DEBT CONTRACTS AND LOSS GIVEN DEFAULT

Dan Amiram

A dissertation submitted to the faculty of the University of North Carolina at Chapel Hill in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Kenan-Flagler School of Business.

Chapel Hill
2011

Approved by:

Robert M. Bushman

Wayne R. Landsman

Jeffery Abarbanell

John R. Graham

Mark H. Lang

Douglas A. Shackelford

ABSTRACT

DAN AMIRAM: Debt Contracts and Loss Given Default
(Under the direction of Robert M. Bushman and Wayne R. Landsman)

This study explores how accounting information available to lenders at the contracting date shapes debt contracts by facilitating lenders' assessment of loss given default (LGD). LGD, defined as the percentage loss experienced per $1 of debt if default occurs, is closely related to the notion of liquidation value which is central to debt contracting theories. LGD, together with probability of default, determines expected credit loss and as such is a critical component of debt contract design. While a large literature examines probability of default, much less is known about the impact of expected LGD on contract design and the information set relevant to lenders in assessing LGD at debt origination. Using a sample of defaulted bonds, I find that a select set of accounting measures available at contract initiation, which is 47 months on average before the default event in my sample, possess significant power for predicting actual creditor losses at the subsequent default date. I then exploit this prediction model to construct an accounting-based measure of expected LGD for a large sample of bond issuances. I find that a one standard deviation increase in this measure is associated with a 58 basis point increase in the issuance date interest rate spread, incremental to probability of default. The positive relation between expected LGD and spread is higher when probability of default and managerial entrenchment are higher. Expected LGD is also associated with an increased probability of the debt being secured, having shorter debt maturity, and having a smaller debt size. These relations also hold for a sample of private loan issuances after controlling for financial covenant strictness, where I also find that higher expected LGD is associated with stricter financial covenants. Moreover, I find evidence that accounting systems that provide more precise information about equity value also provide more precise information about LGD, where the opposite holds for more conservative accounting.

To Mira, Dana, Mom and Dad

ACKNOWLEDGEMENTS

I am grateful to my 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. I thank Razi Avram, Ryan Ball, Dinara Bayazitova, Jesse Blocher, Elicia Cowins, Mary Margaret Frank, Koresh Galil, Sharon Katz, Eva Labro, Katie McDermott, Mark Maffett, Steve Monahan, Ed Owens, Scott Dyreng, Yaniv Konchitchki, Ken Peasnell, Manju Puri, David Remund, Cathy Shakespeare, David Smith, Steve Stubben and Florin Vasvari for helpful comments and discussions. I am also thankful to a managing director at Morgan Stanley who shared with me some of his knowledge on debt markets and distressed debt investing. I appreciate comments and suggestions from workshop participants at the University of North Carolina at Chapel-Hill, North Carolina State University, Tel-Aviv University and the University of Virginia. I thank Michael Roberts for providing the link table between the COMPUSTAT and Dealscan databases. All errors are my own.

TABLE OF CONTENTS

LIST OF TABLES

Table

1. Introduction

This study explores how accounting information that is available to lenders at the contracting date shapes the design of debt contracts. I posit that an important channel through which accounting information affects contracts is by facilitating lenders' assessment of loss given default (LGD). LGD, defined as the percentage loss lenders experience from $1 of outstanding principal in a case of default, is closely related to the notion of liquidation value and is a critical component of credit risk and debt contracting theories.[1] Despite the theoretical importance of LGD, there is little empirical evidence on its effects on debt contracts. Even rarer is evidence regarding how information available to lenders at the contracting date shapes their expectations about LGD and, in turn, affects debt contract terms.

In this study I exploit a dataset of loss given default realizations to estimate a prediction model based on financial accounting information available to lenders at the loan contracting date. I then use this model to study the impact of accounting-based LGD expectations on the design of debt contracts. Specifically, for a sample of defaulted debt instruments, I first examine the extent to which financial accounting information available prior to the contracting date predicts lenders' losses in cases where default occurs. Using the LGD prediction model developed in the first step, I generate an accounting-based measure of expected LGD at loan initiation dates for a large sample of non-defaulted borrowing firms. I then examine whether expected loss given default affects key terms of the debt contract such as interest rate spread, maturity, security and debt size, and also when expected loss given default has stronger effects on lenders. I further examine how cross-

[1] In other words, LGD is the amount that lenders cannot recover from $1 of debt, which implies that LGD is one minus the recovery rate on a debt instrument. The following example illustrates the underlying construct behind LGD. A lender invested $100 in a firm. The firm defaulted on the debt and liquidated as a consequence. The lender received $20 out of the liquidation proceeds. The lender thus recovered 20% of the loan and had a loss given default of 80%.

sectional differences in characteristics of firms' accounting information affect the extent to which lenders use the information about loss given default when they initiate the debt contract.

According to credit risk theory, the price and terms of risky debt depends directly on lenders' assessments of expected losses from the instrument. Expected credit loss is generally conceptualized as the product of the probability of default and expected loss given default. Although a substantial body of research focuses on predicting and evaluating the effects of default probabilities, only recently, as necessary data have became available, has research started to investigate determinates and consequences of LGD. In addition, LGD is intimately related to a firm's liquidation value, where higher liquidation value implies lower LGD. Liquidation value is central to many debt contracting theories, since the optimal debt contract depends on how costly it is for lenders to liquidate the borrower's assets. Higher liquidation values alleviate some of the lenders' concerns about incentive conflicts they have with borrowers (Aghion and Bolton, 1992; Hart and Moore, 1994).

Although these arguments suggest that LGD is important to lenders, there are reasons why *firm-specific* information about LGD may not be useful for debt contracting. For example, some studies suggest that firm-specific LGD is diversifiable (Altman, 2009). In addition, anecdotal evidence suggests that lenders do not use *firm-specific* information to estimate LGD (Gupton and Stein, 2005). Moreover, accounting information available to lenders at the date of the contract (47 months on average before the default date in my sample) may not have power for predicting LGD. Despite its theoretical importance, there is lack of empirical evidence on the relation between LGD and debt contract terms.[2] Of particular interest to this study is the fact that little documented evidence exists regarding how lenders collect, assess and use information on LGD and liquidation value at the contract date.

[2] See discussion on the lack of empirical evidence on the effects of liquidation value and collateral on debt contracts in Benmelech et al. (2005) and Benmelech and Bergman (2009). These papers are also notable exceptions in the literature and provide empirical evidence on this question. See further elaboration of these papers in section 2 below.

This study seeks to provide direct evidence on the link between firm-specific information, LGD and debt contract characteristics such as credit spread, maturity, size and security. A key source of firm-specific information available to lenders at the contract decision date is accounting information from the borrower's financial statements (Tirole, 2007; Standard and Poor's, 2009). I conjecture that publicly available financial statement information available to lenders *at the contracting date* is useful to predict loss given default. I focus on available contracting date accounting information to provide insights into how accounting-based estimates of LGD explain the revealed structure of contracts. Although accounting information at the default date can be used to estimate loss given default, such estimates are ex post in nature and cannot be used to infer how lenders make their lending decision.

I utilize a sample of senior unsecured defaulted bonds for which data on LGD realizations and accounting information in the year before the issuance of the bond exist to construct a prediction model for LGD. The analysis finds that five accounting measures explain a high proportion of the variation in LGD.[3] Cross-validation test results show that the model has significant predictive power for realized LGD out-of-sample. I use the coefficients from the prediction model to construct an expected LGD estimate for all *non-defaulted,* nonconvertible bond issuances in the Securities Data Company (SDC) database with available accounting information at the date of the issuance.

Using these estimates of expected LGD, I next investigate the extent to which LGD affects debt contract design. I expect that interest spreads will be higher for borrowers with higher predicted LGD as lenders will demand compensation for the increased expected losses. Using a

[3] These measures and their predicted coefficient signs are based on insights from prior research on the determinants of LGD *at default date* (Acharya et al. 2004; Varma and Cantor, 2005). In addition, I report that market-based measures such as annual returns, the standard deviation of monthly returns and the Vassalou and Xing (2004) default likelihood indicator, measured at the contracting date, do not explain future LGD and do not add to the explanatory power of the prediction model when the accounting measures are included.

model that includes extensive control variables such as contract terms and industry and year fixed effects, I find that expected LGD is associated with higher credit spreads at the bond issuance date. Expected LGD continues to be a statistically and economically significant determinant of spread after including controls for the probability of default such as the Vassalou and Xing (2004) *DLI* measure, Altman's Z score and S&P credit rating. The results suggest that a one standard deviation increase in LGD expectation adds 58 basis points to the interest rate spread of the debt.

Because LGD manifests only when the borrower defaults, I expect its effect on credit spreads to be stronger when the probability of default is higher. If the probability of default is zero LGD does not matter. However, if the probability of default is close to one, LGD should matter a lot. I also predict that the effect of LGD on debt contracts will be stronger when borrowers have the ability to extract private benefits (Aghion and Bolton, 1992). Consistent with these predictions, I find that the effect of the predicted LGD on spread is stronger when the probability of default is higher and when the entrenchment index of the issuer from Bebchuk, Cohen and Ferrell (2008) is higher.

Spread is not the only contract term likely to be affected by LGD expectations. Lenders may require collateral when they expect LGD to be higher. In addition, lenders may shorten the maturity of loans with higher expected LGD as the higher frequency of re-contracting will allow creditors to refuse contract renewal, ask for a better security or require an increase in interest rate when expected credit losses have increased. Lenders may also place limits on loan amounts for firms with higher expected LGD to limit their exposure to LGD.[4] I find evidence consistent with these predictions.

[4] Another debt contract term that may vary with expected LGD is covenant structure. I do not have access to data on bond covenants to examine this effect. In addition, public bond contracts seldom require the maintenance of financial ratios (Nikolaev, 2010). Analysis of the effects of expected LGD on covenants is provided below for a sample of loans.

I next examine how the precision of accounting information impacts the sensitivity of credit spreads to accounting-based LGD estimates. It is plausible that lenders place more reliance on accounting information in predicting LGD as the precision of the information increases. Appendix B presents a simple analytical model that shows how LGD and information about LGD affects the credit spread. I find that lenders are more sensitive to predicted LGD when contracting with firms characterized as having high value-relevance and timelier accounting. In contrast to arguments in the literature, lenders are more sensitive to the predicted LGD in firms with less conservative accounting.[5,6]

Although private loans differ in many respects from public bonds, I use a sample of private loan issuances to provide evidence that analogous relations between expected LGD and debt contracts also hold in this setting after controlling for financial covenant strictness. In addition, I provide evidence that lenders use stricter covenants when LGD is expected to be higher.

The inferences above are robust to a variety of sensitivity tests, such as inclusion of credit rating fixed effects and different subsets of control variables. Using Monte-Carlo simulations, I also show that an LGD measure constructed using random coefficients with the same sign and magnitude as the coefficients from the prediction model performs poorly relative to the prediction model in explaining spreads. This suggests that the expected LGD measure constructed with the coefficients from the prediction model captures a latent structural variable that is distinct from the individual accounting measures used to estimate it. In addition, I include each of the accounting measures as a control variable and show that none of them affects the inferences described above.

[5] This argument does not speak to the overall efficiency of a specific accounting system to debt contracting. Rather it speaks to the usefulness of an accounting system in the estimation of LGD, which is an important channel in debt contracting. However, as discussed in more detail below, other channels exist, for example lenders' ability to estimate default likelihood.

[6] The arguments that support conservatism's efficiency in debt contracting are based on ex-post changes in managerial behavior, i.e., lenders will demand higher conservatism after providing funds for the firm. The evidence I provide in this study relates to whether conservative accounting is useful to lenders on an ex-ante basis.

This study contributes to the literature along several dimensions. First, I show that accounting information available to lenders at the contracting date is significantly associated with future loss given default. To the best of my knowledge, this paper is the first to do so. Second, I construct an intuitive measure of LGD expectations at the time of debt initiation which could be of use in future research. Third, I show that accounting-based expectations about LGD significantly affect price and non-price terms of the debt contract. This finding contributes to the LGD and liquidation value literature by showing that LGD has significant non-diversifiable effects on debt contracts and to the accounting literature by showing a specific channel through which accounting information is useful in lending decisions. Fourth, this study contributes to the accounting debt contracting literature by providing evidence that lenders put more weight on LGD expectations from accounting systems that are more value-relevant, timely and less conservative. Lastly, the results of this study highlight the valuation role of accounting in debt contracting, by showing that accounting facilitates the estimation of LGD and by implication, liquidation values. This complements the emphasis in prior research on the stewardship role of accounting in contracting.

The remainder of this paper proceeds as follows. Section 2 provides the background and motivation for my predictions. Section 3 describes my data and sample. Section 4 presents my empirical tests and discusses the findings. Section 5 presents several sensitivity tests and section 6 presents summary and concluding remarks.

2. Motivation background and predictions

A substantial body of research in accounting and finance focuses on modeling the likelihood of default. This literature uses accounting ratios (e.g., Beaver 1966; Altman, 1968; Ohlson, 1980) and variations of the Merton (1974) model (e.g., Vassalou and Xing, 2004; Bharath and Shumway, 2008), among other methods, to assess the probability of default. This literature also examines the implications of increased probability of default on debt pricing, equity pricing (Vassalou and Xing, 2004) and debt policy. It is only recently that research about the second major component of credit risk, loss given default, has emerged.[7]

LGD, which is defined as the percentage loss lenders experience from $1 of outstanding principal in a case of default (or 1 minus the recovery rate), interacts directly with the 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 probability of default and loss given default. Although credit risk models may differ significantly in their assumptions about LGD and its determinants, in all models LGD plays an important role in pricing credit risk.[8]

Fundamentally, a firm's net assets and future cash flows provide implicit collateral to lenders. The liquidation value of the implicit collateral is a main determinant of LGD as liquidation value is inversely related to LGD. Since a borrower cannot commit not to withdraw his human

---

[7] See Altman (2009) for a survey of this emerging literature.

[8] Altman (2009) categorizes credit risk modeling into several groups. The first group of models is based on Merton's (1974) framework and is termed first generation structural models. In these types of models, default occurs when the value of a firm's assets is lower than that of its liabilities at maturity. In this case, LGD is based on market value of the firm's assets minus the face value of the debt. The second group of models, second generation structural models, relaxes the assumption that default occurs only at maturity and assumes that default is triggered when the value of the firm's assets reaches an exogenous threshold level. In these models, LGD is exogenous and is independent from the firm's asset value. The third group of models, reduced-form models, introduces different and separate assumptions on the dynamics of the probability of default and LGD and models them independently from the structural features of the firm. The stochastic process determines the price of credit risk. The last category of credit risk models, sometimes called hybrid models, is motivated by the assumption that systematic factors drive defaults. In some of these models, the state of the economy affects default probability and LGD simultaneously.

capital (as in Hart and Moore, 1994) or not to divert cash flows (as in Aghion and Bolton, 1992), there is an incentive conflict between lenders and borrowers. Because of the incentive conflict, lenders will agree to provide funds to borrowers only if the default triggers liquidation. According to these models, the yield decreases in the assets' liquidation value. This occurs because increased liquidation value reduces the cost of liquidation which, in equilibrium, reduces the spread charged by lenders. In addition, debt maturity increases with liquidation values since higher liquidation values increase the assets' durability and make longer maturity feasible (Hart and Moore, 1994). Moreover, these models posit that the funds lenders are willing to provide is directly tied to assets' liquidation values. Despite the importance of LGD in these models, as Benmelech et al. (2005) suggest, empirical evidence on this issue is scarce. In particular, there is very little evidence on how lenders obtain and use information about liquidation values and LGD.

The interest in this issue is exemplified by an important emerging literature. This literature utilizes unique settings to examine the link between liquidation value, collateral and debt characteristics. Benmelech et al. (2005) focus on the redeployability of property assets as determined by commercial zoning regulation and find that more deployable properties receive larger loans, longer maturities and lower interest rates. Benmelech (2009) finds that assets' salability in the 19th century railroad industry leads to longer maturities of debt. Benmelech and Bergman (2009) study a sample of loans in the airline industry and show that collateral and redeployability are negatively correlated with yield spread. I build on this literature by examining the link between information available to lenders at the date of the contract about LGD and debt contract characteristics in a more general setting.

This study is also motivated by a growing literature connecting the quality of accounting information with the design of debt contracts. Bharath et al. (2008) find that accruals quality is associated with the price, maturity and security of debt. Ball et al. (2008) provide evidence that accounting's ability to capture credit deterioration affects the structure of syndicated loans. Graham et al. (2008) show that corporate misreporting leads to a sharp deterioration in debt contract terms for the misreporting firms. Several studies build on Watts (2003) and find evidence that conservative accounting is generally beneficial to debt contracting by limiting the agency problem between lenders and borrowers (Zhang, 2008; Nikolaev, 2010). Sunder et al. (2009) provide evidence that spread is negatively associated with adjusted market to book ratio, suggesting that realized conservatism reduces risk by promoting lenders' confidence in the collateral value of the firm's assets. Recent theoretical studies take differing positions regarding whether conservative accounting increases debt contracting efficiency. Whereas Gox and Wagenhofer (2009) claim that the optimal accounting system for debt contracting is conservative, Gigler et al. (2009) and Li (2008) suggest that since conservative accounting also creates a loss of informativeness, it can reduce the efficiency of debt contracts.

Two recent survey studies call for additional research on these issues. Roberts and Sufi (2009) call for future research that links liquidation values or LGD and the structure of debt contracts. Armstrong, Guay and Webber (2010) review the accounting literature and suggest that lenders are likely to prefer more reliable accounting information to evaluate the firm's collateral. Notably, none of the reviewed papers provide direct evidence to support this hypothesis. Armstrong et al. (2010) also suggest that further research is needed to find the channels through which the quality of financial reporting affects debt contracts. One of the objectives of my paper is to explore such a channel.

Although LGD plays a central role in debt contracting theory and available accounting information may be useful for estimating LGD, it is possible that lenders do not use firm-specific accounting information to assess LGD in the design of debt contracts. First, LGD risk could potentially be diversified away by lenders, and thus it may have no effect on the debt contract

(Gupton and Stein, 2005; Altman, 2009). This line of reasoning suggests that lenders that hold diversified debt portfolios may care only about LGD means across the economy or industry and not firm-specific LGD. A related point is that anecdotal evidence from practitioners suggests that lenders use "lookup tables" of historical LGDs based on industry and seniority type, as inputs for their lending decisions (Gupton and Stein, 2005). These lookup tables, based primarily on lenders' experience, provide lenders with the historical LGD 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. It is also unclear how representative this evidence is and how available information about firm-specific LGD is used in the lending process.

Third, since defaults occur several years after the contracting date, 47 months on average in my sample, accounting information at the contracting date may have no power for predicting future LGD. Fourth, because accounting information is not designed for the purpose of estimation of liquidation value that affects LGD, it therefore might be useless for this purpose. Fifth, lenders may use private information to estimate LGD and put less weight on publicly available financial information. Lastly, LGD is inherently difficult to estimate as evidenced by the fact that lack of consistent empirical evidence on its distribution and importance have led analytical and empirical researchers to often assume LGD is constant across countries or industries, or ignore its role completely (see Acharya et al. 2004 for examples). This inherent difficulty in estimating LGD may cause lenders to use alternative measures to protect themselves against LGD loss. Therefore it remains an open empirical question whether firm-specific information is useful for lenders to assess LGD and whether it affects debt contracts.

I start with the conjecture that information in the financial statements available to lenders at the debt issuance date can predict future losses in the event of default. The informativeness of financial ratios about the probability of default is the core of the seminal work of Beaver (1966), Altman (1968) and many subsequent studies (e.g., Ohlson, 1980 and Zmijewski, 1984). This work shows that information in financial statements can predict defaults. In addition, the LGD literature has suggested that certain accounting measures, when observed at the date of default, can predict LGD.[9] I extend the insights from both literatures and conjecture that certain accounting measures available to lenders at the contracting date can also predict LGD. To the best of my knowledge, this study is the first to examine the relation between measurs based on accounting information that is available to lenders at the *debt issuance date* and LGD.[10]

I use five accounting measures to predict LGD on a sample of 308 defaulted senior unsecured bonds.[11] I use a homogenous set of senior unsecured debt instruments to make sure the accounting measures I use do not capture differences in the seniority and security of debt. Using secured instruments as the benchmark for the prediction model may create measurement problems with assessing the value and nature of the pledged security. In addition, senior unsecured debt is the most common form of debt in the default and LGD dataset (Moody's Default Risk Services,

[9] Varma and Cantor (2005) and Acharya et al. (2007) find some relation between accounting measures and LGD around the default event. Jacobs and Karagozoglu (2007) use a larger sample and different accounting measures and find stronger evidence for this relation.

[10] The largest rating agencies have only recently started issuing independent LGD (recovery rate) 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 was designed. As Gupton (2005) discusses, a primary goal of Moody's LGD "LossCalc 2" model is to help lenders to assess LGD for bank regulatory provisioning purposes required by the Basel accord.

[11] I follow Moody's definition of default which includes three types of credit events. The first is a missed or delayed disbursement of interest and/or principal, including delayed payments made within a grace period. The second is an event that ranges between a filing for bankruptcy, administration, legal receivership, or other legal blocks (perhaps by regulators) to the timely payment of interest and/or principal. The third and final type 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.

DRS database) and the bond issuance data (SDC) that I use in this paper.[12] The five accounting measures I use are extracted from financial reports published in the year before debt issuance to ensure the information was available to lenders. The measures and their predicted associations with LGD are based on the intuition suggested in papers that predict LGD with data contemporaneous to the default event (Acharya et al. 2005; Varma and Cantor, 2005).

The first measure is earnings before interest and tax (EBIT) scaled by total assets (*ROA*). *ROA* is predicted to be negatively associated with LGD. All else equal, the more profitable the firm, the greater the chance of lenders getting a higher price for selling the firm as a going concern or liquidating the assets. The second ratio is net book assets of the firm scaled by the number of shares outstanding (*NET_WORTH*). I predict a negative association between *NET_WORTH* and LGD. The greater the net assets of the firm, the more unencumbered assets lenders have available to sell and recover their investments. The third ratio is intangible to tangible assets (*INTANGIBLE_RATIO*). Many intangible assets are difficult to transfer and thus may yield low value in liquidation, creating a positive association between *INTANGIBLE_RATIO* and LGD. The fourth ratio is short term debt to long term debt (*STTOLTDEBT*). This ratio should be positively related to LGD because short term lenders have the ability either to withdraw their funds from the firm in the near term or refuse to renew them and thus leave lower net assets for long term debt holders in case of default. The final measure is the log of total assets (*LTA*), which is a proxy for the level of complexity in the sale of a firm's assets and thus the liquidity of those assets. In addition, this measure 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. In addition, I use Fama and French 17 industries classification indicators to capture industry effects on LGD.

[12] Another advantage of using defaulted bonds and analyzing LGD in a bond sample, rather than loans, is that bonds seldom have financial covenants, which may complicate the analysis (Begley and Freedman, 2004).

After evaluating the association between the accounting measures and LGD, I next investigate how this information affects debt contract design. Holding probability of default constant, I expect that higher LGD will spur lenders to require higher interest rates to compensate for higher risk. Moreover, lenders should be more sensitive to LGD in firms that have a higher probability of default since LGD by definition occurs only if default occurs. Lenders will use all relevant information to assess expected LGD, including accounting information, and will be more sensitive to signals that provide more precise information about LGD. Appendix B presents a simple analytical model that shows how LGD and information about LGD affects the credit spread.

To examine these predictions, I use the estimated coefficients on the five accounting measures and industry indicators in the prediction model to construct an LGD expectation measure. The measure, *PREDICT_LGD,* is constructed for a sample of all non-defaulted, non-convertible bond issues in the U.S, available on the SDC new issuances database. The measure is effectively the predicted value of LGD using the accounting information available to lenders before the contract is designed. I expect *PREDICT_LGD* to be positively associated with interest rate spread over the treasury benchmark (*SPREAD*). Further, *PREDICT_LGD* should have a distinguishable effect from measures of probability of default, and it should have a stronger effect on firms that have a higher probability of default.

Theory also predicts that the effect of liquidation value and LGD on debt contracts will be larger when borrowers have the ability to extract private benefits (Aghion and Bolton, 1992). Thus I expect that the positive association between *PREDICT_LGD* and spread will be stronger when managerial entrenchment is expected to be higher. The reason for that is that managerial entrenchment increases the possibility that mangers will take risky projects and consume the corporation resources in a way that reduces the value of the firm's net assets.

I also examine the effect of *PREDICT_LGD* on whether security is required in the debt contract. If expected LGD is high, lenders will require borrowers to pledge specific assets against the loan to protect against loss in case of default. Thus, I expect the probability of secured borrowing to increase with *PREDICT_LGD.* In addition, LGD risk may cause lenders to shorten the maturity of the debt in order to better monitor the situation of the firm and facilitate withdrawal of the funds in cases where the probability of default is increasing. This creates a negative expected association between *PREDICT_LGD* and the maturity of debt. Because lenders may limit their exposure to firms with high LGD risk, I expect a negative association between *PREDICT_LGD* and the size of the debt relative to the firm's assets. These additional tests help mitigate concerns that lenders have multiple contracting options to protect themselves against future losses.[13] Consistent evidence on the directional effect of expected LGD across these different debt contract characteristics helps to draw stronger conclusions on the observable effects.

Finally, I predict that *PREDICT_LGD* will have a stronger effect on *SPREAD* in firms whose accounting information provides a more precise signal on LGD. However, it is not obvious which properties of accounting information reflect more precision with respect to predicting LGD. One possibility is that accounting systems that recognize economic losses in a more timely manner (more conservative) also provide more precise information to lenders about LGD, since this conservative system is designed to provide information about the lower bound of liquidation value (Watts, 2003; Sunder et al. 2009). On the other hand, accounting information that more strongly predicts changes in equity value may also reflect more precise information to lenders about the value of the net assets available to them in case of default and thus more precise information on LGD. I examine both possibilities.

[13] For example, lenders could ask for collateral instead of more interest compensation.

Although the prediction model for LGD uses a sample of defaulted bonds, I also assess the effects of *PREDICT_LGD* on a sample of bank loan issuances. Bank loans are different in many aspects from corporate bonds but the line of reasoning regarding the relations between LGD and debt contract features applies to bank loans as well. Most importantly, banks have the ability to ask for information over and above what is provided in financial statements, in addition to the fact that the cost of renegotiation is lower relative to public bonds. Using LGD expectation based on defaulted bonds makes *PREDICT_LGD* a noisy proxy for LGD expectations for bank loans. These additional analyses help to increase the external validity of the *PREDICT_LGD* measure and to improve understanding about whether the mechanism of adjusting debt contracts to expected losses based on accounting information works similarly in private and public debt issuances. In addition, using this sample allows me to control for financial covenant strictness and to examine the prediction that lenders will use stricter covenants when *PREDICT_LGD* is higher to protect against expected losses.

3. Data and sample

I use information about actual LGD's contained in Moody's DRS database. The data contain information on over 1,000 defaults as well as information on 30-day recovery pricing, which is the price of the bond 30 days after the default event. These data allows me to calculate LGD for defaulted bonds. All data are derived from Moody's own proprietary database of issuer and default information. Moody's analysts use these data to perform their own analysis and determine ratings and outlooks for all credits. The database provides the backbone for the Annual Default Study, read by more than 40,000 investors globally. According to Moody's, the data are refreshed monthly to provide the most accurate, detailed portrait of default activity available in the market. A more thorough description of the data is provided in Varma and Cantor (2005).

I merge accounting information for the year before the bond was issued from COMPUSTAT with the DRS dataset based on CUSIP. For reasons that are discussed above I keep only observations of defaulted senior unsecured bonds of non-bank corporations. This sample, which I refer to as the DRS sample, contains information on 308 defaulted bonds that have LGD and industry data as well as the data needed to calculate the five accounting measures used in the prediction model.[14]

Table 1 Panel A provides descriptive statistics for the DRS sample. On average, bonds lose 67 percent of their face value, an amount which is consistent with prior literature (Varma and Cantor, 2005). At the date of issuance, firms are on average profitable (mean *ROA* of 0.05) and have high *NET_WORTH* (Mean of 10.84). On average, firms in the DRS sample have more intangible than tangible assets (mean *INTANGIBLE_RATIO* of 2.57); however, the median of *INTANGIBLE_RATIO* is 0.25, which suggests that most of the firms in the DRS sample have more tangible than intangible assets.

[14] The main reason for the drop in the number of observations is the lack of accounting data in Compustat for the year prior to the bond issuance.

The second step of the analysis requires data on bond issuances that never defaulted. Following Bharath et al. (2008), I obtain data on public bonds from the Securities Data Corporation (SDC) new issuances database. I use data for bond issuances for the period 1988-2008 and exclude convertible bonds. Consistent with prior literature, I also exclude bonds with maturities that are shorter than one year as well as those issued by banks. I merge the data from SDC with accounting data for the year before the issuance from COMPUSTAT based on CUSIP. I require an observation to have all data required for the bond characteristics, *PREDICT_LGD*, and control variables in order to be included in the data. I also eliminate approximately 100 observations that have *PREDICT_LGD* that is larger than one or smaller than zero.[15] The final sample, which I refer to as the "Bond sample", contains 3,599 bond issuances.

Table 1 Panel B provides descriptive statistics for the bond sample. On average the bonds in this sample have a 200 basis point spread over the treasury benchmark. The calculated expected LGD for this sample has a mean of 0.69. The firms in the bond sample are profitable (mean *ROA* of 0.1) and 62 percent of them are above investment grade.

I also utilize a sample of private debt issuances to test the effects of LGD expectations on debt contracts. The sample of private debt issuances is obtained in a similar manner to Bharath et al. (2008) and to the bond sample above. I obtain data for this sample from the Dealscan database provided by Loan Prices Corporation. I use all available loans (facilities) in Dealscan with maturity longer than 12 months for the period 1988-2006.[16] I merge the data from Dealscan to accounting data for the year before issuance from COMPUSTAT based on the link table described in Chava and Roberts (2008).[17] I require an observation to have all data required for the loan characteristics, *PREDICT_LGD*, and control variables in order to be included in the sample. I also eliminate

[15] Including these observations does not change any of the inferences described below.

[16] I stop the sample at 2006 because this is the last Dealscan dataset that is available to me.
[17] I am grateful to Michael Roberts for providing me the link table between COMPUSTAT and Dealscan.

approximately 300 observations that have *PREDICT_LGD* that is larger than one or smaller than zero.[18] This sample, which I refer to as the "Loan sample", contains 13,325 loan facilities.

Table 1 Panel C provides descriptive statistics for the loan sample. On average the loans in this sample have a 183 basis point spread over the Libor benchmark. The calculated expected LGD for this sample has a mean of 0.63. The firms in the loan sample are profitable (mean *ROA* of 0.08). Only 49 percent of the loans have a long term debt rating available in COMPUSTAT, while only 20 percent of the sample have higher than investment grade rating.

[18] Once again, including these observations does not change any of the results described below.

4. Empirical design and results

The empirical design is comprised of several stages. First I examine the association between accounting measures at the debt issuance date and LGD. The second stage uses the results from the first stage to estimate *PREDICT_LGD*. The third stage examines the association between *PREDICT_LGD* and debt contract characteristics as well as how different accounting systems affect this relation.

4.1 The predictive ability of accounting measures at the contract date about future LGD

To empirically assess whether there is an association between accounting ratios and future losses, I estimate the following equation using OLS.[19]

$$LGD_{id} = \beta_0 + \beta_1 * ROA_{i,t-1} + \beta_2 * NET\_WORTH_{i,t-1} + \beta_3 * INTANGIBLE\_RATIO_{i,t-1} + \beta_4 * STTOLTDEBT_{i,t-1} + \beta_5 * LTA_{i,t-1} + \beta_{6-22} * \psi_{ind} + \mu_i \quad (1)$$

LGD_{id}, is loss given default at the default date, and is calculated using data from Moody's DRS dataset as one minus the recovery rate. Where the recovery rate is the price of the instrument one month after the default occurred divided by the face value of the instrument. This method is consistent with practitioner and academic research (Acharya et al. 2004; Varma and Cantor, 2005; Gupton and Stein, 2005), and yields unbiased measure for LGD since there is an active market for defaulted debt for a few months after the default which allows traders to buy and sell the defaulted instrument (Gupton and Stein, 2005).

The five accounting measures I use are *ROA*, *NET_WORTH*, *INTANGIBLE_RATIO*, *STTOLTDEBT* and *LTA*. These measures and their expected associations with LGD are described

[19] Since the dependent variable, *LGD*, is between zero and one, OLS estimated coefficients may be biased. Logit transformation and Pepke and Wooldridge (1996) estimation methods were also used. These methods yield similar results to the ones using OLS, thus for simplicity of the calculations and interpretation I use OLS. In addition, if the coefficients that I based my expected LGD on are biased it would be harder for me to obtain results in the following tests.

more thoroughly in section 2 above.[20] ψ_{ind} are industry indicator variables for each of the Fama-French 17 industries classification.[21] The industry indicators capture mean differences in LGD between different industries and allow the accounting measures to capture differences between firms that are not related to industries. Appendix A discusses the sources of data for the variables.[22]

I estimate equation (1) on the DRS sample described in section 3. Table 2 presents the results from this estimation. Model 1 presents the estimation of equation (1) without industry fixed effects, Model 2 presents the estimation of the regression with just the fixed effects and none of the accounting measures, while Model 3 provides results for the estimation using accounting measures and fixed effects.

The results from the estimation of Model 1 show that the five accounting measures provide information to lenders about LGD. Model 3 suggests that the accounting measures are significant determinants of LGD over and above the industry means that many lenders use as predictors (Gupton and Stein, 2005). As expected *ROA* is negatively associated with LGD (coefficient of -0.907 with a t-statistic of -4.88 in model 1, and coefficient of -0.781 with a t-statistic of -4.11 in model 3), which suggests that firms that were more profitable at the issuance date have higher recovery rates. *NET_WORTH* is also negatively associated with LGD (coefficient of -0.005 with a t-statistic of -3.94 in model 1, and coefficient of -0.004 with a t-statistic of -2.79 in model 3), which as predicted suggests that the greater the net assets of the firm, the lower the losses debt holders incur in case of default. *INTANGIBLE_RATIO*, *STTOLTDEBT* and *LTA* are all positively and

---

[20] The only purpose of this prediction model is to construct an accounting based measure of LGD expectation at the contracting date. Thus I do not claim these measures are the only ones or the best ones to explain LGD and I acknowledge that the prediction model may be improved in future research. I found these measures to be intuitive, available for most firms on COMPUSTAT and statistically sufficient for the analysis presented in this paper.

[21] The industry classification is available on Ken French's website.

[22] I tried several specifications that include more variables that were suggested by prior literature as predictors of LGD at the default date. Among these variables are market-based variables such as returns, standard deviation of returns and *DLI*. None of these variables when measured at the contract date has statistical power in explaining LGD once the accounting measures are included and none adds to the explanatory power of the model. Thus, I omit them from the prediction model and use the model in equation (2).

significantly associated with future LGD. *INTANGIBLE_RATIO* has a coefficient of 0.003 with a t-statistic of 5.04 in model 1 and a coefficient of 0.003 with a t-statistic of 4.17 in model 3, which suggests that firms with higher intangible assets relative to their tangible assets are valued less in case of default. *STTOLTDEBT* has a coefficient of 0.018 with a t-statistic of 2.79 in model 1 and a coefficient of 0.025 with a t-statistic of 2.71 in model 3. This result is consistent with the ability of short-term lenders to pull out their funds in a more timely manner relative to long-term lenders and thus leave the firm with lower net assets in case of default. *LTA* has a coefficient of 0.063 with a t-statistic of 5.83 in model 1 and a coefficient of 0.062 with a t-statistic of 5.07 in model 3. This result is consistent with the fact that the bankruptcy proceedings are more complicated when firms have more assets and that selling more assets in case of default requires larger liquidity discounts.

Model 2 is presented to show that the adjusted R-squared of the estimation of only fixed effects (industry means) is slightly smaller than the adjusted R-squared of using only the accounting measures (R-squared of 0.17 compared to 0.18). More generally, the accounting measures have significant predictive power regarding LGD by themselves (R-squared of 0.18) but more so when industry fixed effects are used (R-squared of 0.28). Taken together the results in table 2 suggest that information in the financial statements, available to debt investors at the issuance date, has significant predictive ability about future LGD.[23]

4.2 Constructing LGD expectation measure-PREDICT_LGD

I use the coefficients from the estimation of equation (1) to construct *PREDICT_LGD.* Using the bond sample described in section 3 above, I multiply each estimated coefficient from equation (1) by the relevant accounting measure in the year before the bond issuance and add them

[23] I also perform out of sample cross-validation tests using holdout samples. I randomly choose 200 observations from the sample and estimate equation (1) using these observations. I continue by constructing the predicted value of LGD for the holdout sample of 108 observations. I then estimate the correlation between the predicted and realized LGD in the holdout sample. I repeat this procedure 50 times. The average correlation is high (0.51).

together with the relevant industry intercept to obtain *PREDICT_LGD* for every bond in the sample. For example *PREDICT_LGD* for a firm j from industry z that issued a bond in a year t is given by equation (2).

$$PREDICT\_LGD_{jt} = \beta_0 + \beta_z + \beta_1 * ROA_{j,t-1} + \beta_2 * NET\_WORTH_{j,t-1} + \beta_3 * INTANGIBLE\_RATIO_{j,t-1} + \beta_4 * STTOLTDEBT_{j,t-1} + \beta_5 * LTA_{j,t-1}, \quad (2)$$

where β_i are the estimated coefficients from equation (1). β_0 is the intercept obtained from equation (1) and β_z is the incremental industry intercept. I use the same method to construct *PREDICT_LGD* separately in the loan sample.

4.3 The relation between PREDICT_LGD and debt contract terms

To assess the relation between lenders' expectation of LGD and debt contract characteristics, I follow a research design used extensively in the debt contracting literature (Bharath et al. 2008, Ivashina, 2008). Specifically, I estimate the association between *PREDICT_LGD* and the price and non-price characteristics of the debt contract.

4.3.1 The relation between PREDICT_LGD and SPREAD

To examine the relation between *PREDICT_LGD* and the price of debt, I start by estimating the following OLS regression.

$$SPREAD_{it} = \gamma_0 + \gamma_1 * PREDICT\_LGD_{i,t-1} + \gamma_2 * X_{i,t-1} + \eta + \varphi + \varepsilon, \quad (3)$$

where *SPREAD* is the interest rate spread over a treasury benchmark at the date of the bond issuance. *PREDICT_LGD* is the estimated predicted LGD for the bond that is obtained from equation (2). *X* is a vector of variables used frequently in the literature to control for other determinants of the credit spread. *X* includes the size of the issuer (*LSIZE),* the leverage of the issuer (*LEV*), the issuer's growth opportunities (*Q*), the size of the debt issuance

(*LFACEAMOUNT*), the maturity of the debt (*LMATURITY*), an indicator variable for secured debt (*SECURED*), an indicator variable for above investment grade debt (*INV_GRADE*), and an indicator variable for rated debt (*SPRATED*). η and φ are industry and year fixed effects, respectively. The presence of industry fixed effects in equation (3) isolates the firm-specific expected LGD from the industry level to identify a unique firm-specific information effect. Appendix A provides further description on the source and construction of the variables.[24]

Results from estimating equation (3) on the bond sample are presented in table 3. Model 1 presents the estimation of equation (3) with industry fixed effects and excludes year fixed effects. Model 2 constrains the industry estimators in the construction of *PREDICT_LGD* to be zero, which effectively uses only the accounting measures to create the ACC_*PREDICT_LGD* measure. By construction, all the coefficients in Model 2, except for the intercept, should be identical to the coefficients in Model 1. Model 2 is included to show that constraining the industry coefficients to be zero is identical to using industry fixed effects. Model 3 presents the estimation of equation (3) with industry and year fixed effects. For the sake of brevity, I discuss only the implication of the results of model 3 and highlight the differences from other models.

The estimation results in model 3 show that *PREDICT_LGD* is positively and significantly associated with *SPREAD* (coefficient of 415.9 with a t-statistic of 9.09). This result is consistent with the explanation that lenders use information about LGD available to them in the financial statements to price debt. The accounting information as reflected in *PREDICT_LGD* explains the cross-sectional variation in *SPREAD* incremental to any industry effect, as is clear from the industry fixed effects estimation and from model 2.[25] The effect is economically significant where

[24] Although they are generally not included in debt contracting research design, in untabulated results, I add to all estimated models described in this paper the equity characteristics annual returns and standard deviation of monthly returns. The addition of these variables does not change any of the inferences described in this paper.
[25] Model 2 confirms that when industry fixed effects are included it is identical to using a measure of *PREDICT_LGD* that constrains the industry estimates from the prediction model to be zero.

a one standard deviation change (14%) in *PREDICT_LGD* translates to a 58 basis point change in *SPREAD* which is 29.1% of the *SPREAD* mean. This result suggests that LGD expectations have a significant economic effect on the pricing of debt contracts.[26,27]

4.3.2 The effect of PREDICT_LGD and SPREAD over and above default likelihood

A concern is that *PREDICT_LGD,* or more generally loss given default, is correlated with default likelihood. A positive correlation between *PREDICT_LGD* and default likelihood is likely since in distressed periods, firms may be forced into fire sales of their assets and liquidation values at these unfavorable times (Shleifer and Vishny, 1992; Acharya et al. 2008).[28] Thus, an important feature of the research design is to distinguish between *PREDICT_LGD* and default likelihood. I use three different measures of default likelihood to isolate the effect of *PREDICT_LGD.* I use the Vassalou and Xing (2004) default likelihood indicator (*DLI*), Altman's (1968) Z score multiplied by negative one (*Z*), and a numeric conversion of S&P long term rating (*SPRATING*). All measures are constructed in a way that their respective higher values are proxies for higher likelihood of default. Although all three measures are proxies for likelihood of default, they are all constructed very differently, which allows me to better identify the unique effect of expected LGD on the contract. *DLI* is based on the Merton (1974) model and is constructed using information in stock prices, debt and assets. Z score is constructed using accounting ratios that were shown to have predictive ability about future defaults. *SPRATING* is based on debt analysts' forecasts about the quality of the firm's long term debt.

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

[27] When I include the five accounting measures in these tests instead of the constructed measure of predicted LGD, I find that some the accounting measures are insignificant in explaining spread. In addition, the five accounting measures do not add to the explanatory power of the model compared to models that include the predicted LGD measure.

[28] Untabulated correlations confirm this intuition. *PREDICT_LGD* is positively and significantly correlated with measures of probability of default (0.2 with Z score and 0.16 with DLI).

To assess whether the effect of *PREDICT_LGD* is over and above the default likelihood, I estimate a variation of equation (3) by adding each of the default likelihood controls one by one and then adding all of the three measures to the regression at the same time.[29] If *PREDICT_LGD* indeed captures the construct of expected loss given default it should have a distinct effect on *SPREAD* that is over and above the probability of default. This feature of LGD is also a clear prediction from the model described in Appendix B.

Table 4 presents results from these tests. Model 1 includes *DLI* as a control variable, Model 2 includes *Z*, and Model 3 includes the S&P credit rating. Model 4 includes all three additional control variables in the regression. Model 5 uses the S&P ratings as fixed effects to estimate the effects of LGD on *SPREAD* within a rating group, i.e., the coefficient on *PREDICT_LGD* in this estimation comes from the variation that is not related to credit risk as represented by S&P credit ratings. In all models, the coefficient on *PREDICT_LGD* is still statistically and economically significant. Model 5 is where the coefficient on *PREDICT_LGD* is the lowest (250.1) and has with a t-statistic of 6.22.[30] Model 4 is where the t-statistic of the *PREDICT_LGD* coefficient is the lowest (4.84) with a coefficient value of 268.19. Taken together the results in table 4 suggest that *PREDICT_LGD* has an incremental, significant effect on debt pricing over and above the probability of default.

4.3.3 The effect of default likelihood on the relation between PREDICT_LGD and SPREAD

Since losses to debt holders occur only when a default event occurs, I expect *SPREAD* to be more sensitive to *PREDICT_LGD* when the likelihood of default is higher. In the extreme case when the probability of default is zero, loss given default means very little to debt investors. However, when the probability of default is close to one, debt investors should put higher weights

[29] This assumes the relation between probability of default and LGD is linear. In the next section I relax this assumption.

[30] The coefficient on Z is statistically insignificant. When I omit *PREDICT_LGD* from the model, *Z* is statistically significant at the 1% level in explaining SPREAD.

on how much they would be able to recover. To examine this effect I partition my sample into two groups of high and low default likelihood. I partition the sample based on each of the default likelihood proxies, i.e., one partition that is based on below and above the median of *DLI*, a second partition that is based on below and above the median of *Z*, and a third partition that is based on below and above *INV_GRADE*. I then estimate equation (3) for each of the groups for every partition variable. For the reasons suggested above, I expect the coefficient on *PREDICT_LGD*, γ_1, to be greater in the high likelihood of default group than it is in the group where the likelihood of default is lower.[31] The comparison of the coefficients across partitions is done using a Monte-Carlo non-parametric simulation technique where I randomly assign observations into the partitions and take the difference between the coefficients 1,000 times.[32]

The results of this analysis are presented in table 5. Model 1 presents estimations based on the partition of over and above the median *DLI*. Model 2 presents estimations based on the partition of over and above the median *Z*. Model 3 presents estimations based on the partition of below and above investment grade. As predicted, in Model 1, the coefficient on *PREDICT_LGD* in the high *DLI* bonds (625.7) is larger than the coefficient on *PREDICT_LGD* in the low *DLI* bonds (154.8) where the difference (470.95) is significant at the 1% level. In Model 2, the coefficient on *PREDICT_LGD* in the high *Z* bonds (626.2) is larger than the coefficient on *PREDICT_LGD* in the low *Z* bonds (366.1) where the difference (260.1) is significant at the 1% level. In Model 3, the coefficient on *PREDICT_LGD* in the below investment grade bonds (498.5) is larger than the coefficient on *PREDICT_LGD* in the above investment grade bonds (101.5) where the difference

[31] This design is conceptually similar to the use of a design that includes in the regression an indicator variable for high probability of default, *PREDICT_LGD* and their interaction, including the interaction of all control variables with the indicator variable.

[32] For more details concerning the theory and technical details behind randomization testing, see Edgington and Onghena (2007) and Owens (2010).

(397.0) is significant at the 1% level. All three models are consistent with the prediction that when the probability of default is higher, lenders are more sensitive to expected LGD.

4.3.4 The effect of managerial entrenchment on the relation between PREDICT_LGD and SPREAD

Theory predicts that lenders will rely more on liquidation values and LGD when agency conflicts between lenders and borrowers are greater. To assess whether lenders require higher interest rate compensation for LGD risk when agency conflicts are greater, I merge my sample with the entrenchment index (*EINDEX*) from Bebchuk et al. (2008) at the year of the bond issuance. This index captures insiders' ability to extract private benefits from the corporation. I partition my sample into high entrenchment and low entrenchment issuers based on the sample median of *EINDEX*, reestimate a variation of equation (3) for each partition, and test for the difference in the coefficients between groups. As above, the test of the difference between the coefficients across partitions is based on Monte-Carlo simulation.

The results of this analysis are presented in table 6. As predicted, the coefficient on *PREDICT_LGD* in the high *EINDEX* corporations (378.5) is larger than the coefficient on *PREDICT_LGD* in the low *EINDEX* (178.6) where the difference (199.9) is significant at the 5% level. This result is consistent with lenders putting more emphasis on liquidation values when the potential for private benefits extraction is greater.

4.3.5 The relation between PREDICT_LGD and the probability of secured debt borrowing

The price of the debt contract (*SPREAD*) is not the only term of the contract that is expected to be affected by LGD. Debt investors potentially can limit their exposure to LGD by asking the debt issuer to pledge assets against the funds. Thus when debt investors expect LGD to be higher, we may observe an increase in the probability the debt will be secured. To examine this possibility I estimate the following logit regression.

$$Prob(SECURED)_{it} = \gamma_0 + \gamma_1 * PREDICT\_LGD_{i,t-1} + \gamma_2 * C_{i,t-1} + \eta + \varphi + \varepsilon, \qquad (4)$$

where *SECURED* and *PREDICT_LGD* are as defined above. As discussed earlier, the coefficient on *PREDICT_LGD,* γ_1, is expected to be positive. C is a vector of the control variables. η and φ are industry and year fixed effects, respectively.

Table 7 presents results from estimating equation (4). Model 1 includes only a binary variable for above investment grade firms as a control variable for probability of default. Model 2 includes two additional variables, *DLI* and *Z,* as controls for probability of default and model 3 includes *SPRATING* as a control. In all three models *PREDICT_LGD* is positively and significantly associated with the probability a bond will be secured (coefficients of 12.9, 9.1, and 13.2 with z-statistics of 5.4, 3.6 and 5.0 in Models 1, 2 and 3 respectively). This finding is consistent with lenders demanding a specific security against their investments when expected losses are larger. Such security may reduce lenders' exposure to LGD.

4.3.6 The relation between PREDICT_LGD and debt maturity

Another measure that lenders can take to reduce their exposure to LGD is to provide funds with shorter maturity. The reason shorter maturity reduces lenders' exposure to LGD is that it enables them to assess the likelihood of default with greater frequency. If the borrower has high expected LGD, the lender will want to monitor the borrower's probability of default more often so if an increase in default likelihood occurs, the lender is able to refuse renewal of the contract. To assess this possibility, I estimate the following OLS regression.

$$LMATURITY_{it} = \gamma_0 + \gamma_1 * PREDICT\_LGD_{i,t-1} + \gamma_2 * P_{i,t-1} + \eta + \varphi + \varepsilon, \qquad (5)$$

where *LMATURITY* and *PREDICT_LGD* are as defined above. As discussed earlier, the coefficient on *PREDICT_LGD,* γ_1, is expected to be negative. *P* is a vector of control variables and η and φ are industry and year fixed effects, respectively.

I present the results from these tests in table 8. Model 1 includes only a binary variable for above investment grade firms as a control variable for probability of default. Model 2 includes two additional variables, *DLI* and *Z,* as controls for probability of default and model 3 includes *SPRATING* as a control. In all three models *PREDICT_LGD* is negatively and significantly associated with the length of the debt contract (coefficients of -0.758, -0.710, -0.680 with t-statistics of -3.5, -2.9 and -3.1 in Models 1, 2 and 3 respectively). This finding is consistent with lenders being willing to lend funds for shorter time periods when the expected losses in case of default are higher. This may occur because lenders want to monitor the debt for higher *PREDICT_LGD* firms more closely and frequently.

4.3.7 The relation between PREDICT_LGD and debt size

The liquidation value literature has suggested that lenders may place limits on loan amounts for firms with low liquidation value. Lenders may want to limit their exposure to LGD risk and thus provide fewer funds to high LGD firms. To examine this possibility I estimate the following OLS regression.

$$SDEBTSIZE_{it} = \gamma_0 + \gamma_1 * PREDICT\_LGD_{i,t-1} + \gamma_2 * E_{i,t-1} + \eta + \varphi + \varepsilon, \qquad (6)$$

where *SDEBTSIZE* is the face value of the debt divided by the borrower's total assets. *PREDICT_LGD* is as defined above. For the reason discussed above, the coefficient on *PREDICT_LGD,* γ_1, is expected to be negative. *E* is a vector of the various variables used in the literature to control for other determinants of debt size. η and φ are industry and year fixed effects, respectively.

I present the results from these estimations in table 9. Model 1 includes only a binary variable for above investment grade firms as a control variable for probability of default. Model 2 includes two additional variables, *DLI* and *Z,* as controls for probability of default and model 3 includes *SPRATING* as a control. *PREDICT_LGD* is negatively and significantly associated with the size of the debt in all models (coefficients of -0.202, -0.246 and -0.214 with t-statistics of -2.5, -2.8 and -2.5 in Models 1, 2 and 3 respectively). This finding is consistent with lenders supplying fewer funds to lenders with high expected LGD in order to limit their exposure.

4.3.8 The effect of the precision of the accounting signal on the relation between PREDICT_LGD and SPREAD

If accounting provides an informative signal about LGD to debt investors, then, investors should put more weight on accounting predictors of LGD from accounting systems that provide more precise information about it.[33] The qualities of an accounting system that generates more precise signals on LGD is an empirical question. I use measures for three accounting system qualities, *RELEVANCE*, *TIMELINESS* and *CONSERVATISM,* to address this question.[34] These qualities are commonly used in the accounting literature with some variation in the way the measures are constructed. I follow Francis et al. (2004) in the construction of the measures. Although all three measures have compelling justification for why they should provide more precise information on LGD, they capture inherently different characteristics. *RELEVANCE* is the explanatory power from a regression of concurrent stock returns on earnings and changes in earnings. More formally, *RELEVANCE* is the R-squared from the following regression, estimated for a firm-specific time series for firms with a maximum of 10 years and a minimum of 4 years of available data before the debt issuance.

$$RET_{it} = \rho_0 + \rho_1 * NIBEX_{it} + \rho_2 * \Delta NIBEX_{it} + \varepsilon, \qquad (7)$$

where *RET* is the cumulative return for the 15 months ended 3 months after the fiscal year end. *NIBEX* is net income before extraordinary items and Δ*NIBEX* is the change in net income before extraordinary items. The construct *RELEVANCE* attempts to capture how well an accounting system captures changes in the value of the firm.

---

[33] In this paper I use the terms signal precision and signal quality interchangeably.

[34] See a discussion on the construction of these measures below.

TIMELINESS is the explanatory power from a regression of earnings on concurrent returns, an indicator variable for negative returns and the interaction between the two. More formally, *TIMELINESS* is the R-squared from the following regression, estimated for a firm-specific time series for firms with a maximum of 10 years and a minimum of 5 years of available data before the debt issuance.

$$NIBEX_{it} = \lambda_0 + \lambda_1 * D_{it} + \lambda_2 * RET_{it} + \lambda_3 * RET_{it} * D_{it} + \varepsilon, \qquad (8)$$

where *RET* and *NIBEX* are defined above and *D* is an indicator variable that takes the value of 1 when *RET* is negative. This measure is aimed to capture how timely earnings are, or how earnings capture the information in concurrent news.

CONSERVATISM is the coefficient on bad news from equation (5) relative to the coefficient on good news from equation (5). More formally *CONSERVATISM* is defined as $(\lambda_3 + \lambda_2)/\lambda_2$. *CONSERVATISM* attempts to capture how timely a firm recognizes bad news.

I partition my sample based on high and low values, based on the median, of each of the three accounting system characteristics, *RELEVANCE*, *TIMELINESS* and *CONSERVATISM*. I then estimate equation (3) separately for each of the high and low groups. If an accounting system characteristic provides more precise information on LGD then the coefficient on *PREDICT_LGD,* γ_1, should be greater in the high group than in the low group and vice versa.[35] As in section 4.3.3, the comparison of the coefficients across partitions is preformed using a Monte-Carlo non-parametric simulation technique.

Table 10 provides results from the estimation of equation (3) based on partitions on the three proxies for information precision. Model 1 partitions the sample for high and low *RELEVANCE* firms. The results of the estimation of Model 1 suggest that the coefficient on

[35] A better strategy empirically to assess this question is to examine first the predictive ability of the LGD prediction model under each partition and then to test whether models with better predictive ability are weighted more heavily by investors. However, sample size limitations at the prediction model stage preclude using this strategy.

PREDICT_LGD in the high *RELEVANCE* firms (374.3) is larger than the coefficient on *PREDICT_LGD* in the low *RELEVANCE* firms (210.8) where the difference (163.5) is significant at the 1% level. This result is consistent with firms that have accounting systems that provide more relevant information about changes in firms' market values, also provide more precise information to lenders about LGD.

Model 2 partitions the sample for high and low *TIMELINESS* firms. The results of the estimation of Model 2 suggest that the coefficient on *PREDICT_LGD* in the high *TIMELINESS* firms (469.8) is larger than the coefficient on *PREDICT_LGD* in the low *TIMELINESS* firms (154.0) where the difference (315.8) is significant at the 1% level. This result is consistent with the claim that firms that have accounting systems that provide information that better maps news (as represented by returns) into earnings, also provide more precise information to lenders about LGD.

On the contrary, Model 3 partitions the sample for high and low *CONSERVATISM* firms. The results of the estimation of Model 3 suggest that the coefficient on *PREDICT_LGD* in the high *CONSERVATISM* firms (190.4) is lower than the coefficient on *PREDICT_LGD* in the low *CONSERVATISM* firms (376.2) where the difference (185.8) is significant at the 1% level.[36] This result suggests that relevant, not conservative, accounting provides valuable information to lenders about liquidation values at the contracting date.

An interesting finding from table 10 is that firms with more conservative accounting systems provide more precise information to lenders about the probability of default. This can be seen from comparing the coefficients on DLI in model 3 between the high (coefficient of 222.5 with t-statistics of 4.58) and low conservatism (coefficient of 86.1 with t-statistics of 1.52) groups. However I leave the exploration of this channel to future research.

---

[36] I also use the equity market-to-book ratio as a proxy for conservatism (Sunder et al. 2009). None of the inferences changes using this proxy.

4.3.9 Bank Loans and *PREDICT_LGD*

Thus far, I have used a sample of bond issuances to assess the relation between LGD and debt contract characteristics. I next apply equation (2) to construct *PREDICT_LGD* for the bank loan sample described in section 3 above. Since the coefficients that comprise *PREDICT_LGD* are based on defaulted bonds, the measurement error of *PREDICT_LGD* in the bank loan sample is greater. However, this fact will tend to bias against finding results in this sample. I repeat the analysis on the relation between *PREDICT_LGD* and debt contract characteristics in the bank loan sample in an attempt to extend the external validity of my findings and to test whether the contract adjustment mechanisms for LGD work in loans and bonds similarly.

I present the results of these tests in table 11-Panel A. The results show that the main findings in the bond sample can be extended to the bank loan sample. Model 1 shows that *PREDICT_LGD* is positively associated with the spread over the Libor benchmark with a coefficient of 195.4 and t-statistic of 11.24. Model 2 shows that *PREDICT_LGD* is positively associated with the probability a loan will be secured (a coefficient of 0.87 and t-statistic of 2.0). I also show, in Model 3, that the maturity of bank loans is negatively associated with *PREDICT_LGD* (a coefficient of -0.97 and t-statistic of -9.70). Lastly, I show, in Model 4, that the size of bank loans is negatively associated with *PREDICT_LGD* (a coefficient of -1.496 and t-statistic of -7.13).[37] These results suggest that the mechanism through which LGD affects bond terms is similar to the mechanism through which it affects loan contracts.

Using to the bank loan sample also allows me to examine how financial covenants affect the results presented in this paper and to evaluate the relation between the strictness of the financial covenants and *PREDICT_LGD.* To do this, I use a measure of covenant strictness (*COV_STRICTNESS*) which is based on Murfin (2010). This measure captures the ex-ante

[37] In this model, I use the natural log of *SDEBTSIZE* because the distribution of this variable is highly skewed in the loan sample. If I do not use the natural log of *SDEBTSIZE,* the coefficient on *PREDICT_LGD* has the predicted sign but it is not statistically significant.

probability of covenants violation based on how far the financial ratios are from the covenants and the standard deviation of the ratios. Table 11-Panel B presents the results of this exercise. Model 1 to Model 4 show that all the results that were documented in Table 11-Panel A hold after controlling for *COV_STRICTNESS* despite the fact that the sample size drops significantly because of the unavailability of the strictness measure. Model 5 shows that *PREDICT_LGD* is positively associated with *COV_STRICTNESS* (coefficient of 0.734 with t-statistic of 6.89). This result is consistent with the predication that lenders tend to give less financial slack to borrowers with high expected LGD.

5. Sensitivity tests

5.1 Does PREDICT_LGD capture the direct effect of the underlying accounting measures that comprise it on contracts, and how unique is the linear combination that comprises it?

One concern about the findings above is that any linear combination of the elements that comprise *PREDICT_LGD* will yield similar results. In other words, the question arises as to how unique is the linear combination the estimation of equation (1) provides. It may be that *PREDICT_LGD* captures the direct effect of the accounting measures it is comprised of on the debt contract (e.g., the direct relation between *ROA* and *SPREAD* or the direct relation between *NETWORTH* and *SPREAD* that is not operating through LGD). Since there are potentially an infinite number of linear combinations for the coefficients, in an attempt to address these questions, I use a simulation technique.

The simulation proceeds as follows. I randomly choose a number from a uniform distribution between zero and one for each of the five coefficients of the accounting measures that make *PREDICT_LGD.* To each random coefficient I attach the sign I obtained from equation (1). For example, the new random coefficient on *ROA* will be a number between negative one and zero and the new random coefficient on *LTA* will be a number between zero and one. I restrict the coefficients to be between zero and one because this is the range of the "true" coefficients obtained originally from equation (1). After obtaining the new five random coefficients, I recalculate *PREDICT_LGD* for the bond sample using the new random coefficients. I estimate equation (3) using the new *PREDICT_LGD* and check the significance level on its coefficient. I repeat this procedure 1,000 times.

Untabulated findings indicate that out of the 1,000 estimations, the coefficient on the new *PREDICT_LGD* is only significant 66 times at the 5 percent level and 0 times at the 1 percent level. In other words, in this technique, I basically guess the coefficients armed with the information about their range and sign. Out of 1,000 guesses, in only 66 attempts do I obtain a linear combination that significantly explains *SPREAD*.[38]

This finding is consistent with the claim that the information about the linear combination obtained from equation (1) is important and not just any linear combination of the coefficients will work. This also means that *PREDICT_LGD* does not capture by construction the effects of the underlying accounting measures on *SPREAD*.

5.2 Additional robustness and sensitivity tests.

I conduct numerous sensitivity tests. Among them are: adding each of the variables that comprise LGD to the regression as a control variable to test that none of them by itself significantly affects the inferences described above;[39] adding the industry LGD means and the accounting predicted LGD separately to the regressions; removing different subsets of control variables, including observations with *PREDICT_LGD* that are below zero and above one; adding DLI, yearly returns and standard deviation of monthly returns to the prediction model; and including yearly returns and the standard deviation of monthly returns as control variables to all tests. None of these additional tests change the inferences from the results presented above.

[38] In an additional test I use a similar technique and choose four coefficients randomly and let the fifth coefficient, (*ROA),* be the one that allows *PREDICT_LGD* of the median firm in the sample and *PREDICT_LGD* of the median firm using the original "true" coefficients to be identical. I find that only in 16 cases the coefficient on *PREDICT_LGD* is statistically significant in explaining *SPREAD*.

[39] Adding all the variables into the regression is not feasible because of full multicolinarity (*PREDICT_LGD* is a linear combination of the variables).

6. Conclusions

This study addresses the effects of information available to lenders in the financial reports about loss given default at the contracting date on price and non-price terms of debt contracts. First, using a sample of defaulted senior unsecured bonds, I show that the information contained in five accounting measures that are available to lenders in the financial statements at the contracting date, is significantly associated with future LGD in a predictable manner. I use the estimation of the relation between these accounting measures and LGD to construct a measure of expected loss given default at the contracting date for non-defaulted debt instruments which I name *PREDICT_LGD*. I predict, using a simple analytical model, and find that *PREDICT_LGD* is positively associated with bond credit spread over the treasury benchmark. This relation is incremental to the effect of the probability of default on spreads. Moreover, as expected, the relation between *PREDICT_LGD* and credit spread is stronger when the probability of default and managerial entrenchment are greater. *PREDICT_LGD* is also strongly associated with non-price contract terms. Bonds of firms with higher expected LGD have a greater probability of being secured and having shorter maturity. In addition, bonds of firms with higher *PREDICT_LGD* are smaller relative to the borrower's assets. I also use a sample of bank loan issuances to show that these findings hold after controlling for covenant strictness and that covenants strictness is higher when expected LGD is higher.

I also find evidence that suggests accounting systems that are more value-relevant and more timely are more useful for lenders in assessing LGD. This finding manifests in a greater sensitivity of credit spread to *PREDICT_LGD* for bonds of firms that have more value-relevant and more timely accounting systems. On the other hand, lenders are more sensitive to *PREDICT_LGD* in firms that have less conservative accounting systems.

Although the relations between *PREDICT_LGD* and credit spread, security and maturity are robust to many sensitivity tests, and consistent with economic theory and intuition, it is possible that other correlated forces drive these relations. Debt contracts are complicated mechanisms and it is therefore possible that *PREDICT_LGD* captures unobserved or unexamined parts of this relation such as debt covenants. Another concern is the fact that I use only defaulted firms to obtain the coefficients that comprise the estimates of *PREDICT_LGD*. A possibility is that the coefficients in the prediction model capture some underlying unobserved characteristics that caused these firms to default. This concern is mitigated by the fact that I am able to control for the probability of default in the second step. In addition, controlling for year and industry fixed effects also mitigates this concern.

This study leaves much room for future research. Questions such as what are the effects of LGD on renegotiation outcomes of debt contracts, and what are the effects of LGD on equity pricing are important in the finance and economic literature and can be addressed using some of the techniques suggested in this study. In addition, further validation and improvement of *PREDICT_LGD*

Appendix A: Definitions

Names of Variables	*Description*	*Detailed Description and Source*
LGD	Loss given default = (1- recovery rate)	Equals to one minus the recovery rate on a defaulted bond. Recovery rate is calculated as the market price of the bond 30 days after default occurred divided by the face value of the bond. Source: Moody's DRS
ROA	*Return on assets*	Earnings before interest and tax (EBIT) scaled by total assets. Source: COMPUSTAT
NET_WORTH	*Net Worth*	Total assets less total liabilities scaled by number of shares outstanding Source: COMPUSTAT
INTANGIBLE_RATIO	*Intangible to tangible ratio*	Intangible assets divided by tangible assets Source: COMPUSTAT
STTOLTDEBT	*Short term to long term debt ratio*	Short term debt divided by long term debt Source: COMPUSTAT
LTA	*Log of total assets*	Equals to the natural log of total assets Source: COMPUSTAT
PREDICT_LGD	*Predicted (expected) LGD*	Is calculated by multiplying the coefficients obtained from equation (1) $LGD_{id} = \beta_0 + \beta_1 * ROA_{i\ t-1} + \beta_2 * NET\_WORTH_{i\ t-1} + \beta_3 * INTANGIBLE\_RATIO_{i\ t-1} + \beta_4 * STTOLTDEBT_{i\ t-1} + \beta_5 * LTA_{i\ t-1} + \beta_{6-22} * \psi_{ind} + \mu$ that is estimated on a sample of defaulted senior unsecured bonds with the relevant accounting measures and industry classification in the bond and loan samples. The calculation is given by equation (2) above. Source: Author's calculation
ACC_PREDICT_LGD	*Accounting predicted (expected) LGD*	Is calculated by multiplying the coefficients obtained from equation (1) $LGD_{id} = \beta_0 + \beta_1 * ROA_{i\ t-1} + \beta_2 * NET\_WORTH_{i\ t-1} + \beta_3 * INTANGIBLE\_RATIO_{i\ t-1} + \beta_4 * STTOLTDEBT_{i\ t-1} + \beta_5 * LTA_{i\ t-1} + \beta_{6-22} * \psi_{ind} + \mu$ that is estimated on a sample of defaulted senior unsecured bonds with the relevant accounting measures and industry classification in the bond and loan samples where the industry coefficients (β_6-β_{22}) are constraint to be zero. Source: Author's calculation
EINDEX	*Entrenchment index*	The E index from Bebchuk et al. (2008). Based on 6 IRRC provisions.

Names of Variables	***Description***	***Detailed Description and Source***
LSIZE	*Log of market value of equity*	Equals to the natural log of the market value of equity Source: COMPUSTAT, CRSP
LEV	*Leverage*	Long term debt divided by total assets Source: COMPUSTAT
Q	*Tobin's Q*	The sum of total liabilities plus market value of equity divided by book assets Source: COMPUSTAT
LFACAMOUNT	*The log of the face value of the issued debt*	Equal to the log of the proceeds from the debt issuance in millions of USD Source: SDC for the bond sample and Dealscan for the loan sample
SDEBTSIZE	*The face value of the issued debt divided by total assets*	Equal to the proceeds from the debt issuance in millions of USD divided by total assets Source: SDC for the bond sample and Dealscan for the loan sample and COMPUSTAT
SECURED	*Secured debt indicator*	An indicator variable that takes the value of one if the debt is secured and zero otherwise Source: SDC for the bond sample and Dealscan for the loan sample
LMATURITY	*The log of the maturity of the issued debt*	The log of the time to maturity in months of the issued debt. Source: SDC for the bond sample and Dealscan for the loan sample
COV_STRICTNESS	*Covenant strictness*	A measure of covenant strictness based on Murfin (2010). Captures the ex-ante probability of covenants violation
DLI	*The default likelihood indicator*	Based on Merton (1974) model and the calculation in Vassalou and Xing (2004) Source: COMPUSTAT, CRSP
Z	*The negative of Altman (1968) Z*	Equals to negative 1 divided by total assets multiplied by the sum of the following five measures 3.3*earnings before income tax, 1*revenue, 1.4* retained earnings, 1.2*current assets net from current liabilities, 0.22* market value of equity. Source: COMPUSTAT, CRSP
MTB	*Market to Book ratio*	Market value of equity divided by the book value of assets minus the book value of liabilities Source: COMPUSTAT, CRSP
SPRATING	*S&P debt rating*	The S&P rating attached to the debt in the bond sample when available, or the S&P long term debt ratings in the loan sample when available. All ratings are converted to numeric values where AAA takes the value of 2 and defaulted debt takes the value of 27. Source: SDC for the bond sample and COMPUSTAT for the loan sample

Names of Variables	***Description***	***Detailed Description and Source***
INV_GRADE	*Investment grade debt indicator*	An indicator variable that takes the value of one when the debt is above investment grade and zero otherwise. Source: SDC for the bond sample and COMPUSTAT for the loan sample
SPRATED	*Rated by S&P indicator*	An indicator variable that takes the value of one for firms that have S&P rating and zero otherwise. Source: SDC for the bond sample and COMPUSTAT for the loan sample
RELEVANCE	*RELEVANCE*	*RELEVANCE* is the R squared from the following regression, estimated for a firm-specific time series for firms with a maximum of 10 years and a minimum of 4 years of available data before the debt issuance. $RET_{it} = \rho_0 + \rho_1 * NIBEX_{it} + \rho_2 * \Delta NIBEX_{it} + \varepsilon$ Where *RET* is the cumulative return for the 15 months ended 3 months after the fiscal year end. *NIBEX* is net income before extraordinary items and Δ*NIBEX* is the change in net income before extraordinary items. Source: CRSP and COMPUSTAT
TIMELINESS	*TIMELINESS*	*TIMELINESS* is the R squared from the following regression, estimated for a firm-specific time series for firms with a maximum of 10 years and a minimum of 5 years of available data before the debt issuance. $NIBEX_{it} = \lambda_0 + \lambda_1 * D_{it} + \lambda_2 * RET_{it} + \lambda_3 * RET_{it} * D_{it} + \varepsilon$ Where *RET* is the cumulative return for the 15 months ended 3 months after the fiscal year end. *NIBEX* is net income before extraordinary items. *D* is an indicator variable that takes the value of 1 when *RET* is negative.
CONSERVATISM	*CONSERVATISM*	*TIMELINESS* is the sum of λ_2 and λ_3 divieded by λ_2 from the following regression, estimated for a firm-specific time series for firms with a maximum of 10 years and a minimum of 5 years of available data before the debt issuance. $NIBEX_{it} = \lambda_0 + \lambda_1 * D_{it} + \lambda_2 * RET_{it} + \lambda_3 * RET_{it} * D_{it} + \varepsilon$ Where *RET* is the cumulative return for the 15 months ended 3 months after the fiscal year end. *NIBEX* is net income before extraordinary items. *D* is an indicator variable that takes the value of 1 when *RET* is negative.

Appendix B: Simple model of LGD and credit spreads

The purpose of this model is to provide simple analytical intuition for the predictions presented in the paper and thus the model makes several assumptions that may not fully describe the contracting environment. The model starts with a borrower that has an investment opportunity to start a project that requires a fixed investment K at time zero. I assume debt is the optimal way to finance the project because of tax reasons, and the lender operates in a competitive industry. Both the borrower and the lender in this model are risk neutral.

I also assume that the project succeeds with probability (1-Pd) and fails (defaults) with probability Pd. If the project succeeds it yields a fixed rate of return, R, on the investment, and the lender gets interest payment of i for every $1 of its investment. If the project fails (with probability Pd) the borrower defaults on the loan and the borrower gets zero. The lender can recover rate of RR from its investment K where RR= (1-LGD). The recovery rate and thus LGD is between zero and 1.

I also assume no agency problems exist, the borrower has no private benefit from the project other than the residual yield of R-i. There is also no information asymmetry between the lender and the borrower, and both have the same information about the parameters of the model. I also normalize the risk free rate to be zero, so i is the spread over the risk free rate.

Case 1 – LGD is a known parameter:

In this case the expected profit of the lender who competes in a competitive market is zero and is given by the following equation:

$$E(\pi_L) = (1-Pd)*(1+i)*K+Pd*(1-LGD)*K-K = 0 \qquad \text{(A1)}$$

This means that the interest rate i that the lender requires for providing funds to the borrower to compensate him for the risk is given by the following equation:

$$i = \frac{Pd*LGD}{(1-Pd)} \qquad \text{(A2)}$$

The comparative static of this simple case yields the following implications. The credit spread, i, is increasing with LGD and Pd (the first derivatives of i with respect to LGD and Pd are positive). The sensitivity of the credit spread to LGD is increasing with Pd (the cross partial derivative with respect to LGD and then with respect to Pd is positive).

Case 2 – LGD is a random variable on which financial statements provide a signal:

In this case LGD is assumed to be a random variable distributed normally. LGD has a prior mean of μ and a precision (1/variance) of h_1. μ can be thought of as all the other information available in the market that is not in the financial statements and that is informative about LGD, like industry classification, price movements, analysts ratings and reports, etc.

Before the debt contract is signed, the lender receives financial statements signal S from the borrower that is informative about LGD. S = LGD + ε , where ε is a noise term that is normally distributed with a mean zero and a precision (1/variance) of h_2.

In this case, the lender will require interest spread, i, that is given by an adjustment of equation (A2):

$$i = \frac{Pd * E(LGD|S)}{(1-Pd)} \tag{A3}$$

Using Bayesian updating yields the following expression.

$$i = \frac{Pd * \frac{\mu * h1 + S * h2}{(h1+h2)}}{(1-Pd)} \tag{A4}$$

The important comparative static from this simple case shows that the interest rate spread, i, is more sensitive to an accounting signal about LGD when S is more precise (the cross partial derivative with respect to S and then h_2 is positive).

Table 1- Descriptive Statistics

The descriptive statistics presented below are taken from the three samples discussed above. Panel A presents the descriptive statistic for the DRS sample of defaulted bonds obtained from Moody's DRS database. Panel B presents descriptive statistic for bond issuances obtained from SDC (bond sample). Panel C presents descriptive statistic for loan issuances obtained from Dealscan (bank loan sample). See Appendix A for detailed variable definitions.

Panel A – DRS sample

Variable	N	Mean	Median	Std Dev	25th Pctl	75th Pctl
LGD	308	0.67	0.81	0.33	0.54	0.92
ROA	308	0.05	0.06	0.09	0.02	0.09
NET_WORTH	308	10.84	9.46	15.69	4.02	17.19
INTANGIBLE_RATIO	308	2.57	0.25	10.10	0.00	0.97
STTOLTDEBT	308	0.37	0.04	1.30	0.01	0.21
LTA	308	7.43	7.64	1.50	6.46	8.57
TIME TO DEFAULT	308	47.11	40.04	30.79	24.74	59.19

Panel B – Bond Sample

Variable	N	Mean	Median	Std Dev	25th Pctl	75th Pctl
SPREAD	3,599	200.64	140.00	167.43	83.00	274.00
PREDICT_LGD	3,599	0.69	0.68	0.14	0.61	0.78
ROA	3,599	0.10	0.09	0.06	0.06	0.13
INTANGIBLE_RATIO	3,599	0.82	0.15	2.50	0.00	0.70
NET_WORTH	3,599	16.50	14.96	11.63	8.82	21.51
STTOLTDEBT	3,599	0.29	0.12	0.75	0.03	0.31
LTA	3,599	8.47	8.47	1.42	7.49	9.43
LEV	3,599	0.30	0.28	0.17	0.19	0.38
LSIZE	3,599	8.19	8.22	1.67	7.11	9.27
Q	3,599	1.65	1.39	0.79	1.17	1.86
LFACAMOUNT	3,599	4.98	5.30	1.43	4.61	5.86
DLI	3,599	0.03	0.00	0.12	0.00	0.00
Z	3,599	-1.64	-1.54	1.03	-2.30	-0.88
SPRATING	3,556	9.00	9.00	3.69	6.00	12.00
INV_GRADE	3,599	0.62	1.00	0.49	0.00	1.00
SPRATED	3,599	0.99	1.00	0.11	1.00	1.00
LMATURITY	3,599	4.65	4.79	0.58	4.42	4.79
MTB	3,599	3.33	2.07	23.06	1.45	3.31
RELEVANCE	3,008	0.26	0.23	0.20	0.09	0.39
TIMELINESS	2,949	0.36	0.34	0.23	0.17	0.53
CONSERVATISM	2,949	-11.49	0.41	437.10	-3.41	3.29

Table 1- Descriptive Statistics – Cont.

Panel C – Loan Sample

Variable	N	Mean	Median	Std Dev	25th Pctl	75th Pctl
SPREAD	13,325	183.46	152.14	137.09	75.00	262.50
PREDICT_LGD	13,325	0.63	0.62	0.16	0.52	0.73
ROA	13,325	0.08	0.08	0.09	0.05	0.12
NET_WORTH	13,325	10.87	8.59	10.24	4.50	14.71
INTANGIBLE_RATIO	13,325	1.27	0.27	3.76	0.01	1.04
STTOLTDEBT	13,325	0.50	0.11	1.52	0.03	0.34
LTA	13,325	6.44	6.40	1.93	5.08	7.77
LEV	13,325	0.27	0.25	0.19	0.14	0.37
LSIZE	13,325	6.10	6.09	2.08	4.60	7.56
Q	13,325	1.60	1.34	1.00	1.08	1.79
LFACAMOUNT	13,325	4.43	4.61	1.76	3.24	5.70
DLI	13,325	0.06	0.00	0.17	0.00	0.01
Z	13,325	-1.82	-1.80	1.28	-2.55	-1.05
SPRATING	6,556	10.45	11.00	3.35	8.00	13.00
INV_GRADE	13,325	0.20	0.00	0.40	0.00	0.00
SPRATED	13,325	0.49	0.00	0.50	0.00	1.00
LMATURITY	13,325	3.67	3.87	0.65	3.22	4.09
MTB	13,325	2.80	1.82	22.61	1.16	2.92

Table 2 - The relation between accounting measures at the debt issuance date and future LGD

This table presents the results of the estimation of Equation (1):

$LGD_{id} = \beta_0 + \beta_1 * ROA_{i,t-1} + \beta_2 * NET\_WORTH_{i,t-1} + \beta_3 * INTANGIBLE\_RATIO_{i,t-1} + \beta_4 * STTOLTDEBT_{i,t-1} + \beta_5 * LTA_{i,t-1} + \beta_{6\text{-}22} * \psi_{ind} + \mu_i$

The dependent variable, LGD equals to 1 minus the amount recovered by investors out of the face value of the defaulted debt. All other variables are described in Appendix A.

**** Significance at the 10% level, ** Significance at the 5% level, * Significance at the 1% level*

	Model 1	Model 2	Model 3
	LGD	***LGD***	***LGD***
ROA	-0.907*		-0.781*
	(4.88)		(4.11)
NET_WORTH	-0.005*		-0.004*
	(3.94)		(2.79)
INTANGIBLE_RATIO	0.003*		0.003*
	(5.04)		(4.17)
STTOLTDEBT	0.018*		0.025*
	(2.79)		(2.71)
LTA	0.063*		0.062*
	(5.83)		(5.07)
Constant	0.292*	0.736*	0.288*
	(3.57)	(30.22)	(3.08)
Observations	308	308	308
R-squared	0.18	0.165	0.276
Fixed effects	*No*	*Ind*	*Ind*

Table 3- The relation between *PREDICT_LGD and SPREAD*

This table presents the results of the estimation of Equation (3):

$SPREAD_{it} = \gamma_0 + \gamma_1 * PREDICT\_LGD_{i,t-1} + \gamma_2 * X_{i,t-1} + \eta + \varphi + \varepsilon$

The dependent variable, $SPREAD_{it}$ is the credit spread over the treasury benchmark. $PREDICT\_LGD_i$ is a measure of expected LGD at the debt issuance date. t-statistics are based on clustered standard errors by firm. All other variables are described in Appendix A.

**** Significance at the 10% level, ** Significance at the 5% level, * Significance at the 1% level*

	Model 1	Model 2	Model 3
	SPREAD	***SPREAD***	***SPREAD***
PREDICT_LGD	436.613*		415.947*
	(8.80)		(9.09)
ACC_PREDICT_LGD		436.613*	
		(8.80)	
LSIZE	-53.005*	-53.005*	-61.579*
	(15.46)	(15.46)	(18.12)
LEV	40.339	40.339	35.658
	(1.08)	(1.08)	(1.04)
Q	20.135*	20.135*	16.951*
	(4.29)	(4.29)	(4.03)
LFACAMOUNT	21.670*	21.670*	12.717*
	(8.63)	(8.63)	(7.30)
LMATURITY	-8.316**	-8.316**	13.528*
	(2.05)	(2.05)	(4.09)
SECURED	142.652*	142.652*	134.436*
	(4.79)	(4.79)	(4.50)
INV_GRADE	-142.610*	-142.610*	-121.872*
	(16.22)	(16.22)	(13.01)
SPRATED	69.214**	69.214**	53.481
	(2.09)	(2.09)	(1.55)
Constant	245.058*	370.792*	235.921*
	(4.74)	(7.69)	(4.96)
Observations	3,599	3,599	3,599
R-squared	0.557	0.557	0.662
Fixed effects	*Ind*	*Ind*	*Ind,Year*

Table 4 - The relation between *PREDICT_LGD and SPREAD over and above default likelihood*

This table presents the results of the estimation of Equation (3) and includes additional control variables for the probability of default.

$SPREAD_{it} = \gamma_0 + \gamma_1 * PREDICT\_LGD_{i,t-1} + \gamma_2 * X_{i,t-1} + \eta + \varphi + \varepsilon$

The dependent variable, SPREAD$_{it}$ is the credit spread over the treasury benchmark. PREDICT_LGD$_i$ is a measure of expected LGD at the debt issuance date. t-statistics are based on clustered standard errors by firm. All other variables are described in Appendix A.

**** Significance at the 10% level, ** Significance at the 5% level, * Significance at the 1% level*

	Model 1	Model 2	Model 3	Model 4	Model 5
	SPREAD	***SPREAD***	***SPREAD***	***SPREAD***	***SPREAD***
PREDICT_LGD	365.200*	401.437*	316.908*	268.191*	250.195*
	(7.40)	(7.67)	(7.45)	(4.84)	(6.22)
LSIZE	-59.216*	-61.211*	-43.402*	-41.145*	-36.947*
	(16.21)	(18.17)	(12.02)	(9.97)	(11.27)
LEV	27.377	30.463	-19.28	-26.781	-38.742
	(0.79)	(0.80)	(0.55)	(0.68)	(1.23)
Q	16.127*	17.435*	20.279*	19.266*	7.082***
	(3.68)	(4.12)	(4.93)	(4.65)	(1.90)
LFACAMOUNT	12.920*	12.697*	7.429*	7.681*	10.206*
	(7.31)	(7.26)	(3.06)	(2.99)	(5.15)
LMATURITY	14.156*	13.465*	17.350*	17.979*	15.987*
	(4.32)	(4.06)	(5.33)	(5.56)	(5.67)
SECURED	121.033*	133.678*	128.617*	115.978*	103.400*
	(4.31)	(4.49)	(4.19)	(4.05)	(3.41)
INV_GRADE	-120.439*	-121.691*			
	(12.79)	(12.94)			
SPRATED	49.163	54.539			
	(1.42)	(1.58)			
DLI	105.204*			107.452*	
	(3.56)			(3.31)	
Z		3.689		-0.818	
		(0.61)		(0.13)	
SPRATING			24.069*	23.883*	
			(17.04)	(16.39)	
Constant	249.531*	248.429*	-45.324	-35.639	66.462**
	(5.23)	(4.36)	(1.28)	(0.71)	(2.18)
Observations	3,599	3,599	3,556	3,556	3,556
R-squared	0.666	0.662	0.694	0.699	0.735
Fixed effects	*Ind,Year*	*Ind,Year*	*Ind,Year*	*Ind,Year*	*Ind,Year,SPRATING*

Table 5- The effects of default likelihood on the relation between *PREDICT_LGD and SPREAD*

This table presents the results of the estimation of Equation (3) of a sample partitioned to high and low likelihood of default subsamples.

$SPREAD_{it} = \gamma_0 + \gamma_1 * PREDICT\_LGD_{i,t-1} + \gamma_2 * X_{i,t-1} + \eta + \varphi + \varepsilon$

The dependent variable, $SPREAD_{it}$ is the credit spread over the treasury benchmark. $PREDICT\_LGD_i$ is a measure of expected LGD at the debt issuance date. t-statistics are based on clustered standard errors by firm. The P-values of the differences between (1) and (2) groups in each model are based on Monte-Carlo non-parametric simulation. All other variables are described in Appendix A.

**** Significance at the 10% level, ** Significance at the 5% level, * Significance at the 1% level*

	Model 1		Model 2		Model 3	
	(1)	(2)	(1)	(2)	(1)	(2)
	LOW DLI	***HIGH DLI***	***LOW Z***	***HIGH Z***	***Below INV_GRADE***	***Above INV_GRADE***
	SPREAD		***SPREAD***		***SPREAD***	
PREDICT_LGD	154.803**	625.748*	366.068*	626.166*	498.489*	101.476*
	(2.35)	(8.51)	(5.55)	(7.27)	(7.05)	(2.88)
LSIZE	-44.475*	-94.699*	-75.332*	-82.716*	-87.573*	-19.888*
	(8.52)	(20.59)	(16.78)	(16.26)	(16.19)	(7.45)
LEV	89.547*	93.056**	55.726***	167.451*	19.328	17.086
	(2.80)	(2.21)	(1.83)	(3.51)	(0.46)	(0.85)
Q	2.464	37.839*	7.183	38.501*	32.262*	-9.502*
	(0.45)	(4.74)	(1.26)	(4.89)	(3.99)	(2.78)
LFACAMOUNT	9.202*	13.776**	15.060*	11.634**	15.098*	6.458*
	(4.06)	(2.05)	(4.94)	(2.32)	(3.35)	(3.55)
LMATURITY	16.226*	10.836	18.457*	2.984	-8.094	20.614*
	(5.94)	(1.51)	(5.45)	(0.44)	(0.68)	(9.95)
SECURED	15.719	102.646*	86.624	113.805*	146.250*	-32.311
	(0.39)	(3.24)	(1.49)	(3.48)	(4.93)	(1.34)
Constant	199.335*	285.112*	315.101*	167.361**	478.211*	60.031*
	(5.25)	(4.45)	(7.08)	(2.45)	(5.64)	(2.82)
Observations	1,800	1,799	1,800	1,799	1,373	2,226
R-squared	0.484	0.563	0.615	0.579	0.482	0.552
Fixed effects	*Ind,Year*	*Ind,Year*	*Ind,Year*	*Ind,Year*	*Ind,Year*	*Ind,Year*
diff of PREDICT_LGD (1)-(2)	-470.95		-266.10		397.01	
P-VALUE of diff of PREDICT_LGD (1)-(2)	<0.01		<0.01		<0.01	

Table 6 - The effects of managerial entrenchment on the relation between *PREDICT_LGD and SPREAD*

This table presents the results of the estimation of a variation of Equation (3) and includes additional control variables for the probability of default.

$SPREAD_{it} = \gamma_0 + \gamma_1 * PREDICT\_LGD_{i,t-1} + \gamma_2 * X_{i,t-1} + \eta + \varphi + \varepsilon$

The sample is partitioned based on the median of EINDEX, which is the entrenchment index from Bebchuk, Cohen and Ferrell (2008).The dependent variable, $SPREAD_{it}$ is the credit spread over the treasury benchmark. $PREDICT\_LGD_i$ is a measure of expected LGD at the debt issuance date. t-statistics are based on clustered standard errors by firm. The P-values of the differences between (1) and (2) groups in each model are based on Monte-Carlo non-parametric simulation. All other variables are described in Appendix A.

**** Significance at the 10% level, ** Significance at the 5% level, * Significance at the 1% level*

	Model 1	
	(1)	(2)
	LOW EINDEX	***HIGH EINDEX***
	SPREAD	
PREDICT_LGD	178.620**	378.514*
	(2.44)	(3.00)
LSIZE	-39.638*	-46.337*
	(6.64)	(5.08)
LEV	-0.106	4.841
	0.00	(0.09)
Q	-1.122	23.853**
	(0.15)	(2.11)
LFACAMOUNT	8.303***	4.461
	(1.84)	(1.17)
LMATURITY	16.484**	7.994
	(2.51)	(0.91)
SECURED	9.466	160.704***
	(0.10)	(1.66)
INV_GRADE	-109.899*	-133.896*
	(6.15)	(6.31)
DLI	300.138**	168.6
	(2.42)	(1.05)
Z	7.365	0.192
	(0.85)	(0.03)
Constant	333.252*	289.129*
	(5.62)	(3.22)
Observations	825	488
R-squared	0.57	0.61
Fixed effects	*Ind,Year*	*Ind,Year*
diff of PREDICT_LGD (1)-(2)	-199.90	
P-VALUE of diff of PREDICT_LGD (1)-(2)	<0.05	

Table 7- The relation between *PREDICT_LGD and SECURED*

This table presents the results of the logit estimation of Equation (4):

$Prob(SECURED)_{it} = \gamma_0 + \gamma_1 * PREDICT\_LGD_{i,t-1} + \gamma_2 * C_{i,t-1} + \eta + \varphi + \varepsilon$

The dependent variable, SECURED is an indicator variable that takes the value of one if the bond is secured. PREDICT_LGD$_i$ is a measure of expected LGD at the debt issuance date. z-statistics are based on clustered standard errors by firm. All other variables are described in Appendix A.

**** Significance at the 10% level, ** Significance at the 5% level, * Significance at the 1% level*

	Model 1	Model 2	Model 3
	SECURED	***SECURED***	***SECURED***
PREDICT_LGD	12.934*	9.148*	13.218*
	(5.40)	(3.65)	(5.01)
LSIZE	-1.029*	-0.878*	-1.108*
	(4.42)	(3.67)	(4.18)
LEV	0.209	-0.666	0.598
	(0.22)	(0.58)	(0.62)
Q	0.116	0.171	0.282
	(0.34)	(0.56)	(1.12)
LFACAMOUNT	-0.068	-0.053	-0.116
	(0.45)	(0.36)	(0.75)
LMATURITY	0.317	0.283	0.445
	(0.62)	(0.56)	(0.81)
SPREAD	0.003**	0.003**	0.003***
	(2.06)	(2.22)	(1.79)
INV_GRADE	0.741	0.725	
	(1.18)	(1.16)	
SPRATED	-0.679	-0.662	
	(0.92)	(0.87)	
DLI		0.907	
		(1.20)	
Z		0.706*	
		(2.62)	
SPRATING			-0.116
			(1.15)
Constant	-8.596*	-6.110**	-7.885**
	(3.24)	(2.13)	(2.45)
Observations	3,194	3,194	3,156
Fixed effects	*Ind,Year*	*Ind,Year*	*Ind,Year*

Table 8- The relation between *PREDICT_LGD* and time to Maturity

This table presents the results of the estimation of Equation (5):

$LMATURITY_{it} = \gamma_0 + \gamma_1 * PREDICT\_LGD_{i,t-1} + \gamma_2 * P_{i,t-1} + \eta + \varphi + \varepsilon$

The dependent variable, $LMATURITY_{it}$ is the natural log of the time to maturity of the bond in months. $PREDICT\_LGD_i$ is a measure of expected LGD at the debt issuance date. t-statistics are based on clustered standard errors by firm. All other variables are described in Appendix A.

**** Significance at the 10% level, ** Significance at the 5% level, * Significance at the 1% level*

	Model 1	Model 2	Model 3
	LMATURITY	***LMATURITY***	***LMATURITY***
PREDICT_LGD	-0.758*	-0.710*	-0.680*
	(3.52)	(2.95)	(3.09)
LSIZE	0.01	0.008	-0.01
	(0.57)	(0.45)	(0.55)
LEV	0	0.002	0.08
	(0.01)	(0.03)	(0.99)
Q	-0.034	-0.031	-0.041***
	(1.54)	(1.47)	(1.79)
LFACAMOUNT	0.056*	0.055*	0.059*
	(4.23)	(4.18)	(4.76)
SECURED	-0.044	-0.025	-0.049
	(0.40)	(0.23)	(0.42)
SPREAD	0.000*	0.000*	0.001*
	(3.58)	(3.75)	(4.32)
INV_GRADE	0.087***	0.087***	
	(1.89)	(1.95)	
SPRATED	0.246*	0.255*	
	(2.77)	(2.92)	
DLI		-0.192**	
		(2.43)	
Z		0.009	
		(0.51)	
SPRATING			-0.029*
			(3.93)
Constant	4.630*	4.623*	5.237*
	(26.22)	(24.09)	(28.86)
Observations	3,599	3,599	3,556
R-squared	0.144	0.146	0.153
Fixed effects	*Ind,Year*	*Ind,Year*	*Ind,Year*

Table 9- The relation between *PREDICT_LGD* and debt size

This table presents the results of the estimation of Equation (6):

$SDEBTSIZE_{it} = \gamma_0 + \gamma_1 * PREDICT\_LGD_{i,t-1} + \gamma_2 * E_{i,t-1} + \eta + \varphi + \varepsilon$

The dependent variable, $SDEBTSIZE_{it}$ is the ratio of the face value of the debt to the borrower's total assets. $PREDICT\_LGD_i$ is a measure of expected LGD at the debt issuance date. t-statistics are based on clustered standard errors by firm. All other variables are described in Appendix A.

**** Significance at the 10% level, ** Significance at the 5% level, * Significance at the 1% level*

	Model 1	Model 2	Model 3
	SDEBTSIZE	***SDEBTSIZE***	***SDEBTSIZE***
PREDICT_LGD	-0.202**	-0.246*	-0.214**
	(2.50)	(2.77)	(2.50)
LSIZE	-0.042*	-0.042*	-0.039*
	(6.28)	(6.46)	(5.45)
LEV	(0.01)	(0.04)	(0.05)
	(0.38)	(0.95)	(1.25)
Q	0.056*	0.060*	0.058*
	(4.98)	(4.87)	(4.89)
LMATURITY	-0.005	-0.007***	-0.004
	(1.46)	(1.75)	(0.97)
SECURED	0.014	0.021	0.033
	(0.25)	(0.38)	(0.56)
SPREAD	0.000*	0.000*	0.000*
	(4.06)	(4.16)	(3.78)
INV_GRADE	-0.002	-0.001	
	(0.20)	(0.11)	
SPRATED	0.036	0.046***	
	(1.51)	(1.93)	
DLI		-0.099*	
		(3.32)	
Z		0.022*	
		(2.70)	
SPRATING			0.006*
			(3.02)
Constant	0.422*	0.482*	0.398*
	(9.09)	(7.74)	(8.39)
Observations	3,599	3,599	3,556
R-squared	0.33	0.34	0.33
Fixed effects	*Ind,Year*	*Ind,Year*	*Ind,Year*

Table 10- ***The effect of the precision of the accounting signal on the relation between PREDICT_LGD and SPREAD***

This table presents the results of the estimation of Equation (3) of a sample partitioned to high and low accounting system qualities subsamples.

$SPREAD_{it} = \gamma_0 + \gamma_1 * PREDICT\_LGD_{i,t-1} + \gamma_2 * X_{i,t-1} + \eta + \varphi + \varepsilon$

The dependent variable, $SPREAD_{it}$ is the credit spread over the treasury benchmark. $PREDICT\_LGD_i$ is a measure of expected LGD at the debt issuance date. t-statistics are based on clustered standard errors by firm. The P-values of the differences between (1) and (2) groups in each model are based on Monte-Carlo non-parametric simulation. All other variables are described in Appendix A.

**** Significance at the 10% level, ** Significance at the 5% level, * Significance at the 1% level*

	Model 1		Model 2		Model 3	
	(1) LOW RELEVANCE	(2) HIGH RELEVANCE	(1) LOW TIMELINES	(2) High TIMELINES	(1) LOW CONSERVATISM	(2) High CONSERVATISM
	SPREAD		SPREAD		SPREAD	
PREDICT_LGD	210.837*	374.304*	153.971**	469.794*	376.212*	190.414*
	(2.69)	(5.53)	(2.07)	(6.51)	(4.74)	(2.62)
LSIZE	-42.159*	-61.353*	-41.780*	-64.658*	-65.103*	-39.746*
	(7.83)	(11.56)	(8.29)	(11.20)	(11.42)	(7.76)
LEV	-50.476	109.97	-33.113	85.184	51.09	-1.026
	(1.39)	(1.34)	(0.89)	(1.00)	(0.71)	(0.03)
Q	-3.57	21.854*	-3.887	20.568*	21.310*	-3.858
	(0.58)	(3.13)	(0.67)	(2.86)	(3.09)	(0.63)
LFACAMOUNT	11.478*	11.037*	16.805*	9.823*	15.085*	7.758*
	(4.70)	(3.59)	(4.85)	(4.09)	(6.69)	(2.68)
LMATURITY	13.710*	11.927*	14.779*	18.475*	17.958*	12.589*
	(4.10)	(2.68)	(3.99)	(3.98)	(3.85)	(3.29)
SECURED	90.784***	95.876**	84.931***	29.71	107.377	60.341
	(1.74)	(2.20)	(1.91)	(0.42)	(1.25)	(1.38)
INV_GRADE	-129.495*	-110.579*	-125.894*	-107.190*	-110.942*	-121.325*
	(10.47)	(8.04)	(8.67)	(7.96)	(8.19)	(9.08)
SPRATED	93.199**	137.630*	129.840**	100.520*	170.365*	76.347**
	(2.01)	(3.22)	(2.48)	(3.30)	(3.39)	(2.02)
DLI	355.885*	43.145	291.082*	56.735	86.094	228.489*
	(8.06)	(1.21)	(5.81)	(1.16)	(1.52)	(4.58)
Z	3.575	-1.446	2.853	0.091	-1.988	7.793
	(0.47)	(0.19)	(0.37)	(0.01)	(0.22)	(1.04)
Constant	216.789*	165.214**	182.390**	132.191***	76.843	268.144*
	(3.03)	(2.37)	(2.50)	(1.85)	(0.93)	(4.37)
Observations	1,504	1,504	1,469	1,480	1,476	1,473
R-squared	0.656	0.654	0.637	0.651	0.615	0.672
Fixed effects	*Ind,Year*	*Ind,Year*	*Ind,Year*	*Ind,Year*	*Ind,Year*	*Ind,Year*
diff of PREDICT_LGD (1)-(2)	-163.46		-315.83		185.80	
P-VALUE of diff of PREDICT_LGD (1)-(2)	<0.01		<0.01		<0.01	

Table 11- The relation between *PREDICT_LGD* and loan contract characteristics

This table presents the results of the OLS estimation of equation (3),(5) and a variation of equation (6):

$SPREAD_{it} = \gamma_0 + \gamma_1 * PREDICT\_LGD_{i\ t-1} + \gamma_2 * X_{i,t-1} + \eta + \varphi + \varepsilon$ (3)

$LMATURITY_{it} = \gamma_0 + \gamma_1 * PREDICT\_LGD_{i,t-1} + \gamma_2 * P_{i,t-1} + \eta + \varphi + \varepsilon$ (5)

$LSDEBTSIZE_{it} = \gamma_0 + \gamma_1 * PREDICT\_LGD_{i,t-1} + \gamma_2 * E_{i,t-1} + \eta + \varphi + \varepsilon$ (6)

And logit estimation of Equation (4):

$Prob(SECURED)_{it} = \gamma_0 + \gamma_1 * PREDICT\_LGD_{i,t-1} + \gamma_2 * C_{i,t-1} + \eta + \varphi + \varepsilon$ (4)

Panel A presents the results of these estimations without controlling for financial covenant strictness. Panel B controls for financial covenant strictness and presents the results of the estimation of the effects of PREDICT_LGD on covenant strictness. The dependent variable, $SPREAD_{it}$ is the credit spread of the loan over the Libor. The dependent variable, SECURED is an indicator variable that takes the value of one if the loan is secured. The dependent variable, $LMATURITY_{it}$ is the natural log of the time to maturity of the loan in months. The dependent variable, $LSDEBTSIZE_{it}$ is the natural log of the face value of the debt divided by the borrower's total assets. $PREDICT\_LGD_i$ is a measure of expected LGD at the debt issuance date. t-statistics and z-statistics are based on clustered standard errors by firm. All other variables are described in Appendix A.

Panel A –without controlling for financial covenant strictness

**** Significance at the 10% level, ** Significance at the 5% level, * Significance at the 1% level*

	Model 1	Model 2	Model 3	Model 4
	SPREAD	***SECURED***	***LMATURITY***	***LSDEBTSIZE***
PREDICT_LGD	195.404*	0.872**	-0.968*	-1.496*
	(11.24)	(2.01)	(9.70)	(7.13)
LSIZE	-27.736*	-0.389*	-0.013	-0.224*
	(14.59)	(8.50)	(1.10)	(7.38)
LEV	49.829*	-0.135	0.334*	0.086
	(4.88)	(0.67)	(8.08)	(0.90)
Q	4.908*	0.180*	-0.024**	0.162*
	(4.01)	(4.49)	(2.42)	(5.17)
SPREAD		0.007*	0	-0.002*
		(12.90)	0.00	(7.27)
LFACAMOUNT	-14.116*	0.087**	0.096*	
	(8.44)	(2.46)	(10.70)	
LMATURITY	-0.009	0.480*		0.268*
	0.00	(9.44)		(10.25)
SECURED	58.589*		0.151*	0.077**
	(17.73)		(9.98)	(2.38)
INV_GRADE	-50.018*	-1.517*	-0.306*	-0.032
	(11.44)	(9.64)	(10.73)	(0.56)
SPRATED	28.016*	0.407*	0.086*	0.085***
	(6.64)	(4.66)	(3.95)	(1.70)
DLI	48.912*	-0.539**	-0.034	-0.378*
	(4.83)	(2.25)	(0.70)	(4.69)
Z	7.227*	0.109*	-0.001	-0.004
	(5.04)	(3.30)	(0.08)	(0.26)
Constant	264.004*	-1.582*	4.000*	-1.115*
	(16.69)	(4.44)	(50.62)	(4.03)
Observations	13,325	13,325	13,325	13,325
R-squared	*0.501*		*0.196*	*0.285*
Fixed effects	*Ind,Year*	*Ind,Year*	*Ind,Year*	*Ind,Year*

Table 11- Cont.
Panel B –controlling for financial covenant strictness and the effects of *PREDICT_LGD* on loan financial covenant strictness
**** Significance at the 10% level, ** Significance at the 5% level, * Significance at the 1% level*

	Model 1	Model 2	Model 3	Model 4	Model 5
	SPREAD	***SECURED***	***LMATURITY***	***SDEBTSIZE***	***COV STRICTNESS***
PREDICT_LGD	224.727*	1.305***	-0.864*	-0.317*	0.734*
	(8.18)	(1.65)	(5.53)	(3.43)	(6.89)
LSIZE	-28.640*	-0.453*	-0.025***	-0.044*	-0.039*
	(12.40)	(5.56)	(1.77)	(3.86)	(4.11)
LEV	57.226*	0.587	0.355*	0.039	0.428*
	(3.95)	(1.42)	(5.47)	(0.91)	(8.78)
Q	11.525*	0.107	-0.019	0.047*	-0.019***
	(5.71)	(1.49)	(1.26)	(4.54)	(1.91)
SPREAD		0.011*	0.000	-0.000*	0.000***
		(7.70)	(1.17)	(5.22)	(1.88)
SECURED	51.108*		0.169*	0.005	-0.023
	(11.12)		(7.46)	(0.27)	(1.45)
LMATURITY	3.473	0.677*		0.070*	-0.041*
	(1.17)	(6.97)		(8.03)	(3.95)
LFACAMOUNT	-15.230*	0.01	0.115*		0.011***
	(7.76)	(0.15)	(10.69)		(1.71)
COV STRICTNESS	11.971***	-0.341**	-0.117*	0.048***	
	(1.83)	(1.97)	(3.92)	(1.90)	
INV_GRADE	-48.346*	-1.551*	-0.292*	-0.028**	0.046***
	(8.65)	(6.10)	(8.21)	(2.16)	(1.75)
SPRATED	29.481*	0.415*	0.132*	-0.002	-0.023
	(4.19)	(2.62)	(4.91)	(0.14)	(1.06)
DLI	63.792*	-0.214	-0.197**	-0.104*	-0.043
	(3.41)	(0.40)	(2.51)	(3.31)	(0.74)
Z	6.898*	0.087	-0.002	0.007	0.015**
	(3.27)	(1.50)	(0.18)	(1.00)	(2.17)
Constant	183.529*	-1.670**	3.831*	0.447*	0.201**
	(8.54)	(2.54)	(37.45)	(5.76)	(2.44)
Observations	4,584	4,584	4,584	4,584	4,584
R-squared	*0.559*		*0.262*	*0.139*	*0.262*
Fixed effects	*Ind,Year*	*Ind,Year*	*Ind,Year*	*Ind,Year*	*Ind,Year*

References:

Acharya, V. V, S. T Bharath, and A. Srinivasan. 2007. Does industry-wide distress affect defaulted firms? Evidence from creditor recoveries. *Journal of Financial Economics* 85, no. 3: 787–821.

Acharya, Viral V., Sreedhar T. Bharath, and Anand Srinivasan. 2004. Understanding the Recovery Rates on Defaulted Securities. *Working Paper*.

Aghion, P., and P. Bolton. 1992. An incomplete contracts approach to financial contracting. *The review of economic Studies* 59, no. 3: 473–494.

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

Altman, E. I, and V. M Kishore. 1996. Almost everything you wanted to know about recoveries on defaulted bonds. *Financial Analysts Journal* 52, no. 6: 57–64.

Altman, E., A. Resti, and A. Sironi. 2004. Default recovery rates in credit risk modelling: a review of the literature and empirical evidence. *Economic Notes* 33, no. 2: 183–208.

Altman, E. I, B. Brady, A. Resti, and A. Sironi. 2005. The Link between Default and Recovery Rates: Theory, Empirical Evidence, and Implications. *The Journal of Business* 78, no. 6.

Altman, E. 2009. Default recovery rates in credit risk modelling: a review of the literature and empirical evidence. *Working Paper*.

Armstrong, C., W. R Guay, and J. Weber. 2010. The Role of Information and Financial Reporting in Corporate Governance and Debt Contracting. *Working Paper*.

Ball, Ryan, Robert M. Bushman, and Florin P. Vasvari. 2008. The Debt-Contracting Value of Accounting Information and Loan Syndicate Structure. *Journal of Accounting Research* 46, no. 2 (5): 247-287.

Beatty, A., J. Weber, and J. J Yu. 2008. Conservatism and debt. *Journal of Accounting and Economics* 45, no. 2: 154–174.

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

Beaver, W.H. 1968. Alternative accounting measures as predictors of failure. *Accounting review* 43, no. 1: 113–122.

Beaver, W.H. 1968. Market Prices, Financial ratios, and the prediction of failure. *Journal of Accounting Research* 6, no. 2: 179-192.

Bebchuk, L., A. Cohen, and A. Ferrell. 2008. What matters in corporate governance? *Review of Financial Studies* 22, no. 2: 783-827.

Benmelech, E., M. J Garmaise, and T. J Moskowitz. 2005. Do Liquidation Values Affect Financial Contracts? Evidence from Commercial Loan Contracts and Zoning Regulation. *The Quarterly Journal of Economics* 120, no. 3: 1121–1154.

Benmelech, E., and N. K Bergman. 2008. Liquidation values and the credibility of financial contract renegotiation: evidence from US airlines. *The Quarterly Journal of Economics* 123, no. 3: 1635-1677.

Benmelech, E. 2009. Collateral pricing. *Journal of Financial Economics* 91, no. 3: 339–360.

Bharath, S. T, and T. Shumway. 2008. Forecasting default with the Merton distance to default model. *Review of Financial Studies* 21, no. 3: 1339.

Bharath, Sreedhar T., Jayanthi Sunder, and Shyam V. Sunder. 2008. Accounting Quality and Debt Contracting. *The Accounting Review* 83, no. 1: 1-28.

Carey, M., and M. Gordy. 2004. Measuring Systematic Risk in Recoveries on Defaulted Debt I: Firm-Level Ultimate LGDs. *Working Paper*.

Chava, S., and M. R Roberts. n.d. How does financing impact investment? The role of debt covenants. *Journal of finance* 63, no. 5: 2085–2021.

Edgington,, E., and P. Onghena, 2007. *Randomization Tests*. 4th ed. Chapman & Hall.

Francis, J., R. LaFond, P. M Olsson, and K. Schipper. 2004. Costs of equity and earnings attributes. The *Accounting Review* 79, no. 4: 967–1010.

Göx, R. F, and A. Wagenhofer. 2009. Optimal impairment rules. *Journal of Accounting and Economics* 48, no. 1: 2–16.

Gigler, Frank, Chandra Kanodia, Haresh Sapra, and Raghu Venugopalan. 2009. Accounting Conservatism and the Efficiency of Debt Contracts. *Journal of Accounting Research* 47, no. 3 (6): 767-797.

Graham, J. R, S. Li, and J. Qiu. 2008. Corporate misreporting and bank loan contracting. *Journal of Financial Economics* 89, no. 1: 44–61.

Hart, O., and J. Moore. 1994. A theory of debt based on the inalienability of human capital. *The Quarterly Journal of Economics* 109, no. 4: 841–879.

Hillegeist, S. A, E. K Keating, D. P Cram, and K. G Lundstedt. 2004. Assessing the probability of bankruptcy. *Review of Accounting Studies* 9, no. 1: 5–34.

Ivashina, Victoria. 2009. Asymmetric Information Effects on Loan Spreads. *Working Paper*.

Li, J. Accounting conservatism and debt contract: Efficient liquidation and covenant renegotiation. *Working Paper*.

Merton, R. C. 1974. On the pricing of corporate debt: The risk structure of interest rates. *Journal of finance* 29, no. 2: 449–470.

Nikolaev, Valeri V. 2010. Debt Covenants and Accounting Conservatism. *Journal of Accounting Research* 48, no. 1 (3): 51-89.

Murfin, J. 2010. The Supply-Side Determinants of Loan Contract Strictness. *Working Paper*.

Ohlson, James A. 1980. Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research* 18, no. 1: 109-131.

Owens, E. L. 2010. Bankruptcy Contagion and the Market Response to Intra-Industry Earnings News. *Working Paper*.

Papke, L. E, and J. M Wooldridge. 1996. Econometric methods for fractional response variables with an application to 401 (k) plan participation rates. *Journal of Applied Econometrics* 11, no. 6: 619–632.

Roberts, M. R, 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. W Vishny. 1992. Liquidation values and debt capacity: A market equilibrium approach. *Journal of Finance* 47, no. 4: 1343–1366.

Shumway, T. 2001. Forecasting Bankruptcy More Accurately: A Simple Hazard Model. *The Journal of Business* 74, no. 1: 101–124.

Standard and Poor's. 2009. *A Guide to the Loan Market*.

Sunder, J., S. V Sunder, and J. Zhang.2009. Borrower Conservatism and Private Debt Contracting. *Working Paper*.

Tirole, J. 2007. *The theory of corporate finance*. Princeton University Press Princeton, NJ.

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, no. 4: 29–44.

Vassalou, M., and Y. Xing. 2004. Default risk in equity returns. *Journal of Finance* 59, no. 2: 831–868.

Watts, Ross L. 2003. Conservatism in Accounting Part I: Explanations and implications. *Accounting Horizons* 17, no. 3: 207-221.

Zhang, J. 2008. The contracting benefits of accounting conservatism to lenders and borrowers. *Journal of Accounting and Economics* 45, no. 1: 27–54.

Zmijewski, M. E. 1984. Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research*: 59–8