test the validity of the covenant strictness measure is the credit spread (All-In-Drawn), obtained from the Dealscan database. I exclude all refinanced loans and loans with missing data. The merge between the probability of covenant violation and credit spread data generates 4018 observations. Table 2 shows the summary statistics.

TABLE 2
SUMMARY STATISTICS: CREDIT SPREAD

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Credit Spread (All-In-Drawn)	4,060	219.5	143.6	5	1,600
CII	4,060	3.443	1.830	0	6
Total # of Covenants	4,060	4.316	2.562	1	11
Probability of Violation	4,060	0.407	0.428	0	1
Secured	4,060	0.740	0.439	0	1
Size	4,060	5.084	1.676	-0.734	9.989
Maturity	4,018	48.17	25.67	1	252
Term Loan	4,060	0.347	0.476	0	1

EMPIRICAL SETUP AND RESULTS

First, I use the difference between loan ratings and firm ratings as the dependent variable to how each covenant strictness measure predicts the difference. I control for loan size and maturity and fixed effects including year, one-digit SIC code, loan purpose and firm rating. Firms issue loans for different purposes including general corporate purpose, debt refinancing, recapitalization, and LBO or merger and acquisition. Loans with different purposes have varying credit risks and therefore I control for this variation. Similarly, firm rating can be an important determinant of the rating difference. Although I assign rating scores across the rating scale uniformly, a difference of one notch at different rating levels may represent different risks. Therefore, it is important to control for firm-rating as well. The setup for the basic regression is

$$Rating\_diff = \beta_0 + \beta_1 measure + \beta_2 loan_{size} + \beta_3 loan_{type} + \beta_4 maturity + FE \tag{1}$$

where measure is the one of the three covenant strictness measures defined in the last section including the popular CII. Table 3 shows how these covenant strictness measures perform in explaining the rating difference.

TABLE 3
TEST STRICTNESS MEASURES WITH CREDIT RATING DIFFERENCE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Probability of Violation		0.246***				0.333***	0.292***		0.339***
		(2.884)				(3.851)	(3.399)		(3.909)
Total # of Covenants			-0.0613***			-0.0748***		-0.0814***	-0.102***
			(-3.866)			(-4.636)		(-2.595)	(-3.233)
Covenant Intensity Index				-0.0778***	0.124***		-0.0917***	0.0386	0.0521
				(-2.952)	(5.449)		(-3.456)	(0.743)	(1.007)
Secured	1.403***	1.332***	1.603***	1.628***		1.550***	1.583***	1.557***	1.487***
	(13.71)	(12.68)	(14.05)	(12.79)		(13.58)	(12.44)	(12.00)	(11.43)
Size	0.106***	0.122***	0.0895***	0.0937***	0.0737**	0.108***	0.111***	0.0903***	0.109***
	(3.140)	(3.580)	(2.641)	(2.757)	(2.018)	(3.166)	(3.234)	(2.662)	(3.203)
Maturity	-0.00283	-0.00218	-0.00144	-0.00203	0.00275	-0.000243	-0.00111	-0.00138	-0.000143
	(-1.346)	(-1.031)	(-0.678)	(-0.960)	(1.230)	(-0.114)	(-0.522)	(-0.650)	(-0.0670)
Term Loan	-0.110	-0.121*	-0.0896	-0.0931	-0.0563	-0.0998	-0.103	-0.0912	-0.102
	(-1.586)	(-1.747)	(-1.296)	(-1.343)	(-0.755)	(-1.453)	(-1.492)	(-1.320)	(-1.488)
Observations	1,167	1,167	1,167	1,167	1,167	1,167	1,167	1,167	1,167
Adjusted R-squared	0.297	0.302	0.306	0.302	0.192	0.315	0.309	0.306	0.315
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
One Digit SIC FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Table 3, column (1) shows the effects with no covenant measures, where collateral and loan size have a positive impact on credit ratings. I list the effects of probability of violation, total number of covenants and CII in columns (2) to (4). A high probability of covenant violation translates to a higher relative credit rating, which is consistent with the prediction. However, neither the total number of covenants nor CII produce a positive correlation, suggesting that randomly adding up the number of covenants does not seem to be a good measure for strictness. Column (5) shows a positive relation for CII in the absence of collateral, as collateral is one component of the CII index. Columns (6) to (9) show how probability of violation dominates the other two covenant strictness measures. Rating agencies construct credit ratings based on the probability of default and loss given default. Credit ratings reflect the credit risk based on the analysis and opinions by the rating agencies. Another objective measure of credit risk is the credit spread, which is the difference between a risk-free rate and the loan yield of the same maturity. Therefore, credit spread itself is the measure of the market risk of the debt product. Generally speaking, a riskier loan will have a higher credit spread as investors need to be compensated for the extra risk. Knowing this, I use the credit spread (All-In-Drawn) from the Dealscan database as the other benchmark for the effectiveness of covenant strictness measures. However, credit spread includes both loan-level and firm-level credit risk. In order to limit the risk variation at the loan level, I apply fixed effects at the firm level, therefore eliminating the firm level variation. It is also important to control for time fixed effects as market conditions vary significantly over time. I therefore control for firm-year fixed effects, which addresses the time varying market condition and still allows enough variation within each fix-effect subgroup.

Table 4 shows the results of different covenant strictness measures in explaining the variation of credit spread. With a similar setup as Table 3, column (1) shows the basic effect without any strictness measures. The coefficients for collateral and loan size are significant and negative, which means having collateral or a larger size translates to a lower credit spread, therefore lowering credit risk. Columns (2) to (4) list the effect of three covenant strictness measures. Surprisingly they are all positive and significant. First of all, a higher probability of violation should indeed translate into higher risk, hence higher spread. A large number of covenants and a high CII also seem to be associated with high credit spread, which means the market thinks a loan with a large number of covenants means higher risk. However, once I put all three measures into one regression, only the total number of covenants drives the effect.

TABLE 4
TEST STRICTNESS MEASURES WITH CREDIT SPREAD

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Probability of Violation		52.85***				31.12	42.53**	31.12	32.45
		(2.766)				(1.579)	(2.211)	(1.579)	(1.640)
Total # of Covenants			17.85***			16.20***		16.20***	12.65**
			(4.723)			(4.133)		(4.133)	(2.129)
Covenant Intensity Index				25.80***	16.69***		23.67***		7.858
				(3.991)	(2.792)		(3.625)		(0.795)
Secured	-45.82**	-45.37**	-61.40***	-80.66***		-59.69***	-77.41***	-59.69***	-67.19***
	(-2.214)	(-2.198)	(-2.952)	(-3.608)		(-2.868)	(-3.460)	(-2.868)	(-2.940)
Size	-32.73***	-32.75***	-50.41***	-44.91***	-39.79***	-48.78***	-43.91***	-48.78***	-48.98***
	(-4.264)	(-4.277)	(-5.939)	(-5.462)	(-4.892)	(-5.709)	(-5.340)	(-5.709)	(-5.728)
Maturity	0.0383	0.0237	0.0177	0.0596	0.0243	0.0110	0.0461	0.0110	0.0212
	(0.348)	(0.215)	(0.162)	(0.543)	(0.222)	(0.101)	(0.420)	(0.101)	(0.192)
Term	27.32***	27.40***	27.17***	26.90***	26.69***	27.23***	27.00***	27.23***	27.14***
	(8.093)	(8.136)	(8.110)	(8.008)	(7.912)	(8.132)	(8.048)	(8.132)	(8.097)
Obs	4,018	4,018	4,018	4,018	4,018	4,018	4,018	4,018	4,018
Adjusted R-squared	0.796	0.797	0.800	0.799	0.797	0.800	0.799	0.800	0.800
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
One Digit SIC FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

CONCLUSION

In this paper, I present three major categories of covenant strictness measures and compare the pros and cons of each category. The first category involves a simple count of covenants included in a loan agreement. This measure is straightforward and easy to calculate, but it often fails to capture the true risk associated with covenant strictness, as it does not account for the specific nature or severity of the covenants. The second category assesses the stringency of individual covenants, evaluating how strict or lenient each covenant is in terms of financial metrics or performance thresholds. While this approach provides a more nuanced view, it can be subjective and inconsistent across different loan agreements. The third category, which I argue is the most comprehensive, measures the probability of covenant violation. This approach considers not only the presence and stringency of covenants but also the likelihood that a borrower will breach these covenants based on their financial health and performance metrics. Next, I construct and compare three covenants' strictness measures using both credit ratings and credit spread as benchmarks. The goal is to test whether these measures accurately reflect the overall risk of loans. Credit ratings, provided by rating agencies, offer a qualitative assessment of credit risk, while credit spreads provide a market-based quantitative measure of risk. By comparing covenant strictness measures against these benchmarks, I aim to determine their effectiveness in predicting loan risk.

The results suggest that the strictness measure using the probability of covenant violation best explains loan risk. This measure provides a more accurate reflection of the overall risk because it integrates the likelihood of covenant breaches, which directly impact the borrower's financial stability and, consequently, the loan's risk profile. In contrast, a simple or arbitrary count of covenants fails to capture this complexity and does not correlate well with loan risk. Similarly, while assessing individual covenant stringency can offer insights, it lacks the predictive power of the probability measure due to its subjectivity and potential inconsistency.

However, the probability of covenant violation is not without limitations. One significant drawback is the reliance on historical data and financial forecasts, which can be uncertain and subject to change. Additionally, this measure may not fully capture the dynamic interactions between different covenants and their cumulative impact on loan risk. There is also the challenge of accurately estimating the likelihood of violation, which requires sophisticated modeling and continuous monitoring of the borrower's financial performance. There are certainly more areas to explore without limiting the strictness solely to the likelihood of violation. Future research could investigate the interplay between different covenants and their combined effect on loan risk, considering factors such as the borrower's industry, economic conditions, and market trends. Additionally, incorporating qualitative assessments from loan officers and financial experts could enhance the understanding of covenant strictness and its implications for loan risk. By broadening the scope of analysis and integrating multiple dimensions of covenant strictness, we can develop more robust measures that better reflect the complexities of loan agreements and their associated risks.

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