Journal of Accounting and Economics 61 (2016) 433–447

Contents lists available at ScienceDirect

Journal of Accounting and Economics

journal homepage: www.elsevier.com/locate/jae

Measuring the probability of financial covenant violation in private debt contracts[☆]

Peter R. Demerjian[a,*], Edward L. Owens[b,1]

[a] Foster School of Business, University of Washington, 470 Paccar Hall, Box 353226, Seattle, WA 98195, USA
[b] Goizueta Business School, Emory University, 1300 Clifton Road, Atlanta, GA 30322, USA

ARTICLE INFO

Article history:
Received 5 March 2014
Received in revised form
22 October 2015
Accepted 4 November 2015
Available online 18 November 2015

Keywords:
Debt covenants
Dealscan
Covenant violation

JEL classification:
G30
M40
M41

ABSTRACT

We measure the probability that a borrower will violate financial covenants in private debt contracts. We analyze hand-coded data and specify standard covenant definitions using Compustat data that minimize measurement error for all individual Dealscan covenants. We use these definitions to create a measure of aggregate probability of violation, which can be used across all covenants in a loan or among covenant subsets of interest. We provide evidence that our aggregate probability measure is superior to alternatives used in prior literature.

1. Introduction

Recent years have seen a renewed interest in accounting research on debt contracting and, in particular, in studies that examine the inclusion of accounting-based financial covenants and their implications. Many debt contracting studies test theories about the probability that borrowers will violate a financial covenant on their loan contract, either in aggregate (e.g., DeFond and Jiambalvo, 1994; Dichev and Skinner, 2002; Sweeney, 1994) or among certain subsets of covenants (e.g., Christensen and Nikolaev, 2012; Demerjian, 2011).[2] The probability of financial covenant violation holds a significant place in positive accounting theory. For example, the debt covenant hypothesis predicts that borrowers close to covenant

☆ We appreciate the helpful comments of Dan Amiram, Vic Anand, Dave Burgstahler, Hans Christensen (reviewer), John Core (editor), Anna Costello, Ilia Dichev, John Lyon, Valeri Nikolaev, Regina Wittenberg-Moerman, Justin Murfin, Jerry Zimmerman, anonymous reviewers, and participants at the AAA FARS 2014 Midyear meeting and the 2014 UTS Australian Summer Accounting Conference. Demerjian gratefully acknowledges the financial support of the Foster School of Business and the Goizueta Business School. Owens gratefully acknowledges the financial support of the Simon School of Business and Goizueta Business School. Special thanks to Lew Thorson for assistance with data.

* Corresponding author. Tel.: +1 206 221 1648.
E-mail addresses: pdemerj@uw.edu (P.R. Demerjian), ed.owens@emory.edu (E.L. Owens).
[1] Tel.: +1 404 727 6642.

[2] Many studies refer to this construct as financial covenant "slack," "tightness," or "strictness." We believe, however, that "probability of violation" is the best term to describe this construct. We reserve the term "slack" to refer to the unscaled distance between the actual realization of a covenant variable and its specified threshold, whereas the probability of violation depends not only on the level of covenant slack but also on underlying measure variability. Managers' incentives likely depend more on probability of violation than slack, per se.

http://dx.doi.org/10.1016/j.jacceco.2015.11.001
0165-4101/

thresholds will make accounting choices to avoid technical default (Watts and Zimmerman, 1978, 1986). More generally, the probability of covenant violation is often considered a proxy for borrower riskiness or the degree of agency conflicts.

Early empirical work on debt covenants operationalized the construct of the comprehensive probability of covenant violation using borrower leverage (Duke and Hunt, 1990; Press and Weintrop, 1990; Watts and Zimmerman, 1986). The introduction of Dealscan, a machine-readable database of private loan agreements, which includes the details of covenant inclusion, greatly assisted research efforts in this area. Dealscan provides details on thousands of private loan contracts and allows researchers to test hypotheses in large-sample, generalizable settings (e.g., Dichev and Skinner, 2002). Although Dealscan provides information on the general types of covenants that are used and their violation threshold values, it does not provide definitional details of the actual construction of the covenant in the loan contract, which inhibits precise calculation of violation probability. For example, suppose that Dealscan indicates that a given loan includes an interest coverage covenant with a threshold value of three (i.e., if the borrower's interest coverage ratio dips below three, the covenant is violated). To calculate violation probability, the researcher must be able to measure the borrower's actual interest coverage ratio and to compare it to the threshold value of three. Dealscan, however, does not provide the actual definition of interest coverage used in the contract. Although loan contracts generally define interest coverage as the ratio of earnings to interest expense, earnings could take on many different definitions (e.g., net income, EBIT, EBITDA), and interest could be accrual- or cash-basis. This is of particular concern, given that covenants are frequently customized (El-Gazzar and Pastena, 1991; Leftwich 1983), and there is variation in the definitions of various contract variables based on features of the borrower and the loan (Li, 2010, 2015).

Researchers acknowledge this lack of detail and its potential to introduce measurement error. For instance, Zhang (2008) notes, "Due to the diversified nature of financial covenants and the customized definition of covenant items, such an ideal measure [of covenant tightness] is difficult to calculate" (p. 36). Frankel and Litov (2007) state, "As the exact nature of individual covenants can be quite intricate, a valid continuous measure, reflecting the details of each covenant is unrealistic" (p. 16).

Due to this perceived measurement error in Dealscan covenant data, researchers have not developed measures of covenant violation probability using the full set of Dealscan covenants. Instead, researchers commonly use two other proxies built from Dealscan data. First, some studies restrict attention to a small number of covenants for which measurement error is presumed to be minimal and implicitly assume that these few covenants reflect the overall probability of covenant violation. For example, Dichev and Skinner (2002) conduct their analysis using only current ratio and net worth covenants, noting that their analysis "require[s] covenant measures that are standardized and relatively unambiguous" (p. 1101).[3] Second, some studies do not attempt to measure covenant slack at all and, instead, use a count of the number of financial covenants attached to a loan as a measure of violation probability. For example, Demerjian (2011) predicts that the "balance sheet perspective" has affected both the use and the probability of violation of balance sheet covenants. Lacking actual covenant definitions, however, Demerjian focuses on the use of covenants and does not attempt to analyze the probability of violation. As another example, Christensen and Nikolaev (2012) develop a theory that relates to the restrictions put on borrowers through performance vs. capital covenants but measure intensity of covenant use through covenant counts rather than through violation probability.[4]

Murfin (2012), in a study that posits a theory about the relation between lender-specific shocks and probability of covenant violation, uses Dealscan to develop an aggregate probability of violation measure (i.e., covenant "strictness") based on the number of covenants in a loan, the estimated slack of these covenants, and the covariance between the financial measures that underlie the covenants. Although the Murfin measure has many appealing characteristics, Murfin does not address the Dealscan covenant measurement error problem. Rather, Murfin suggests that any measurement error will be absorbed in the model's error, as his study uses aggregate strictness as a dependent variable. This provides little comfort to researchers who want to use an aggregate measure of violation probability as an independent variable. Moreover, the Murfin measure is computationally cumbersome and imposes parametric assumptions that limit estimation flexibility and result in loss of observations.

In this paper, we develop a measure of aggregate covenant violation probability that is superior to commonly used alternatives, while simultaneously addressing measurement error concerns that are inherent in working with Dealscan. Specifically, we propose a measure that incorporates the logic of the Murfin (2012) measure, includes more covenant categories, uses covenant-specific definitions that minimize measurement error, and uses a nonparametric estimation approach, which is more flexible, easier to implement, and calculable for a larger sample of loans.

Our aggregate measure incorporates individual covenant violation probabilities for all covenants included in a loan. Thus, a prerequisite to computing our measure is the determination of "standard definitions" for each covenant category in Dealscan that can be applied to minimize measurement error. We use a hand-coded sample of loans for which actual covenant definitions are available to determine the best definition for each covenant category, which, for most covenant categories, is simply the most frequent definition used in the hand-coded sample. Then, we compare the expected likelihood of violation using the standard definition to the violation likelihood based on the actual definition. We find that, for most covenants, the average error is insignificantly different from zero, suggesting that, in most cases, our standard definition serves as a reasonable proxy when the actual contract-level covenant definition is not known (i.e., when working with Dealscan data). We elaborate on this analysis in Section 2 of the paper. In Section 3, we explain the computation of our aggregate probability of violation measure using Dealscan and Compustat data and include a discussion of key research design choices.

[3] Other studies that follow this approach include Frankel and Litov (2007), Chava and Roberts (2008), Demiroglu and James (2010), and Franz et al. (2014).

[4] Other examples include Bradley and Roberts (2004) and Billett et al. (2007).

Table 1
Descriptive statistics.

Panel A: Tearsheets sample (1987–2004; N=2,100)							
	Mean	Std. dev.	Min.	P25	Median	P75	Max.
FACILITY	722.447	1,188.650	7.000	200.000	350.000	750.000	15,000.000
MATURITY	52.995	23.533	6.133	36.500	59.750	63.900	121.733
SPREAD	121.254	100.678	0.000	36.000	88.000	200.000	878.380
NCOV	2.622	1.013	1.000	2.000	3.000	3.000	6.000
SYNDSIZE	16.708	14.232	1.000	7.000	13.000	22.000	149.000
Panel B: Dealscan sample (1987–2004; N=7,216)							
FACILITY	277.736	727.287	0.685	23.000	81.864	250.000	25,000.000
MATURITY	43.603	25.787	1.000	24.333	36.533	60.867	365.933
SPREAD	178.810	112.046	1.500	87.500	162.500	250.000	1,071.000
NCOV	2.697	1.099	1.000	2.000	3.000	3.000	7.000
SYNDSIZE	6.601	8.459	1.000	1.000	3.000	9.000	108.000

Panel A presents descriptive statistics for the Tearsheets sample (2,100 loan packages). Panel B presents the full Dealscan sample, which spans the same sample period. *FACILITY* is the aggregate face amount of all loan facilities in a loan package in millions of U.S. dollars. *MATURITY* is the facility amount-weighted average loan maturity in months. *SPREAD* is the facility amount-weighted average interest rate in excess of LIBOR, in basis points. *NCOV* is the number of distinct financial covenants attached to the loan package. *SYNDSIZE* is the number of distinct lenders who are participating in the loan.

Table 2
Borrower characteristics.

Panel A: Tearsheets sample (1987–2004; N=2,100)							
	Mean	Std. dev.	Min.	P25	Median	P75	Max.
ASSETS	4,432	12,756	0	501	1,277	3,258	209,204
SALES	3,104	6,312	0	438	1,076	3,012	91,241
ROA	0.030	0.087	−1.078	0.007	0.036	0.066	0.358
GROWTH	0.170	0.343	−1.421	0.002	0.090	0.240	2.069
MTB	1.718	1.012	0.482	1.172	1.431	1.938	13.319
LEVERAGE	0.378	0.242	0.000	0.222	0.351	0.507	1.946
Panel B: Dealscan sample (1987–2004; N=7,216)							
ASSETS	1,789	11,558	0	86	283	967	689,600
SALES	1,153	3,855	0	76	229	771	137,352
ROA	0.012	0.173	−5.880	0.001	0.035	0.038	0.760
GROWTH	0.336	0.601	−0.509	0.039	0.171	0.414	4.216
MTB	1.845	1.344	0.577	1.114	1.416	2.041	13.648
LEVERAGE	0.293	0.215	0.000	0.119	0.276	0.427	1.053

Panel A presents descriptive statistics for borrowing firms in the Tearsheets sample (2,100 loan packages). Panel B presents descriptive statistics for borrowing firms in the full Dealscan sample, which spans the same sample period. *ASSETS* is total assets in millions of U.S. dollars, *SALES* is annual sales in millions of U.S. dollars, *ROA* is annual operating income before depreciation divided by beginning-of-year total assets, *GROWTH* is the annual sales growth rate, *MTB* is the market-to-book ratio, and *LEVERAGE* is total debt divided by total assets.

Section 4 contains the empirical analysis that demonstrates the superiority of our aggregate measure relative to alternative measures used in the literature. Specifically, we document that our measure is more predictive of actual covenant violations than either a measure based on covenant count or a measure that closely follows the implementation in Murfin (2012). As an additional illustration of the usefulness of our measure, we reexamine a non-result from the prior literature. Using slack measured from a small set of covenants, Frankel and Litov (2007) find no empirical support for their hypothesis that borrower asymmetric timeliness is associated with covenant violation probability. Replacing their measures of individual covenant slack with our aggregate probability of violation measure yields significant results in the direction predicted by their theory.

We make two broad contributions in this study. First, we offer a comprehensive measure of aggregate probability of covenant violation that is superior to alternatives used in the literature. Moreover, the methodology we describe is flexible enough to allow computation of violation probability among specific subsets of interest, such as balance sheet covenants or income statement covenants. Use and further refinement of our measure should prove useful to researchers in a number of contexts, both for investigations of the causes and consequences of financial covenants and, more generally, as a proxy for incentives related to financial covenants.[5] Second, as a precursor to the development of our measure, we provide a detailed analysis of how financial

[5] We make our probability of violation measure and the related SAS code available at both faculty.washington.edu/pdemerj and sites.google.com/site/edowensphd/home.

covenants are measured in practice, which allows us to identify "standard" definitions that minimize measurement error in working with Dealscan. This should enable researchers to examine existing lines of inquiry related to specific covenants using either individual covenants of interest (not just a limited few) or the full set of financial covenants, where appropriate.

2. Covenant definitions that minimize measurement error

An aggregate measure of covenant violation probability incorporates the probabilities of violation of each individual covenant in a loan. Computing the probability of violation of individual covenants requires comparing the contractually specified covenant thresholds to the borrower's actual financial results. Dealscan, however, does not provide definitions by which individual covenants are measured (as specified in the underlying loan contract), which presents an obstacle to the accurate calculation of the borrower's relevant financial metrics. Thus, as a prerequisite to developing an aggregate measure, for each Dealscan covenant category, we determine the definition that minimizes measurement error (i.e., the definition that is used most frequently in actual contract terms). To determine these "standard definitions," we analyze a hand-coded subset of loans for which we can obtain actual covenant definitions (i.e., the Tearsheets database) and assess how much measurement error would result from applying these modal definitions to the Dealscan universe, where actual definitions are not provided. We describe this process in more detail in the following sections.

2.1. Data overview

The Tearsheets database provides detailed information for a subset of loans from Dealscan. According to Thompson Reuters LPC, a Tearsheets report is available for the more complex or uniquely structured deals in the market. Notably, for our purposes, a Tearsheets report provides actual covenant definitions for each contract. For example, whereas Dealscan would simply indicate that a loan includes an interest coverage covenant and its violation threshold, a Tearsheets report additionally indicates how both earnings and interest expense are defined for purposes of that specific contract.[6] The Tearsheets database includes records of 2,683 loan packages from 1,773 borrowers, which we match to Compustat to generate a sample of 2,100 loan packages with closing dates between 1987 and 2004.[7]

Panel A of Table 1 provides descriptive statistics for the Tearsheets loan sample. The average deal's principal amount (*FACILITY*) is $722M, with an average stated term to maturity of 53 months. The facility-weighted average spread over LIBOR (*SPREAD*) is 121 basis points. Most of the loans are syndicated, and the average loan package has over 16 lenders (*SYNDSIZE*). For comparison, Panel B of Table 1 presents statistics for the full Dealscan sample during the Tearsheets sample period (1987–2004). Consistent with their status as "bellwether" loans, Tearsheets loans are generally larger than are typical Dealscan loans; however, covenant use is similar across these two samples.

Panel A of Table 2 presents summary Compustat data on Tearsheets borrowers, for which we match Tearsheets observations to the Compustat fiscal quarter-end most closely preceding loan inception. In Panel B of Table 2, we present corresponding statistics for all Dealscan borrowers over the Tearsheets sample period. Relative to the full Dealscan sample, on average, Tearsheets borrowers are larger (total assets of $4.4 billion vs. $1.8 billion), more profitable (ROA of 3.0% vs. 1.2%), more mature (asset growth of 17.0% vs. 34%), and have higher leverage (debt-to-assets of 0.38 vs. 0.29).

To develop a Tearsheets covenant classification scheme, we turn to the Dealscan database. In Dealscan, financial covenant data are contained in the "FinancialCovenant" and "NetWorthCovenant" datasets.[8] Together, these two datasets present 15 distinct categories of financial covenants, as indicated in Tables 3 and 4.[9] We sort each observed financial covenant from Tearsheets loans into the 15 Dealscan categories to make our classification of Tearsheets covenants consistent and to aid in quantifying measurement error. We analyze data on the definitions of all covenants in all loans in the Tearsheets sample. We summarize these data in Table 3, where we separately document definitions used in the numerator and denominator of the ratio-based covenants.[10] The next column shows the number of distinct definitions used in each covenant category across all Tearsheets loans. The final column shows the "heterogeneity index," which we define as the number of distinct definitions in a covenant category divided by the number of loans in which that covenant category appears.

[6] In some cases, a Tearsheets report either does not provide a definition for the covenant or provides a definition that is too vague to allow for calculation of the underlying ratio value (e.g., definitions that feature terms such as "fixed charges" or "non-cash items"). We exclude these covenants from the sample. Because this comprises only 142 covenants (2.7%), we do not believe it affects the generalizability of our findings.

[7] Loan packages are sets of loan facilities from the same lead lender to the same borrower. For example, a single loan package may include two separate facilities, a revolving line of credit, and a term loan. Because all facilities in a loan package are subject to the same covenants, our analysis is at the package level.

[8] These are the dataset names used in Dealscan downloaded via WRDS.

[9] Dealscan also includes Max. Capex and Max. Loan to Value covenants in the "FinancialCovenant" dataset. These are not, however, accounting-based financial covenants. Recent vintages of Dealscan also include the following covenants: Max. Long-term Investment to Net Worth, Max. Net Debt to Assets, Max. Total Debt (including Contingent Liabilities) to Tangible Net Worth, Min. Equity to Asset Ratio, Min. Net Worth to Total Asset, and Other Ratio. Each of these covenants, however, appears in an immaterial percent (i.e., $<0.05\%$) of Dealscan loan contracts and does not exist as a separate Dealscan category during the Tearsheets coverage period. Therefore, we omit these covenants from our study.

[10] We present the classification rubric we use for sorting observed Tearsheets covenants into the 15 Dealscan categories in an online supplement to the paper.

Table 3
Summary of covenant definitions.

Covenant	N	Freq.	Numerator Primary	Numerator Secondary	Denominator Primary	Denominator Secondary	Definitions	Heterogeneity index
Min. Interest Coverage	953	45.4%	10	16	2	n/a	34	0.036
Min. Cash Interest Coverage	69	3.3%	3	4	1	n/a	6	0.087
Min. Fixed Charge Coverage	592	28.2%	12	30	36	n/a	356	0.601
Min. Debt Service Coverage	145	6.9%	7	19	8	n/a	48	0.331
Max. Debt-to-EBITDA	865	41.2%	3	7	6	8	24	0.028
Max. Senior Debt-to-EBITDA	161	7.7%	2	2	4	2	8	0.050
Max. Leverage	498	23.7%	5	7	2	10	25	0.050
Max. Senior Leverage	53	2.5%	2	0	2	0	3	0.057
Max. Debt-to-Tangible Net Worth	153	7.3%	3	4	1	5	15	0.098
Max. Debt-to-Equity	309	14.7%	8	7	5	12	40	0.129
Min. Current Ratio	283	13.5%	1	5	1	2	10	0.035
Min. Quick Ratio	15	0.7%	5	n/a	2	n/a	5	0.333
Min. EBITDA	156	8.6%	3	5	n/a	n/a	5	0.032
Min. Net Worth	670	31.9%	3	15	n/a	n/a	56	0.084
Min. Tangible Net Worth	372	17.7%	1	21	n/a	n/a	31	0.083
Total	5,294						666	

Table 3 presents summary data on the definitions of financial covenants in Tearsheets. "Covenant" refers to the covenant class based on the Dealscan classification. *N* is the number of times the covenant is used in distinct Tearsheets loan packages; "Freq." is the frequency of the covenant over the 2,100 Tearsheets loans. "Primary" and "Secondary" refer to the number of primary and secondary elements for the Numerator and Denominator, respectively, where primary elements are those that are part of the fundamental construct of the covenant (e.g., earnings and interest expense for interest coverage covenants), and secondary elements are all other elements. Entries of "n/a" indicate that element does not exist by definition (e.g., all denominator elements in IC, CIC, FCC, and DSC are classified as "Primary"). "Definitions" refers to the number of different definitions found in the Tearsheets observations. "Heterogeneity Index" is the number of covenant definitions divided by the number of observations, where higher values indicate greater heterogeneity in measurement of that covenant.

Table 4
Covenant standard definitions.

Dealscan covenant	**Standard definition**	**Compustat implementation**	**Frequency**
Min. Interest Coverage	EBITDA/Interest Expense	OIBDPQ/XINTQ	76.3%
Min. Cash Interest Coverage	EBITDA/Interest Paid	OIBDPQ/INTPNY	76.8%
Min. Fixed Charge Coverage	EBITDA/(Interest Expense + Principal + Rent Expense)	OIBDPQ/XINTQ + lag(DLCQ) + XRENT	2.7%
Min. Debt Service Coverage	EBITDA /(Interest Expense + Principal)	OIBDPQ/XINTQ + lag(DLCQ)	37.9%
Max. Debt-to-EBITDA	Debt/EBITDA	DLTTQ + DLCQ/OIBDPQ	91.0%
Max. Senior Debt-to-EBITDA	Senior Debt/EBITDA	DLTTQ + DLCQ–DS/OIBDPQ	89.4%
Max. Leverage	Debt/Assets	DLTTQ + DLCQ/ATQ	84.5%
Max. Senior Leverage	Senior Debt/Assets	DLTTQ + DLCQ–DS/ATQ	86.8%
Max. Debt-to-Tangible Net Worth	Debt/TNW	DLTTQ + DLCQ/ATQ–INTANQ–LTQ	52.9%
Max. Debt-to-Equity	Debt/NW	DLTTQ + DLCQ /ATQ–LTQ	47.6%
Min. Current Ratio	Current Assets/Current Liabilities	ACTQ/LCTQ	95.4%
Min. Quick Ratio	Account Receivable + Cash and Equivalents/Current Liabilities	RECTQ + CHEQ/LCTQ	66.7%
Min. EBITDA	EBITDA	OIBDPQ	97.4%
Min. Net Worth	NW	ATQ–LTQ	33.7%/96.9%
Min. Tangible Net Worth	TNW	ATQ–INTANQ – LTQ	32.5%/99.5%

Table 4 presents the most common definitions of the 15 covenant classes in Dealscan based on data from Tearsheets. Implementation is based on quarterly Compustat variables. All flow variables are annualized (summing the current plus prior three quarters) for both income statement and statement of cash flow variables. For the Min. Fixed Charge Coverage covenant, we present the definition that minimizes measurement error based on subsequent analysis, as no *ex ante* modal standard definition arises. For Tearsheets loans that include a given covenant category, "Frequency" reports the % of loans where the actual covenant definition is identical to our standard definition. For Min. Net Worth and Min. Tangible Net Worth, we report two frequencies: including/excluding the effects of escalators.

The data in Table 3 provide a variety of descriptive insights. First, even covenants that are generally considered homogeneously defined (e.g., current ratio and net worth covenants) exhibit heterogeneity.[11,12] Second, some covenants

[11] Much of the variation in definitions for net worth and tangible net worth can be attributed to "escalators" (Beatty et al., 2008). These provisions add values, such as net income or equity issuance proceeds, to the threshold of the covenant in the periods following loan inception. As such, if researchers are interested in measuring the *initial* slack in net worth or tangible net worth covenants (as we are), there are considerably fewer definitions used (five and two for net worth and tangible net worth, respectively).

[12] Dichev and Skinner (2002) identify this variation and use Tearsheets data to supplement Dealscan in measuring net worth covenant slack.

feature a great deal of heterogeneity. Most striking is fixed charge coverage, with 356 definitions across 592 loans. Third, some covenants feature relatively few definitions despite past assumptions of high definitional heterogeneity. The heterogeneity index illustrates this variation: both debt-to-EBITDA (0.028) and interest coverage (0.036) have low indices, similar to current ratio (0.035). In contrast, the index for fixed charge coverage is very high (0.601), which suggests that each definition is used, on average, in fewer than two loan contracts.

Using the detailed data that provide the basis for Table 3, we identify the modal definition for each covenant category, which we term the "standard definition" of that covenant. This allows us to assess another dimension of definitional heterogeneity. Specifically, even if a covenant category features a large number of definitions, if a large percentage of observations are concentrated in the modal definition, the likelihood of measurement error is reduced. We present covenant standard definitions in Table 4, which includes how the standard definition is implemented with Compustat variables and the frequency with which the standard definition is used (conditional on the inclusion of the covenant in the loan). The results show that standard definitions are indeed used frequently for many of the covenants. For example, for ten covenant categories, the standard definition is used in over 75% of loans.[13] We consider each modal definition as the standard even if it does not comprise the majority of observations. The only category that has no clear *ex ante* standard definition is fixed charge coverage (no single definition is used in even 5% of loans). Thus, rather than using the modal definition as the standard for fixed charge coverage, we select the definition (among several candidate definitions) that minimizes measurement error, whereby we compute measurement error as described in the following section.

2.2. Measurement error analysis

We next estimate individual covenant violation probabilities using both our standard definitions and actual covenant definitions for the full Tearsheets sample of 2,100 loans. We then quantify the measurement error in estimated violation probability that arises from the use of our standard definitions rather than from the actual definitions used in the loan contract.

We begin by measuring individual covenant violation probability using our standard definitions. Specifically, for each covenant in each loan package in the Tearsheets sample, we observe the specified violation threshold ($\underline{R}$) and compute the borrower's realized value of the financial measure that underlies the loan covenant at loan inception (R_{STD}) using the standard definitions from Table 4. Next, we compute covenant slack as the difference between the realized value of the financial measure and the covenant threshold, where slack captures how much the underlying financial measure can change before the threshold is violated.[14] We measure variability of the underlying financial measure as the standard deviation of the financial measure realizations over the 12 quarters immediately preceding loan inception ($\sigma_{R_{STD}}$), for which more variable financial measures lead to a higher probability of violation. Using slack and standard deviation, we calculate the individual covenant violation probability under the assumption that the covenant financial measure is normally distributed:

$$P(R_{STD} < \underline{R}) = 1 - \Phi\left[\frac{(R_{STD} - \underline{R})}{\sigma_{R_{STD}}}\right] \tag{1}$$

where Φ is the normal cumulative distribution function.

We then repeat this computation using the Tearsheets actual definitions (instead of the standard definitions), yielding R_{ACT} and $\sigma_{R_{ACT}}$. Substituting R_{ACT} and $\sigma_{R_{ACT}}$ into Eq. (1) (noting that $\underline{R}$ is the same whether we are using the standard or actual definition to compute the financial measure realization) yields the individual covenant violation probability using the actual covenant definition, $P(R_{ACT} < \underline{R})$. To quantify measurement error (*ERROR*) arising from the use of our standard definitions, we examine the difference between covenant violation probabilities using the standard and actual definitions, i.e., $ERROR = \left[P(R_{STD} < \underline{R}) - P(R_{ACT} < \underline{R})\right]$.

We tabulate results from this analysis in Table 5. Columns (1) and (2) present the total incidence of each covenant type across Tearsheets loans with sufficient data to calculate these metrics. Columns (3) and (4) present average individual covenant violation probabilities using standard and actual definitions, respectively. We report average *ERROR* in Column (5) and *t*-statistics for the test of whether average *ERROR* is different from zero in Column (6). Among the 15 covenant categories, only Min. Debt Service Coverage yields an average *ERROR* that is significant at conventional levels (*t*-statistic $= -2.18$). These results suggest that, even when there is substantial definitional heterogeneity in a particular covenant category, significant measurement error seldom occurs, on average.

2.3. Validity threats

We next conduct a series of tests that address potential issues inherent in using Tearsheets and Compustat data, and we conclude that our use of these databases does not constitute a significant threat to the validity of our findings. In this section, we summarize our untabulated findings.[15]

The first issue involves our use of Tearsheets data to determine actual contract-specific covenant definitions. Although Tearsheets data provide a greater level of detail than do Dealscan data, they still lack very precise information in some cases.

[13] The frequencies for net worth and tangible net worth are for definitions that include and exclude escalators, respectively. The second, larger number can be interpreted as the frequency with which a loan uses the standard for initial slack for that covenant.

[14] This slack definition applies to minimum threshold covenants, such as interest coverage and net worth. For maximum threshold covenants, slack is defined as $(\underline{R} - R_{STD})$, and Eq. (1) computes $P(\underline{R} < R_{STD})$.

[15] We present tabulated results in an online supplement to the paper.

Table 5
Standard definitions and individual covenant measurement error.

	N		Mean Covenant Violation Probability			
Column:	*Total* (1)	*Difference* (2)	*Standard* (3)	*Actual* (4)	*ERROR* (5)	*t-Stat* (6)
Min. Threshold Covenants						
Interest Coverage	843	195	0.201	0.227	−0.026	−1.30
Cash Interest Coverage	66	16	0.185	0.241	−0.056	−0.79
Fixed Charge Coverage	459	448	0.448	0.437	0.011	0.34
Debt Service Coverage	120	79	0.260	0.392	−0.132**	−2.18
Current Ratio	266	7	0.251	0.250	0.001	0.03
Quick Ratio	15	3	0.268	0.341	−0.073	−0.43
EBITDA	136	4	0.306	0.311	−0.005	−0.09
Net Worth	595	23	0.286	0.284	0.002	0.08
Tangible Net Worth	311	2	0.266	0.264	0.002	0.06
Max. Threshold Covenants						
Debt to EBITDA	788	69	0.270	0.282	−0.012	−0.53
Sr. Debt to EBITDA	99	7	0.300	0.318	−0.018	−0.27
Leverage	403	55	0.054	0.063	−0.009	−0.54
Senior Leverage	43	5	0.206	0.185	0.021	0.25
Debt to TNW	135	62	0.215	0.189	0.026	0.53
Debt to Equity	265	102	0.297	0.269	0.028	0.72

Table 5 presents the tabulations of parametrically estimated probability of violation of individual covenants using both our standard definitions and the actual definitions from Tearsheets. Column (1) presents the total number of covenants in the Tearsheets loan sample with sufficient data to calculate probabilities of violation. Column (2) presents the number of covenants from the total where the standard and actual definitions differ. Columns (3) and (4) show the average estimated probability of violation of individual covenants based on standard and actual definitions, respectively. Covenant violation probability is defined as the measured slack of the covenant divided by the standard deviation of the prior 12 quarters of the value of the borrower's underlying financial measure. Column (5) shows mean *ERROR* (the difference between the standard and precisely measured probabilities of violation). Column (6) presents a t-statistic for the test of whether mean *ERROR* differs from zero, where ** indicates statistical significance at the 5% level.

For example, Tearsheets may indicate that a covenant is measured with EBITDA but not provide an exact definition. As a result, we must approximate the value of EBITDA using an assumed definition (Compustat variable *OIBDP*). To understand the extent of error induced by using such assumed definitions, we measure eight common covenant elements from 300 randomly selected loan contracts (from 10-K, 10-Q, and 8-K filings). By measuring the difference between the actual value and our assumed value, we find little error induced by the assumed definitions.

The second issue concerns our use of detailed Tearsheets data to draw inferences on the broader Dealscan universe. Because we know that the Tearsheets population represents "bellwether" loans (Dichev and Skinner, 2002), we validate the extent to which Tearsheets loans are representative. We do this in two ways. First, we examine whether the rate of standardization of covenants is similar between the two databases. Using a hand-collected sample of loan contracts from Dealscan that are not in Tearsheets, we find that the rate of standardization is virtually identical. Next, we examine the consistency between the two databases in measuring covenants. We find that, in most cases, the same covenants are reported for loans in both databases. Further, the evidence does not suggest a systematic inconsistency in covenants between the two databases. These tests suggest, collectively, that Tearsheets covenant data can be generalized to the broader Dealscan universe.

Finally, we examine whether there are systemic determinants of covenant standardization. We examine the relation between standardization and a variety of borrower, loan, and macro-economic characteristics. We find few significant associations, which suggests that there are no predictable determinants for the measurement error induced by using our standard covenant definitions.[16]

3. Measure of aggregate probability of covenant violation

3.1. Conceptual background

Consider a loan with a single minimum net worth covenant. The probability of covenant violation is a function of initial covenant slack and the volatility of the borrower's net worth (i.e., lower slack or greater volatility in the underlying measure

[16] As an additional test, we examine whether lender fixed effects explain the likelihood that a loan contract includes standardized covenants. In unreported analysis, we find only seven of the 257 lender fixed effects coefficients to be significant, which suggests a minimal effect of lenders.

of net worth results in a greater probability of violation). Next, consider a loan with two covenants—a minimum net worth covenant and a minimum current ratio covenant. The probability of covenant violation is a function of the initial slack of each covenant, the volatility of net worth and of current ratio, and the correlation between net worth and current ratio (i.e., a lower correlation results in a greater probability of violation). Generalizing to a loan with 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 measure that underlies each covenant, and the correlations among the N financial measures that underlie the N covenants. As pointed out by Murfin (2012), a conceptually appealing measure of aggregate covenant violation probability across multiple covenants on a given loan will incorporate these features.

To fix intuition, suppose a borrower's loan package has three financial covenants: minimum current ratio with a threshold of 1.4, minimum interest coverage with a threshold of 3.0, and maximum debt-to-equity with a threshold of 2.0. In addition, suppose that the borrower's most recent quarterly financial statements indicate the following actual values for the underlying financial metrics: current ratio of 1.5, interest coverage of 3.2, and debt-to-equity of 1.7. To compute the probability that any one of these three covenants is violated during the subsequent quarter, we forecast the borrower's one-quarter-ahead current ratio, interest coverage, and debt-to-equity and then observe the frequency of violation instances generated by those forecasts.

Suppose that the first simulation iteration yields one-quarter-ahead forecasts of the borrower's financial measures as follows: current ratio of 1.58, interest coverage ratio of 2.94, and debt-to-equity of 1.68. This iteration yields a covenant violation, as the simulated interest coverage ratio breaches the 3.0 minimum threshold (i.e., $2.94 < 3.0$). We repeat this 1,000 times, whereby each iteration yields another independent forecast of the borrower's one-quarter-ahead financial measures, and we compute this loan package's aggregate probability of covenant violation (hereafter referred to as *PVIOL*) as the proportion of the 1,000 iterations for which a violation of any one of the three included covenants is indicated (by construction, *PVIOL* ranges between zero and one). In the next section, we discuss implementation details, including the data that we use and our method for simulating the one-quarter-ahead forecasts for the borrower's financial measures.

3.2. Simulation details

We begin with a sample of private loan packages from Dealscan with loan inception years 1996 through 2008 for which we can obtain a Compustat link and have non-missing data for loan facility amount, maturity, security requirements, and interest spread (hereafter referred to as the "loan package sample").[17] Using Compustat data, for each observation we use our standard definitions to compute the financial statement measures that underlie all covenants in the borrower's loan package (which will be a subset of the 15 possible covenant categories reported in Table 4), using the borrower's most recent quarterly data preceding loan inception date.

We next construct a "match firm sample" from which we draw vectors of quarterly changes in financial measures that we use to simulate the one-quarter-ahead values of covenant financial measures for borrowers in the loan package sample. We begin with all levered firm-quarter observations in the Compustat quarterly file, and, for each firm-quarter, we compute the quarterly change (in ratio form) for each of the 15 financial measures that underlie the 15 Dealscan covenant categories, using the standard definitions described in Table 4. For example, if the current ratio decreases from 1.5 in quarter $t-1$ to 1.3 in quarter t, then the quarter t current ratio change is $1.3/1.5 = 0.867$. Note that, if a financial measure increases (decreases) from quarter $t-1$ to t, the change variable is greater than one (between zero and one). We delete observations with missing data for any of the 15 financial measure change variables and truncate all change variables at the upper and lower percentiles. With the loan package and match firm samples in place, we simulate the borrower's aggregate covenant violation probability following several steps.

In the first step, we sort the match firm sample into 12 size-profitability bins. Specifically, within each sample year, we rank firm-quarter observations into size quartiles based on average total assets. Within each size quartile and year, we further divide firms into return-on-asset (ROA) terciles, whereby we compute ROA as operating income before depreciation divided by average total assets. We include each borrower's firm-quarter observation most recently preceding loan inception date in this ranking procedure, so that each borrower is assigned to one of the 12 size-profitability bins in proper relation to all match firms. This approach follows the logic developed by Barber and Lyon (1996) and Blouin et al. (2010). Specifically, Barber and Lyon show that matching on size and profitability at time $t-1$ generates a well-specified model of a firm's expected performance beginning in year t (in part because this matching approach captures mean reversion in income). A size-based approach to forecasting future financial metrics is further supported by recent evidence that firms of similar size are more alike with regard to accounting characteristics than are firms within the same industry classifications (e.g., Albuquerque, 2009; Ecker et al., 2013). Blouin et al. extend the logic of Barber and Lyon and reason that, if firms matched on size and profitability share similar future performance, the distribution of changes in the firms' future performance will likewise be similar. Thus, we reason that the distribution of quarterly changes in a wider range of firms' future accounting-based characteristics will be similar for firms matched on recent size and profitability.

[17] We end the sample in 2008 because we use actual covenant violation data from Nini et al. (2012) in our empirical analysis to calibrate our measure, and their data stop in 2008.

In the second step, we simulate the borrower's one-quarter-ahead financial measures that correspond to the covenants in each loan package. To do so, we randomly draw a firm-quarter observation from the match firm sample that corresponds to the borrower's size-profitability bin, for which we limit the possible matches to firm-quarters from years $y-2$ or $y-1$ (relative to loan issuance year y).[18] We then multiply the borrower's quarterly financial measures (for the quarter most closely preceding loan inception date) by the vector of financial measure change variables in the randomly drawn match firm observation. For example, if the borrower has a current ratio of 1.6, and the randomly drawn match firm observation indicates a quarterly current ratio change of 0.867, then the borrower's one-quarter-ahead forecasted current ratio is 1.387 (1.6*0.867). This step yields a forecast of the borrower's financial measures that underlie each covenant in the loan package for the quarter immediately following loan inception.

In the third step, we compare the borrower's forecasted financial measures with the loan covenant thresholds and record whether a violation has occurred on any covenant. We repeat the second and third steps 1,000 times, randomly drawing (with replacement) a new match firm-quarter observation in each iteration. Finally, we compute *PVIOL* as the number of the 1,000 iterations where a violation is indicated divided by 1,000 (e.g., if the borrower breaches any included loan covenant in 88 of the 1,000 iterations, *PVIOL* for that loan is 0.088).[19]

3.3. Discussion of alternative parametric approaches

An alternative to our nonparametric simulation approach is a parametric simulation approach, as in Murfin (2012). Specifically, Murfin assumes that quarterly changes in financial measures that underlie the covenants follow a multivariate lognormal distribution. This parametric approach requires computation of financial measure quarterly-change covariance matrices using the match firm sample, which then are used to generate vectors of financial measure changes following the parametric assumption (whereas we generate our vectors of financial measure changes by simply drawing them from actual match firm data realizations). However, as noted by Murfin, financial measures do not likely follow a multivariate lognormal (or any other) distribution, and the distributional assumption is imposed for computational convenience. Our nonparametric approach imposes no distributional assumptions on the data, which, in our view, makes it conceptually more appealing. Additionally, using our nonparametric approach avoids implementation issues that arise when using the parametric approach.[20] Finally, we believe that our method is simpler than the parametric method and, thus, should be more accessible to other researchers.

In the following section, one of our central analyses is a formal comparison of the performance of *PVIOL* with a parametric-based measure that more closely follows the approach in Murfin (2012). Accordingly, in the analyses that follow, we limit our sample to observations for which we can calculate both the nonparametric and parametric-based measures.

4. Empirical analysis

4.1. Descriptive comparison between PVIOL and other measures

We first explore some basic properties of *PVIOL* relative to other measures of covenant violation probability that have been used in the literature. In Panel A of Table 6, we present descriptive statistics for *PVIOL* sorted by the number of covenants in the loan package (*NCOV*), a commonly used alternative proxy for probability of covenant violation. The mean value of *PVIOL* is monotonically increasing in *NCOV*. Examining the tails of the distribution across *NCOV* subsamples, however, suggests that relying on *NCOV* as a proxy for probability of covenant violation could be problematic. For example, 25% of loans with four covenants have a probability of violation of less than 0.069. In contrast, 25% of loans with only two covenants have a greater than 0.275 probability of violation. This shows that, although the number of covenants is positively correlated with the probability of covenant violation, there is significant variation within groups.

Current ratio slack is another proxy for covenant violation probability used in the literature (e.g., Franz et al., 2014). Within our loan package sample, 1,237 loans have current ratio covenants. We quintile rank each of these observation by *PVIOL* and inverse current ratio slack (so that probability of covenant violation is increasing in quintile rank) and present a cross-tabulation of these quintile ranks in Panel B of Table 6. If current ratio slack is a perfect proxy for aggregate probability of covenant violation, all observations will lie on the diagonal. As shown, this is not the case. For example, in the middle *PVIOL* quintile, the observations are spread quite evenly across the five slack quintiles, which suggests that reliance on current ratio slack as a proxy for aggregate probability of covenant violation is imprecise, as we expect. In untabulated

[18] It is the drawing of this vector from actual match firm data realizations that characterizes our approach as nonparametric. Under a parametric approach, we would instead place a distributional assumption on quarterly changes in financial ratios and generate the vector from that parametric assumption. We discuss this distinction further in Section 3.3.

[19] Note that our nonparametric simulation also permits straightforward computation of the probability of violation of any desired subset of covenant categories. For example, the probability of violating an income statement-based (balance sheet-based) covenant can be computed as the number of the 1,000 simulation iterations where a violation of any one of the income statement-based (balance sheet-based) covenants is indicated, divided by 1,000.

[20] For example, when using a parametric approach with lognormal transformations, the aggregate measure cannot be computed for any borrower with a negative value for a financial metric on which a covenant is written because log is defined only for positive values.

Table 6
Descriptive comparison between aggregate *PVIOL* and other proxies.

Panel A: *PVIOL* descriptives by *NCOV* subsamples

NCOV	*N*	Mean	Std	Min	P25	P50	P75	Max
1–8	8,304	0.373	0.410	0.000	0.015	0.129	0.888	1.000
1	518	0.160	0.314	0.000	0.000	0.016	0.073	1.000
2	1,784	0.232	0.366	0.000	0.000	0.022	0.275	1.000
3	3,192	0.347	0.398	0.000	0.017	0.111	0.827	1.000
4	1,811	0.483	0.411	0.000	0.069	0.368	0.952	1.000
5–8	999	0.617	0.396	0.000	0.168	0.828	0.988	1.000

Panel B: *PVIOL* and current ratio slack quintile cross-tabulation; *N* = 1,236

	(Inverse) Current Ratio Slack Quintile				
***PVIOL* Quintile**	**1**	**2**	**3**	**4**	**5**
1	113	101	31	0	1
2	57	49	92	51	0
3	26	38	39	103	41
4	33	37	52	45	78
5	18	23	33	49	127

Panel A presents descriptive statistics for *PVIOL* for subsamples based on the number of distinct financial covenants attached to the loan package (*NCOV*). *PVIOL* is an aggregate measure of loan inception date probability of covenant violation computed using 15 financial covenant categories via non-parametric simulation. Panel B (using a subsample 1,236 of observations that contain current ratio covenants) presents cross-tabulated quintile ranks of *PVIOL* and the inverse of current ratio covenant slack, where each cell contains the number of observations. Current ratio slack is measured as the actual value of the borrower's current ratio divided by the current ratio covenant violation threshold.

analyses, we examine the other financial covenants commonly used as proxies for aggregate violation probability (e.g., debt-to-EBITDA, net worth) and find similar results.

4.2. Predictive ability for actual covenant violations

4.2.1. Research design

Next, we test how well *PVIOL* performs relative to alternative measures of covenant violation probability based on predictive ability for realized covenant violations. We first examine the measures in univariate in-sample predictive models (Eq. (4)) because univariate analysis provides useful comparisons of the measures as standalone proxies for covenant violation probability. We further compare the efficacy of the measures in multivariate models that include controls for other factors associated with covenant violation (Eq. (5)). Specifically, we merge our loan package sample with the sample of realized covenant violations from Nini et al. (2012) and estimate logit regressions of the following form:

$$Pr(VIOL\_YR1_l) = f\left(\beta_0 + \beta_1 Measure_l + \varepsilon\right) \tag{4}$$

$$Pr(VIOL\_YR1_l) = f\left(\beta_0 + \beta_1 Measure_l + Controls + YearFE + IndustryFE + \varepsilon\right) \tag{5}$$

where *VIOL_YR1* is an indicator variable that equals one if there was a covenant violation during the initial year of the term of the loan and zero otherwise.[21] $Measure_l$ refers to three alternative measures of aggregate probability of covenant violation (our main variables of interest)—a count of the number of covenants attached to the loan (*NCOV*), our nonparametric simulation-based measure (*PVIOL*), as described in Section 3.2, and an alternative parametric simulation-based measure, $PVIOL^M$, which we describe next.

To compute $PVIOL^M$, we closely follow Murfin's (2012) implementation. Specifically, we use only the 10 financial covenants used in Murfin rather than the full set of 15.[22] Further, we use a parametric simulation whereby we assume that quarterly changes in financial ratios follow a multivariate lognormal distribution, as discussed in Section 3.3. Under this

[21] All of the analyses in our study are based on covenant terms at loan inception. Loans are often renegotiated after inception (e.g., Roberts and Sufi, 2009), and contract provisions may change. Accordingly, we focus on violations during the first year after loan inception, when contract modification is relatively unlikely.

[22] Specifically, Murfin (2012) omits cash interest coverage, debt service coverage, senior debt-to-EBITDA, leverage, and senior leverage covenants. Further, Murfin includes CAPEX, whereas we do not, as we do not view CAPEX as an accounting-based financial covenant.

parametric simulation, we generate the vectors of financial measure changes using a single covariance matrix calculated from the pooled match firm sample.[23] Otherwise, the simulation proceeds as described in Section 3.2.

Controls refers to a set of borrower- and loan-specific variables that likely affect the probability of covenant violation (e.g., Murfin, 2012). Specifically, we include an indicator that equals one if the firm's most recently (prior to loan inception) available long-term S&P credit rating is in an investment grade category and equals zero otherwise (*INVGRADE*). *BSMPROB* is the Black-Scholes-Merton estimated default probability, computed following the methodology outlined in Hillegeist et al. (2004). Loan-specific controls include the natural log of *MATURITY*, the natural log of *FACILITY*, and *SECURE*, where all variables are defined in the Table 7 notes. Other controls include tangible net worth, debt-to-tangible net worth ratio, fixed charge coverage ratio, and current ratio. *YearFE* and *IndustryFE* refer to fixed effects based on loan issuance year and borrower one-digit SIC, respectively. When estimating Eqs. (4) and (5), we cluster standard errors by firm.

4.2.2. Empirical results

Panels A and B of Table 7 present descriptive statistics and correlations, respectively, for variables used in this analysis. The median loan has a term just under three years and a face value of $150 million and includes three covenants with an aggregate probability of violation of 0.129 (i.e., a 12.9% chance that one of the covenants will be violated during the quarter subsequent to loan inception). The correlation between *PVIOL* and $PVIOL^M$ is 0.92, which indicates that the two alternative simulation-based measures are capturing the same construct. The significant positive correlation between *PVIOL* and *NCOV* (0.32) is consistent with the intuition that a greater number of covenants is associated with a higher aggregate probability of violation, *ceteris paribus*.

We report the results of Eqs. (4) and (5) in Panel C of Table 7. Columns (1)–(3) present Eq. (4) univariate specification. All three alternative measures are significantly positively associated with realized covenant violations during the first year of the loan term. The log pseudolikelihood of the *PVIOL* model is significantly greater than both alternative models (at the 0.001 level or better), based on Vuong (1989) tests, which indicates that *PVIOL* is a superior standalone measure compared to either $PVIOL^M$ or *NCOV*.[24]

In the multivariate Eq. (5) specification reported in Columns (4)–(6), all three alternative measures retain their positive association with realized covenant violation during the first year of the loan term when control variables and fixed effects are added to the model. In comparing the log pseudolikelihood statistics, again, the model that includes *PVIOL* has the largest (i.e., least negative) value, although it is statistically indistinguishable from the model that includes $PVIOL^M$. Given the predictive contribution of the control variables and fixed effects that are constant across models, it is not surprising that the overall model fits are similar. Nonetheless, a Vuong test confirms that the model that includes *PVIOL* has significantly greater predictive ability than does the model that includes *NCOV* (p-value = 0.024).

4.2.3. Estimating the measure subsequent to loan inception

Our measure technically estimates the probability of covenant violation during the first quarter following loan inception, and our above predictive analysis focuses on covenant violations that occur during the first year of the loan. In principle, it is straightforward to update *PVIOL* for a particular loan each time the borrower reports new quarterly financial statement data simply by repeating the simulation using the borrower's new accounting data and the inception date covenant thresholds. One concern with updating *PVIOL* subsequent to loan inception, however, is that covenant violation thresholds may be modified after initial contracting (e.g., Li et al., forthcoming), and any such changes are not reported in Dealscan. This has the potential to introduce additional measurement error. Nonetheless, we suspect that useful measures of aggregate probability of covenant violation in periods subsequent to loan inception can be obtained using updated borrower accounting data without regard to any specific threshold adjustments that may occur.

To explore this issue, we filter our sample to include only those observations where no covenant violation exists during the initial year of loan tenure. We then repeat the Eqs. (4) and (5) estimations, after replacing *VIOL_YR1* with *VIOL_YR2* and *PVIOL* with *PVIOL2*. *PVIOL2*, the aggregate probability of covenant violation during the first quarter of the second year of the loan term, is computed exactly as *PVIOL*, except that we use the borrower's most recent accounting data available as of the one-year anniversary of loan inception rather than as of loan inception. *VIOL_YR2* is an indicator variable that equals one if there was a covenant violation during the second year of the term of the loan and zero otherwise. Although we expect some association between inception date *PVIOL* and future-year covenant violations, we expect the association to be stronger when using the updated measure *PVIOL2*.

We report results of this analysis in Table 8, where we report the univariate (multivariate) results in Columns (1)–(3) (Columns (4)–(6)).[25] Whereas *PVIOL* and *NCOV* are positively associated with second-year covenant violations, the model that uses *PVIOL2* is dominant in both univariate and multivariate model comparisons (all Vuong (1989) tests are significant at the 0.001 level or better). As expected, one-year-ahead measures of aggregate violation probability yield useful predictive insights even in the absence of data on covenant threshold adjustments subsequent to loan inception.

---

[23] Murfin (2012), in his main analysis, sorts match firms by one-digit SIC. He notes, however, "substantially the same as results using a single pooled variance-covariance estimate" (p. 1573), so we follow this computationally less demanding approach.

[24] To implement the Vuong (1989) test of non-nested models, we construct a test statistic by treating the difference in log likelihoods of each individual observation across models as a random variable and constructing a chi-squared estimator based on that difference. Please refer to http://www.econometricsbysimulation.com/2013/01/tests-of-model-fit.html for implementation details.

[25] Note that we have fewer observations relative to the Table 7 analysis because we delete observations with a covenant violation during the first year of the loan term.

Table 7
Predictive ability for actual covenant violations.

Panel A: Descriptive statistics

	N	**Mean**	**Std**	**Min.**	**P25**	**P50**	**P75**	**Max.**
PVIOL	8,304	0.373	0.410	0.000	0.015	0.129	0.888	1.000
$PVIOL^M$	8,304	0.359	0.378	0.000	0.007	0.199	0.716	1.000
NCOV	8,304	3.149	1.141	1.000	2.000	3.000	4.000	8.000
BSMPROB	6,989	0.031	0.100	0.000	0.000	0.000	0.004	0.683
MATURITY	8,301	32.815	21.459	0.066	12.000	32.400	50.182	276.000
FACILITY	8,304	391.978	804.423	0.140	50.000	150.000	400.000	25000.000
SECURE	8,304	0.618	0.482	0.000	0.000	1.000	1.000	1.000

Panel B: Correlation matrix – Pearson (Spearman) above (below) the diagonal

VARIABLE	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
PVIOL (1)		0.916	0.320	0.165	−0.062	−0.106	0.267
$PVIOL^M$ *(2)*	0.909		0.347	0.141	−0.041	−0.100	0.264
NCOV (3)	0.389	0.405		−0.008	−0.017	−0.112	0.270
BSMPROB (4)	0.366	0.312	0.132		−0.124	−0.085	0.211
MATURITY (5)	−0.059	−0.024	0.002	−0.216		−0.048	−0.047
FACILITY (6)	−0.206	−0.132	−0.066	−0.404	0.095		−0.212
SECURE (7)	0.319	0.288	0.276	0.374	−0.032	−0.340	

Panel C: Logit model results

Dep. Var.:	*VIOL_YR1*					
Column:	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	−2.110***	−2.204***	−2.072***			
	(−39.90)	(−20.52)	(−38.64)			
PVIOL	1.086***			0.795***		
	(14.14)			(6.78)		
$PVIOL^M$		1.057***			0.844***	
		(12.57)			(6.73)	
NCOV			0.176***			0.174***
			(5.84)			(4.26)
INVGRADE				−0.425***	−0.403***	−0.393***
				(−3.23)	(−3.09)	(−2.98)
BSMPROB				1.881***	2.085***	1.956***
				(4.28)	(4.73)	(4.46)
log(*MATURITY*)				−0.136*	−0.164**	−0.140*
				(−1.66)	(−1.97)	(−1.71)
log(*FACILITY*)				−0.191***	−0.209***	−0.209***
				(−4.69)	(−5.14)	(−5.08)
SECURE				0.765***	0.795***	0.768***
				(6.58)	(6.73)	(6.61)
TNW, *DTNW*, *FIXEDCC*, *CRATIO* Included	No	No	No	Yes	Yes	Yes
Fixed Effects	No	No	No	I, Y	I, Y	I, Y
N	8,304	8,304	8,304	5,205	5,205	5,205
Pseudo R^2	0.032	0.026	0.006	0.132	0.132	0.125
Log pseudolikelihood	−3570.77	−3593.23	−3666.23	−1903.04	−1903.20	−1919.77
Vuong test p-value: Col (1) vs. Col. (2)/(3)		0.001	0.000			
Vuong test p-value: Col (4) vs. Col. (5)/(6)					0.964	0.024

Panel A (Panel B) presents descriptive statistics (a correlation matrix) for variables used in the analysis. Panel C presents results of logit estimation of Eqs. (4) and (5). *VIOL_YR1* is an indicator that equals one if the borrower realized a covenant violation during the first year following loan inception, and equals zero otherwise. *PVIOL* is an aggregate measure of loan inception date probability of covenant violation computed using 15 financial covenant categories via nonparametric simulation. $PVIOL^M$ is an alternative aggregate measure of loan inception date probability of covenant violation computed using parametric simulation that assumes that quarterly changes in financial measures follow a multivariate log-normal distribution. *NCOV* is the number of distinct financial covenants attached to a given loan package. *BSMPROB* is the Black-Scholes-Merton market-based probability of default measured in the month preceding loan inception. *MATURITY* is the facility amount-weighted average loan maturity in months. *FACILITY* is the aggregate face amount of all loan facilities in a loan package in millions of U.S. dollars. *SECURE* is an indicator variable that equals one if a loan package requires collateral, and equals zero otherwise. *TNW* is tangible net worth, measured as total assets less intangible assets minus total liabilities. *DTNW* is debt-to-tangible net worth, measured as total debt divided by *TNW*. *FIXEDCC* is the fixed charge coverage ratio, measured as operating income before depreciation divided by [interest expense + current debt + rent expense]. *CRATIO* is current ratio, measured as current assets over current liabilities. Fixed effects are included but not reported where their use is indicated, where I and Y refer to one-digit SIC and year of loan inception, respectively. Robust z-statistics based on clustered standard errors at the firm level are reported in parentheses. *, **, and *** indicate significance (two-sided) at the 10%, 5%, and 1% levels, respectively.

Table 8
One-year-ahead aggregate probability of covenant violation.

Dep. Var.:	VIOL_YR2					
Column:	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	−2.512***	−2.325***	−2.566***			
	(−38.31)	(−37.43)	(−19.57)			
PVIOL2	1.147***			1.102***		
	(11.47)			(7.84)		
PVIOL		0.701***			0.558***	
		(7.14)			(3.77)	
NCOV			0.162***			0.166***
			(4.32)			(3.32)
INVGRADE				−0.228	−0.228	-0.205
				(−1.52)	(−1.51)	(-1.36)
BSMPROB				1.310**	1.244**	1.550***
				(2.18)	(2.12)	(2.66)
log(*MATURITY*)				0.064	0.061	0.021
				(0.57)	(0.55)	(0.19)
log(*FACILITY*)				−0.085*	−0.061	-0.073
				(−1.76)	(−1.26)	(-1.52)
SECURE				0.314**	0.386***	0.378***
				(2.34)	(2.89)	(2.78)
TNW, *DTNW*, *FIXEDCC*, *CRATIO* Included	No	No	No	Yes	Yes	Yes
Fixed Effects	No	No	No	I, Y	I, Y	I, Y
N	6,347	6,347	6,347	3,991	3,991	3,991
Pseudo R^2	0.0324	0.012	0.005	0.087	0.068	0.067
Log pseudolikelihood	−2181.72	−2227.30	−2243.68	−1243.03	−1268.79	-1271.13
Vuong test *p*-value: Col (1) vs. Col. (2)/(3)		0.000	0.000			
Vuong test *p*-value: Col (4) vs. Col. (5)/(6)					0.000	0.001

Table 8 presents results of logit estimation of variants of Eqs. (4) and (5) using a subsample of loan packages that did not experience a covenant violation in the first year following loan inception. *VIOL_YR2* is an indicator that equals one if the firm realized a covenant violation during the second year of loan tenure and equals zero otherwise. *PVIOL* is an aggregate measure of loan inception date probability of covenant violation computed using 15 financial covenant categories via nonparametric simulation. *PVIOL2* is an aggregate measure of probability of covenant violation computed as of the one-year anniversary of loan inception using 15 financial covenant categories via nonparametric simulation. *NCOV* is the number of distinct financial covenants attached to a given loan package. *BSMPROB* is the Black-Scholes-Merton market-based probability of default measured in the month preceding loan inception. *MATURITY* is the facility amount-weighted average loan maturity in months. *FACILITY* is the aggregate face amount of all loan facilities in a loan package in millions of U.S. dollars. *SECURE* is an indicator variable that equals one if a loan package requires collateral, and equals zero otherwise. *TNW* is tangible net worth, measured as total assets less intangible assets minus total liabilities. *DTNW* is debt-to-tangible net worth, measured as total debt divided by *TNW*. *FIXEDCC* is the fixed charge coverage ratio, measured as operating income before depreciation divided by [interest expense + current debt + rent expense]. *CRATIO* is current ratio, measured as current assets over current liabilities. Fixed effects are included but not reported where their use is indicated, where I and Y refer to one-digit SIC and year of loan inception, respectively. Robust *z*-statistics based on clustered standard errors at the firm level are reported in parentheses. *, **, and *** indicate significance (two-sided) at the 10%, 5%, and 1% levels, respectively.

4.3. Frankel and Litov (2007)

To provide another illustration of the usefulness of our measure, we revisit a non-result from prior literature. An unpublished working paper by Frankel and Litov (2007) (hereafter FL) examines the link between borrowers' reporting characteristics and financial covenants.[26] FL predict a negative association between the probability of covenant violation (which FL measure using covenant slack) and asymmetric timeliness in the borrower's financial reporting. However, FL find limited statistical association. On this basis, they conclude, "Overall these results do not support the belief that timely [loss] recognition is a substitute for covenant slack" (p. 26). FL limit their attention to three specific covenants, each presumed to be relatively free of measurement error: current ratio, net worth, and tangible net worth. To examine whether *PVIOL* is superior to the use of individual covenants as a measure of probability of covenant violation in the FL setting, we replicate FL's analysis using *PVIOL*.

Specifically, we focus on the Ball and Shivakumar (2006) measure of timely loss recognition and estimate the following regression following FL:

$$\frac{ACC_{i,t}}{TA_{i,t-1}} = \alpha_0 + \alpha_{1,j} D_{OCF_{i,t}<0} + \alpha_{2,j}\frac{OCF_{i,t}}{TA_{i,t-1}} + \alpha_{3,j}\frac{OCF_{i,t}}{TA_{i,t-1}} * D_{OCF_{i,t}<0} + \varepsilon_{i,t} \quad (6)$$

where *ACC* is accruals, *OCF* is cash flows from operations, *TA* is total assets, and *D* is an indicator that equals one if the value of *OCF* is negative and equals zero otherwise, *i* indexes firm, *t* indexes year, and *j* indexes three-digit SIC. We estimate Eq. (6)

[26] We downloaded this working paper on March 19, 2008; to the best of our knowledge, it is the most recent version of the manuscript. The downloaded version can be found on SSRN at the following address: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=978711.

Table 9
Frankel and Litov (2007) replication.

Dep. Var.:	Pred. Sign	*PVIOL* Coefficient	Coefficient from Frankel and Litov (Table 4, Panel B, all accounting covenants)
$\hat{\alpha}_2$ (timeliness)	–	−0.018**	−0.145
		(−2.14)	(−1.55)
$\hat{\alpha}_3$ (loss timeliness)	–	−0.015***	−0.055
		(−2.92)	(−1.55)
N		8,138	6,161

Table 9 presents results of logit estimation of Eq. (7). *PVIOL* is an aggregate measure of loan inception date probability of covenant violation computed using 15 financial covenant categories via nonparametric simulation. Test and control variables are included and defined as in Frankel and Litov (2007). For consistency with the presentation in Frankel and Litov, we report only the coefficients for timeliness ($\hat{\alpha}_2$) and loss timeliness ($\hat{\alpha}_3$). *T*-statistics based on clustered standard errors at the firm level are reported in parentheses. *, **, and *** indicate statistical significance (two-sided) at the 10%, 5%, and 1% levels, respectively.

by industry-year using rolling five-year windows of data that span FL's sample period (1994–2004). The coefficient α_3 captures timely loss recognition.

Next, to examine the association between timely loss recognition and probability of covenant violation, we estimate the following OLS regression following FL, after replacing their covenant slack-based dependent variable with *PVIOL*:

$$PVIOL_{i,t} = \beta_0 + \beta_1 MTB_{i,t-1} + \beta_2 Tangibility_{i,t-1} + \beta_3 ROA_{i,t-1} + \beta_4 Size_{i,t-1} + \beta_5 RVol_{i,t-1} + \beta_6 Rating_{i,t-1} + \beta_7 \hat{\alpha}_{2,t-1} + \beta_8 \hat{\alpha}_{3,t-1} + \varepsilon_{i,t} \quad (7)$$

We report the results of this estimation in Table 9, along with the results reported in FL's Table 4 Panel B.[27] To facilitate comparison, we follow FL and report only the coefficients for overall timeliness ($\hat{\alpha}_2$) and loss timeliness ($\hat{\alpha}_3$). FL predict a negative coefficient on loss timeliness. As shown in Table 9, there is a significantly negative relation between timely loss recognition and *PVIOL*. This contrasts with the insignificant result reported in FL, which we also report in the table. This statistically significant finding suggests that the non-result in FL was due not to lack of a latent underlying relation but, rather, to a deficiency in measuring probability of covenant violation.

5. Conclusion

Many research questions in accounting, finance, and economics require a measure of the probability of financial covenant violation. Although the preeminent machine-readable data source for private loans, Dealscan, provides sufficient data to determine when a given type of financial covenant is used in a loan, it does not provide actual contract-level covenant definitions. This perceived shortcoming has impeded progress in the debt contracting literature due to presumed measurement error concerns. These concerns have led to the use of inferior proxies for probability of covenant violation, such as covenant counts, and have limited the scope of numerous studies to a few covenants with relatively homogeneous definitions.

Using hand-coded data from detailed loan agreements, we determine an implementable standard definition for each Dealscan financial covenant category that minimizes measurement error. We find that, for nearly all of the Dealscan covenant categories, the average error in computing probability of individual covenant violation using our standard definitions vs. the actual contractually specified definitions is insignificant. Finally, we construct a Dealscan-based measure of aggregate probability of covenant violation across the entire set of covenants included in a loan and demonstrate that this measure outperforms alternative measures that are commonly used in the literature. Moreover, the methodology we describe is flexible enough to allow computation of violation probability among specific covenant subsets of interest, such as balance sheet covenants or income statement covenants.

Our study is not without limitations. Although we have illustrated that the use of our standard covenant definitions does not introduce systematic measurement error, these findings apply to the large cross-section of loans that we examine and for the time period covered by our sample. Applying these definitions to small or idiosyncratic subsamples of loans may introduce more measurement error than we document here. Moreover, if common covenant definitions change in future years, our standard definitions should be revisited. Further, our analysis focuses on computing aggregate probability of violation at loan inception. Dealscan does not provide transparency concerning details of how covenant threshold values may change over time (e.g., through trend adjustments). Therefore, our ability to analyze violation probability as loans mature is limited. However, we provide evidence that useful measures of violation probability in years subsequent to loan inception can be developed, despite this limitation.

[27] We note that, because FL use individual covenant slack measures as dependent variables, they employ a Heckman two-stage estimation approach to account for selection of the covenant. Because *PVIOL* naturally imbeds covenant inclusion or exclusion, we do not need to similarly control for selection issues in this specification.

Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.jacceco.2015.11.001.

References

Albuquerque, A., 2009. Peer firms in relative performance evaluation. Journal of Accounting and Economics 48, 69–89.
Ball, R., Shivakumar, L., 2006. The role of accruals in asymmetrically timely gain and loss recognition. Journal of Accounting Research 44 (2), 207–242.
Barber, B., Lyon, J., 1996. Detecting abnormal operating performance: the empirical power and specification of test statistics. Journal of Financial Economics 41, 359–399.
Beatty, A., Weber, J., Yu, J., 2008. Conservatism and debt. Journal of Accounting and Economics 45, 154–174.
Billett, M., King, T., Mauer, D., 2007. Growth opportunities and the choice of leverage, debt maturity, and covenants. Journal of Finance 62 (2), 697–730.
Blouin, J., Core, J., Guay, W., 2010. Have the tax benefits of debt been overestimated? Journal of Financial Economics 98, 195–213.
Bradley, M., Roberts, M., 2004. The structure and pricing of corporate debt covenants. Working Paper. Duke University and the University of Pennsylvania.
Chava, S., Roberts, M., 2008. How does financing impact investment? The role of debt covenants. Journal of Finance 63 (5), 2085–2121.
Christensen, H., Nikolaev, V., 2012. Capital versus performance covenants in debt contracts. Journal of Accounting Research 50 (1), 75–116.
DeFond, M., Jiambalvo, J., 1994. Debt covenant violation and manipulation of accruals. Journal of Accounting and Economics 17, 145–176.
Demerjian, P., 2011. Accounting standards and debt covenants: has the "balance sheet approach" led to a decline in the use of balance sheet covenants. Journal of Accounting and Economics 52, 178–202.
Demiroglu, C., James, C., 2010. The information content of bank loan covenants. Review of Financial Studies 23 (10), 3700–3737.
Dichev, I., Skinner, D., 2002. Large-sample evidence on the debt covenant hypothesis. Journal of Accounting Research 40 (4), 1091–1123.
Duke, J., Hunt, H., 1990. An empirical examination of debt covenant restrictions and accounting-related debt proxies. Journal of Accounting and Economics 12, 45–63.
Ecker, F., Francis, J., Olsson, P., Schipper, K., 2013. Estimation sample selection for discretionary accruals models. Journal of Accounting and Economics 56, 190–211.
El-Gazzar, S., Pastena, V., 1991. Factors affecting the scope and initial tightness of covenant restrictions in private lending agreements. Contemporary Accounting Research 8 (1), 132–151.
Frankel, R., Litov, L., 2007. Financial accounting characteristics and debt covenants. Working Paper. Washington University in St. Louis.
Franz, D., HassabElnaby, H., Lobo, G., 2014. Impact of proximity of to debt covenant violation on earnings management. Review of Accounting Studies 19, 473–505.
Hillegeist, S., Keating, E., Cram, D., Lundstedt, K., 2004. Assessing the probability of bankruptcy. Review of Accounting Studies 9, 5–34.
Leftwich, R., 1983. Accounting information in private markets: evidence from private lending agreements. The Accounting Review 58 (1), 23–42.
Li, N., 2010. Negotiated measurement rules in debt contracts. Journal of Accounting Research 48 (5), 1103–1144.
Li, N., 2015. Performance measures in earnings-based financial covenants in debt contracts. Working Paper. University of Texas at Dallas.
Li, N., Vasvari, F., Wittenberg-Moerman, R., 2015. Dynamic threshold values in earnings-based covenants. Journal of Accounting and Economics. (forthcoming).
Murfin, J., 2012. The supply-side determinants of loan contract strictness. Journal of Finance 67 (5), 1565–1601.
Nini, G., Smith, D., Sufi, A., 2012. Creditor control rights, corporate governance, and firm value. Review of Financial Studies 25 (6), 1713–1761.
Press, E., Weintrop, J., 1990. Accounting-based constraints in public and private debt agreements: Their association with leverage and impact on accounting choice. Journal of Accounting and Economics 12, 65–95.
Roberts, M., Sufi, A., 2009. Renegotiation of financial contracts: evidence from private credit agreements. Journal of Financial Economics 93 (2), 159–184.
Sweeney, A., 1994. Debt-covenant violations and managers' accounting responses. Journal of Accounting and Economics 17, 281–308.
Vuong, Q., 1989. Likelihood ratio tests for model selection and non-nested hypotheses. Econometrica 57, 307–333.
Watts, R., Zimmerman, J., 1978. Towards a positive theory of the determination of accounting standards. The Accounting Review 53 (1), 112–134.
Watts, R., Zimmerman, J., 1986. Positive Accounting Theory. Prentice Hall, Englewood Cliffs, NJ.
Zhang, J., 2008. The contracting benefits of accounting conservatism to lenders and borrowers. Journal of Accounting and Economics 45, 27–54.