Review of Accounting Studies
https://doi.org/10.1007/s11142-023-09772-x

Accounting-based expected loss given default and debt contract design

Dan Amiram[1] · Edward Owens[2]

Accepted: 3 April 2023

Abstract

We investigate an unexplored channel—loss given default (LGD)—through which accounting information can shape the design of debt contracts. Using a sample of defaulted bonds, we find that borrower accounting information available at contract initiation possesses significant power for predicting realized LGD at the subsequent default date. We then use this model to construct an accounting-based measure of expected LGD at the contracting date for a large sample of bond issuances. We find that this measure is positively associated with issuance date interest spread and covenant use, and document that these relations are not artifacts of an association between LGD and probability of default. We then show that accounting-based expected LGD has a stronger association with issuance date spread when the borrower's underlying accounting is more conservative and when the accounting-based LGD predictors are more persistent. Our results increase our understanding of both the informational role and contracting role of accounting information.

Keywords Debt contracts · Loss given default · Accounting properties · Stepwise regression

JEL Classification G12 · M40 · M41

1 Introduction

Financial reports are an important source of firm-specific information available to lenders at the contracting date and thus may affect lenders' behavior in the design of debt contracts. Whereas prior literature focuses on the usefulness of accounting

✉ Dan Amiram
danamiram@tauex.tau.ac.il

Edward Owens
ed.owens@eccles.utah.edu

1 Coller School of Management, Tel Aviv University, P.O. Box 39040, Tel Aviv 6997801, Israel

2 David Eccles School of Business, University of Utah, 1655 Campus Center Dr., Salt Lake City, UT 84112, USA

Published online: 28 April 2023

information for probability of default assessment (e.g., Beaver 1966; Altman 1968; Shumway 2001), this study suggests that accounting information may also shape contracts by facilitating lenders' assessment of loss given default. Loss given default, defined as the percentage loss that lenders experience from $1 of outstanding principal in a case of default, is a critical component of credit risk and debt contracting theories.[1] Despite the theoretical importance of loss given default, there is little empirical evidence regarding how accounting information available to lenders at the contracting date is associated with their expectations about loss given default. This study is the first to provide evidence that accounting information *at the contracting date* is a useful predictor of realized loss given default and that lenders behave as if they use accounting information about loss given default to design debt contracts.

According to debt contracting theory, the price and terms of debt depend directly on lenders' assessments of expected losses, where expected credit loss is a function of both probability of default and expected loss given default. Prior literature and practitioners suggest that these two determinants of credit loss are separately evaluated to determine credit risk. A substantial body of research focuses on the informativeness of accounting information with respect to probability of default. However, there is very little research concerning the informativeness of accounting information with respect to loss given default, particularly *at the contracting date*. A key source of firm-specific information available to lenders at the contracting date is accounting information from the borrower's financial statements (e.g., Tirole 2006; Standard and Poor's 2013). Thus, financial statement information available to lenders at the contracting date may be useful in predicting loss given default and thus may shape the design of debt contracts. However, anecdotal evidence suggests that lenders may not use firm-specific information to estimate loss given default (Gupton and Stein 2005). Moreover, accounting information available to lenders at the date of the contract may not have the power to predict eventual loss given default, given the relatively long period between bond issuance and eventual default. Therefore, accounting information may not be associated with contracting terms through the loss given default channel.

We first examine whether borrower accounting information *at the contracting date* is predictive of loss given default. Specifically, we use a sample of senior unsecured defaulted bonds for which data on realized recovery rates (and thus loss given default) exist to estimate an accounting-based prediction model for loss given default at bond initiation. Based on insights from prior research on the determinants of loss given default at the default date (e.g., Acharya et al. 2007; Varma and Cantor 2005), we select a broad set of potential accounting-based predictors and perform stepwise regression to determine the best model, given this broad set of candidate predictors (e.g.,Elgers 1980; Brown et al. 1998). The stepwise regression selects five predictors, yielding a parsimonious model that

[1] In other words, loss given default is the amount that lenders cannot recover from $1 of debt, which implies that loss given default is one minus the recovery rate on a debt instrument. As an example, consider a lender that invests $100 in a firm which defaults and is liquidated as a consequence. If the lender receives $20 out of the liquidation proceeds, the lender has loss given default of 80%.

explains a high proportion of the variation in realized loss given default, both in sample and out of sample. Further, we show that the predictive ability of our accounting-based model is incremental to information contained in historical industry-based LGD data, which prior literature suggests are used as the industry standard (Gupton and Stein 2005).

Although it may be possible to create a superior prediction model using *non-accounting* variables (e.g., firm-specific market-based measures, bond characteristics, macroeconomic variables), this approach would yield a "mixed-source" measure of expected loss given default, where it would be difficult to identify the predictive ability of the accounting variables themselves. Such a measure would therefore not be suitable to address our research questions of interest—whether contracting date *accounting information* is informative about realized loss given default, and whether lenders behave as if they are using the information in contracting-date accounting data about loss given default to set contract terms. Moreover, any lack of power in our prediction model will only bias against our ability to find significant associations between our measure of expected loss given default and debt contracting terms.

The finding that contracting-date accounting information is predictive of eventual realized loss given default is particularly striking, given that, in our sample, the average time to default from contract initiation is more than five years. We next use the estimated coefficients from the prediction model to construct an accounting-based measure of expected loss given default at the issuance date for a broad sample of senior unsecured bonds. Consistent with our expectation, we find that accounting-based expected loss given default is associated with higher credit spreads at bond issuance. Specifically, our results suggest that a one standard deviation increase in the accounting-based loss given default expectation is associated with an approximate 21 basis point increase in the interest spread on the bond. Further, because loss given default manifests only when the borrower defaults, we predict and find that our results are stronger when the borrower's probability of default is higher.[2]

Importantly, we obtain our results after controlling for the information in the five accounting-based predictors about probability of default. Specifically, we construct an estimated probability of default for each borrower using our five loss given default accounting predictors, and verify that our results hold after including this accounting-based probability of default measure in the analysis. This additional analysis confirms that the association we document between bond interest spread and our measure of accounting-based loss given default is not simply reflecting information in those accounting variables about probability of default. In addition, we include a control for default probability in all analyses.

Lenders have at their disposal contracting terms other than spread that they may use to protect against expected credit loss, such as covenants, maturity,

[2] Our results do not imply that lenders use the same accounting predictors (or even a related deterministic model of predicted loss given default) to estimate and price loss given default. Rather, our results simply suggest that lenders price debt in a way that is consistent with their use of accounting information as captured by our analyses.

and debt size. Moreover, the set of terms attached to a given debt contract may reflect a complex set of negotiated tradeoffs among these terms. Therefore, in all analyses, we control for these alternative contracting terms. In addition, because covenants are key protection mechanisms used by lenders, we examine directly whether covenant usage is similarly associated with accounting-based expected loss given default, and document a positive association. Further, we find that the covenant association is particularly strong for covenants that restrict the borrowers' payments to shareholders and that preserve the subject bond's place in the priority structure. Taken together, our findings that greater accounting-based expected loss given default is associated with both higher spread and more covenant use suggest that our primary spread results do not simply reflect a tradeoff between alternative lender protection mechanisms.

Finally, we examine how the association between accounting-based predicted LGD and spread varies based on properties of the borrower's accounting information. First, we provide evidence that the association is stronger when the borrower exhibits relatively high accounting conservatism. This is consistent with the idea, in many foundational studies in the literature (e.g., Watts 2003), that lenders' desire for an upper bound estimate of loss given default is a key driver of lenders' demand for accounting conservatism. Second, we provide evidence that the association is stronger when the accounting-based predictors are more persistent, consistent with the intuition that accounting information with higher persistence is more reliable for predicting future outcomes.

This study contributes to the literature along several dimensions. First, we show that accounting information available to lenders at the contracting date is informative about future loss given default. To the best of our knowledge, this study is the first to do so. This finding complements the literature which shows that accounting measures are informative about probability of default at the contracting date, and therefore enhances our understanding of the informational role of accounting. Second, we show that lenders behave as if their accounting-based expectations about loss given default significantly affect price and non-price terms of the debt contract. This finding contributes to the literature that examines the role of accounting information in debt contracting by providing new evidence of a specific channel through which accounting information is associated with debt contract design. Third, we contribute to the literature that examines lenders' demand for accounting conservatism. For example, Dyreng et al. (2017) provide evidence that lenders do not demand conservatism in measures that are connected to performance measurement for debt covenants, and further suggest that lenders' demand for conservatism likely manifests through other channels. Consistent with that conjecture, Beatty et al. (2008) provide evidence that lenders have a demand for conservatism in the context of net worth covenant measurement. This evidence concerning net worth covenants suggests that lenders' demand for conservatism relates to liquidation value estimates, which are intimately connected to loss given default. Our study provides evidence that LGD estimation is indeed a source of lenders' demand for accounting conservatism. Finally, our intuitive, parsimonious measure of accounting-based expected loss given default at the time of debt initiation may be of use in future research.

2 Motivation and background

Loss given default, which is defined as the percentage loss that lenders experience from $1 of outstanding principal in a case of default (i.e., one minus the recovery rate), interacts with probability of default in determining credit risk (Gupton and Stein 2005). The credit risk modeling literature discusses how credit spreads or the prices of risky bonds and loans are determined as a function of both probability of default and loss given default. Although credit risk models may differ significantly in their assumptions about loss given default and its determinants, loss given default plays an important role in pricing credit risk in all such models (e.g., Altman 2008). While the credit risk literature and practitioners note that loss given default and probability of default are correlated, they also indicate that these determinants of credit risk are estimated separately (e.g., Gupton and Stein 2005).

A substantial body of research in accounting and finance focuses on modeling probability of default. The informativeness of accounting information about probability of default is at the core of the seminal work of Beaver (1966), Altman (1968), and many subsequent studies (e.g.,Ohlson 1980; Zmijewski 1984; Shumway 2001; Beaver et al. 2012). It is only recently that research about the second major component of credit risk, loss given default, has emerged.[3] In practice, typical loss-given-default prediction models (e.g., Moody's LossCalc v2) estimate loss given default with two horizons—"immediately" and with a "one-year horizon" (Gupton 2005). While lenders certainly can use these models at the debt issuance date, the models' use is more common during the life of the debt instrument (i.e., subsequent to the issuance date) for purposes of ongoing portfolio risk determination. Moreover, the leading models include relatively little firm-specific accounting information and typically rely on characteristics of the debt instrument (e.g., collateral, seniority class), industry (e.g., historical recovery rates), and macroeconomic or geographical factors (Gupton 2005).[4] While the emerging loss-given-default literature suggests that certain accounting measures, when observed *at the date of default*, can predict loss given default (Varma and Cantor 2005; Acharya et al. 2007), to our knowledge there is no evidence concerning whether accounting information *at the contracting date* is informative about realized loss given default. Consistent with this, Benmelech et al. (2005) suggest that there is a paucity of empirical evidence on how lenders obtain and use information about loss

[3] See Altman (2008) for a survey of this emerging literature.

[4] The largest rating agencies have only recently started issuing independent loss given default ratings for debt instruments. These ratings are not available for many firms and were not available to lenders for most of the years in the sample. In addition, some of these ratings are available only after the contract has been designed. As Gupton (2005) discusses, a primary goal of Moody's LossCalc v2 model is to help lenders to assess loss given default for bank regulatory provisioning purposes required by the Basel accord.

given default at the contracting date, and Roberts and Sufi (2009) call for research that links loss given default and the structure of debt contracts.[5]

Although loss given default plays a central role in debt contracting theory and although available accounting information may be useful in estimating loss given default, it is possible that lenders do not behave as if they use firm-specific accounting information to assess loss given default in the design of debt contracts. First, anecdotal evidence from practitioners suggests that lenders use "lookup tables" of historical loss given default based on industry and seniority type as primary inputs for their lending decisions (Gupton and Stein 2005). These lookup tables provide lenders with the historical loss given default rate for a debt instrument for a given industry and seniority. Although Gupton and Stein (2005) note that lenders augment these historical tables with subjective judgment, the nature and the basis of these judgments is unclear. Second, because defaults typically occur several years after debt issuance, accounting information at the contracting date may have little power for predicting future realized loss given default and thus may have no association with debt contract terms through this channel. Therefore, it remains an open empirical question whether firm-specific accounting information is useful for lenders in assessing loss given default at the contracting date, and whether such information indeed affects contract design.

3 Research design and sample selection

Our empirical design has several stages. First, we examine the informativeness of borrowers' debt-contracting-date accounting measures about realized loss given default using a sample of defaulted bonds from Moody's Default Risk Services (DRS) database in a prediction model framework. Next, we use results from the first-stage prediction model to estimate predicted loss given default at the contracting date for a broad sample of bond issues from Mergent FISD. We then examine the association between predicted loss given default and bond characteristics (e.g., interest spread and covenant use).

3.1 Predicting loss given default using contracting-date accounting information

To develop our accounting-based LGD prediction model, we use stepwise regression—a model selection procedure whose use is appropriate when there is a large number of potential explanatory variables (e.g., Elgers 1980; Brown et al. 1998). Our first task is to determine the initial set of accounting variables we will feed into the stepwise regression. There is no general agreement about the best set of accounting ratios to use to assess credit risk, nor is it possible to specify the correct way to define specific ratios (e.g., Easton et al. 2018). Easton et al. (2018) suggest the use of both "flow" (i.e.,

[5] Unrelated to whether debt contracts are viewed through a complete or incomplete contracting framework (e.g., Aghion and Bolton 1992; Hart and Moore 1994; Christensen et al. 2016), lenders always have the need to estimate probability of default and loss given default at the contracting date.

income-statement-based) and "stock" (i.e., balance-sheet-based) variables to assess credit risk (pp. 4–10). In predicting LGD immediately prior to default, Varma and Cantor (2005) include leverage, tangibility, and profitability ratios and indicate that they select their variables based on intuition and data availability (p. 8). Similarly based on intuition, Acharya et al. (2007) consider several accounting variables (measured one year prior to default)—profit margin, leverage, (log) assets, and tangibility.

Using this prior literature as guidance, we initially select 13 accounting variables as candidate predictors to include in the stepwise regression. These variables can be categorized into profitability, coverage, and solvency measures. For profitability measures, we include return on assets (*ROA*) and profit margin (*ProfitMargin*). For coverage measures, we include times interest earned (*TimesInterest*) and asset turnover (*ATO*). For solvency measures, we include two different variations of net worth (*LnNetWorth*, *LnNetWorth2*), intangibles ratio (*IntanRatio*), short-term debt ratio (*ShortDebtRatio*), size (*LnTotalAssets*), three different variations of leverage (*Leverage*, *DebtToEquity*, *LiabToEquity*), and total debt (*Debt*). All variables are defined in the Appendix.

We construct a sample of defaulted bond issues from Moody's Default Risk Services (DRS) database. This database provides the backbone for the Annual Default Study, which is read by more than 40,000 investors globally. According to Moody's, the data are refreshed monthly to provide the most accurate and detailed portrait of default activity available in the market. A more thorough description of the data is provided in Varma and Cantor (2005). The data contain information on over 4,000 defaulted debt instruments for which there is information on 30-day recovery pricing (i.e., the price of the instrument 30 days after the default event). These data allow us to calculate loss given default for defaulted bonds.

Because we require accounting data from Compustat, we delete default observations for which we cannot obtain a valid CUSIP-GVKEY match or issuance date, which reduces the default sample to 2,145 observations. From this sample, we retain only senior unsecured "straight" bonds, which reduces the sample to 1,164 observations, with issuance years ranging from 1965 to 2008 and default years ranging from 1977 to 2009.[6] We limit our sample to a relatively homogeneous set of senior unsecured debt instruments to ensure that the accounting measures do not capture differences in bond seniority or security.[7] Including secured instruments in the analysis would also create measurement issues with assessing the value and nature of the

[6] Consistent with terminology used in practice, we use the term "straight" bond to refer to a bond that has no special features (e.g., is non-callable, non-convertible). In practice, these are also referred to as "plain vanilla" bonds.

[7] We follow Moody's definition of default, which includes three categories of credit events. The first is a missed or delayed disbursement of interest and/or principal. The second includes filing for bankruptcy, legal receivership, and other legal blocks to the timely payment of interest and/or principal (perhaps by regulators). The third is a distressed exchange, which occurs when (i) the issuer offers bondholders a new security or package of securities that amounts to a diminished financial obligation (such as preferred or common stock, or debt with a lower coupon or par amount, lower seniority, or longer maturity), or (ii) the exchange had the apparent purpose of helping the borrower avoid default. The definition of a default is intended to capture events that change the relationship between the bondholder and bond issuer from the relationship which was originally contracted, and which subjects the bondholder to an economic loss. Technical defaults (covenant violations, etc.) are not included in Moody's definition of default.

pledged security. In addition, senior unsecured debt is the most common form of debt in the DRS dataset (and in Mergent FISD, used in subsequent analyses).

We next bring in the most recently available annual accounting data (from Compustat) released during the 365 days immediately preceding the bond issuance, and estimate the following "forward selection" stepwise regression model using a subsample of the 529 defaulted bonds for which we have non-missing data for all variables included in the model:

$$\begin{aligned} LGD_{i,b,d} = {} & \delta_0 + \alpha_1 ROA_{i,t} + \delta_2 ProfitMargin_{i,t} + \delta_3 TimesInterest_{i,t} + \delta_4 ATO_{i,t} \\ & + \delta_5 LnNetWorth_{i,t} + \delta_6 LnNetWorth2_{i,t} + \delta_7 IntanRatio_{i,t} + \delta_8 ShortDebtRatio_{i,t} \\ & + \delta_9 LnTotalAssets_{i,t} + \delta_{10} Leverage_{i,t} + \delta_{11} DebtToEquity_{i,t} + \delta_{12} LiabToEquity_{i,t} \\ & + \delta_{13} Debt_{i,t} + \varepsilon \end{aligned} \tag{1}$$

where i, b, d, and t index the firm, bond, default date, and firm fiscal year most recently preceding the bond issuance, respectively. *LGD* is realized loss given default at the default date, and is calculated as one minus the recovery rate. Consistent with practitioner and academic research (e.g., Acharya et al. 2007; Varma and Cantor 2005; Gupton and Stein 2005), we compute the recovery rate as the price of the bond one month after the default divided by the bond face value. This method yields an unbiased measure of the recovery rate because there is an active market for defaulted bonds for a few months after the default (Gupton and Stein 2005).

The stepwise forward selection model in Eq. (1) adds one explanatory variable at a time and retains any variable that has statistical significance at the $p<0.10$ level. The predictive model generated by this stepwise process includes five of the 13 original accounting-based predictors from Eq. (1): *LnNetWorth*, *ROA*, *IntanRatio*, *ShortDebtRatio*, and *LnTotalAssets*. To preserve as many sample observations as possible, we return to the Moody's DRS data and estimate Eq. (2) with the DRS data using a subsample of 582 senior unsecured defaulted bonds for which we have non-missing data for these five predictive variables (hereafter referred to as the "DRS sample"). Specifically, to empirically assess whether there is an association between accounting variables available to lenders at the contracting date and future realized loss given default, we estimate the following model with the DRS sample using ordinary least squares with robust standard errors[8]:

$$\begin{aligned} LGD_{i,b,d} = {} & \beta_0 + \beta_1 LnNetWorth_{i,t} + \beta_2 ROA_{i,t} + \beta_3 IntanRatio_{i,t} + \beta_4 ShortDebtRatio_{i,t} \\ & + \beta_5 LnTotalAssets_{i,t} + \varepsilon, \end{aligned} \tag{2}$$

3.2 Predicted loss given default and contract characteristics

In the next stage of the analysis, to investigate whether lenders utilize the information in accounting variables about loss given default to design debt contracts, we

[8] Because the dependent variable, *LGD*, is between zero and one, OLS estimated coefficients may be biased. We also considered a fractional response model (Papke and Wooldridge 1996). Because this method yields similar results (untabulated) to the OLS results, we present OLS results for simplicity of calculation and interpretation.

apply the predicted coefficients from Eq. (2) (estimated using the DRS sample) to a broad sample of bond issues (irrespective of their eventual default status).[9] Therefore, we require this broad bond sample to have features consistent with the defaulted bonds in the DRS sample from which the predicted coefficients were generated. To this end, we construct a general sample of bond issues from Mergent FISD and include only "straight" senior unsecured bonds that are denominated in U.S. dollars. We delete observations for which we cannot obtain a valid CUSIP-GVKEY match or issuance date, and observations with missing offering yield data, which yields a sample of 5,082 observations. Next, we merge in the most recently available annual accounting data (from Compustat) released during the 365 days immediately preceding the bond issuance, and delete bonds issued by financial institutions (i.e., SIC codes from 6000 to 6300), which leaves 2,794 observations. Finally, we delete observations without all accounting and bond characteristic data needed for our subsequent analyses. This yields a final sample of 1,916 bond issuance observations, with issuance years ranging from 1978 to 2013. Hereafter, we refer to this as the "bond issue sample."

For each observation in the bond issue sample, we compute an estimate of accounting-based predicted LGD at the contracting date (*PredLGD_Acct*) as follows:

$$\begin{aligned} PredLGD\_Acct_{i,t} = \widehat{\beta}_0 + \widehat{\beta}_1 LnNetWorth_{i,t} + \widehat{\beta}_2 ROA_{i,t} + \widehat{\beta}_3 IntanRatio_{i,t} \\ + \widehat{\beta}_4 ShortDebtRatio_{i,t} + \widehat{\beta}_5 LnTotalAssets_{i,t}, \end{aligned} \tag{3}$$

where $\widehat{\beta}_n$ are the estimated coefficients from Eq. (2) and where the accounting variables are from the most recently available annual financial reports prior to bond issuance.

To investigate whether lenders utilize the information in accounting variables about loss given default to design debt contracts, we estimate the following OLS regression using the bond issue sample:

$$\begin{aligned} Spread_{i,b} = \gamma_0 + \gamma_1 PredLGD\_Acct_{i,t} + \gamma_2 BSMProb_{i,t} + \sum \gamma_n FirmControls_{i,t} \\ + \sum \gamma_n BondControls_{i,b} + IndustryFE + YearFE + \varepsilon, \end{aligned} \tag{4}$$

where *Spread* is the interest rate spread on bond *b* over a Treasury benchmark at the date of bond issuance. *BSMProb* is a measure of default probability (e.g., Hillegeist et al. 2004) as of the end of the most recent month prior to bond issuance. Holding probability of default constant, we expect that higher accounting-based predicted loss given default will spur lenders to require higher interest rates to compensate for higher risk. Therefore, we expect *PredLGD_Acct* to be positively associated with *Spread*.

As indicated, we include a vector of firm-specific explanatory variables to control for other known determinants of interest spread. Specifically, we include firm size

[9] Less than 5% of observations in our broad bond sample are also included in the default sample. If we remove these overlapping observations from the bond sample, our inferences are unchanged.

(*LnMVE*), growth opportunities (*Q*), and leverage (*Leverage*), where the accounting variables are from the most recently reported financial statements prior to bond issuance.

Further, we include a vector of bond-specific controls because there may be tradeoffs with interest spread across the various alternative bond terms which are determined simultaneously. Specifically, we include the par value of the debt issuance (*FaceAmt*), the maturity of the bond (*Maturity*), and an index that captures the extent of covenant use (*CovIndex*).[10] We also include an indicator variable that captures whether the bond is rated by Standard & Poor's (*Rated*), and industry fixed effects to control for systematic differences in credit pricing between industries that are also correlated with accounting-based loss given default. We include year fixed effects to control for macroeconomic factors that affect credit pricing (such as cyclical variation in the tightness of lender credit standards) (e.g., Murfin 2012) and because prior literature indicates that loss given default depends on the state of the economy (e.g., Acharya et al. 2007). All variables are further defined in the Appendix. In supplemental analyses, we augment Eq. (4) with additional control variable structures. We describe these modifications in Sect. 4 along with the associated analyses. In all analyses, we cluster standard errors by firm.[11]

3.3 Descriptive statistics

Panel A of Table 1 provides descriptive statistics for the DRS sample. The average bond defaults approximately five years (i.e., 63 months) after issuance and loses 68 percent of its face value, an amount consistent with prior literature (Varma and Cantor 2005). At the date of bond issuance, the median borrower is profitable (median *ROA* of 0.02) and has 4.7% of its total assets held as intangibles. Average borrower size is approximately \$2.5 billion in total assets (i.e., mean *LnTotalAssets* of 7.81).

Panel B of Table 1 provides descriptive statistics for the bond issue sample. On average, the bonds in this sample have a 117-basis-point spread over the Treasury benchmark (i.e., mean *Spread* of 1.168). The accounting-based predicted loss given default for this sample has a mean of 0.69, which is very close to the realized loss given default (*LGD*) in the DRS sample. The median borrower is profitable (median *ROA* of 0.047) and has 3.9% of its total assets held as intangibles. Average borrower size is relatively large, with approximately \$6.8 billion in total assets (i.e., mean *LnTotalAssets* of 8.84). In terms of the bond issues, approximately 95% are rated by Standard & Poor's. The issues, on average, have a maturity of 11 years and a \$255 million face amount. Panel C of Table 1 presents correlations among variables in the bond issue sample.

[10] In untabulated analyses, we find identical inferences to our main analyses when we estimate a system of equations using seemingly unrelated regression where each bond term (i.e., *Spread*, *FaceAmt*, *Maturity*, *CovIndex*) is used as a dependent variable in the Eq. (3) structure.

[11] Our inferences remain unchanged if we instead cluster by year of bond issuance.

Table 1 Descriptive statistics and correlations

	N	Mean	Std. Dev	P25	P50	P75
Panel A: DRS sample						
MonthsToDefault	582	63.408	48.514	30.181	52.323	78.148
LGD	582	0.680	0.322	0.552	0.805	0.927
LnNetWorth	582	7.190	1.909	5.961	7.147	8.386
ROA	582	0.000	0.121	-0.015	0.020	0.050
IntanRatio	582	0.106	0.159	0.000	0.047	0.142
ShortDebtRatio	582	0.095	0.132	0.009	0.045	0.123
LnTotalAssets	582	7.813	1.798	6.681	7.771	8.863
Panel B: Bond issue sample						
	N	**Mean**	**Std. Dev**	**P25**	**P50**	**P75**
Spread	1,916	1.168	1.032	0.602	0.898	1.399
PredLGD_Acct	1,916	0.692	0.097	0.628	0.693	0.752
PredLGD_Ind	1,916	0.808	0.364	0.591	0.676	0.910
PredPD_Acct	1,916	0.004	0.006	0.002	0.003	0.004
LnNetWorth	1,916	8.428	1.381	7.554	8.432	9.256
ROA	1,916	0.049	0.054	0.022	0.047	0.073
IntanRatio	1,916	0.102	0.142	0.000	0.039	0.156
ShortDebtRatio	1,916	0.097	0.108	0.023	0.066	0.134
LnTotalAssets	1,916	8.835	1.343	7.926	8.831	9.698
BSMProb	1,916	0.001	0.006	0.000	0.000	0.000
LnMVE	1,916	8.453	1.435	7.533	8.399	9.255
Q	1,916	1.572	0.744	1.108	1.324	1.753
Leverage	1,916	0.642	0.141	0.547	0.635	0.736
FaceAmt	1,916	255.4	270.4	100.0	200.0	300.0

Table 1 (continued)

Maturity	1,916	10.999	7.876	5.083	10.167	10.25							
CovIndex	1,916	3.879	2.645	2.000	5.000	6.000							
Rated	1,916	0.946	0.226	1.000	1.000	1.000							
Panel C: Bond issue sample correlation matrix													
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*	*(13)*
Spread (1)		-0.011	0.076	0.024	-0.227	-0.301	0.009	0.003	-0.183	0.419	-0.312	-0.187	0.128
PredLGD_Acct (2)	-0.056		0.077	0.309	0.735	-0.305	0.494	-0.250	0.792	0.057	0.601	-0.122	0.427
PredLGD_Ind (3)	0.028	0.069		0.031	-0.086	-0.043	0.167	-0.064	-0.059	-0.017	-0.039	-0.052	-0.069
PredPD_Acct (4)	-0.055	0.798	0.025		0.220	-0.140	0.161	0.437	0.337	0.035	0.166	-0.058	0.282
LnNetWorth (5)	-0.257	0.764	-0.058	0.686		0.067	0.111	0.015	0.981	-0.016	0.838	0.039	0.223
ROA (6)	-0.325	-0.330	-0.022	-0.278	-0.027		0.026	-0.018	0.004	-0.173	0.323	0.523	-0.411
IntanRatio (7)	-0.071	0.387	0.179	0.360	0.157	0.147		-0.055	0.140	-0.024	0.271	0.177	-0.009
ShortDebtRatio (8)	-0.105	-0.160	-0.104	0.343	0.092	0.050	0.023		0.083	0.029	0.048	0.068	0.066
LnTotalAssets (9)	-0.214	0.813	-0.043	0.786	0.982	-0.089	0.169	0.129		0.008	0.825	0.010	0.322
BSMProb (10)	0.426	0.084	0.017	0.106	-0.043	-0.344	-0.063	0.016	-0.003		-0.093	-0.110	0.112
LnMVE (11)	-0.380	0.615	-0.024	0.602	0.843	0.286	0.303	0.129	0.828	-0.190		0.477	-0.014
Q (12)	-0.303	-0.111	0.035	-0.085	-0.041	0.636	0.359	0.019	-0.071	-0.314	0.413		-0.216
Leverage (13)	0.153	0.432	-0.038	0.482	0.232	-0.469	0.020	0.034	0.318	0.227	0.010	-0.256	

Panel A of Table 1 presents descriptive statistics for variables used in our loss given default prediction model, which employs the default sample from Moody's DRS. *MonthsToDefault* is the time in months from the bond issue date until the eventual bond default date. Panel B (Panel C) of Table 1 presents descriptive statistics (correlations, with Pearson/Spearman reported above/below the diagonal) for variables used in the remainder of our analyses, which employ the bond issue sample from Mergent FISD. Variable definitions are presented in the Appendix

4 Accounting-based loss given default prediction model

4.1 Primary analysis

Based on the literature discussed above, we can posit some predictions regarding the associations between LGD and the predictive variables in Eq. (2) (i.e., those variables selected by the stepwise regression model in Eq. 1). We predict a negative association for *LnNetWorth* because higher net worth equates to more unencumbered assets that lenders have available to liquidate in order to recover their investment. We predict a negative association for *ROA*, because the more profitable the firm, the greater the chance of lenders getting a high price for selling the firm as a going concern or for liquidating the firm's assets. *IntanRatio* is the ratio of intangible assets to total assets, which we predict will have a positive association with *LGD*. Many intangible assets are difficult to transfer and thus may yield a low value in liquidation. *ShortDebtRatio* is debt in current liabilities divided by total liabilities, which we predict will be negatively associated with *LGD*. By its nature, short-term debt maturity is used as a monitoring mechanism by lenders because of its frequently required renewals. Therefore, we expect that firms with a relatively high proportion of short-term debt in their capital structure will be less likely to operate in a way that will reduce lenders' ability to recover assets. *LnTotalAssets* is the natural log of total assets, which we predict will have a positive association with *LGD*.[12] Whereas net assets captures unencumbered assets available to lenders in liquidation (and thus should be negatively associated with loss given default), total assets is a proxy for the level of complexity faced by lenders in the liquidation of a firm's assets, which affects the liquidity of those assets.[13] In addition, total assets is associated with the complexity of the firm's bankruptcy procedures in case of a default, which yields lower recovery rates and thus higher predicted *LGD*.[14]

Column (1) of Table 2 presents results from estimating Eq. (2) using the DRS sample. As indicated, each of the five accounting variables is significantly associated with realized loss given default in the expected directions. *LnNetWorth* is negatively associated with *LGD* (coefficient -0.075; t-statistic -2.98). Likewise, *ROA* is negatively associated with *LGD* (coefficient -0.454; t-statistic -5.28). The degree of intangibles in the asset structure is significantly positively associated with realized loss given default (*IntanRatio* coefficient 0.230; t-statistic 2.66). A higher concentration of short-term debt in the capital structure is negatively associated with realized loss given default (*ShortDebtRatio* coefficient -0.330; t-statistic -3.04). Finally, total assets are positively associated with loss given default (*LnTotalAssets* coefficient

[12] We note that by including both net worth and assets in the regression, we are implicitly including leverage (i.e., the difference between assets and net worth).

[13] Shleifer and Vishny (1992) analytically show that when more similar assets are dumped into the market during liquidation, prices are depressed.

[14] We acknowledge that it is possible to conceive of stories that suggest opposing predictions. For example, rather than providing monitoring benefits (which would reduce LGD), short-term debt could indicate financial instability, which may translate into higher LGD. Either way, we are more concerned with whether the variables are useful for predicting LGD than with their particular directional associations.

Table 2 Loss given default prediction model using bond-issuance-date accounting information

Dep. Var.:	*LGD*	*LGD*	*LGD*	*LGD*	*LGD*
Column:	(1)	(2)	(3)	(4)	(5)
Intercept	0.203***	0.729***	0.196***	0.483***	0.161***
	(3.73)	(32.25)	(2.88)	(11.45)	(2.73)
LnNetWorth	-0.075***		-0.071***		-0.072***
	(-2.98)		(-2.74)		(-2.92)
ROA	-0.454***		-0.430***		-0.410***
	(-5.28)		(-4.77)		(-4.84)
IntanRatio	0.230***		0.238**		0.162*
	(2.66)		(2.50)		(1.83)
ShortDebtRatio	-0.330***		-0.311***		-0.191*
	(-3.04)		(-2.65)		(-1.77)
LnTotalAssets	0.131***		0.131***		0.118***
	(4.88)		(4.61)		(4.46)
IndAvgLGD				0.369***	0.214***
				(5.28)	(3.12)
Fixed Effects		I	I		
N	582	582	582	560	560
Adj. R^2	0.150	0.045	0.180	0.052	0.143

Table 2 presents results of OLS estimation of Eq. (1) using our default sample. *LGD* is realized loss on firm *i*'s defaulted bond *b* on date *d*, calculated as one minus the realized recovery rate, using data from Moody's DRS. Recovery rate is calculated as the market price of the bond 30 days after default divided by the face value of the bond. All variable definitions are presented in the Appendix. *, **, and *** indicate significance (two-sided) at the 10%, 5%, and 1% levels, respectively, with robust standard errors. In column (2), the reported *Intercept* is simply the omitted industry category. "I" refers to Fama–French 17-industry classification fixed effects

0.131; t-statistic 4.88), consistent with the fact that liquidating more assets in case of default requires larger liquidity discounts.

4.2 Out-of-sample prediction

If the model lacks power, it is likely to bias against finding a significant association between *Spread* and *PredLGD_Acct* in Eq. (4). Although the strength of the results in column (1) of Table 2 suggests that our model indeed has significant in-sample predictive power, we also examine its predictive power using two alternative out-of-sample tests to ensure that the model's in-sample success is not due to overfitting or related concerns. First, we randomly choose 500 observations from the sample and estimate Eq. (2) using these observations. We continue by constructing *PredLGD_Acct* for a holdout sample of 82 observations. We then estimate the correlation between *PredLGD_Acct* and realized loss given default in the holdout sample, and repeat this process 100 times. The average correlation between *PredLGD_Acct* and realized loss given default across these 100 iterations is approximately 0.40 and is statistically significant in 96 out of 100 iterations. Further, the mean values of *PredLGD_Acct* and realized loss given default across the 100 iterations are 0.682 and 0.681, respectively, with a mean observation-level difference (i.e., bond *i*'s realized *LGD* minus bond *i*'s *PredLGD_Acct*) of -0.001. Second, we estimate Eq. (2) using all sample observations with a default year of 2005 or prior (i.e., the estimation sample; *N*=441), then use the resulting coefficient estimates to construct *PredLGD_Acct* for the sample observations with a default year after 2005 (i.e., the test sample; *N*=141). The mean values of *PredLGD_Acct* and realized loss given default in the test sample are 0.7495 and 0.7440, respectively, with a correlation of 0.212 (p=0.01). This evidence suggests that the prediction model captures the underlying construct of expected loss given default.

4.3 Accounting variables versus industry-based LGD prediction

Anecdotal evidence from practitioners suggests that lenders use "lookup tables" of historical loss given default based on industry, adjusted using their professional judgment, as inputs for their lending decisions (Gupton and Stein 2005). This implies that lenders view industry averages as providing critical information about expected future loss given default *at the time of contracting*. We are not aware of any other *statistical* forecasting method used by lenders to predict loss given default *at the date of debt issuance*. This motivates us to consider whether firm-specific accounting variables provide valuable information about future loss given default over and above industry averages.

First, in column (2) of Table 2, we present results from a simple model where we regress *LGD* on industry fixed effects based on Fama–French 17-industry classifications. As reported, the industry fixed effects model has meaningful explanatory power (i.e., adjusted-R^2 of 0.045), which provides some support for the practice of using industry means to estimate future loss given default.[15] In column (3) of Table 2, we report a variant of Eq. (1) where we add industry fixed effects to the five accounting predictors. As reported, all of the accounting predictors retain their strong significance in the presence of industry fixed effects. Moreover, the adjusted-R^2 quadruples relative to the industry-fixed-effects-only model in column (2) (i.e., 0.180 versus 0.045). Second, for each firm-default observation, we compute average recovery rates across the default sample in that firm's Fama–French 17 industry using all defaults that occurred prior to the firm's default (*IndAvgLGD*), then include this variable in the prediction model instead of industry fixed effects. As we now report in column (4) of Table 2, this industry-average LGD on its own is predictive of realized future LGD (coefficient 0.369; t-statistic 5.28). More importantly, column (5) of Table 2 documents that our accounting-based predictors are each statistically significant after controlling for industry-average LGD, and the adjusted-R^2 almost triples compared to column (4). Together, these analyses yield evidence that

[15] In this fixed-effects-only model, the reported intercept simply captures the constant effect of one industry that is necessarily omitted during model estimation.

firm-specific accounting variables provide substantial information about future loss given default, both independently and over and above the information contained in industry averages.

5 Accounting-based predicted loss given default and bond interest spread

5.1 Primary analysis

Column (1) of Table 3 presents results from estimating Eq. (4) on the bond issue sample, where *PredLGD_Acct* is computed based on coefficient estimates from column (1) of Table 2 (i.e., Eq. 3). As reported, accounting-based predicted loss given default is positively and significantly associated with bond interest spread (*PredLGD_Acct* coefficient 2.20; t-statistic 3.13). The effect is economically significant, with a one-standard-deviation change (0.097) in *PredLGD_Acct* translating into a 21-basis-point change in *Spread,* which is 18% of the *Spread* mean. This result suggests that accounting-based loss given default expectations are associated with significant economic effects on the pricing of debt contracts.[16]

In columns (2) and (3), we continue our exploration of whether information in accounting-based predicted loss given default is incremental to information in industry averages. Specifically, we compute industry-based predicted loss given default (*PredLGD_Ind*) using estimated coefficients from the Table 2 column (2) regression. In column (2), we document that *PredLGD_Ind* is significantly positively associated with bond spread, as expected. More importantly, in column (3) we include *PredLGD_Ind* and *PredLGD_Acct* together. As reported, there is little effect on the estimated *PredLGD_Acct* coefficient. We therefore conclude that the incremental (to industry-average) information in firm-specific contracting-date accounting variables about future loss given default is priced. Indeed, the coefficient on *PredLGD_Ind* is statistically insignificant, which further suggests that any pricing implications of industry-average loss given default information are subsumed by the accounting-based loss given default information.[17]

Taken together, the results in Table 3 suggest that information in accounting-based expected loss given default is significantly associated with debt pricing. This is consistent with lenders behaving as if they are using accounting information to determine loss given default expectations in the design of debt contracts.

[16] For the sake of brevity, we do not discuss the results of the control variable estimates for any of the estimations in this study except in cases where these results are important to the purposes of this paper. However, we note that these estimates are generally consistent with prior literature.

[17] The separate addition of each of the five accounting predictors that comprise *PredLGD_Acct* to the regression as a control variable does not change the inferences described above. We note that adding all of the accounting predictors to the regression together is not feasible because of full multicollinearity, as *PredLGD_Acct* is a linear combination of the five accounting predictors.

Table 3 Accounting-based predicted loss given default and bond interest spread

Dep. Var.:	*Spread*	*Spread*	*Spread*
Column:	(1)	(2)	(3)
PredLGD_Acct	2.201***		2.315***
	(3.13)		(3.18)
PredLGD_Ind		0.136*	0.070
		(1.71)	(0.96)
LnMVE	-0.450***	-0.330***	-0.452***
	(-8.59)	(-10.28)	(-8.51)
Q	0.077	-0.023	0.109*
	(1.21)	(-0.51)	(1.82)
Leverage	0.475*	0.776***	0.237
	(1.89)	(3.52)	(1.02)
BSMProb	39.934***	43.395***	42.002***
	(4.29)	(4.52)	(4.41)
FaceAmt	0.000**	0.000**	0.000***
	(2.44)	(2.57)	(2.78)
Maturity	0.010***	0.010***	0.010***
	(4.87)	(4.58)	(4.93)
CovIndex	0.018	0.028*	0.023
	(1.17)	(1.87)	(1.60)
Rated	-0.580***	-0.474***	-0.517***
	(-3.31)	(-2.91)	(-3.09)
Fixed Effects	I, Y	Y	Y
N	1,916	1,916	1,916
Adj. R^2	0.493	0.468	0.480

Table 3 presents results of OLS estimation of Eq. (3) using our bond issue sample. *Spread* is the interest spread on firm *i*'s bond *b*, calculated as the bond offering yield to maturity minus the benchmark Treasury rate. *PredLGD_Acct* is firm *i*'s contracting-date accounting-based predicted loss given default, constructed as in Eq. (2). *PredLGD_Ind* is firm *i*'s predicted loss given default using only industry fixed effects, based on the Fama–French 17-industry classifications. All variable definitions are presented in the Appendix. *, **, and *** indicate significance (two-sided) at the 10%, 5%, and 1% levels, respectively, with standard errors clustered by firm. Intercepts and fixed effects coefficients are included but not reported for fixed effects estimations, where I and Y refer to Fama–French 17-industry classification fixed effects and year fixed effects, respectively

5.2 The effect of default probability

Because losses to debt holders occur only when a default event occurs, we expect *Spread* to be more sensitive to accounting-based expected loss given default when the likelihood of default is higher. Stated differently, loss given default means very little to debt investors if probability of default is zero. In contrast, when probability of default is close to one, debt investors should assign great importance to their recovery expectations. To examine this prediction, we estimate Eq. (4) separately for sample partitions where bond issuers have relatively low versus high estimated

Table 4 Default probability effects

Sample	Low *BSMProb*	High *BSMProb*	
Dep. Var.:	*Spread*	*Spread*	
Column:	(1)	(2)	Diff (2)-(1)
PredLGD_Acct	0.457	3.359***	2.902***
	(0.80)	(3.48)	
LnMVE	-0.233***	-0.607***	
	(-6.25)	(-8.43)	
Q	-0.001	0.068	
	(-0.01)	(0.62)	
Leverage	0.318	0.822**	
	(1.11)	(2.05)	
FaceAmt	0.000**	0.000	
	(2.39)	(1.34)	
Maturity	0.012***	0.008**	
	(5.24)	(2.07)	
CovIndex	0.034**	0.011	
	(2.21)	(0.51)	
Rated	-0.541**	-0.720***	
	(-2.12)	(-3.22)	
Fixed Effects	I,Y	I,Y	
N	958	958	
Adj. R^2	0.400	0.487	
Mean *BSMProb*	0.000%	0.214%	

Table 4 presents results of OLS estimation of Eq. (3) using our bond issue sample, partitioned into low and high default probability based on median *BSMProb*. *BSMProb* is firm *i*'s estimated default probability at the end of the month immediately preceding bond issuance. *Spread* is the interest spread on firm *i*'s bond *b*, calculated as the bond offering yield to maturity minus the benchmark Treasury rate. *PredLGD_Acct* is firm *i*'s contracting-date accounting-based predicted loss given default, constructed as in Eq. (2). All variable definitions are presented in the Appendix. *, **, and *** indicate significance (two-sided) at the 10%, 5%, and 1% levels, respectively, with standard errors clustered by firm. Intercepts and fixed effects coefficients are included but not reported for fixed effects estimations, where I and Y refer to Fama–French 17-industry classification fixed effects and year fixed effects, respectively

default probabilities based on median *BSMProb* (and, accordingly, we remove *BSMProb* from the set of control variables included in the regression).

Table 4 presents the results of this analysis, where the low (high) default probability sample partition has mean *BSMProb* of 0.000% (0.214%). As indicated in column (1), there is no significant association between accounting-based predicted loss given default and bond spread when default probability is relatively low (*PredLGD_Acct* coefficient estimate 0.457; t-statistic 0.80). In contrast, as reported in column (2), there is a strong positive association between *PredLGD_Acct* and *Spread* when default probability is relatively high (coefficient estimate 3.359; t-statistic 3.48). Moreover, the 2.902 difference in these coefficient estimates is statistically significant with p-value 0.003 (untabulated, based on a statistical test using seemingly unrelated regression on the column 1 and column 2 models). These results are consistent with our prediction and provide further assurance that *PredLGD_Acct* indeed captures lenders' expectation of loss given default.[18]

5.3 Additional considerations

5.3.1 Is *PredLGD_Acct* simply capturing probability of default?

Potential correlation between loss given default and probability of default gives rise to a concern that the positive association that we document between *PredLGD_Acct* and *Spread* may be attributable to unmodeled components of default risk that are correlated with *PredLGD_Acct*. Although we control for probability of default in our main analyses (*BSMProb*), we conduct an additional analysis to provide comfort against the concern that the relation we document between *PredLGD_Acct* and *Spread* is instead picking up some predictive power that our accounting variables have with respect to probability of default that is not captured by *BSMProb*.

Specifically, we construct an estimated probability of default measure using the same five accounting predictors that we use to estimate *PredLGD_Acct*, and include the resulting accounting-based probability of default measure in Eq. (4) as an additional control. Specifically, we estimate a default prediction model following a commonly used reduced-form, discrete-time hazard model approach using a multiperiod logit model with time-varying covariates (e.g., Shumway 2001; Chava and Jarrow 2004; Campbell et al. 2008). We form a broad sample of default and non-default firm-year observations by intersecting the Moody's Default Risk Services bond default sample (without requiring observations to have recovery pricing data) with the Compustat annual file, where we limit the default sample to the first observed default for each firm. We then delete all firm-year observations in Compustat for the defaulting firms subsequent to the default year. The resulting sample consists of 320,360 firm-year observations, comprised of 30,399 distinct firms with 475 firm defaults. We then estimate the accounting-based probability of default for firm i in year t using the following logit-based hazard model structure:

$$P(Default_{i,t+1} = 1) = f\left(\begin{array}{c} \alpha_0 + \alpha_1 LnNetWorth_{i,t} + \alpha_2 ROA_{i,t} + \alpha_3 IntanRatio_{i,t} \\ + \alpha_4 ShortDebtRatio_{i,t} + \alpha_5 LnTotalAssets_{i,t} \end{array} \right) \quad (5)$$

where *Default* is an indicator variable that equals one if the firm defaults in year $t+1$ and zero otherwise. We measure the accounting predictor variables at the end of year t, where t is the date of the most recently available data prior to $t+1$. We

[18] As indicated in Table 1, consistent with prior studies, *BSMProb* is close to zero for more than 75% of our observations. Accordingly, we alternatively define high default probability based on a split at the 75th percentile (rather than at the median, as reported), and our inferences remain. Specifically, the coefficient estimate on *PredLGD_Acct* in the low (high) group is 1.14 (3.69), where both estimates are individually statistically significant and the difference is significant at the 5% level.

include each year a firm survives as a non-failure observation and include defaults as a failure observation only in the year of failure. Thus, *Default* equals zero for all firm-year observations of firms that never default, as well as for all firm-year observations of defaulted firms in years *t*-1 and earlier.

As reported in Panel A of Table 5, results from estimation of Eq. (5) indicate that each of the five accounting variables is significantly predictive of future default ($p < 0.01$ in each case) in the expected direction (e.g., higher *LnNetWorth* and *ROA* are negatively associated with default). We next construct the accounting-based probability of default measure, *PredPD_Acct*, as follows:

$$\begin{aligned} PredPD\_Acct_{i,t} = \widehat{\alpha}_0 + \widehat{\alpha}_1 LnNetWorth_{i,t} + \widehat{\alpha}_2 ROA_{i,t} + \widehat{\alpha}_3 IntanRatio_{i,t} \\ + \widehat{\alpha}_4 ShortDebtRatio_{i,t} + \widehat{\alpha}_5 LnTotalAssets_{i,t}, \end{aligned} \tag{6}$$

where $\widehat{\alpha}_n$ are the estimated coefficients from Eq. (5), and where the exponential function is applied to the right-hand side of Eq. (6) because the coefficients were estimated using a logistic model.[19]

Panel B of Table 5 presents results from estimating Eq. (4) with the additional *PredPD_Acct* control variable. As reported, *PredLGD_Acct* remains significantly positively associated with *Spread* (coefficient estimate 2.211; t-statistic 3.14). Further, *PredPD_Acct* is not significantly associated with *Spread*, which is not surprising given that we continue to control for probability of default with *BSMProb* (i.e., *BSMProb* subsumes all information in *PredPD_Acct* about probability of default). Given that we are using the same accounting predictors for both loss given default and probability of default, these results mitigate the concern that our loss given default accounting predictors are related to spread only through probability of default, rather than loss given default.

5.3.2 Accounting-based predicted loss given default and bond covenants

Our interpretation of the preceding analyses is that lenders use information in contracting-date accounting variables about expected loss given default to design bond contracts, where higher accounting-based expected loss given default is associated with a higher degree of lender protection imbedded in the contract (i.e., a higher interest rate). However, because bond contracts involve a menu of terms that are simultaneously determined, our interpretation is subject to the concern that lenders may be trading off protection mechanisms (i.e., increasing spread while relaxing other protection mechanisms) rather than increasing overall contract protections in the face of higher expected loss given default. In addition to interest rate, covenants are a key protection mechanism used by lenders. Therefore, to further assess this concern, we next examine directly whether covenant usage is associated with accounting-based expected loss given default.

[19] Subsequently reported inferences are unchanged if we instead estimate the Eq. (5) default prediction model using OLS and then construct *PredPD_Acct* using the linear coefficient estimates.

Table 5 Controlling for accounting-based predicted default probability

Panel A: Predicting default with the accounting-based loss given default predictors	
Dep. Var.:	*Default*$_{t+1}$
Column:	(1)
Intercept	-9.353***
	(-78.32)
LnNetWorth$_t$	-1.037***
	(-30.77)
ROA$_t$	-1.533***
	(-16.70)
IntanRatio$_t$	1.160***
	(5.10)
ShortDebtRatio$_t$	1.162***
	(4.80)
LnTotalAssets$_t$	1.363***
	(38.34)
N	320,360
Pseudo-R^2	0.122
Panel B: Bond interest spread regression	
Dep. Var.:	*Spread*
Column:	(1)
PredLGD_Acct	2.211***
	(3.14)
PredPD_Acct	-1.059
	(-0.24)
LnMVE	-0.450***
	(-8.58)
Q	0.077
	(1.21)
Leverage	0.485*
	(1.92)
BSMProb	39.912***
	(4.29)
FaceAmt	0.000**
	(2.45)
Maturity	0.010***
	(4.83)
CovIndex	0.018
	(1.16)
Rated	-0.581***
	(-3.32)
Fixed Effects	I,Y
N	1,916
Adj. R^2	0.493

Table 5 (continued)

Panel A of Table 5 presents results of logit estimation of Eq. (5) using a Moody's DRS and Compustat merged sample. *Default* is an indicator that equals one if firm *i* defaults in year $t+1$, zero otherwise. Panel B of Table 5 presents results of OLS estimation of Eq. (4), augmented with the additional variable *PredPD_Acct*, which is the bond-issuance-date predicted probability of default, constructed as in Eq. (6). *Spread* is the interest spread on firm *i*'s bond *b*, calculated as the bond offering yield to maturity minus the benchmark Treasury rate. *PredLGD_Acct* is firm *i*'s contracting date accounting-based predicted loss given default, constructed as in Eq. (3). All variable definitions are presented in the Appendix. *, **, and *** indicate significance (two-sided) at the 10%, 5%, and 1% levels, respectively, with standard errors clustered by firm. Intercepts and fixed effects coefficients are included but not reported for fixed effects estimations, where I and Y refer to Fama–French 17-industry classification fixed effects and year fixed effects, respectively

Specifically, we estimate a variant of Eq. (4) where we replace the dependent variable (*Spread*) with *CovIndex*, a numeric count of the number of covenants included in the bond contract (e.g., Amiram et al. 2017; Nikolaev 2010).

Column (1) of Table 6 reports the results of this analysis, which documents a significant positive association between accounting-based predicted loss given default and the number of included covenants (coefficient estimate 3.822; t-statistic 2.38). The fact that predicted loss given default is positively associated with both interest spread and the number of covenants suggests that lenders respond to increased expected loss given default by increasing both price and non-price protections.

To further corroborate this interpretation, we extend this analysis and examine the association between *PredLGD_Acct* and specific types of covenants. Our intuition is that higher expected loss given default should be associated with specific covenants that protect the lender by restricting borrower payouts or preserving the bond's priority in the capital structure, and should not be associated with covenants that have less to do with protecting the lender. Accordingly, we create two indicator variables: *RestrictPmtCov*, which equals one if the bond includes a covenant that restricts payments (including dividends) to shareholders and zero otherwise; and *PriorityCov*, which equals one if the bond includes either a cross-default or cross-acceleration covenant (i.e., which induces default or accelerates payment requirements if an event of default occurs under any other debt of the borrower) and zero otherwise. For an example of a covenant that we expect to not be associated with *PredLGD_Acct*, we create the indicator variable *RestrictStock*, which equals one if the bond includes a covenant that restricts the borrower from issuing additional common stock and zero otherwise. As reported in columns (2) and (3) of Table 6, there is indeed a significantly positive association between *PredLGD_Acct* and both *PriorityCov* and *RestrictPmtCov*. Further, there is no significant association between *PredLGD_Acct* and *RestrictStock* (untabulated).

5.3.3 Selection bias

Because LGD is, by definition, conditional on default occurring, we must estimate *PredLGD_Acct* using a sample of defaulted firms. A potential concern could be that

Table 6 Accounting-based predicted loss given default and bond covenant inclusion

Dep. Var.:	*CovIndex*	*PriorityCov*	*RestrictPmtCov*
Column:	(1)	(2)	(3)
PredLGD_Acct	3.822**	1.139***	0.209**
	(2.38)	(3.29)	(1.98)
LnMVE	-0.220*	-0.107***	-0.015**
	(-1.94)	(-3.92)	(-2.20)
Q	-0.058	0.041	0.013
	(-0.37)	(0.95)	(1.41)
Leverage	-0.501	-0.231	-0.001
	(-0.71)	(-1.44)	(-0.02)
BSMProb	-22.910	-6.385**	-1.971*
	(-1.40)	(-2.47)	(-1.68)
FaceAmt	-0.000	-0.000	0.000
	(-0.36)	(-0.11)	(1.46)
Maturity	-0.005	-0.001	-0.001***
	(-0.63)	(-0.32)	(-3.64)
Spread	0.153	0.015	0.036***
	(1.14)	(0.76)	(3.33)
Rated	-0.261	0.022	-0.060*
	(-0.58)	(0.30)	(-1.92)
Fixed Effects	I,Y	I, Y	I, Y
N	1,916	1,916	1,916
Adj. R^2	0.332	0.192	0.106

Table 6 presents results of OLS estimation of a variant of Eq. (4) using our bond issue sample. *CovIndex* is a count of the number of covenants included on firm *i*'s bond *b*. *PriorityCov* (*RestrictPmtCov*) is an indicator variable that equals one if firm *i*'s bond *b* includes a covenant that protects bond *b*'s priority (that restricts firm *i*'s payments to shareholders). *PredLGD_Acct* is firm *i*'s contracting-date accounting-based predicted loss given default, constructed as in Eq. (2). *PredLGD_Ind* is firm *i*'s predicted loss given default using only industry fixed effects, based on the Fama–French 17-industry classifications. All variable definitions are presented in the Appendix. *, **, and *** indicate significance (two-sided) at the 10%, 5%, and 1% levels, respectively, with standard errors clustered by firm. Intercepts and fixed effects coefficients are included but not reported for fixed effects estimations, where I and Y refer to Fama–French 17-industry classification fixed effects and year fixed effects, respectively

there are underlying unobserved characteristics (correlated with expected LGD) that caused these firms to default.[20] However, the fact that the research design employed in this study takes into account that LGD is conditional on default, and that any useful measure of contracting-date expected LGD also needs to measure LGD conditional on default, should mitigate this concern. This concern is also mitigated by

[20] For example, Glover (2016) shows that estimation of the cost of bankruptcy using a sample of bankrupt firms can be biased because of self-selection.

the fact that we control for probability of default in the second stage. Further, as previously discussed, if the coefficient estimates obtained from the defaulted sample are indeed somehow biased due to self-selection, this would bias against our ability to find significant associations between *PredLGD_Acct* and debt contracting terms.

5.4 LGD and properties of accounting

5.4.1 Accounting conservatism

The conceptual idea that lender demand for conservatism is connected to estimation of LGD permeates extant literature. For example, Watts (2003) posits that lenders are interested in "verifiable lower bound measures of the current value of net assets," and that "the orderly liquidation concept underlies conservative accounting" (p. 212). Consistent with this, Zhang (2008) states that one potential benefit of conservatism is that "conservative reporting also gives lenders a measure of the lower bound of the collateral's value" (p. 31). Likewise, Christensen and Nikolaev (2012) suggest that conservatism may facilitate the role of capital covenants by providing lower bound estimates of liquidation value (i.e., upper bound estimates of loss given default). Beatty et al. (2008) present evidence that lenders demand conservatism in the context of net worth covenant measurement, which in our view is connected to estimation of liquidation values. Further, recent studies present evidence that borrower conservatism is associated with higher lender recovery rates in default (Carrizosa and Ryan 2013; Donovan et al. 2015).

This conceptual connection between conservatism and loss given default leads us to predict that lenders will rely more on accounting-based estimates of LGD at the contracting date if the borrower exhibits more accounting conservatism. To provide novel evidence on this question, we extend our analysis by examining the relation between our measure of accounting-based expected LGD and borrower conservatism. Stated differently, our chief inference—that lenders use accounting-based expected LGD to shape debt contracts—is strengthened if we indeed can document that the association between accounting-based LGD and contract terms is stronger when the borrower has greater accounting conservatism.

Using the bond sample, we first measure firm *i*'s year *t* conservatism as the coefficient ratio $(\beta_3+\beta_1)/\beta_1$ in the following firm-specific time-series regression, using at least five, but no more than ten, years of firm *i*'s data ending in year *t* (e.g., Francis et al. 2004; Zhang 2008):

$$Earn_{i,t} = \beta_0 + \beta_1 Ret_{i,t} + \beta_2 DRret_{i,t} + \beta_3 DRet * Ret_{i,t} + \varepsilon_{i,t}, \quad (7)$$

where *Earn* is earnings before extraordinary items scaled by beginning-of-year market value of equity (from Compustat), *Ret* is 12-month return ending three months after fiscal year-end (from CRSP), and *DRet* is an indicator that equals one if $Ret < 0$.

Table 7 Accounting-based predicted LGD and properties of accounting

Cross-sectional Analysis:	*Conservatism*		*Persistence*	
Sample:	*HighConserv* = 0	*HighConserv* = 1	*HighPersist* = 0	*HighPersist* = 1
Dep. Var.:	*Spread*	*Spread*	*Spread*	*Spread*
Column:	(1)	(2)	(3)	(4)
PredLGD_Acct	0.518	3.852***	1.118	2.388***
	(0.52)	(3.78)	(1.28)	(3.53)
LnMVE	-0.410***	-0.517***	-0.359***	-0.400***
	(-5.50)	(-7.69)	(-4.69)	(-7.00)
Q	-0.045	0.208**	-0.116	0.113
	(-0.34)	(2.52)	(-1.22)	(1.31)
Leverage	0.995*	0.558	0.572	0.909*
	(1.84)	(1.57)	(1.34)	(1.73)
BSMProb	49.161**	6.604	40.312***	40.589**
	(2.19)	(0.79)	(2.79)	(2.39)
FaceAmt	0.000	0.000*	0.000**	0.000
	(0.09)	(1.88)	(2.49)	(1.36)
Maturity	0.014***	0.018***	0.012***	0.013***
	(3.20)	(5.51)	(3.41)	(4.15)
CovIndex	0.017	0.055**	0.015	0.020
	(0.56)	(2.19)	(0.70)	(1.03)
Rated	-0.089	0.093	-0.166	-0.315
	(-0.18)	(0.55)	(-0.34)	(-1.38)
N	372	390	525	604
Adj. R^2	0.676	0.671	0.678	0.513

Table 7 presents results of OLS estimation of Eq. (4) using a subset of our bond issue sample for which we are able to compute firm-level measures of conservatism and persistence of accounting predictors. *HighConserv* is an indicator variable that equals one if firm *i*'s year *t* accounting conservatism is above the sample median and zero otherwise. *HighPersist* is an indicator variable that equals one if the average of the decile ranks of the persistence of firm *i*'s year *t* *LnNetWorth*, *ROA*, *IntanRatio*, *ShortDebtRatio*, and *LnTotalAssets* is above the sample median and zero otherwise. *Spread* is the interest spread on firm *i*'s bond *b*, calculated as the bond offering yield to maturity minus the benchmark Treasury rate. *PredLGD_Acct* is firm *i*'s contracting-date accounting-based predicted loss given default, constructed as in Eq. (2). All variable definitions are presented in the Appendix. *, **, and *** indicate significance (two-sided) at the 10%, 5%, and 1% levels, respectively, with standard errors clustered by firm. Intercepts and fixed effects coefficients are included but not reported for fixed effects estimations, where I and Y refer to Fama–French 17-industry classification fixed effects and year fixed effects, respectively

We then estimate Eq. (3) separately for partitions of the bond sample based on a median split of borrower conservatism (*HighConserv*).

We report the results in Table 7.[21] Columns (1) and (2) report results consistent with our expectation that accounting-based expected LGD is associated with

[21] Note that our sample size is reduced to 762 observations because of data requirements associated with estimating Eq. (7) in firm-specific time series.

contract-date loan spread only for borrowers with relatively high conservatism. Intuitively, conservatism is a critical property of accounting for establishing lenders' expectation of loss given default. Thus, lenders do not appear to rely as much on an accounting-based prediction of LGD if the underlying accounting numbers are not generated from a conservative accounting system.

5.4.2 Persistence of accounting numbers

As discussed above, default occurs, on average, 63 months from bond issuance. The value of accounting-based predicted LGD likely depends on the persistence of the predictive variables themselves. Accordingly, we predict that there will be a stronger association between our measure of accounting-based predicted LGD and spread when our five predictive variables are more persistent. To examine this prediction, we use the bond sample and create a measure of the average persistence of firm *i*'s year *t* *LnNetWorth*, *ROA*, *IntanRatio*, *ShortDebtRatio*, *and LnTotalAssets*. Specifically, we first compute the persistence of each variable (*Var*) for firm *i* in year *t* as the coefficient from the following firm-specific regression:

$$Var_{i,t} = \beta_0 + \beta_1 Var_{i,t-1} + \varepsilon_{i,t}. \tag{8}$$

Next, we rank each variable's firm-year persistence into sample deciles and take a simple average of the decile ranks to obtain a firm-year average persistence, upon which we split the sample at the median (*HighPersist*). Columns (3) and (4) of Table 7 report results consistent with our expectation that accounting-based expected LGD is significantly associated with contract-date loan spread only when the accounting-based predictive variables have relatively high persistence.

6 Conclusion

A substantial body of research focuses on the informativeness of accounting information with respect to probability of default. However, there is very little research concerning the informativeness of accounting information with respect to loss given default, particularly at the contracting date. There exists some ancillary evidence in extant literature regarding the informativeness of accounting data about loss given default *at the time of default*. However, given the relatively long time between debt issuance and eventual default, this evidence says little about whether accounting information is useful to lenders in assessing expected loss given default *at the contracting date*—when lenders need information the most.

This study contributes to the literature along several dimensions. First, using a sample of defaulted bonds, we show that accounting measures available to lenders at the contracting date are informative about future loss given default. To the best of our knowledge, this study is the first to do so. This finding complements the literature which shows that accounting measures are informative about probability of default and therefore enhances our understanding of the informational role of accounting. Second, we construct an intuitive measure of accounting-based expected loss given default at the time of bond contract initiation, which could be of use in future research. Third, we show that lenders behave as if their accounting-based expectations about loss given default significantly affect price and non-price terms of bond contracts. We provide evidence that the association is stronger when the accounting-based predictors are more persistent, consistent with the intuition that accounting information with higher persistence is more reliable for predicting future outcomes. This finding contributes to the literature on the role of accounting information in debt contracting by showing a specific channel through which accounting information may be useful in lending decisions. Finally, our results provide important evidence that establishes a direct link between accounting-based LGD estimation and lenders' demand for financial reporting conservatism.

Several caveats are in order. First, although our LGD model predictive variables were selected based on statistical optimization (i.e., stepwise regression) from an initial set of theory- and literature-based candidate predictors, the actual set of potential LGD-relevant accounting predictors is virtually unbounded (i.e., any combination or transformation of accounting variables might be suggested). Accordingly, we leave the task of continued refinement of loss-given-default prediction models to future research. Relatedly, we do not intend to suggest that lenders are using our model (or any similar deterministic model). For example, the association between accounting-based predicted LGD and bond interest rates may simply be capturing the essence of lenders' professional judgement as applied to their review of borrower financial statements. Nonetheless, our results imply that lenders' decisions are consistent with their incorporation of contracting-date accounting information about loss given default into contract design.

Appendix

Variable definitions

$ATO_{i,t}$	Firm *i*'s year *t* asset turnover, calculated as sales (Compustat sale) divided by average total assets
$BSMProb_{i,m}$	Firm *i*'s estimated default probability at the end of month *m* using the Black–Scholes-Merton option pricing model modified for dividends, closely following the methodology outlined in Hillegeist et al. (2004). Estimation requires initial estimates of market value of assets (*VA*), asset volatility (*SIGA*), dividend rate (*DIVRATE*), and risk-free rate (*R*). We compute *VA* as total liabilities plus market value of equity in month *m*. We compute *SIGA* as firm *i*'s stock price volatility using one year of daily stock returns ending in month *m*, multiplied by the equity-to-asset value ratio. *DIVRATE* requires annual Compustat data for common and preferred dividends, which we set to zero if missing. We set the risk-free rate to the one-year T-bill rate for month *m*. Finally, we set the time horizon to one year
$CovIndex_{i,b}$	A count of the number of covenants attached to firm *i*'s bond *b*, as categorized and identified by the Mergent bond issue file
$Debt_{i,t}$	Firm *i*'s total debt at the end of year *t*, calculated as long-term debt (Compustat dltt) plus debt in current liabilities (Compustat dlc)
$DebtToEquity_{i,t}$	Firm *i*'s debt-to-equity ratio at the end of year *t*, calculated as total debt divided by common equity (Compustat (dltt + dlc)/ceq)
$Default_{i,t}$	An indicator variable that equals one if firm *i* defaults in year *t* and zero otherwise
$FaceAmt_{i,b}$	The par value of firm *i*'s bond *b* in millions, calculated as Mergent OFFERING_AMT divided by 1,000
$HighConserv_{i,t}$	An indicator variable that equals one if firm *i*'s year *t* accounting conservatism is above the sample median and zero otherwise. We measure firm *i*'s year *t* conservatism as the coefficient ratio $(\beta_3+\beta_1)/\beta_1$ in the following firm-specific time-series regression (using at least five but no more than ten years of firm *i*'s data, ending in year *t*): $Earn_{i,t}=\beta_0+\beta_1 Ret_{i,t}+\beta_2 DRret_{i,t}+\beta_3 DRet{*}Ret_{i,t}+\varepsilon_{i,t}$ (Basu 1997), where *Earn* is earnings before extraordinary items scaled by beginning-of-year market value of equity, *Ret* is 12-month return ending three months after the fiscal year-end, and *DRet* is an indicator that equals one if $Ret<0$
$HighPersist_{i,t}$	An indicator variable that equals one if the average decile rank persistence of firm *i*'s year *t* *LnNetWorth*, *ROA*, *IntanRatio*, *ShortDebtRatio*, and *LnTotalAssets* is above the sample median and zero otherwise. We first measure firm *i*'s year *t* persistence of each variable (*Var*) with the coefficient from the following firm-specific time-series regression (using at least five but no more than ten years of firm *i*'s data, ending in year *t*): $Var_{i,t}=\beta_0+\beta_1 Var_{i,t-1}$. We next rank each variable's persistence into firm-year sample deciles, then average those decile ranks for each firm year. Finally, we split the average decile ranks at the sample median
$IndAvgLGD_{i,b}$	The average LGD of all defaulted bonds in firm *i*'s Fama–French 17 industry occurring prior to firm *i*'s bond *b* default
$IntanRatio_{i,t}$	The percentage of firm *i*'s assets in year *t* that are intangible, calculated as intangible assets (Compustat intan) divided by total assets (Compustat at)
$Leverage_{i,t}$	Firm *i*'s leverage in year *t*, calculated as total liabilities (Compustat lt) divided by total assets (Compustat at)
$LiabToEquity_{i,t}$	Firm *i*'s liabilities-to-equity ratio at the end of year *t*, calculated as total liabilities divided by common equity (Compustat lt/ceq)
$LGD_{i,b,d}$	Realized loss on firm *i*'s defaulted bond *b* on date *d*, calculated as one minus the realized recovery rate, using data from Moody's DRS. Recovery rate is calculated as the market price of the bond 30 days after default divided by the face value of the bond

$LnMVE_{i,t}$	The natural log of firm *i*'s market value of equity at the end of year *t*, where market value of equity is computed as the number of common shares outstanding (Compustat csho) times the closing price per share at the end of the year (Compustat prcc_f)
$LnNetWorth_{i,t}$	Firm *i*'s net worth at the end of year *t*, calculated as (the natural log of) total assets (Compustat at) minus total debt, where total debt is computed as long-term debt (Compustat dltt) plus debt in current liabilities (Compustat dlc)
$LnNetWorth2_{i,t}$	Firm *i*'s net worth at the end of year *t*, calculated as (the natural log of) total assets (Compustat at) minus total liabilities (Compustat lt)
$LnTotalAssets_{i,t}$	The natural log of firm *i*'s total assets in year *t* (Compustat at)
$Maturity_{i,b}$	The years to maturity (at issuance) of firm *i*'s bond *b*, calculated as Mergent (MATURITY-OFFERING_DATE)/360
$PredLGD\_Acct_{i,t}$	Firm *i*'s year *t* accounting-based predicted loss given default, estimated in two steps. First, using a sample of defaulted bonds from Moody's DRS, we regress realized loss given default on a set of five contracting-date accounting variables (*LnNetWorth*, *ROA*, *IntanRatio*, *ShortDebtRatio*, and *LnTotalAssets*), as in Eq. (1). Second, we apply the estimated coefficients to firm *i*'s year *t* accounting data, as in Eq. (2). When working with the Mergent bond issue sample, we use firm *i*'s most recent accounting data prior to the issuance of bond *b*
$PredLGD\_Ind_{i,t}$	Firm *i*'s industry-based predicted loss given default, estimated in two steps. First, using a sample of defaulted bonds from Moody's DRS, we regress realized loss given default on a set of industry fixed effects based on the Fama–French 17-industry classifications. Second, using a broad sample of bond issues from Mergent FISD we apply the estimated coefficients to firm *i*'s most recent industry classification prior to the issuance of bond *b*
$PredPD\_Acct_{i,t}$	Firm *i*'s accounting-based predicted probability of default, estimated in two steps. First, using a sample of defaults from Moody's DRS intersected with the Compustat annual file, we estimate a standard logit-based default hazard model using the same set of five accounting variables that we use to estimate *PredLGD_Acct* (*LnNetWorth*, *ROA*, *IntanRatio*, *ShortDebtRatio*, and *LnTotalAssets*), as in Eq. (4). Second, using a broad sample of bond issues from Mergent FISD, we apply the estimated coefficients to firm *i*'s most recent accounting data prior to the issuance of bond *b*, as in Eq. (5)
$PriorityCov_{i,b}$	An indicator that equals one if firm *i*'s bond *b* includes a cross default or cross acceleration covenant and zero otherwise (Mergent Cross_default, Cross_acceleration)
$ProfitMargin_{i,t}$	Firm *i*'s year *t* profit margin, calculated as net income divided by sales (Compustat ni/sale)
$Q_{i,t}$	Firm *i*'s Tobin's q ratio at the end of year *t*, computed as the sum of total liabilities (Compustat lt) and market value of equity, divided by total assets (Compustat at). Market value of equity is computed as the number of common shares outstanding (Compustat csho) times the closing price per share at the end of the year (Compustat prcc_f)
$Rated_{i,b}$	An indicator variable that equals one if firm *i* has a long-term S&P credit rating in place within the most recent year prior to the issuance of firm *i*'s bond *b* and zero otherwise. We base this indicator on the Compustat variable splticrm (we consider splticrm = "SD" to be unrated)
$RestrictPmtCov_{i,b}$	An indicator that equals one if firm *i*'s bond *b* includes a covenant that restricts the firm's payments to shareholders (including dividends restrictions) and zero otherwise (Mergent Restricted_payments, Dividends_related_payments_sub, Dividends_related_payments_is)
$ROA_{i,t}$	Firm *i*'s return on assets in year *t*, computed as firm *i*'s earnings before extraordinary items in year *t* (Compustat ib) divided by year *t* and *t*-1 average total assets (Compustat at)

ShortDebtRatio$_{i,t}$	The proportion of short-term debt in firm *i*'s total liability structure in year *t*, computed as debt in current liabilities (Compustat dlc) divided by total liabilities (Compustat lt)
Spread$_{i,b}$	The interest spread on firm *i*'s bond *b*, calculated as the bond offering yield to maturity (Mergent OFFERING_YIELD) minus the benchmark Treasury rate (i.e., the prevailing rate during the month of bond issue of a same-maturity Treasury bond; data obtained from the Federal Reserve)
TimesInterest$_{i,t}$	Firm *i*'s year *t* times interest earned ratio, calculated as earnings before interest and taxes divided by interest expense (Compustat ebit/xint)

Acknowledgements Dan is grateful to his dissertation committee members, Robert Bushman (co-chair), Wayne Landsman (co-chair), Jeff Abarbanell, John Graham, Mark Lang, and Doug Shackelford for continuous support and advice. The authors would also like to thank Razi Avram, Ryan Ball, Mary Barth, Dinara Bayazitova, Anne Beatty, Nittai Bergman, Anne Beyer, Dirk Black, Alexander Bleck, Jesse Blocher, John Core, Elicia Cowins, Peter Demerjian, Scott Dyreng, Mary Margaret Frank, Koresh Galil, Joseph Gerakos, Wayne Guay, Trevor Harris, Ron Kasznik, Alon Kalay, Sharon Katz, Yaniv Konchitchki, Andrei Kovrijnykh, Eva Labro, Roby Lehavy, Christian Leuz, Lynn Li, Katie McDermott, Maureen McNichols, Mark Maffett, Steve Monahan, Valeri Nikolaev, Bugra Ozel, Ken Peasnell, Manju Puri, Shiva Rajgopal, Dick Rendleman, Gil Sadka, Richard Sansing, Cathy Shakespeare, Abbie Smith, David Smith, Steve Stubben, Phil Stocken, Florin Vasvari, Rodrigo Verdi, Joe Weber, Chris Williams, Regina Wittenberg-Moerman, and Tzachi Zach for helpful comments and discussions. We are also thankful to a managing director at Morgan Stanley who shared his knowledge on debt markets and distressed debt investing. We appreciate comments and suggestions from workshop participants at the University of Chicago, Columbia University, Dartmouth College, Duke University, Emory University, University of Michigan, MIT, New York University, University of North Carolina at Chapel-Hill, North Carolina State University, The Ohio State University, University of Pennsylvania, Tel-Aviv University, Stanford University, and the University of Virginia.

References

Acharya, V., S. Bharath, and A. Srinivasan. 2007. Does industry-wide distress affect defaulted firms? Evidence from creditor recoveries. *Journal of Financial Economics* 85: 787–821.

Aghion, P., and P. Bolton. 1992. An incomplete contracts approach to financial contracting. *Review of Economic Studies* 59: 473–494.

Altman, E. 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance* 23: 589–609.

Altman, E. 2008. Default recovery rates and LGD in credit risk modeling and practice: An updated review of the literature and empirical evidence. In Advances in Credit Risk Modelling and Corporate Bankruptcy Prediction (Quantitative Methods for Applied Economics and Business Research, ed. S. Jones and D. Hensher, 175–206. Cambridge: Cambridge University Press.

Amiram, D., A. Kalay, and G. Sadka. 2017. Industry characteristics, risk premiums, and debt pricing. *The Accounting Review* 92: 1–27.

Basu, S. 1997. The conservatism principle and the asymmetric timeliness of earnings. *Journal of Accounting and Economics* 24: 3–37.

Beatty, A., J. Weber, and J. Yu. 2008. Conservatism and debt. *Journal of Accounting and Economics* 45: 154–174.

Beaver, W. 1966. Financial ratios as predictors of failure. *Journal of Accounting Research* 4: 71–111.

Beaver, W., M. Correia, and M. McNichols. 2012. Do differences in financial reporting attributes impair the predictive ability of financial ratios for bankruptcy? *Review of Accounting Studies* 17: 969–1010.

Benmelech, E., M. Garmaise, and T. Moskowitz. 2005. Do liquidation values affect financial contracts? Evidence from commercial loan contracts and zoning regulation. *Quarterly Journal of Economics* 120: 1121–1154.

Brown, S., W. Goetzmann, and A. Kumar. 1998. The Dow Theory: William Peter Hamilton's track record reconsidered. *The Journal of Finance* 53: 1311–1333.

Campbell, J., J. Hilscher, and J. Szilagyi. 2008. In search of distress risk. *Journal of Finance* 63: 2899–2939.

Carrizosa, R., and S. Ryan. 2013. Conservatism, covenants, and recovery rates. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2197513. Accessed February 9, 2023.

Chava, S., and R. Jarrow. 2004. Bankruptcy prediction with industry effects. *Review of Finance* 8: 537–569.

Christensen, H., and V. Nikolaev. 2012. Capital versus performance covenants in debt contracts. *Journal of Accounting Research* 50: 75–116.

Christensen, H., V. Nikolaev, and R. Wittenberg-Moerman. 2016. Accounting information in financial contracting: The incomplete contract theory perspective. *Journal of Accounting Research* 54: 397–435.

Donovan, J., R. Frankel, and X. Martin. 2015. Accounting conservatism and creditor recovery rate. *The Accounting Review* 90: 2267–2303.

Dyreng, S., R. Vashishtha, and J. Weber. 2017. Direct evidence on the informational properties of earnings in loan contracts. *Journal of Accounting Research* 55: 371–406.

Easton, P., M. McAnally, G. Sommers, and X. Zhang. 2018. *Financial Statement Analysis & Valuation* (fifth edition). Cambridge Business Publishers.

Elgers, P. 1980. Accounting-based risk predictors: A re-examination. *The Accounting Review* 55: 389–408.

Francis, J., R. LaFond, P. Olsson, and K. Schipper. 2004. Costs of equity and earnings attributes. *The Accounting Review* 79: 967–1010.

Glover, B. 2016. The expected cost of default. *Journal of Financial Economics* 119: 284–299.

Gupton, G. 2005. Advancing loss given default prediction models: How the quiet have quickened. *Economic Notes* 34: 185–230.

Gupton, G., and R, Stein. 2005. LossCalc V2: Dynamic prediction of LGD. *Moody's Investors Service* 3:31–44.

Hart, O., and J. Moore. 1994. A theory of debt based on the inalienability of human capital. *Quarterly Journal of Economics* 109: 841–879.

Hillegeist, S., A. Keating, D. Cram, and K. Lundstedt. 2004. Assessing the probability of bankruptcy. *Review of Accounting Studies* 9: 5–34.

Murfin, J. 2012. The supply-side determinants of loan contract strictness. *Journal of Finance* 67: 1565–1601.

Nikolaev, V. 2010. Debt covenants and accounting conservatism. *Journal of Accounting Research* 48: 51–89.

Ohlson, J. 1980. Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research* 18: 109–131.

Papke, L., and J. Wooldridge. 1996. Econometric methods for fractional response variables with an application to 401 (k) plan participation rates. *Journal of Applied Econometrics* 11: 619–632.

Roberts, M., and A. Sufi. 2009. Financial contracting: A survey of empirical research and future directions. *Annual Review of Financial Economics* 1: 207–226.

Shleifer, A., and R. Vishny. 1992. Liquidation values and debt capacity: A market equilibrium approach. *Journal of Finance* 47: 1343–1366.

Shumway, T. 2001. Forecasting bankruptcy more accurately: A simple hazard model. *Journal of Business* 74: 101–124.

Standard and Poor's. 2013. *A Guide to the U.S. Loan Market*. https://www.lcdcomps.com/lcd/na/2012/09/07/2013%20Guide%20To%20The%20US%20Loan%20Market.pdf. Accessed February 9, 2023.

Tirole, J. 2006. *The Theory of Corporate Finance*. Princeton, NJ: Princeton University Press.

Varma, P., and R. Cantor. 2005. Determinants of recovery rates on defaulted bonds and loans for North American corporate issuers: 1983–2003. *Journal of Fixed Income* 14: 29–44.

Watts, R. 2003. Conservatism in accounting part I: Explanations and implications. *Accounting Horizons* 17: 207–221.

Zhang, J. 2008. The contracting benefits of accounting conservatism to lenders and borrowers. *Journal of Accounting and Economics* 45: 27–54.

Zmijewski, M. 1984. Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research* 22: 59–82.