Composition Risk:
How Debt Structure Impacts Debt Contracting*

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Abstract

In a subordinated debt setting, the credit risk of a lender depends not only on the value of the defaulting firm but the relative sizes of each creditor's claim. I test if this channel of risk, which I title composition risk, is reflected in creditors' contracts. Using a novel source of data (assembled via a machine learning technique unique to this paper) on the universe of syndicated lending covenants, I perform one of the first apples-to-apples comparisons of the covenant packages of comparable bonds and loans issued by the same firm at about the same time. I document that bank lenders enjoy a significant covenant 'protection premium' over comparable bonds and that the composition risk implied by the debt structure of the firm is a strong determinant of the strength of this premium, even after controlling extensively for credit quality. As the size of the senior debt tranche grows to unity, senior bank lenders demand relatively stronger covenant protections while bondholders demand relatively higher credit spreads. Using a structural model of subordinated default, I show that this disparity in responses can potentially be explained by the low recovery risk tolerance of bank lenders.

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One of the foundational insights of the literature on debt contracting is that the covenant restrictions included debt contracts help to resolve the agency conflicts that naturally arise between equityholders and debtholders. These agency conflicts arise because debt contracts and equity contracts have opposing payoff structures and this, combined with a division of control, creates the potential for equityholders to take actions which might be to the detriment of debtholders. This model of credit risk is sufficient if there is just one class of creditor. In this case, the only source of risk that matters to creditors is the agency risk associated with lending. However in the case of a subordinated debt structure with multiple classes of creditor, the payoffs of a debtholder will depend not just on the agency risk associated with lending but also where they rank in the priority structure and relative sizes of junior and senior creditor's claims. This credit risk arising from the subordination of the debt structure presents a heretofore unexplored source of risk for senior and subordinated creditors which I call 'composition risk'.

Composition risk is a form of credit risk which can operate entirely independently of the traditional agency channel. Mechanically, a *ceteris paribus* proportional increase in the size of the senior tranche lowers recovery rates (i.e. amount recovered per dollar invested) for both junior and senior creditors, even if the value of the firm recovered in default stays exactly the same. For senior creditors, proportionally increasing the size of the senior tranche mechanically dilutes their claim. On the other hand, increasing the size of the senior tranche mechanically concentrates the claim of junior creditors but (as I will show in the following section) this is more than offset by the fact that junior creditors first have to ensure that senior creditors recover the entire size of their (now larger) tranche. Thus the credit risk of *both* lenders is increased as the size of the senior debt tranche grows. Since the payoffs of equityholders are not directly affected by changing the debt structure of the firm (assuming a proportional change where total leverage stays constant), I interpret this risk arising from proportional changes in debt structure as a purely supply-side phenomenon. From this observation, I hypothesize that both senior and junior creditors should demand stricter terms in their contracts as the size of the senior tranche increases.

Composition risk is more than a purely theoretical notion. By examining the recovery rates of defaulted debt instruments, I show empirically that recovery rates for both classes of creditor are indeed decreasing functions of the size of the senior debt tranche. I then test how this composition risk is empirically reflected in the contracts of public and private debt. I examine the relative features (most notably, covenant protections and credit spreads) of bond and loan contracts and find that, even after controlling extensively for traditional measures of credit quality, the degree to which the debt structure is tranched between junior and senior debt does seem to be an important predictor of the relative covenant packages demanded by bondholders and bank lenders. Specifically, bank lenders demand relatively stronger covenant packages as they make up more of the debt structure. This suggests that covenant package inclusion is not driven solely by agency concerns but also by creditor concerns about how the debt structure of the firm affects their expected payoffs in default.

To perform a clean examination of the relative features of bonds and loans, I construct my sample so that the firm-level credit risk and agency concerns are the same for both debt contracts I examine. I accomplish this by considering pairs of debt contracts which are issued by the same firm at very close to the same time (maximum difference is one year but average in the sample is 6 months). I conduct my analysis in a sample of 1,283 bond-loan pairs issued by 359 firms. In each of these pairs, I examine a matched set of 16 debt covenants which are common to both bonds and loans[1] and see how bonds and loans make use of the same basic types of covenants.[2] I also compare the credit spread of the publicly traded bond with that of its matched loan counterpart matched as close as possible to the issuance date of the loan.[3] In this clean sample of comparable debt contracts, relative differences in one given feature of

[1]Specifically, I use the universe of bond covenants reported by Mergent FISD and a subset of the universe of loan covenants reported by my own data. As I discuss later in the paper, most of my results will be driven by variation in loan covenant usage so this selection procedure represents at worst a potential bias against finding a result.

[2]I define my relative protections outcome variable as the unweighted sum of the number of bond covenants included divided by the unweighted sum of the number of loan covenants included in a bond-loan pair.

[3]This is also expressed as a ratio so relative protections and relative spreads can be readily compared.

the debt contracts (say covenants) should largely be due to either 1) relative recovery rates between different classes of debtholders or 2) how the given feature trades off with the other features of the contract in equilibrium. I test to see how a variable which proxies for the former (i.e. the proportional size of the senior tranche) explains relative protections while controlling for the latter by including all of the observable characteristics of the respective contracts as controls.

Comparing covenants between bonds and loans is complicated by the fact that existing datasets on syndicated lending covenants (most importantly, LPC DealScan) tend to ignore the type of covenants most commonly employed by bond indentures. These types of covenants are called capital restrictions covenants and limit the scope of capital actions the firm can take. These include restrictions on actions such as the sale of unsecured assets, investments in entities outside of the credit group, merging with another entity, modifying liens or transacting with affiliates, to name a few. For a comprehensive overview, Ivashina and Vallee (2019) provide an excellent overview of such covenants and the types of risks they cover. In general, capital restrictions covenants are extremely common in syndicated lending agreements and that they frequently include carve-outs which weaken their application limiting the instances in which the restriction binds.[4] Despite their ubiquity in lending agreements and bond indentures, capital restrictions covenants are rarely covered by existing datasets on lending covenants.

In order to perform a true apples-to-apples comparison of covenant protections between junior and senior debt contracts, I assemble my own dataset on syndicated lending covenants sourced from a large sample of syndicated lending agreements as disclosed on SEC EDGAR. From these source documents I create a novel database of the universe of loan covenants using a machine learning technique that is also unique to this paper. I title this technique Title-Recombination K-Means (TRKM) and describe its process in detail in the Data section

[4]For example, investments or inter-company loans might be permitted in the case of restricted subsidiaries (who are subject to the same covenant restrictions as the parent) but not in the case of unrestricted subsidiaries.

and in Appendix A. Intuitively, the technique can be seen as a clustering exercise which uses contextual information from the contract to ensure quality of the clusters according to some intuitive criterion.[5] To verify the quality of my data, where overlapping covenant data exists in alternative datasets, I compare my data against it covenant-by-covenant and in almost all cases find that my data compares favorably with them.

My database has three distinct advantages over previous efforts and existing databases, all of which lack some or all of these features. First, my database captures the *universe* of covenants used by syndicated loans to public borrowers. LPC DealScan, the most commonly used source used of data on loan covenants, only has accurate data on *financial* loan covenants (commonly referred to as tripwires) whereas my data captures both the inclusion of financial covenants as well as capital restrictions covenants. Second, my database is historical in that it covers the vast majority of time since SEC filings were required to be digital (1996-2016). And third, my technique is reproducible and assembled from public data so it can be made available to other researchers.[6] In total, my database represents one of the most complete (in terms of both size and scope) databases on loan covenants ever assembled. My database contains about 30K contracts, each containing hundreds of potential covenants.[7] About 10K of these loan contracts match to LPC DealScan for data on pricing and other loan observables. Of these, about 7K of the contracts are issued by non-financial/utilities filers, and this comprises my primary sample of loans.

This paper has three main sets of empirical findings. The first set of findings establishes some new stylized facts about covenant usage in bonds and loans. First, I document that bank lenders make extensive usage of capital restriction covenants and note that their usage is heavily correlated with both the credit quality of the firm and the composition risk of

[5]A more technical description of my technique is that I use a two-step K-means clustering approach to first classify clause vectors of (up to) tri-grams into K overly-fine clusters which in a second step are then re-combined into larger clusters using contextual information about the titles of each section. I describe the technique in more detail in the Data section and in Appendix A.

[6]Data on the covenant packages used in this papers is posted on my academic website www.stevenfortney.com

[7]The database actually includes the measurable universe of *all* clauses employed by syndicated credit agreements but for the sake of simplicity I only focus on the negative covenants in this paper.

creditors. Second I find that that relative to bondholders, bank lenders enjoy a 'protection premium'. On average, syndicated lending agreements use covenants more intensively than matched bond indentures with the same credit risk. Bank lenders and bondholders also use different *types* of covenants as well. Bondholders employ covenant packages which tend to protect the value of unsecured assets while bank lenders use covenant packages designed to protect the value of secured assets as well as the priority of their claims. This is consistent with their roles as secured and unsecured creditors. Third, I find that the protection premium for loans grows as firms either approach default or as senior debt makes up more of the debt structure. A major reason the protection premium grows is because bank lenders increasingly include covenants which protect the unsecured value of the firm as well.

The second set of empirical findings examines what drives the protection premium for loans. I find that, consistent with the composition risk hypothesis, the debt structure of the firm is a strong predictor of the protection premium for loans, even at a within-firm level. Since bank-dependent firms are more likely to also be of lower credit quality, I verify that all results are robust to the inclusion of extensive battery of controls for the credit quality of the firm. Due to the lack of any exogenous instruments for the debt structure of the firm, I cannot claim that the results I present are truly causal. Rather, the results should be best interpreted to say that the debt structure of the firm explains within-firm variation in relative covenant protections in a way that traditional measures of credit quality cannot. As an additional robustness check to establish that the protection premium matters, I show that a commonly accepted assumption in the literature–that junior debt equally benefits from senior covenant protections due to cross-default/acceleration clauses– is not supported by the data. This implies that the protection premium confers a unique benefit to bank lenders vs bondholders. Finally, I show that the economic mechanism of composition risk holds in another context and can also explain why loan covenant intensity generally falls after a firm's first bond IPO.

Third, I find that the protection premium enjoyed by bank lenders can help make sense of the 'puzzling' fact posed in Schwert (2020) that bank lenders earn significantly lower credit spreads across the cross section of credit quality. I again establish this result via fixed-effect regressions at the within-firm level. Pairs of contracts with higher levels of relative protections for the loan also have higher relative levels of credit spreads for the bond. The intuition for this result is that when bank lenders have stronger covenant protections (which push up their rate of recovery in default), their equilibrium credit spreads can be lower. Bond holders also seem to respond to increased covenant protections for the loan by demanding modestly higher credit spreads themselves, suggesting that senior creditor covenant protections come potentially at the expense of junior creditors' recovery. Overall, this dynamic generates the interesting stylized fact that for firms that are majority bank financed, credit spreads for bonds are about twice as high as they are for loans and loans use covenants twice as intensely as bonds. However as bonds make up more of the debt capital structure, loans rapidly dispense with covenant protections and bonds demand lower levels of credit spreads until contracts look identical.

To further establish the theoretical consistency of the proposed mechanism, I show that the high sensitivity of lending covenant packages to the size of the senior tranche can be predicted by an adjusted version of the workhorse Merton model of default with subordinated debt. The adjustment I make in my model is to let the default threshold of the debt contract be freely variable. This allows me to accommodate covenant strictness into the model following the intuition of Black and Cox (1976).[8] I calibrate this model to an average firm in the data and consider what patterns of relative covenant usage are consistent with the historical recovery rates of senior and junior creditors. The key intuitive takeaway of this model is that because senior creditors expect high rates of recovery, they tend to contract in a region where the marginal recovery benefit of an additional covenant is low and so they need to include many covenants (compared to the bond) to meet their desired recovery

[8] In their model, covenant strictness is equated with the default threshold of the contract. Intuitively, contracts with higher default thresholds (i.e. they default sooner going into bankruptcy) should use more covenants and have tighter covenant packages.

threshold. This is significantly and asymmetrically relaxed when there is a larger junior tranche to absorb losses and so the model predicts that relative protections for loans should be weaker as the firm relies more on bonds to finance itself. This is the exact result I find above.

In terms of contribution, this paper extends the existing literature on a number of dimensions. This paper is arguably the first to examine relative protections of bonds and loans at a truly granular level. Though other papers have considered relative protections in the aggregate, the advantage of my data is that I only compare debt contracts with the exact same covenants written on almost the exact same fundamental asset (priority claims to said asset notwithstanding). The key insight that comes out of this analysis is that the debt structure of the firm asymmetrically affects the recovery rates and hence the contracts of senior and subordinated creditors and this source of risk explains the protection premium that loans enjoy over bonds. This is true even if the credit risk of the firm is held entirely constant. I also show that the puzzling patterns of bond-loan credit spreads documented in Schwert (2020) can at least partially be explained by a countervailing pattern of bond-loan covenant usage. The main covenant dataset used to answer these questions is both new to this paper and created via a novel machine learning method which is reproducible and tests well out-of-sample. Finally, I contribute to the theoretical understanding of this mechanism by extending a Merton model of subordinated default to accommodate a freely variable default threshold (which proxies for covenant demand). This allows me to generate predictions of relative covenant usage which line up well with those observed in the data.

This paper proceeds as follows. Section 1 describes the economic mechanism of composition risk and how debt structure mechanically impacts creditor returns. Section 2 discusses related literature. Section 3 describes my data-sources and sample construction. Section 4 describes the main findings of the paper. Section 5 presents a structural model of default with two features, 1) subordinated debt claims and 2) a variable default threshold and shows that this model can generate the patterns of covenant usage found in the data. Section 6 concludes.

1 Economic Mechanism and Hypothesis Construction

To illustrate how composition risk affects the returns of debtholders, I consider a simple model of expected creditor recovery rates when the expected value of the firm in default is completely general. This simple model can be thought of as a general case of the structural model I will present at the end of this paper. This example will imagine a simple subordinated debt arrangement and show that recovery rates (defined as the amount recovered divided by the amount invested) for *both* classes of creditor are decreasing in the proportional size of the senior tranche. The senior lender S will intuitively represent the bank lender and the junior lender J will intuitively represent the bondholder.

In this example, I assume that the total combined value of both debt claims is $K_T = K_S + K_J$ where K_T is fixed so K_S should be interpreted as the proportion of the debt capital structure which is funded by senior debt. The deterministic value of the firm which is entering bankruptcy $E[V|D]$ is set to be some value less than to the face value of debt, $E[V|D] \leq K_T$ This means at least one party (and possibly both) will expect to incur some losses as a result of the bankruptcy. Fixing the value of the defaulting firm to some deterministic value can be conceptualized as fixing the level of agency concerns between equity and debt as a whole to a level that incurs this amount of loss in bankruptcy.

The other assumption I make to characterize the problem is that borrowing demand is completely elastic so if creditors want to lend more they can always find willing borrowers to lend to at no penalty.[9] Under this assumption, the important consideration for creditors becomes the *rate* of recovery, not the absolute value of any one investment. This assumption makes sense given the generally diversified investing behavior of both banks lenders and bondholders.

[9]Alternatively, one can assume that the lenders in this problem have no market power and so can lend infinitely to any number of borrowers at no penalty.

The recovery rates (per dollar invested) of senior and junior creditors can be written as,

$$E[R_S|D] = \min\left[\frac{E[V|D]}{K_S}, 1\right] \qquad \text{and,} \qquad E[R_J|D] = \min\left[\max\left[\frac{E[V|D] - K_S}{K_T - K_S}, 0\right], 1\right] \quad (1)$$

One important fact to note is that in the above model, recovery rates are a function of the debt structure of the firm. The degree to which the debt structure is subordinated represents a potential form of dilution/creditors for creditors, however this specific form of dilution can operate even if the total amount of debt outstanding stays exactly the same. In this simple model where recovery rates are deterministic, it is easy to show that the following theoretical proposition holds.

Proposition 1: Composition Risk. *Recovery rates (per dollar invested) for both classes of creditor are decreasing in* K_S*, or,*

$$\frac{\partial E[R_X|D]}{\partial K_S} \leq 0 \quad \text{for} \quad V \geq 0 \qquad (2)$$

Proof: I consider each class of creditor in turn. Note that since K_S is in the denominator for senior creditor recovery rates, then the recovery rate of senior creditors is unambiguously decreasing in the size of the senior tranche. Taking the derivative of R_S with respect to K_S I obtain the following expression for the marginal effect of debt capital structure on senior creditor recovery rates,

$$\frac{\partial E[R_S|D]}{\partial K_S} = -\frac{E[V|D]}{{K_S}^2} \qquad (3)$$

The recovery rates of junior creditors ($0 \leq R_J \leq 1$) are also decreasing in the size of the senior tranche as well. Taking the derivative of R_J with respect to K_S, I obtain the following expression for the marginal effect of debt structure on junior creditor recovery rates, or the subordination effect for junior creditors.

$$\frac{\partial E[R_J|D]}{\partial K_S} = \frac{E[V|D] - K_T}{(K_T - K_S)^2} \tag{4}$$

This expression is always negative whenever the recovered value of the firm ex-post of bankruptcy (V) is less than the total face value of debt (K_T). If the recovered value is larger than the total face value of debt ($V > K_T$) then all creditors always recover 100% or 1. In this region the derivative is zero. Thus, $\frac{\partial R_J}{\partial K_S} \leq 0$ everywhere $V > 0$ and the recovery rate of junior creditors is *also* a decreasing function of the size of the senior tranche. ■

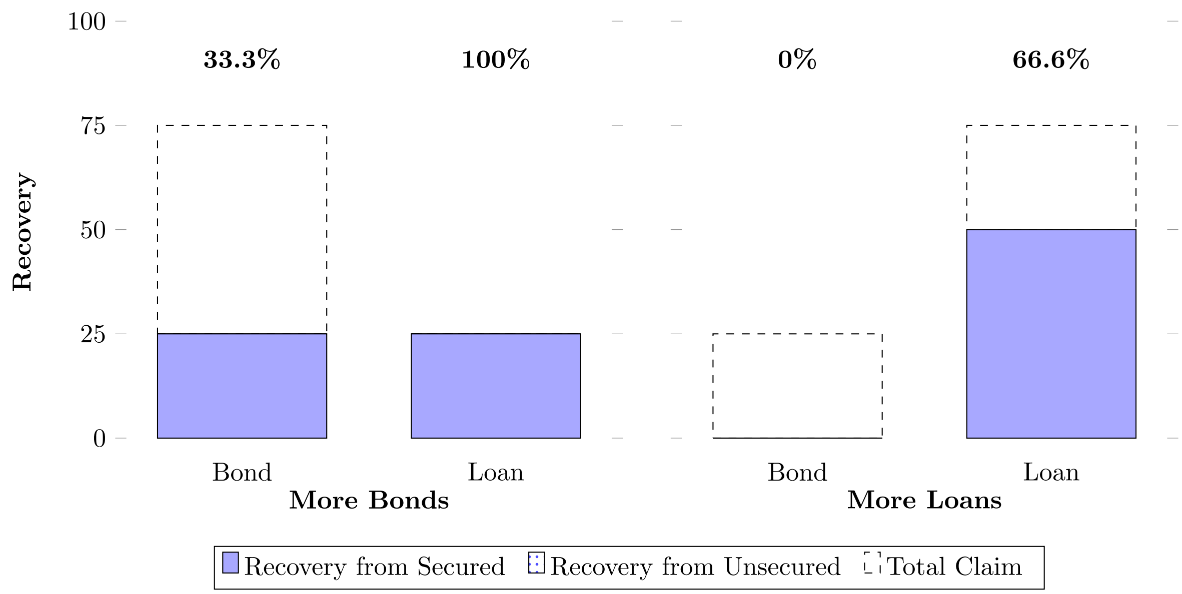
1.1 An applied example of composition risk

To visually illustrate Proposition 1, the Included Figure 1 considers an applied example which shows the recovery rates for each class of creditor under two potential debt structures, one with less senior debt and one with more senior debt. In this applied example I will choose bank lenders to represent the most senior tranche of debt and bondholders to represent second-most senior tranche of debt.[10] The total value of outstanding firm debt will be assumed to be 1 dollar and value of the defaulting firm will be deterministically set to 50 cents. The first case considers a firm with a debt structure of 75 cents of bonds and 25 cents of loans, and the second case considers the reverse.

[10] As Table E1 in Appendix E shows using data from Moody's, this assumption tracks well with the data. Though bonds can indeed be the most senior creditor if there is no bank debt, when both bonds and loans simultaneously exist in the debt capital structure, bonds are virtually never senior to loans in the priority structure. This only happens in 5 of 687 non-financial/utility defaults recorded by Moody's, or 0.7% of the time.

Included Figure 1:

Impact of debt structure on creditor recovery rates



As the figure above shows, when the majority of the firm's debt is financed by senior debt, the recovery rates (in bold) for *both* classes of creditors falls.[11] Recovery rates for bank loans fall from 100% to 66% and recovery rates for bonds fall from 33% to 0%. This is true even though the value of the firm V recovered in default stayed exactly the same.

While this result may seem initially counter-intuitive, it merely represents the simultaneous dilution of senior and junior creditor's claims. Senior creditors' claims are diluted when they finance proportionally more of the firm's debt. Meanwhile, junior creditors' claims are concentrated by proportionally financing less of the firm's debt but this is more than offset by the fact that, due to absolute priority, junior creditors have to ensure that a larger senior debt tranche is made whole before they can recover anything.

Considering the common analogy of junior and senior creditors as people "in line" to collect on their claims is also illustrative. In the event of bankruptcy, senior creditors would

[11] This will strictly hold in any case where the recovery value of the firm is less than the total combined value of all debt claims.

prefer to have less people jointly at the front of the line with them. Likewise, junior creditors would like there to be less people strictly ahead of them in line, even at the expense of there being more people jointly at the back of the line with them.

1.2 Hypothesis Construction

Proposition 1 implies an obvious empirical hypothesis to test which I formalize below:

Hypothesis 1: Composition risk. *Recovery rates for both classes of creditor are decreasing functions of the size of the senior debt tranche.*

If this hypothesis holds then this leads to an additional hypothesis regarding how creditors respond to composition risk.

Hypothesis 2: Creditor compensation for composition risk. *In a competitive market, lenders whose debt contracts which are made riskier due to composition risk should be able to demand additional contractual concessions in the form of stricter covenants, higher credit spreads, shorter maturities, etc.*

In the absence of a more detailed theory on what features of their contracts junior and senior creditors will adjust in response to an increase in composition risk, it is impossible to predict exactly what sorts of concessions creditors will demand in response to their riskier contracts. Thus the hypothesis merely predicts that contractual terms will tighten along at least one dimension in response to an increase in composition risk. I test both of these hypotheses in Section 4, I find strong evidence for Hypothesis 1 and mixed evidence for Hypothesis 2. Senior bank lenders respond strongly to an increase in composition risk while junior bondholders don‘t seem to respond directly to this risk. Bondholders do however respond indirectly to the the response of bank lenders. The type of contractual concession demanded by bank lenders takes the form of relatively higher covenant protections and junior creditors respond to this loss in relative protections by demanding higher credit spreads in their own contracts. In section 5 I explore a more detailed structural model of subordinated default and show that, under the assumptions of an average borrower, a covenant protection premium for senior creditors is needed to rationalize the high rates of recovery they empirically capture.

2 Related Literature

2.1 Debt covenants

Broadly speaking, this paper fits into a wider stream of literature that looks empirically at covenant usage in debt contracts and broadly tries to understand the design of them. In the space of private bank debt, Nini et al. (2009) and Nini et al. (2012) show that covenants are used by creditors to prevent firms from taking actions that might adversely affect them and also as a form of governance. Demiroglu and James (2010), Murfin (2012), Demerjian and Owens (2016) and Wang (2017) attempt to measure the "slack" inherent in included covenants and find that the intensive margin of covenant inclusion matters in addition to the extensive margin. Roberts and Sufi (2009) and Roberts (2015) establish that covenant packages are frequently renegotiated.[12] Chodorow-Reich and Falato (2019) show that covenant violations are a channel by which banks can ratchet down loan obligations or demand concessions. Covenant protections and security interests can differ even within the same loan package. Berlin, Nini and Yu (2019) show that institutional tranches of loans have far less control rights than the non-institutional tranches. There is also a smaller body of literature examining covenant usage in debt contracts which are not bank loans. Smith and Warner (1979), Berlin and Loeys (1988), Deng, et. al. (2016), Green (2018), De Franco, et. al. (2020) all consider the use of covenants in bonds. Gompers (1998) and Kaplan and Stromberg (2003) consider their use in venture capital debt contracts.

One thread that unites nearly all of the above papers is the idea that covenants provide a degree of control for creditors which helps mitigate agency conflicts between equityholders

[12] Gorton and Kahn (2000) theorize that the potential for renegotiation of these control rights makes contractual terms reflect this possibility as well as the true risk of default.

and debtholders. Bradley and Roberts (2015) call this idea the Agency Theory of Covenants (ATC) and note that because including covenants remedies a fundamental inefficiency, this should lead creditors to accept lower credit spreads in exchange for more covenants. [13] Bradley and Roberts (2015) test this hypothesis and find that covenants and credit spreads are substitutes once you condition on the fact that the unobserved quality of borrowers who use covenants is lower.[14] Under the ATC, the implicit assumption is that covenants proxy for risks arising from agency concerns. In this paper I show that for borrowers with subordinate tranches, covenant inclusion can be also driven by the risks the creditors bear due to composition risk as well.

This paper is also one of the first to examine the *universe* of covenants used by senior bank debt. Bank debt typically uses two types of negative covenants, financial covenants and capital restrictions covenants. The vast majority of papers in this space consider only the financial covenants.[15][16] Two of the first papers which attempt to consider the universe of covenants in a comprehensive manner are Ganglimir and Wardlaw (2017) and Ivashina and Vallee (2019). Ganglimir and Wardlaw (2017) construct their data in an analogous manner to my own using machine learning techniques on the sample of loan contracts collected by Sufi (2009). On the other hand, Ivashina and Vallee (2019) look at the capital restrictions covenants from a proprietary sample of about 1000 loans from industry data source, Street Diligence.[17] As I discuss in Section 2, both of these sources of data are insufficient either in terms of precision (the former) or history (the latter) for the analysis of relative contracting I conduct in this paper.

[13] As Bradley and Roberts (2015) note, one of the "important implications of the ATC [is]...a negative relation between the promised yield on corporate debt and the presence of covenants".

[14] Matvos (2013) performs a similar exercise of trying to estimate the strength of this negative relationship.

[15] All of the above papers use DealScan as their main source of data on loan covenants so this fact is almost certainly a reflection of the fact that DealScan only has comprehensive data on financial covenants.

[16] In addition to this, my data also collects the Affirmative covenants which I do not explicitly consider in this paper but are the primary mechanism by which banks monitor their loans.

[17] Ivashina and Vallee show that negative covenants are frequently weakened by 'carve-outs' which let the borrower engage in a limited amount of the restricted action.

2.2 Debt Structure

Though this paper is the first (to this author's best knowledge) to consider how the debt structure of the firm serves as a source of risk for creditors, this is not the first paper to consider the general effects of a firm's debt capital structure on firm outcomes. An important paper related paper on debt structure is Rauh and Sufi (2010). They compare the usage of bond covenants (4 types) with loan covenants (2 types) in the unidentified aggregate (they compare bonds and loans by grouping by credit quality) and find that low credit quality firms use "bank debt with tight covenants and subordinated non-bank debt with loose covenants." I find the same basic patterns at a granular level but my covenant data is more comprehensive[18] so I can make much stronger inferences. Low quality borrowers *simultaneously* use bank debt with lots of covenants and bonds with few covenants and the *types* of covenants used by each party suggest very different goals. Because my data identifies truly comparable bonds and loans, I can infer what is actually driving this pattern. Within-firm variation in relative protections seems to actually be driven by changes in the debt capital structure that occur concurrent with a deterioration in credit quality. Though Rauh and Sufi note that low quality firms also have a multi-tiered debt capital structure, they do not make the connection (or cannot test this because of the aggregate nature of their data) that it is precisely this multi-tiered debt capital structure that is a key driver of these covenant patterns.[19]

Another important paper in this space is Lou and Otto (2018) who consider how financial covenants usage for (only) loans varies with heterogeneity in the debt capital structure. They find that firms with more concentrated debt capital structures[20] use less loan covenants. They do not consider bond covenant usage. In contrast (and consistent with Rauh and Sufi

[18] I compare 16 covenants, all of which are mutually common to both types of debt

[19] As further evidence which is consistent with this story, Carey and Gordy (2016), examine the impact of debt capital structure on the firm-wide recovery rate in bankruptcy and find that debt capital structure "has a more economically material empirical influence on recovery rates than all other variables we try taken together".

[20] As measured by the HHI of seven classes of debt.

(2010)), I find no relation with debt capital structure concentration *per-se* but instead I find the directional result that the *type* of concentration matters. Firms with debt capital structures concentrated around bank debt use more loan covenants overall (both absolutely and relatively) but firms with debt capital structures concentrated around bond debt use less loan covenants overall.[21]

2.3 Textual Analysis

Finally, this paper adds to the literature on textual analysis of financial documents by describing a new textual analysis technique which is uniquely suited to parsing contractual data (or any document with titled subsections where one expects some degree of standardization in the language). Though initial papers in this space restricted themselves to considering one covenant of interest which could be scraped (Nini et al. (2009) is an example of this), textual analysis techniques have become increasingly more sophisticated in recent years. From the cosine similarity methods used to quantify textual difference[23] to the more advanced topic modeling style techniques used to taxonomize textual similarity[24], textual analysis techniques are becoming more widely-used and accepted tools in the literature. My technique uses one of the simplest forms of off-the-shelf machine learning (K-means clustering) and combines it with an intuitive criterion specifically designed for legal contracts (namely, that lawyers like to use descriptive titles and these can be used to refine the clusters), to create a database of loan covenants that is larger in both scope and size than any such database before it. I describe the details of the technique below in Section 3 and in Appendix A.

[21] I also use a formal structural model to motivate my results and show that my results are consistent with this model. Other notable distinctions are that I consider a much more comprehensive database of covenants[22] and my results also extend to explaining within-firm variation in covenant usage.

[23] Hanley and Hoberg (2010), Brown and Tucker (2011), Hoberg and Phillips (2015), Lang and Stice-Lawrence (2015) and Cohen et al. (2020) all do some version of this.

[24] Ganglimir and Wardlaw (2017) and Kelly et al. (2019) both employ this type of technique.

3 Data

In this section I describe the data used to test Hypotheses 1 and 2 as described in Section 1.

3.1 Recovery rate data

To empirically test the first hypothesis, that composition risk negatively impacts the recovery rates of both junior and senior lenders, I use data from Moody's Ultimate Recovery Database. This data tracks debt instrument-level recovery rates for a large sample of defaulted corporate instruments. For consistency with the rest of my sample, I exclude financial and utilities from the analysis and report summary statistics in Table 12.

Moody's also reports where each debt instrument ranks in the priority structure of the firm. This is titled the instrument's collateral rank.[25] Using this data, I can impute what the proportion of senior debt (or, collateral rank = 1) is in the firm at the time of default. By taking the size of the most senior tranche (as a fraction of all outstanding debt claims) averaged across 688 bankruptcy events reported by Moody's I estimate that the average size of the most senior debt tranche is 43.23% in each bankruptcy event. I use this data below to test Hypothesis 1 and show that the recovery rate of creditors is a strong negative function of the size of the senior debt tranche entering default.

3.2 Bond and loan data

To test the second hypothesis, I create a database of the relative covenant protections and relative spreads of both public bonds and private banks loans, this paper uses a number of data sources. One of them is completely new to this paper and another is a novel combination of existing data. Data on relative covenant protections comes from combining data on bond covenants from Mergent FISD with a new dataset of historical loan covenants created via machine learning (I refer to this dataset as the Historical dataset for brevity). Data on

[25] Multiple instruments can share a collateral rank. For example, multiple senior secured loan facilities might all be equally ranked as first in the priority structure.

relative spreads comes from combining Loan All-in-Drawn Spread data from LPC DealScan with a public proxy of Schwert's proprietary Bond Swap Spread data from Bank of America Merrill-Lynch (BAML). I reconstruct a public proxy of Schwert's proprietary BAML Bond Swap Spreads data by using data from WRDS Bond Returns as well as well as data on Treasury Swaps from the Chicago FRB plus data on TED Spreads from FRED.

Data on relative protections/spreads is identified by considering pairs of bonds and loans matched by issuer and time of issuance. The goal behind the sample selection procedure is to find clean pairs of debt contracts which are identical in the agency conflicts between debt and equity and as close as possible in the observable characteristics of the debt contracts. In this section I begin by discussing the details of my sample selection procedure and how I match bonds and loans together. This is followed by a discussion of my data sources and how I define relative protections and relative spreads. Finally, I discuss two test variables of interest, debt capital structure and distance-to-default.

3.3 Sample Selection

Table 1 describes the process of constructing my sample which I detail in this section. I start with a sample of 434,810 bonds from Mergent FISD and a sample of 10,204 loans from my historical loan covenant database[26] merged with LPC DealScan. Since covenants contracting occurs at the package level for loans[27] and the series level for bonds, I only use one facility from each loan package and one bond issue from each series of notes (identified by multiple bonds issued by the same firm on the same day). Facilities in a package are chosen by taking the facility in a package with the longest maturity (since bonds are almost uniformly longer maturity than loans). Bonds in a series (where applicable) are generally differentiated by their maturity date and so for each bond in a series I chose the bond with the best maturity

[26] Details of the construction of this historical loan covenant database are found in Section 3.2 and in Appendix A.

[27] Murfin (2012)

match to the loan to represent the series.[28] After dropping (in both datasets) observations with no covenant data, restricting both datasets to the same sample period (1996-2016) and dropping financial firms (SIC code 6000-6999) and utilities (SIC 4900-4999), I am left with two samples. These are a sample of 18,305 bonds to 5,158 firms and a sample of 7,705 loans to 3,615 firms.

I then match together pairs of bonds and loans from the two samples based on two criteria. First, the bond and loan must be issued by the same firm and second, the bond and the loan must be concurrently active. This gives me a matched sample of 10,904 bond-loan pairs to 1,053 firms.[29] However, there remains the problem that even within the same firm, credit quality can change over time and thus any observed difference in contracting might be due to time varying factors. Because of this, I restrict my sample to only consider bond-loan pairs which are issued within a maximum one year of one another. This leaves me with a sample of 2,392 bond-loan pairs issued to 721 firms. While 1 year is the maximum allowed difference, the average difference in issuance dates is much closer to six months. This allows me to be much more confident that I am capturing a pair of contracts which have almost exactly the same level of agency concerns. At this point I also match observations to Compustat by using the closest quarterly observation before the first issuance date in the bond-loan pair. [30]

For 72 of the 2,392 observations (about 3% of observations), the number of loan covenants included in the loan is 0. To create a ratio variable without undefined values, I drop these 72 observations. The number of bonds with 0 covenants is far higher so I do not use the inverse of this ratio. As a quick placebo test to ensure that dropping these observations is not

[28]Since covenants generally apply to all facilities in a package and bond in a series of bonds, the specific facility/bond that is chosen is not of foremost importance for the analysis of this paper. Nonetheless, I include both loan-type fixed effects for loans and maturity controls for bonds for to account for any systematic effect that the choice of one specific facility or bond might have on my outcome variables.

[29]In this paper, an observation will refer to a bond-loan pair meeting these criteria.

[30]I also keep track of the absolute difference (in days) between the issuance days as well as a binary variable indicating if the loan was issued before the bond and include them as controls in all of my regressions. These are frequently denoted as "Match Controls" and are rarely significant. Results are always robust to either including or excluding them so I report all results with them included.

materially affecting my results, I consider the counterfactual where these 72 observations are instead set equal to the next closest discrete value of 1 and find very similar results. After making this cut I am left with 2,320 to 709 firms.

I then merge the data with the Capital IQ database. Capital IQ is a database that tracks the composition of debt in a firm's debt capital structure. After doing this merge I am left with 1,696 observations for 523 firms. I then further clean the bond data by dropping secured, convertible and non-publicly issued bonds. This leaves me with 1,340 observations for 393 firms. Finally, I drop micro-cap firms (market capitalization less than 300 MM). This leaves me with a final sample of 1,283 bond-loan pairs issued to 359 firms.

One final important note is that I do not perform any explicit cuts on the security level of the loan as reported by LPC DealScan. The reason for this is because of the inadequacy of the existing data on whether or not loans are secured[31] and the safety of the assumption given the legal details of how bank loans are actually secured in practice.[32] Effectively, I am assuming that all loans in my sample are secured.[33] As Table D1 confirms, data from Moody's confirms that this assumption is a good one as only 5% of defaulted loans are reported as completely unsecured.

3.3.1 Matched bond-loan sample characteristics

Table 2 reports the summary statistics for the sample of matched bonds and loans. Generally speaking, my sample is composed of larger, publicly traded firms than the average firm. This is because the main source of my data for loan contracts is SEC filings and also because firms which issue bonds are larger than the average firm (even among publicly traded firms). The average firm in my sample has a market capitalization of 20.6 billion dollars with about

[31]The majority (55%) of observations for whether or not a facility is secured in LPC DealScan are empty.

[32]So called, 'Dragnet' clauses can be used to secure either ex-post or ex-ante other loans from the same lender that might be unsecured. They are commonly included in security agreements (which are frequently a distinct document from the publicly available credit agreements) and state that the currently considered security interest can be used to secure any of the secured party's future (or occasionally, past) claims against the debtor. This is true even if it is not explicitly stated in the unsecured contract.

[33]Schwert (2020) also makes this same assumption.

7 billion dollars of total (long-term plus short-term) debt outstanding. The average loan facility in my sample has a face value of about 1.2 billion and the average bond in my sample has a face value of 500 million dollars.

Consistent with the fact that bonds typically have longer maturities than bonds, the average bond in my sample has a maturity of 138 months or 11.5 years while the average loan has a maturity of 56 months or 4.6 years. As an alternative, it is possible to match bonds and loans on closest maturity (Schwert (2020) does this) which might close this gap. However, doing so would necessarily come at the expense of matching to the closest issuance. Since debt maturity is an observable characteristic of the debt which can be directly controlled for, I choose to prioritize matching on issuance date. This ensures that I control for as much of the unobservable variation in agency concerns as possible.[34]

In terms of covenants, loans tend to use covenants more intensively on average than bonds. The average loan uses 5.7 covenants while the average bond uses 3.4 covenants (out of a possible total of 16). In terms of credit spreads (compared at the day of the loan origination), the average loan in my sample has an All-in-Drawn spread (over LIBOR) of 164 basis points while the average bonds has a proxied bond swap spread spread of 214 basis points (over LIBOR). Already in the aggregate summary statistics, one can see a general pattern emerging. Loans, which are have priority, typically use higher levels of protections and have lower levels of credit spreads. Bonds, which are do not have priority, have lower levels of covenant protection and modestly higher spreads. This is a fact which will be established rigorously later on in the paper.

Table 3 compares the summary statistics of my matched bond-loan sample against the component datasets which were used to construct it. From this, I can conclude that my sample is in the 'middle' of the sample of bonds from Mergent and the sample of loans from my historical dataset. In terms of firm characteristics, firms in my sample have characteristics that makes them look bigger than the average loan issuer and marginally smaller than the

[34]As an additional desirable characteristic, not matching on maturity helps my sample of bonds better reflect the average maturity of bonds in the general population.

average bond issuer. This is consistent with Rauh and Sufi's (2010) conclusion that firms with a tiered capital structure are relatively medium-low quality compared to the average bond issuer.

3.4 Measuring Relative Covenant Protections

To construct a measure of the relative covenant protections between bonds and loans, the first step is to collect data on the historical universe of both loan covenants and bond covenants. For bond covenants, Mergent FISD provides relatively detailed and complete data on the historical universe of covenants employed by public debt. For loan covenants, the existing available data is either incomplete in 1) scope or 2) history. The most commonly used database on covenant protections for loans is LPC DealScan. While the historical coverage for LPC DealScan is quite good, the scope of covenants it relatively covers is primarily limited to the financial covenants. As Ivashina and Valle (2019) note, "studies looking at credit agreements have a narrow coverage of contractual provisions". For the most commonly used databases (including LPC DealScan), "the variables on contractual provisions exhibit a majority of missing values, creating the risk of significant composition effects". Another set of data commonly used by practitioners but less so by academics is the FactSet Current Bank Loans dataset. While this data reliably captures the universe of covenants, it is only available for currently active loans which significantly limits the sample. While the limitations of these datasets make them unsuitable for the scope of this project, they do serve as useful checks to verify the accuracy of my data I collect. As is seen in Figures 11 and 12, the data I collect compares well with both FactSet and DealScan where they overlap.

For the two reasons mentioned above, I collect my own data on loan covenants which is historical and more universal in scope by applying a novel machine learning technique (detailed in the next section) to scraped credit agreements from SEC EDGAR. This technique allows me to gather the universe of covenants employed by bank loans. In fact, instead of gathering just covenants, this technique actually gathers the universe of *all* clauses used by bank lending contracts. However, for this paper, I only focus on the covenants since the question under consideration is one of relative covenant protections between bonds and loans.

3.4.1 Loan Covenants Data and TRKM Methodology

Data on the historical universe of loan covenants is collected via a novel application of a common machine learning technique to scraped credit agreements from SEC EDGAR. The steps of the process which I call Title-Recombination K-Means (TRKM) can be summarized as follows.

First, I scrape the loan credit agreements from SEC EDGAR. Second, I use an adaptive algorithm[35] to parse each lending agreement text into its component subsections. Third, I vectorize these subsections, transforming them from text snippets into numerical vectors. Fourth, I cluster the numerical vectors together using an off-the-shelf K-means algorithm but I choose to deliberately over-cluster. This will create overly-small or overly-specific clusters which will them be recombined using contextual information from the contract in the next step. And fifth, I recombine clusters of subsections which have the same modal title. Since each subsection in a contract comes with a title attached, I find the most common title of all the subsections inside each cluster and then recombine clusters which report the same modal title. The result is a dataset of *all* the possible groups of subsections which might be included in a lending contract and if each lending contract contains an element of that group. Intuitively, the method finds all the potential clauses which might exist in a contract and reports their presence for each contract. This is coded as a 1-0 binary variable. I discuss the economically important insights from this method below while relegating a discussion of the technical details to Appendix A.

Importantly, I verify the quality my data out of sample and find that the results output from this technique compare very favorably against the covenant datasets previously men-

[35] Created via a combination of Python and Regex.

tioned. Figures 11 and 12 show how my data compares (where it happens to overlap) with data from 4 sources.[36] In both comparisons, my covenant data seems to capture the broad moments (Figure 11) and co-movements (Figure 12) of their publicly available counterparts for almost all covenants. In the few covenants categories where there exists a discrepancy, it can generally be explained by the way each dataset chooses to categorize and aggregate potentially different covenants together as one category.

3.4.2 Comparing TRKM with previous approaches

Before moving on, it is important to note that the spirit of this exercise is very similar to what has been done in past literature, albeit on an entirely different scale. Exploiting the structure and relatively standardized language of legal contracts to extract information is hardly new. Perhaps the first paper to do at scale this is Nini and Sufi (2009) which uses text parsing techniques to identify contracts which contain Capital Expenditures restrictions. Their analysis is possible because the same basic set of words is used in most capital expenditures restrictions covenants. Many other papers have performed a similar manual exercise to identify small numbers of covenants in which they have a particular interest. The process can be roughly boiled down to two steps; 1) reading a large number of contracts to identify key phrases which can, in turn, be used to identify a given covenant with a minimum of error and, 2) writing code to parse the text looking for these key phrases. At its core, the idea depends on the relatively standardized nature of legal language.

The machine learning technique which I use in this paper can be simplistically viewed as a formalization of this two step process. My technique can also be expressed in two basic steps; 1) take each subsection in a contract and express it numerically (as a vector) in such a way that the words (and groups of words) which are relatively more common in that subsection are highlighted and, 2) group together subsections based on these highlighted words which are common to the subsection but uncommon to the rest of the corpus. The

[36]Ganglmair and Wardlaw (2017) do not provide data on the composition of their covenants and so I cannot compare my data against theirs as I do others.

connection to the manual technique is that the process of finding words (or groups of words) which are common to one subsection and uncommon to the rest of the corpus is very similar in spirit to the process of manually finding key phrases to recognize specific covenants. The technique I use in this paper simply formalizes what is typically an ad-hoc, manual process in a more reproducible way.

3.4.3 Bond Covenants Data

Bond covenant data comes from Mergent FISD. Unlike the available datasets for loans, Mergent FISD is both complete in scope and historical. The data from Mergent FISD is structured similarly to my own. Like my own data, binary variables indicate if a given covenant is present or not in each bond indenture.

Though Mergent tracks a total of 31 covenants[37] for both the parent and its subsidiaries[38], I only use covenant data which applies directly to the parent. After applying this restriction I get a total of 16 restrictive covenants from Mergent FISD. I match each bond covenant category to its loan covenant counterpart.

3.5 Relative Covenant Intensity Index

Using the previously described data on the universe of bond and loan covenants, I construct a matched set of covenant categories that are common to both loans and bonds. To do this, I first consider each bond covenant in Mergent FISD and then hand-match each bond covenant to its loan analogue in my own data.[39] One covenant in Mergent FISD can match to potentially multiple covenants in my own dataset.[40] In total, I match 16 covenants between

[37] These are found in the "Additional Issuer Information" file of Mergent FISD.

[38] An example might be a restriction on the parent issuing dividends vs. a restriction on the subsidiary issuing dividends.

[39] For full details of the exact way in which I hand-match covenants between bonds and loans, see Table 12.

[40] As an example, I hand-match the Mergent FISD covenant 'Assets Sale' to the "Sale of Assets" and "Disposition of Assets" covenants (among others) in my own dataset, as a disposition is a commonly used legal term for a sale.

Mergent FISD and my own dataset.[41]

Then, after constructing a matched set of covenants, I construct an index of relative covenant intensity for each bond-loan pair. I define this as the ratio of the number of covenants included in the bond over number of covenants included in the loan.

$$BC/LC = \frac{\sum_{i=1}^{16} BC_i}{\sum_{i=1}^{16} LC_i} \tag{5}$$

Where i indexes the category of covenant and BC_i and LC_i indicate if the category of covenant i is present in the bond or loan, respectively.

The exercise of creating an unweighted index which counts the number of covenants included in a contract follows Bradley and Roberts (2015) who construct a similar covenant intensity index for loans using the covenants found in LPC DealScan.[42] Though it might be possible to construct a weighted index which might better capture the degree of protection offered by each covenant, I use a simple unweighted index for the same reason as Bradley and Roberts. As they note, "this approach is both transparent and reproducible. It also facilitates interpretation of the results and avoids any judgment regarding the efficacy or wealth effects of any of the covenants."

3.6 Measuring Relative Credit Spreads

To construct a measure of relative credit spreads between bonds and loans, one first needs to find a comparable type of credit spread that can be compared between the two types of debt. For both types of debt, this spread will be defined as the annual spread (in basis points) that the borrower pays above LIBOR to borrow. For loans this is simply defined as the All-In-Drawn spread (as reported in LPC DealScan). While this exactly meets the definition

[41]In order of frequency of use (by loans) the matched covenant categories are; liens, indebtedness, consolidations and mergers, transactions with affiliates, dividends related payments, sale of assets, investments, leverage ratio, restricted payments, interest coverage ratio, sales and leasebacks, maintenance of net worth, fixed charge coverage ratio, senior debt issuance, subordinated debt issuance and funded debt.

[42]Billet et al. (2007), Demiroglu and James (2010) and Lou and Otto (2018) also construct similar types of holistic measures

of a credit spread, this measure is really only valid around the date of issuance for the loan. As Roberts and Sufi (2009) and Roberts (2015) show, loans frequently renegotiate both the price (interest rates) and non-price (covenants) terms of their credit agreements. These renegotiations are not tracked by DealScan. Conversely, the coupons of bonds are almost never renegotiated[43] so their interest rates do not suffer from this immediacy problem but it is more difficult to impute what the appropriate spread above LIBOR would be for a bond. Schwert (2020) accomplishes this by using proprietary data on Bond Swap Spreads from Bank of America Merrill-Lynch (BAML). He defines the Bond Swap Spread as the option-adjusted bond yield minus the maturity matched LIBOR swap rate.

Since I do not have access to this proprietary dataset from BAML, I construct an proxy of Schwert's Bond Swap Spread measure using publicly available data. I do this by taking bond yields (in basis points)[44] and subtracting the sum of 1) the maturity-matched treasury swap rate and 2) the 3-Month TED spread (defined as the difference between the 3-month LIBOR and a 3-month treasury note). Bond yields to maturity are collected from WRD's Bond Returns, Maturity Matched Treasury Swap Rates are from Chicago FRB and 3-Month TED spreads are from FRED. If the time to maturity of the bond (in months) is T, then this approximation can be written,

$$BSS\_Proxy_T = YieldToMaturity_T - Treasury\_Swap_T - TED\_Spread_3 \tag{6}$$

The obvious departure with this approximation is that the TED spreads are not matched to the maturity of the yield and the treasury swap. It is worth asking how this affects the

[43] Their indentures typically require every bondholder to consent to such a renegotiation which is effectively impossible.

[44] Importantly, since the overwhelming majority (99.7% percent) of bonds in my sample are callable, I do not do any sort of options adjustment on my yields. The reason for this is that most loans are effectively callable as well due to pre-payment clauses. For this reason, the comparable credit spread for a callable loan is actually the credit spread for a callable bond. This implies that for the purposes of comparing with loan spreads, one should perform an option adjustment for the *non-callable* bonds. However, since non-callable bonds are such a minute part of the sample I do not perform any specific correction for these. In tables that available on request, the main results of this paper are robust to the exclusion of the non-callable bonds.

results. In Appendix C, I consider the term structure of the TED spread and find that before the 2009 Financial Crisis there is virtually no discernible term structure.[45] Thus, before this period, the error inherent in my approximation is likely to be small. I also compare my data against Schwert's BAML data and find that my data exhibits less variance over the cross section of credit quality. This would suggest that my relative spread variable understates the actual magnitude of the spread differential which would be a bias[46] against finding any results.

Using my bond swap spread proxy and the all-in-drawn spread from the loan, I define the relative spread ratio as the ratio of these two variables. Since the loan spread is only current on the date of issuance, this ratio is calculated on the day that the loan is issued in the bond-loan pair. For consistency with the above-defined covenant intensity ratio, I define the ratio with the bond spread in the numerator and the loan spread in the denominator.

$$BS/LS = \frac{BSS\_Proxy}{All\_in\_Drawn} \tag{7}$$

3.7 Test Variables

Finally, I construct two potential test variables to see if either can explain the patterns of variation I find in relative protections as well as the patterns that Schwert finds with relative spreads. The two variables I consider are the credit quality of the firm as well as the debt capital structure of the firm.

3.7.1 Distance-to-Default

Credit quality is proxied for by Bharath and Shumway's (2008) measure of distance-to-default. As in their paper, I construct distance to default as,

[45] Interestingly, this roughly corresponds with the time period in which the LIBOR price-fixing cartel was most active.

[46] Assuming variance in the cross-section of credit quality is representative of variance in the cross-section of debt capital structure.

$$DtD = \frac{\ln(V/D) - (r - .5\sigma^2)T}{\sigma\sqrt{T}} \tag{8}$$

Where V is market cap, D is short term debt plus half of long-term debt, r is the trailing one-year stock return, and σ is the one-year asset volatility and $T = 1$. This variable can roughly be interpreted as how many standard deviations a firm is away from defaulting within one year.[47] In addition to Distance-to-Default, I also consider a panel of 14 additional controls which might proxy for the overall credit quality of the firm, these are taken from Compustat and wherever possible scaled by the total assets for the firm.

3.7.2 Debt structure

The debt structure of the firm is proxied for by the percentage of total drawn debt that is financed via bank loans, as reported in S&P CapitalIQ. The reason I use bank debt percent as opposed to, bond debt percent, is that bank loans are assumed to be at the top of the priority structure. Because of this, it is always clear what a change in bank debt percent implies for the debt capital structure of the firm. Though I do not explicitly consider them, certain forms of debt (such as commercial paper) come in even lower on the priority structure than bonds and so observing a shift away from bonds (in isolation) implies an ambiguous change in the total debt capital structure of the firm.

4 Results

In this section I present the results of testing the hypotheses laid out in Section 1.

[47]Under the implicit assumption that default happens when the value of the firm falls below the face value of debt.

4.1 Empirically testing for composition risk

I begin by showing that, consistent with Hypothesis 1, the empirical recovery rates in default of both classes of creditor are decreasing functions of the size of the senior tranche. I also show that, for a symmetric change in debt structure, the recovery rates of bank lenders are more affected by composition risk than those of bondholders.

To test hypothesis 1, I exploit the fact that Moody's reports instrument-level recovery rates to directly test how debt capital structure impacts recovery rates. I regress the recovery rate (in percent) of the debt instrument on the size of the senior debt tranche in default, as well as a number of controls for the type of default. I also include both year and industry fixed effects to control for any systematic difference in industry level recovery rates or secular trends in recovery.

Table 13 reports the results of this test. I split my sample by the collateral rank of creditor as reported by Moody's and run two sets of regressions. The first set of regressions reports results for the class of creditor designated as the highest priority (Collateral Rank = 1) and the second set of regressions reports results for the class of creditor designated as the second-highest priority (Collateral Rank = 2). Though I do not report results for lower-ranking classes of creditor (Collateral Rank ≥ 3), the results for creditors further down in the priority structure also mirror those at the top, though decreasing in statistical strength due to a decreasing number of observations.[48]

The results suggest that the marginal effect of one percent increase in the size of the senior debt tranche is stronger for senior creditors (Collateral Rank = 1) as it is for junior creditors (Collateral Rank = 2). Reporting results from the regression specification with 4-Digit SIC code fixed effects, the effect of a 1% increase in the size of the senior debt tranche is associated with a 0.429% decrease in recovery rates for senior debt instruments and a 0.192% decrease in recovery rates for junior debt instruments.[49] Using the marginal effects

[48]The same economic mechanism which makes the second-highest priority creditor desire a smaller senior tranche also apply for third-highest priority creditor, etc.

[49]This conclusion is further bolstered by the the relatively high R_2 values reported by both sets of

as reported by the regression coefficients (denoted with hats), one can calculate the ratio of marginal effects described in equations 3 and 4 $\frac{E[\partial R_S/\partial K_S]}{E[\partial R_J/\partial K_S]} = \frac{\widehat{\partial R_S/\partial K_S}}{\widehat{\partial R_J/\partial K_S}} \approx 2.230$. This implies that composition risk affects the recovery rates of senior creditors are at least twice as much as those of junior creditors.

4.2 Capital restrictions covenants: Stylized Facts

Using data from my historical database of syndicated lending covenants, I note three key facts about the usage of capital restrictions covenants in debt contracts.

First, capital restrictions covenants are ubiquitous and their inclusion in contracts is highly correlated with measures of both credit quality and debt structure. Table 4 shows that some capital restrictions covenants are unconditionally present in almost half of lending contracts. These include restrictions on mergers, indebtedness, liens, and transactions with affiliates.[50] Figure 1 plots the incidence of 12 capital restrictions covenants and 4 financial covenants across the cross-section of firm credit quality. What becomes apparent from this graph is that, as firms get closer to default, contracts use all classes of capital restrictions covenants more intensively. Compared to a firm with a distance-to-default measure of 0, a firm who is far from default is about 50% less likely to see restrictions on dividends, investments and sales of assets and about 25-50% less likely to see restrictions on mergers, indebtedness, restricted payments, sales leasebacks, senior and subordinated debt issuance, and transactions with affiliates.

Second, compared to bondholders, bank lenders enjoy a general 'protection premium'. Bank lenders tend to use more covenants in general and the types of covenants they use relatively protect secured assets more than unsecured assets. In Figure 2 I plot the com-

regressions. Even without any controls or fixed-effects, the regression model for senior creditors which includes debt capital structure explains 28% of the cross-sectional variation. This rises to 37% with controls and to 71% when including industry-level fixed effects.

[50] Figures 11 and 12 compare these numbers with those reported by other data sources. The unconditional means I report are extremely similar to numbers reported in the small sample available from FactSet and are broadly similar, though universally lower than the number reported by Ivashina and Vallee (2019) from their sample of highly leveraged loans. This make sense since my dataset is comprised of more creditworthy firms who have access to public bond markets.

parative incidence of lending covenants for bonds and loans. Consistent with the findings in aggregate, I find that for 12 of the 16 covenants, loans use the covenant more intensively than bonds. The 4 covenant categories which do not conform to this are Fixed Charge Coverage Ratio (albeit weakly), Consolidation and Mergers, Sales Leasebacks, and Sales of Assets. The common theme which unites the last three is that these covenants protect the value of unsecured assets, either from dilution or direct disposition. In contrast, the covenant categories used more intensively by loans are more concerned with issues of monitoring or the value or safety of secured claims. One interesting fact to note though is that as senior creditors make up more of the debt structure of the firm, they increasingly protect unsecured assets as well. As can be seen in Table 5, covenants with the highest sensitivity to composition risk are restrictions on dividends, investments, sales of unencumbered assets and general restrictions on indebtedness. This makes sense since as senior creditors make up proportionally more of the debt structure, their recovery rates in default depend more on the unsecured value of the firm as well.

Third, though loans enjoy a protection premium on average, bonds sometime contain *more* covenant protections than their matched loan counterparts. As can be seen in figure 4, for pairs of debt contracts issued by the same firm at about the same time, relative covenant intensity for bonds and loans can vary dramatically. Figure 4 plots the density histogram of bond-loan covenant ratios in my sample. This is defined as the covenant intensity of the bond over the covenant intensity of the loan. At the extremes, there are a small number of contracts where the comparable bond uses up to 3 times the number of covenants that the loan does; there is also a significant mass where the bond uses no covenants at all and the loan uses some non-zero amount. Further examination shows that this variation is not random but heavily correlated with the credit quality and debt structure of the firm. As Panel A in Figure 2 shows, when firms are very far from default/make use of proportionally less bank debt, bond and loan covenant intensities are about equal (4.2 vs 3.3) with a slight advantage for loans. However, this gap expands significantly as firms approach default/use proportionally more bank debt. Such firms protect their loans much more intensely than their bonds (7.7 vs 4.5, respectively). The results suggest that both credit quality and bank debt percent are potential drivers of variation in relative protections. In the next section I attempt to disentangle which of these two factors is the true empirical driver of this result.

4.3 Composition risk and the bond-loan covenant ratio

To test if the variation I observe is driven by the credit quality or debt structure, I regress the Bond-Loan Covenant ratio on the firm's debt structure, measured by Bank Dept Percent (BDP) ex-ante of the time of issuance.[51] I also include multiple proxies of credit quality including the firm's Distance-to-Default, the market capitalization of the firm and its S&P institutional credit rating of the firm prior to issuance as additional controls to ensure that the variable of interest explains variation in the outcome independent of variation in credit quality. I test this using the following regression:

$$\begin{aligned}\mathrm{BC/LC}_{i,t,l,ind,firm} = \beta_1 BDP_i + \sum_{j=2}^{5}\beta_j \mathbf{B}_{j_i} + \sum_{k=6}^{8}\beta_k \mathbf{L}_{k_i} + \sum_{m=9}^{10}\beta_m \mathbf{M}_{m_i} + \sum_{n=11}^{13}\beta_n \mathbf{C}_{n_i} \\ + l_{i,l} + \tau_{i,t} + \xi_{i,ind} + \eta_{i,firm} + \epsilon_{i,t,l,ind,firm}\end{aligned} \tag{9}$$

Where $\mathbf{B}$ is a matrix of bond-specific controls (amount, maturity, spread), $\mathbf{L}$ is a matrix of loan-specific controls (amount, maturity, spread), $\mathbf{M}$ is a matrix of match-specific controls (loan before and difference in days) and $\mathbf{C}$ is a matrix of controls for firm credit quality (distance-to-default, log market capitalization and S&P institutional credit rating). Variables l, τ, ξ, η capture loan type, year, industry and firm-level fixed effects, respectively. Finally the dependent variable is BC/LC or the ratio of bond covenant intensity divided by loan covenant intensity.

As the above regression is a within-firm regression, the intuitive idea behind the regression

[51] I measure the time of issuance as the minimum of the two matched contracts issuance dates.

is to compare multiple pairs of matched contracts written on the same asset at various times and see if it is within-firm variation in credit quality or debt structure which drives the observed variation in covenant protections.

The results of this regression are reported in Table 6. I find that the debt capital structure of a firm is a significant predictor of both cross-sectional and within-firm variation in relative protections and this is true even in the presence of controls for credit quality. Unlike Distance-to-Default (results in Table 7), the results are still significant when including various levels of fixed effects. In terms of magnitudes, the effect is economically significant as well. A two standard deviation shock in Bank Debt Percentage implies a .56 decrease in relative bond protections. As both panels in Figure 2 show, relative protections range from about .5 on the low end of the cross-section to about 1 on the high end of the cross-section. In light of this, a .56 change in relative protections is extremely economically significant. Within firms, a one standard deviation increase in bank debt percent implies a .37 standard deviation decrease in relative protections.

Table 7 tests if this is merely a relative phenomenon or if debt structure can also explain absolute levels of bond and loan covenant intensity. Table 7 tests this using the following regression:

$$\begin{aligned}\mathrm{LC}_{i,t,l,ind,firm} = \beta_1 BDP_i + \sum_{j=2}^{5}\beta_j \mathbf{B}_{j_i} + \sum_{k=6}^{8}\beta_k \mathbf{L}_{k_i} + \sum_{m=9}^{10}\beta_m \mathbf{M}_{m_i} + \sum_{n=11}^{13}\beta_n \mathbf{C}_{n_i} \\ + l_{i,l} + \tau_{i,t} + \xi_{i,ind} + \eta_{i,firm} + \epsilon_{i,t,l,ind,firm}\end{aligned} \tag{10}$$

I find that the debt structure of the firm is a strong predictor of within-firm variation in loan covenant intensity while not explaining much of the variation in bond covenant intensity. This second result is unsurprising as bond covenant packages exhibit very little variation in general. The obvious interpretation of these results is that increasing the size of the firm's senior tranche primarily impacts senior creditors and that they respond the most by tightening their covenant packages while bond covenant packages stay the same.

The results are suggestive of the following story. Composition risk primarily affects the recovery rates of lenders in default. Senior creditors are the party who is 1) most affected by composition risk and 2) the party who is likely to care the most about their recovery rates in default. Note that senior bank lenders are subject to leverage and risk-based capital requirements in a way that a diffuse group of junior bondholders are generally not. This creates a particular incentive for senior bank lenders to ensure that their recovery rates in default stay high, even as they make up more and more of the debt structure. One way they maintain high recovery rates is by including capital restrictions covenants to first protect the secured value of the firm and then, as they finance more of the firm's debt, the unsecured value as well. In this way, relative contracting reflects the debt structure of the firm.

4.3.1 Robustness Check 1: Does debt structure proxy for credit quality?

While the above regression implicitly controls for the credit quality of the firm by both the matching procedure as well as explicit controls for credit quality, one might be concerned that the included variables do not adequately capture the credit risk of the firm. To alleviate this concern, I run the following robustness test which checks to see if variation in 14 additional measures of a firm's credit quality can also explain within-firm variation in its relative protections,

$$\begin{aligned}\text{BC/LC}_{i,t,l,ind,firm} = \beta_1 BDP_i + \sum_{j=2}^{5}\beta_j \mathbf{B}_{j_i} + \sum_{k=6}^{8}\beta_k \mathbf{L}_{k_i} + \sum_{m=9}^{10}\beta_m \mathbf{M}_{m_i} + \sum_{n=11}^{27}\beta_n \mathbf{C}_{n_i} \\ + l_{i,l} + \tau_{i,t} + \xi_{i,ind} + \eta_{i,firm} + \epsilon_{i,t,l,ind,firm}\end{aligned} \tag{11}$$

The specification is identical to the one used previously but with the addition of 14 additional measures which might proxy for the credit quality of the firm. These variables include advertising, asset maturity, capital expenditures, cash flow volatility, cash holdings, disposition of assets, dividends paid (flag for paid within the last year), the firm age in Compustat, market-to-book value, book leverage, market leverage, R&D, sales, and tangibility. Where appropriate, measures are scaled by the assets of the firm.[52] I test each variable both individually and jointly to ensure that the effect I observe which I attribute to composition risk is not just proxying for another measure of credit risk.

The results of this regression are reported in Table 8. I find that, at a within-firm level, only the level of capital expenditures and the level of cash-holdings are significant predictors of variation in the bond-loan covenant ratio. However, the inclusion of these control variables only has a negligible effect on the composition risk channel I document previously. Even with the joint inclusion of all controls, the economic and statistical significance of the coefficient on bank debt percent is virtually the same.

I also test in a panel of firms through time how the 14 measures of credit quality described above determine the debt structure of the firm. I regress the quarterly measure of bank debt percent from Capital IQ on the 14 lagged measures of credit quality.

$$\mathrm{BDP}_{t,firm} = \sum_{n=1}^{14} \beta_n \mathbf{C}_{n_i} + l_{i,l} + \tau_{i,t} + \xi_{i,ind} + \eta_{i,firm} + \epsilon_{i,t,l,ind,firm} \tag{12}$$

The results of this regression are reported in Table D3 of Appendix D. Of the 14 measures, only cash holdings, book leverage, sale and tangibility significantly explain debt structure. However, as reported above, the effect of composition risk is still significant even after the joint inclusion of all 14 measures. From this evidence, I conclude that the composition channel of credit risk is distinct from the traditional channels of credit risk which proxy for the level of agency concerns between debt and equity.

4.3.2 Robustness check 2: Cross-default protections

An alternative story one might tell to explain the above results is the following. If junior bonds are protected by cross-default provisions (which force the bond into default if any other

[52] For example, R&D indicates R&D expenditures as a fraction of the total asset value of the firm.

debt contract by the same firm defaults), then the relative weakening of their protections as firms approach default is wholly unsurprising. If senior loans increase their protections, then junior bonds do not need to do the same because cross-default provisions will let them reap the benefits of the senior protections. On the face of it, this assumption seems plausible enough and it has some history of being employed in the literature.[53] The idea behind the assumption is that, if bonds and loans contractually enter default at the same time, then the question of which contract actually contains the covenant that triggers default is irrelevant.

In practice, the question of which contract contains the covenant is relevant because junior debt frequently eschews true cross-default protections for the much weaker cross-acceleration protections. Only 12% of the bonds in my matched sample contain true cross-default clauses while 72% contain cross-acceleration clauses. To see the difference between the two, I first note that cross-acceleration provisions in bonds state that the bond only defaults if the some other debt contract from the same firm *accelerates*[54]. Acceleration is virtually always concurrent with bankruptcy and so the difference between the two lies in the difference between entering default and declaring bankruptcy. Only a small portion of firms who default or technically default on senior debt actually declare bankruptcy. This is because banks have wide latitude to renegotiate, forgive and waive defaults.[55] Thus, from a legal standpoint, eschewing true cross-default protections for cross-acceleration protections is equivalent to ceding authority to decide when the firm enters bankruptcy to the senior lenders. Viewed in this way, cross-acceleration provisions can be reasonably viewed as little better than the automatic stay imposed for all creditors when a debtor files a petition for bankruptcy.

As evidence that this theoretical legal distinction is economically meaningful, I show that firms with cross-default provisions contract very differently than firms with cross-acceleration

[53]Both Schwert (2020) and Duffie and Singleton (1999) make this assumption to preclude considering different covenant protections between bonds and loans.

[54]Acceleration is a legal term meaning that the lenders demands full and immediate repayment of the loan

[55]Hassabelnaby (2006), Griffin, Nini and Smith (2019) and Chodorow-Reich and Falato (2019) all discuss waivers of default where a firm can enter technical default but does not enter bankruptcy.

provisions. Tables 10 and 11 show this. As expected, bonds which include cross-default provisions use marginally less covenants in their contracts. Bonds with cross-default provisions however, use significantly *more* covenants in their contracts. Intuitively, bonds with cross-acceleration provisions seem to hedge their bets and do not depend on .

This difference holds even more strongly if one considers *overlapping* covenant protections. The idea behind this measure is that, if cross-default protections are really helping the bond, then there is no benefit for the bond to 'double up' on covenants already included in the loan. This measure is constructed by counting the number of covenants which are cover the same risk and are in both contracts. An example might be a capital expenditures clause found in both contracts. Similar to above, I find that bonds with cross-default provisions have significantly less overlapping covenants. However, I find no evidence of this relation however for cross acceleration provisions and in fact the result goes significantly in the opposite direction again.

From this, I conclude that true cross-default protections for junior debt are relatively rare[56] and don't provide nearly the same level of protection as more inclusive cross-default provision. Thus bonds and loans can have meaningfully different levels of covenant protections.

4.3.3 Robustness check 3: Covenant package changes around first Bond IPO

My primary tests of how composition risk impacts contracting occur in a sample of large firms with ample access to bond markets. However, the economic mechanism of composition risk should also apply to smaller firms, especially ones who are first entering bond markets. A firm's first Bond IPO is an event which creates a dramatic tilt towards bond financing in the firm's debt structure. This tilting away from senior debt should lower composition risk for senior creditors. I examine the covenant packages of 2486 bank loans issued by borrowers

[56]As another potential reason why bonds eschew cross-default provisions, Li, Lou and Vasvari (2012) note that, " borrowing firms can repurchase the bond via an open market tender or an exercise of a call provision to make the default clauses ineffective."

within the same industry both one year before and after the firm's first public Bond IPO and find that covenant packages for loans are significantly less strict after entrance into public bond markets.[57] The results of this regression are reported in Table 14. I find that after a firm first enters public bond markets, covenant intensity falls by about 15%[58] relative to what it was before for a firm in the same industry. While this regression is obviously limited by the fact that entering public bond markets is an endogenous choice and not an exogenous shock, the regression provides additional evidence that covenant packages tend to loosen in response to decrease in the size of the senior debt tranche, which is consistent with the idea of composition risk.

4.4 Bond-Loan Covenant Ratio and Bond-Loan Spread Ratio

Having established that debt structure is a significant predictor of the Bond-Loan Covenant ratio, a reasonable question to ask might be, to what extent does the Bond-Loan Covenant ratio matter for firm outcomes? In this section I show that variation in the bond-loan covenant ratio can also explain within-firm variation in the bond-loan spread ratio.

Schwert (2020) documents the 'puzzling' fact that for similarly matched contracts, loan spreads are systematically lower than bond spreads across the entire cross-section of credit quality.[59] I will refer to this relative under-performance as a 'spread deficit' for loans. In this section I argue that the 'spread deficit' puzzle can potentially be explained by a countervailing 'protection premium' senior lenders enjoy in their contracts. Since senior creditors have stronger covenant protections, in equilibrium they should also demand lower credit spreads. I will also show that stronger loan covenant protections don't just affect loan credit spreads but matched *bond* credit spreads as well.

To test how relative covenant protections interact with relative spreads, I regress the

[57] Due to sample size limitations, for this test I use data on loan covenant intensity as reported by LPC DealScan.

[58] The unconditional mean of DealScan covenant intensity is about 1.5 covenants per contract.

[59] It should be noted that though Schwert notes this same *prima facie* fact, he interprets the fact very differently, as a premium for bank lending. I discuss how to reconcile these two views below.

bond-loan spread ratio on the bond-loan covenant ratio with year, industry and firm fixed effects. At its strictest specification, the regression can be thought of as comparing two pairs of debt contracts issued by the same firm whose only difference should be their relative covenant packages. The test is to take these pairs of debt contracts and see if a change in the bond-loan covenant ratio implies a change in the bond-loan spread ratio. The regression specification I consider is the following,

$$\begin{aligned} \mathrm{BS/LS}_{i,t,l,ind,firm} = \beta_1 \mathrm{BC/LC}_{i,t,l,ind,firm} + \sum_{j=2}^{5} \beta_j \mathbf{B}_{j_i} + \sum_{k=6}^{8} \beta_k \mathbf{L}_{k_i} + \sum_{m=9}^{10} \beta_m \mathbf{M}_{m_i} + \sum_{n=11}^{13} \beta_n \mathbf{C}_{n_i} \\ + l_{i,l} + \tau_{i,t} + \xi_{i,ind} + \eta_{i,firm} + \epsilon_{i,t,l,ind,firm} \end{aligned} \tag{13}$$

The results of this regression are in Table 9. I find that firms which have larger protection premiums (for loans) also have larger spread deficits (for loans). This relationship is robust even to the inclusion of multiple controls for credit quality. The results are economically significant as well, a one unit increase in the bond-loan covenant ratio implies a 0.24 unit decrease in the bond-loan spread ratio. Converting these numbers into standard deviations, the results imply that a 1 standard deviation increase in the bond-loan covenant ratio implies a 0.12 standard deviation decrease in the bond-loan spread ratio.[60]

The economic significance of this result can perhaps best be seen graphically in Figure 6. In panel A of Figure 6, I graph the average protection premiums (of bonds) and the spread premiums (of bonds) along the axis of Distance-to-Default. Panel B does the same along the axis of Debt Capital Structure. The strong negative relationship is seen clearly in both panels. When the spread premium for bonds is high, the protection premium for bonds is low, and vice-versa. For firms that have most of their debt financed by bank loans, the spread premium for bonds is 2X while the protection premium for bonds is 0.5X. For firms

[60]The sample standard deviation of the bond-loan covenant ratio is 0.76 and the sample standard deviation of the bond-loan spread ratio is 1.52.

that have most of their debt financed by bonds, both premiums are close to 1X, or equality.

4.5 Is there a bank debt premium?

The above result can potentially explain some of the 'puzzling' credit spread patterns found in Schwert (2020). What Schwert describes as puzzling is the fact that bond spreads and loan spreads converge as firms get far away from default. The puzzle comes from the fact that due to seniority, loans should always recover at higher rates than bonds. Because of this it is surprising that their credit spreads converge, rather than maintaining a gap as firms become more creditworthy. Schwert interprets this convergence as evidence of a bank debt premium. The results of this paper suggest that this convergence in relative spreads for healthy firms can be explained by the simultaneous loss of covenant protections that occurs in senior creditor's lending contracts as default becomes less likely. If this is true, then it would suggest that contracts *without* such capital restrictions covenants would have a far more difficult time enforcing the priority of their claims.

As discussed in Ivashina and Vallee (2019), this story makes sense because capital restrictions covenants explicitly protect against actions which might transfer or otherwise liquidate secured value inside the firm. If a healthy firm were to quickly enter default and their loan package lacked such covenant protections, the management of such a firm would have significant latitude to liquidate or transfer secured assets in an attempt to gain additional debt financing or stay afloat. Ivashina and Vallee (2019) show that such risks are priced by borrowers. They examine the price response of lending contracts which had these covenants vs those that did not following a 2017 event in which the management of J. Crew expropriated secured value via the weakness of capital restrictions covenants. Loans in the lowest quartile of such covenant protections saw significant declines in value following this event. In total, the results of this paper are broadly consistent with this hypothesis that capital restrictions covenants play a vital role in protecting the priority of secured lenders' claims. I interpret the convergence puzzle noted by Schwert (2020) as evidence that, in the absence of such protections, senior creditors would recover at similar rates to junior creditors due to the actions management could take to expropriate value from secured creditors.

4.6 Bond-Loan Covenant Ratio and Bond Swap Spreads

The obvious interpretation of the above result is that relatively stronger covenant packages allow bank lenders to demand lower equilibrium levels of credit spreads as compensation for their increased protection. While this is what drives a large part of the result, in this section I show that this effect on relative spreads is at least somewhat driven by movement in the credit spread of the bondholder's contract as well.

To test this, I run the following regression where the outcome variable is the credit spread of the matched bond. This should isolate if the above result is purely driven by the effect that loan covenant packages have on the credit spread of the loan or if some of the result is also driven by the effect that loan covenant packages have on the credit spread of the matched bond.

$$\begin{aligned}\mathrm{BS}_{i,t,l,ind,firm} = \beta_1 \mathrm{BC/LC}_{i,t,l,ind,firm} + \sum_{j=2}^{5} \beta_j \mathbf{B}_{j_i} + \sum_{k=6}^{8} \beta_k \mathbf{L}_{k_i} + \sum_{m=9}^{10} \beta_m \mathbf{M}_{m_i} + \sum_{n=11}^{13} \beta_n \mathbf{C}_{n_i} \\ + l_{i,l} + \tau_{i,t} + \xi_{i,ind} + \eta_{i,firm} + \epsilon_{i,t,l,ind,firm}\end{aligned} \tag{14}$$

Table 10 reports the results of this regression. I find that relative covenant protections also significantly explain within-firm variation in the credit spread of the bond. In terms of economic significance, a back of the envelope calculation implies that an relative increase of one covenant in the loan contract implies about a 9 basis point increase in the credit spread demanded by the bond.[61]

[61] This calculation equates a one-half unit increase in the bond-loan covenant ratio with an increase of 4 covenants for the loan. This change of four relative covenants is the total amount change that is observed as the bond-loan covenant ratio moves from .5 to 1 over the entire cross-section of credit quality.

The results suggest that having more relative protections for the loan is detrimental to the bond. This result is consistent with the above story that loan covenants increase the secured value of the firm in default. If increasing the secured value of the firm comes at the expense of restricting actions which might allow creditors transform secured value into unsecured value, then it makes sense that junior creditors would demand slightly higher credit spreads in compensation.

5 Theory

To better understand the theoretical mechanism behind why senior creditors seem to prefer contractual concessions in the form of covenant protections, I examine a structural model of default which captures the relative incentives senior and junior creditors have to include covenants in their contracts. These incentives will importantly depend on the amount of the debt capital structure each party finances. The structural model I will examine is an extension of the workhorse Merton model of expected recovery in default with two salient features, 1) junior and senior debt and 2) a variable default threshold. The first feature is borrowed from Schwert's 2020 paper while the inclusion of the second feature is a contribution of this paper. While it may initially seem strange to apply a model of valuation to explaining covenant usage in debt contracts, the reason it makes sense in this setting is because I am comparing two debt contracts written on what is essentially the *same exact risky asset.* When the underlying credit risk of the borrower is exactly the same for both contracts, then the agency concerns which are normally pointed to to explain covenant usage should theoretically be the same for both contracts as well. Under this scenario, the only factor which should impact *relative* covenant usage is the relative payoffs of each class of debtholder. Hence the use of a valuation model. As Schwert puts it, "the key difference between loans and bonds is that banks are senior to bondholders in bankruptcy". This model seeks to understand how this tranching of bonds and loans affects the incentives of each party to include covenants in their contract.

As readers familiar with the Merton model of default might note, neither the Merton model nor the extension of Schwert's paper provide any explicit accommodation for covenant protections. I include covenants in my model by assuming that demand for covenant protections is proxied for by the default threshold of the debt contract. This same assumption was also used by Black and Cox (1976) in their seminal paper on covenants and contracting. Effectively, a firm's default threshold will be used as a proxy for the number of covenants it should include in its contract. Higher default thresholds imply higher levels of covenant usage.

This assumption makes sense because, in reality, debt covenants are the main contracting lever that contract writers can use to determine where and when a borrower defaults on its debt. Though virtually all debt contracts include nonpayment of scheduled interest as an event of default, solvency per-se is often insufficient to protect debtholder's interests because there are a myriad of actions that an unrestricted borrower can take to remain solvent at the expense of the debtors. [62] [63] For a firm with deteriorating credit quality, all else equal, more covenants imply that default will happen sooner and less covenants imply that default will happen later. Financial covenants explicitly accomplish this objective by ensuring that if a firm falls below some proscribed level or ratio that the firm will enter default. Capital restrictions covenants accomplish this indirectly by limiting the scope of actions an increasingly desperate firm might be more likely to take as it gets closer to insolvency. [64]

The key contribution of the model is to give a framework for thinking about how the inclusion of covenants impacts the expected payoffs of junior and senior debt. Since the only material difference between junior and senior debt issued on the same firm is their priority of

[62] This intuition is found in the construction of the Murfin (2012) measure.

[63] Griffin, Nini, and Smith (2019) Find that the recent development of cov-lite led to a 70% drop in the proportion of firms reporting a covenant violation. Freudenberg, Imbierowicz, Saunders and Steffen (2013), show that firms who violate covenants are significantly more likely to default and each marginal covenant increases the total likelihood of violation.

[64] Many of the actions prohibited by capital restrictions (such as asset sales or taking on additional indebtedness) allow firms to theoretically stave off bankruptcy by selling unencumbered assets until there is no value left inside the firm for unsecured debt-holders to collect on.

payoffs in bankruptcy, then it is reasonable to think that for two classes of debt issued *within the same firm and time*, covenant intensity should be a function of expected recoveries for each class of debt. Simply put, for each class of creditor, there is a trade-off in the model between covenant intensity and expected payoffs in bankruptcy. Figure 8 shows how this trade-off is different for each class of creditor.[65]

5.1 Expected Recovery Rates

Calculation of expected recovery rates for junior and senior debt closely follows that of Schwert (2020) with the addition of safety covenants in the spirit of Black and Cox (1976). In this model, adding or removing debt covenants is equivalent to contractually adjusting the percent of face value at which default occurs. The intuition is, if a firm has many covenants in its debt contract, default can occur well before the value of the falls below the face value of debt.

The value recovered in default depends on the seniority of the debt claim. Let K_J equal the face value of a junior debt claim and K_S equal the face value of a senior debt claim. Then $K_{total} = K_J + K_S$ is the total face value of all debt.[66]

To begin, I will start by examining the classic Merton (1974) model of default. Under this model, the value of the firm is distributed log-normally:

$$\ln(V_T) = N\left(\ln(V_0) + \left(r - \delta - \frac{1}{2}\sigma^2 T\right), \sigma^2 T\right) \tag{15}$$

Where, V_0 is the starting value, r is the growth rate, δ is the coupon payout and σ is yearly volatility, and T is the maturity of the debt in years. A key assumption of the Merton model is that a firm will default if the value of the firm is less than the face value of its debt. I generalize this assumption in the spirit of Black and Cox (1976) by assuming that default occurs at some percentage ρ of the firm's face value of debt. Following this assumption and

[65] Under assumptions of an average firm

[66] K_{total} will be normalized to 1 whenever not explicitly stated otherwise.

using the distribution of firm values, we know that the risk-neutral probability of a firm defaulting by time t is,

$$P(V_t \leq \rho K_{total}) = \Phi\left(\frac{\ln(\rho K_{total}) - \ln(V_0) - \left(r - \delta - \frac{\sigma^2}{2}\right) t)}{\sigma\sqrt{t}}\right) \tag{16}$$

Here, the variable $\rho \in (0, \infty)$, determines percentage of K_{total} at which default occurs. I will assume that K_S is value of senior debt claim, K_J is value of junior debt claim, and $K_S + K_J = K_{total}$.

Using probabilities of the above form, one can define the expected recovery rates for junior and senior creditors given default as,

$$E[R_J^t|D] = \frac{P(I0_J) \cdot 0 + P\left(I_J\right) \cdot E\left[\pi_J^t|I_J\right] + P(W_J) \cdot K_J}{P(D) \cdot K_J} \tag{17}$$

and,

$$E[R_S^t|D] = \frac{P(I_S) \cdot E[\pi_S^t|I_S] + P(W_S) \cdot K_S}{P(D) \cdot K_S} \tag{18}$$

Where the the events I and W denote the events in which a class of creditor is made whole or impaired and D denotes the event of default. For impaired senior creditors, there will always be some non-zero payoff, no matter how small. For junior creditors, impairment includes the real possibility of being completely wiped out and recovering nothing. This is captured by the event $I0$. Derivations of these probabilities of these events are defined in Appendix D. Recovery values are constant (with respect to the default threshold) outside of the region in which a creditor is impaired. Outside this region they either recover their full investment (K_J or K_S), or they receive nothing.

[67] Of additional note is that the payoffs in the numerator are absolute recovery values and

[67]Only in the region in which a creditor is impaired does their expected payoff depend on the default threshold. This expected payoffs are captured by $E[\pi|I]$. For junior and senior creditors, these can be written as,

$$E\left[\pi_J^t|I_J\right] =$$

so each recovery value is divided by the amount invested (K_J or K_S) to get a proportional rate of return for each class of creditor.

Each expected recovery can be thought of as a weighted sum of two recoveries, the recovery when impaired and the recovery when made whole. The weights are the probabilities of these two states. Figure 8 plots expected recoveries against covenant intensity (which is proxied for in the model by default threshold) both junior and senior debt. The figure shows that, as one would expect, senior creditors recover more than junior creditors everywhere. The model also shows that contracts with more covenants have higher recoveries. [68]

5.2 Linking recovery rates and covenant usage

Fixing the rest of the variables in the model, the above expected recovery functions can be thought of as a mapping between expected recoveries and selected features of the debt contracts. I will consider three features of the debt contract which might affect expected recoveries, covenant intensity ρ, starting leverage V_0 (which is the model proxy for distance-to-default) and senior debt percent K_S (which is the model proxy for bank debt percent).

Treating as constant all variables in the model except ρ and V_0, we can write:

$$\frac{e^{\ln(V_0)+(r-\delta)t}\left[\Phi\left(\frac{\ln(\min[\rho K_{total},K_{total}])-\ln(V_0)-\left(r-\delta+\frac{\sigma^2}{2}\right)t}{\sigma\sqrt{t}}\right)-\Phi\left(\frac{\ln(\min[K_S,\rho K_{total}])-\ln(V_0)-\left(r-\delta+\frac{\sigma^2}{2}\right)t}{\sigma\sqrt{t}}\right)\right]}{P(\min[K_S,\rho K_{total}]\leq V_t\leq\min[\rho K_{total},K_{total}])}-K_S$$

and,

$$E[\pi_S^t|I_S]=\frac{e^{\ln(V_0)+(r-\delta)t}\Phi\left(\frac{\ln(\min[\rho K_{total},K_S])-\ln(V_0)-\left(r-\delta+\frac{\sigma^2}{2}\right)t}{\sigma\sqrt{t}}\right)}{P(0\leq V_t\leq\min\left[\rho K_{total},K_S\right])}$$

These are adapted from the derivations of Schwert (2020). Full details in Appendix D.

[68] As can be seen in Figure 8, these expected recovery functions each have a concave 'kink' at $\rho=\frac{K_S}{K_{total}}$ (for the senior creditor) and $\rho=1$ (for the junior creditor). These values of ρ each respectively denote the first value for which the expected probability of being made whole in default is greater than 0. The intuitive reason for this kink is that creditors cannot recover more than the face value of their debt claim. Though firms get some benefit in expected recovery from setting the default threshold higher, the marginal benefit is much lower above the face value of each creditor's debt claim.

$$E[R] = f_1(\rho \mid V_0) \tag{19}$$

Similarly, treating as constant all variables in the model except ρ and K_S, we can write:

$$E[R] = f_2(\rho \mid K_S) \tag{20}$$

Then I will consider what happens if we fix the expected recovery to some value $\overline{E[R]}$. This implies that, given V_0 or K_S, there is some value of ρ which solves the equation. Because of the nature of the normal CDF, it is impossible to derive an analytical solution of the following hypothetical form $\rho = F_1(E[\bar{R}], V_0)$. It is possible however to solve numerically for the value ρ^* which solves the equation given V_0 and K_S. [69],

$$\overline{E[R]} = f_1(\rho^* \mid V_0) \tag{21}$$

and,

$$\overline{E[R]} = f_2(\rho^* \mid K_S) \tag{22}$$

The final missing piece for this exercise is to decide what value to use for $\overline{E[R]}$. The values I use for each class of creditor are the historical expected recovery rates for each respective class. These come courtesy of Schwert (2020) and are $\overline{E[R_S]} = .84$ for senior creditors and $\overline{E[R_J]} = .38$ for junior creditors. As I will discuss later, the results are relatively sensitive to the values of $\overline{E[R]}$ I choose so this is one of the more important assumptions I will make. Because of this, it is important to use historical values which directly correspond to the variable in question.

Figure E1 in the appendix shows a graphical depiction of this solution exercise. In Figure D4, expected recoveries are plotted against default thresholds (which correspond to covenant

[69] Since f_1 and f_2 are strictly increasing functions of ρ for all values of V_0 and K_S, there is a unique value of ρ which always satisfies this equation.

intensity). Then, given an historical expected recovery rate, there is a default threshold $\rho*$ which is consistent with this. Panel A plots the $\rho*$ for junior and senior creditors for a firm which is very levered, V_0, at a rate of 1-1.[70] Panel B shows the same for a firm which is less levered at a rate of 1-10. Figure D5 repeats the exercise but with debt structure, K_S. Panel A depicts the solution ρ^* for a firm with a 15-85 mix of senior and junior debt. Panel B shows the opposite.

5.3 Model Predictions

From these graphs, two important predictions emerge. First is that both leverage and debt capital structure induce large changes in absolute covenant usage but only debt capital structure seems to induce changes in *relative* covenant usage. These conclusions are confirmed in Panel B of Figures 9 and 10 which perform a more rigorous comparative statics exercise. For an average firm, relative protections for bonds (on the vertical axis), fall as firms get further away from default and use more senior debt. However, this pattern is much more pronounced for changes in debt capital structure (or senior debt levels).

Second, these changes are sensitive to the chosen recovery rates of each class of creditor. The reason in this model why senior creditors are much more sensitive (compared to junior creditors) to changes in credit conditions is because they expect to recover more in default. Note the kink in each graph. Senior creditors expectation of recovering 84 cents on the dollar in bankruptcy means that most of their contracting happens in the region above this kink where the marginal impact of an additional covenant is much lower. Conversely, in the model, the majority of contracting for junior creditors happens in the region where the marginal benefit of an additional covenant is high. Because of this, they do not need to use as many covenants to achieve their historical rate of recovery.[71] In total, this structural model, combined with assumption of higher historical recovery rates for senior creditors, is

[70] Average firm leverage is about 30% or approximately 1-3

[71] In practice, there are other legal reasons why covenants would be less valuable for junior creditors. This is probably why the model predicts even more variance in covenant usage for junior creditors than what we observe in practice.

enough to generate the same patterns of relative covenant usage I observe in the data.

6 Conclusion

This paper makes a number of contributions to the literature. Perhaps most importantly, I examine a clean comparison of covenant usage between comparable bonds and bank loans, a first in the literature. The data I use to identify loan covenant protections is both novel to the literature and created using a new machine learning method which is new to this paper and especially well-suited to the task of classifying contracts. The resulting data is of high quality. It tests well out-of-sample against existing data sources and it is larger in both scope of covenants covered and history than any previous attempt.

Using this data I establish a number of new stylized facts about how bonds and loans relatively use debt covenants in their contracts. I document that even between debt contracts which should theoretically have the same level of debt-equity agency concerns, loans enjoy a protection premium that grows as bank lenders finance more of the firm's debt structure. I interpret this change in the protection premium as a response to the composition risk each creditor bears as a result of tranching the debt capital structure. The larger the size of the senior tranche, the lower the expected recovery rate (per dollar invested) of both classes of creditor. Senior bank lenders, seeing this decrease in recovery rates, include more covenants in new debt issuance to protect themselves. Junior bondholders respond to the increased covenant protections of senior bondholders by demanding higher equilibrium levels of credit spreads.

Since a firm's debt structure is highly correlated with firm-level measures of credit quality, I examine a battery of proxies for the credit quality of the firm and show that none of them can explain the variations I find in relative covenant usage. I also show that the these patterns of covenant usage cannot empirically be explained by the inclusion of cross-default provisions in bond contract. Finally, as an additional placebo test, I also test how covenant usage differs around a firm's first entry into public bond markets. I find that around such events, covenant usage falls by a significant amount, consistent with the composition risk hypothesis.

As an additional test, I show that the protection premium I document can explain some of the other puzzling facts noted in the literature about the relative pricing of bonds and loans. The protection premium that loans enjoy over matched bonds is directly negatively related to the spread premium that bonds enjoy over their matched loan. This happens both because stronger covenant protections for the loan imply lower equilibrium spreads for the loan but also because stronger covenant protections for the loan imply higher equilibrium spreads for the bond.

From these results, I argue that the composition risk is an important direct driver of the covenant packages that bonds and loans receive as well as an indirect driver of the their relative pricing. This can explain the empirical fact that firms which are mostly bond financed have bond and loan contracts which look almost identical (along the dimensions of credit spreads and covenant intensity). Meanwhile firms that are mostly bank financed have wildly divergent contracts. For such firms, covenant intensity for the loan is twice that of the comparable bond and credit spreads are twice as high for the bond as they are for the loan.

I finally show that the disproportionate covenant response of senior creditors to composition risk is predicted by a structural model of subordinated default in the spirit of Merton (1976). An important assumption in this model is the assumption of higher recovery rates for the senior tranche. This assumption is consistent with bank lender's documented preference for recovery of principal over interest payments and this is what generates the increased covenant sensitivity of senior creditors that I also document in the data. Importantly, in the model as well as the data, covenant packages are only sensitive to changes in debt capital structure, not distance-to-default. The specific mix of debt a firm uses to finance itself turns out to be an extremely relevant factor in the way it chooses to contract as well.

The results of this paper suggest that the canonical way of thinking of debt covenants – as a mechanism to resolve agency conflicts between equityholders and one monolithic class of debtholder – misses important interactions that also happen between different classes of debtholders. As tranched debt capital structures are extremely common in large corporate borrowers, understanding how and why these debt structures impact contracting is important to understanding the whole picture of contract design. The results also suggest that papers which only consider one type of debt contract in isolation (notably loan contracts) may be missing part of the economic story.

Looking forward, this paper provides a number of interesting avenues for further research. One very plausible interpretation of these results is that the economic efficiencies of tranching (avoiding the lemons' problem and the creation of money-like assets) are easiest to capture when junior debt makes up a large portion of the debt capital structure. Thus the additional covenant inclusion I observe reflects the need to add more complexity into the contract to make up for structural shortfalls in the senior-junior debt arrangement. It would be interesting to explore this with other measures of contractual complexity apart from covenants. Additionally, while this paper only looks at newly issued debt, the same forces which drive covenant inclusion in newly issued debt should also drive existing loans to include new covenants in renegotiations. Finally, the new source of data I use in this paper captures not just covenants but *all* types of clauses included in syndicated lending contracts. This rich dataset can be used to examine other non-covenant features of the debt contract to see if these are actually salient feature of the contract or only perfunctorily included out of legal necessity. All of these topics offer fruitful areas for future research.

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Figures:

Figure 1: Difference in Covenant Package Composition for Bonds and Loans (Loans-Bonds)

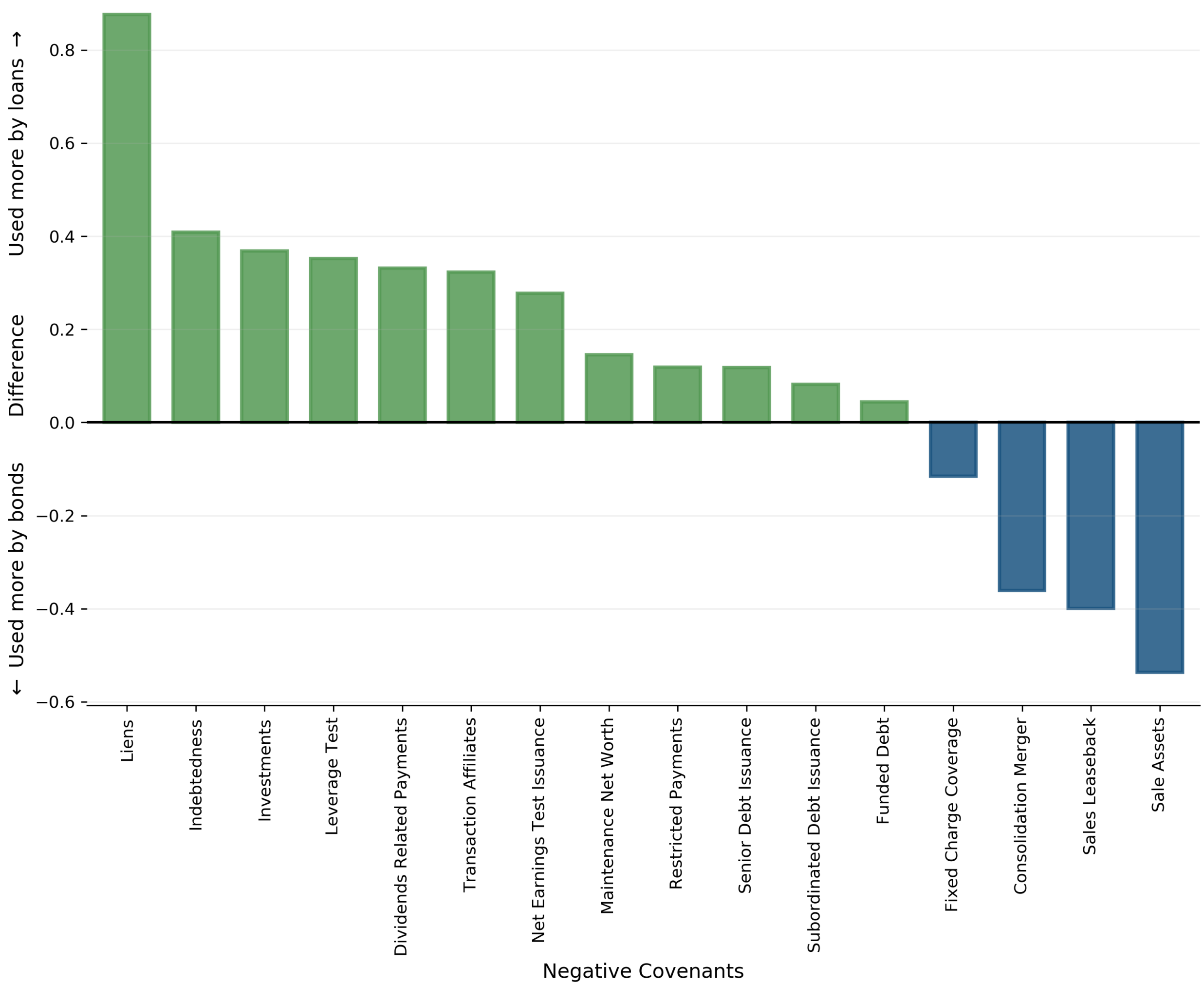


Figure 2: Covenant Frequency as a Function of Distance-to-Default

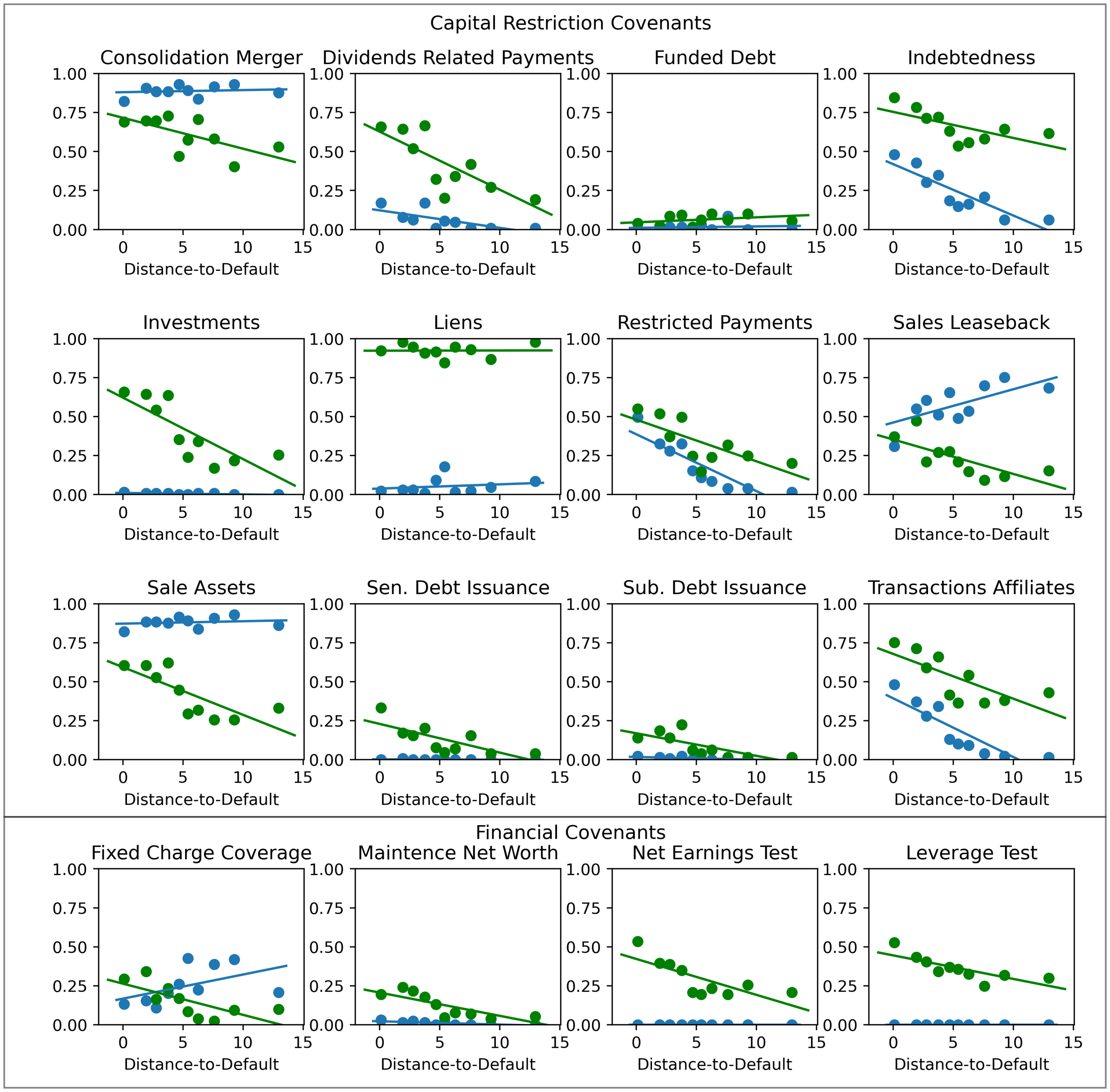
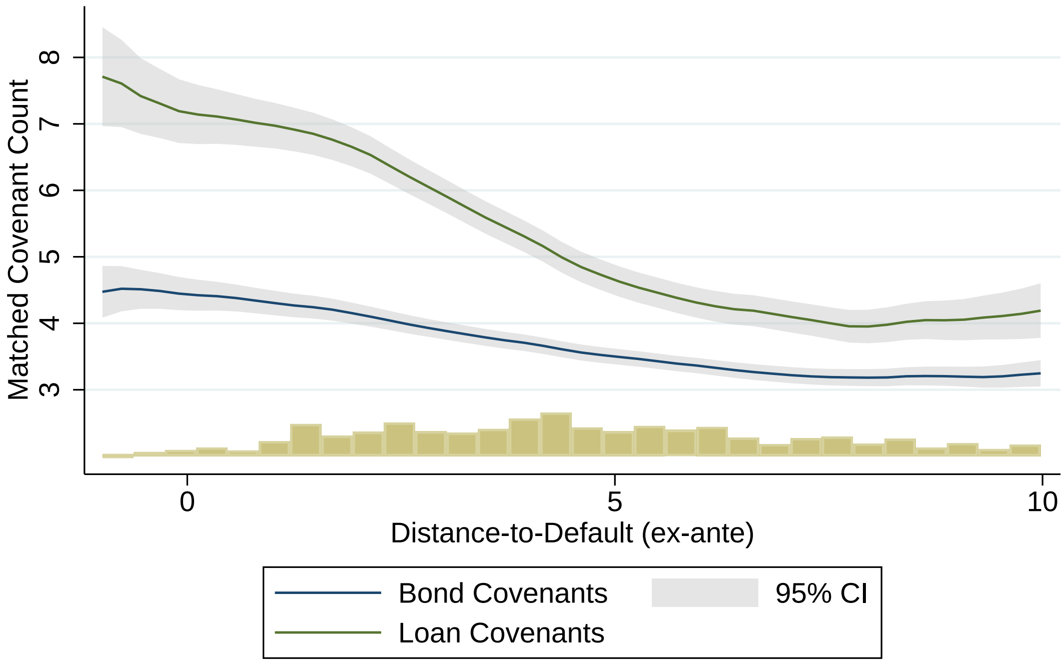


Figure 2: Absolute Covenant Intensity

Panel A: Non-Parametric Regression of Covenant Intensity on Distance-to-Default



Panel B: Non-Parametric Regression of Covenant Intensity on Bank Debt Share

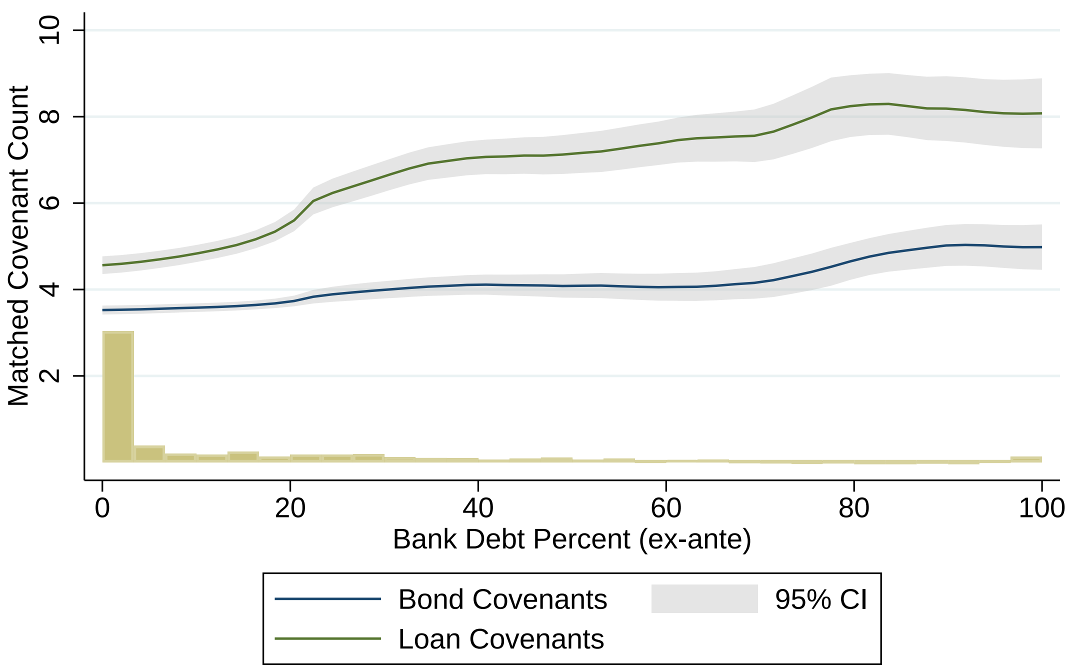
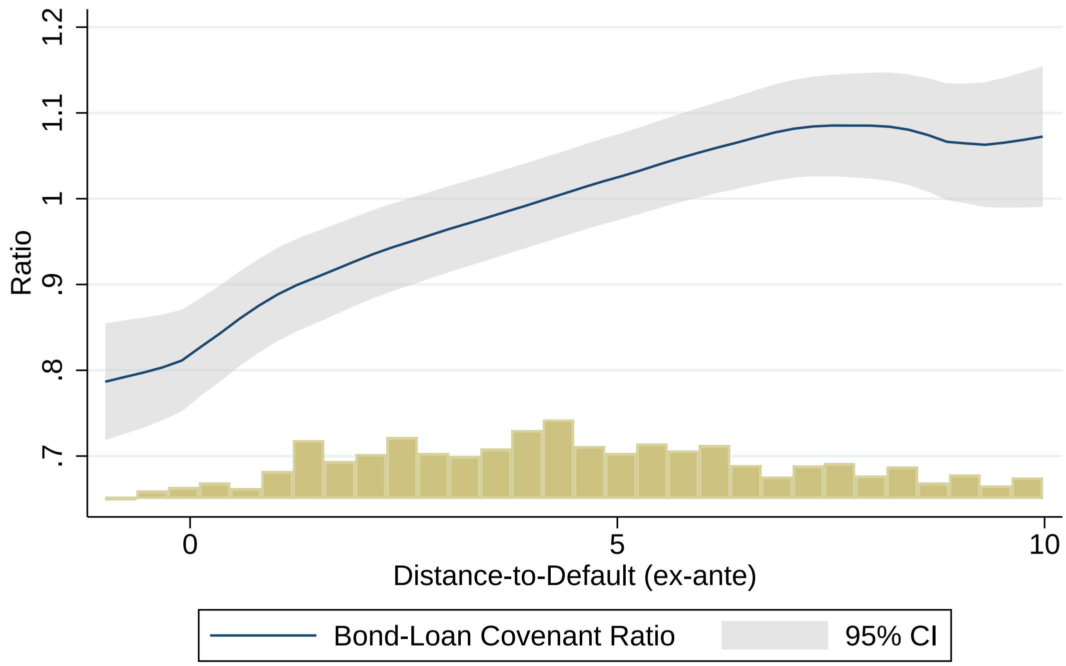


Figure 3: Relative Bond Covenant Intensity

Panel A: Non-Parametric Regression of Relative Bond Covenant Intensity on Distance-to-Default



Panel B: Non-Parametric Regression of Relative Bond Covenant Intensity on Bank Debt Share

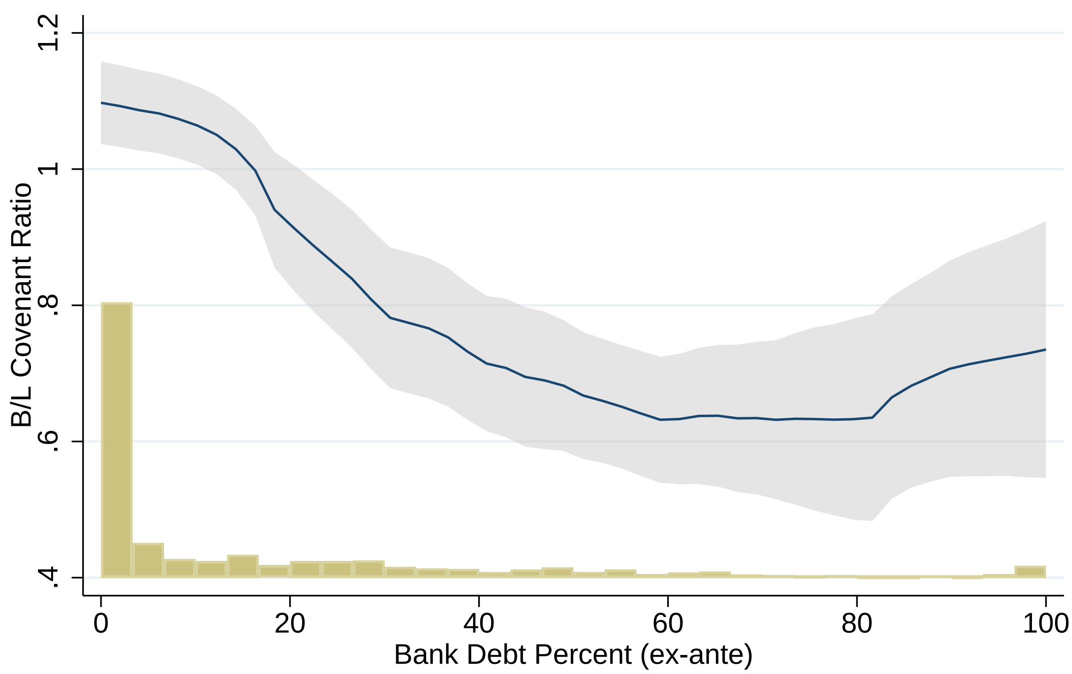


Figure 4: Histogram of Relative Bond Covenant Intensity

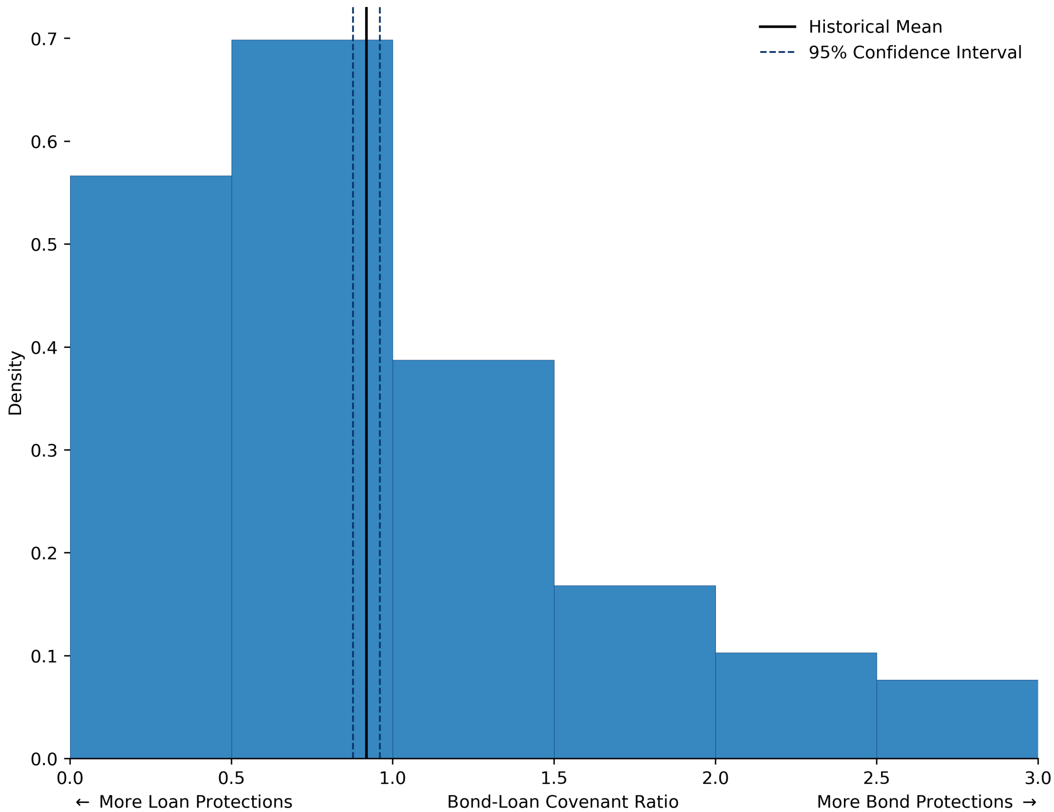


Figure 5: Non-Parametric Regression of Bond Swap Spreads (Public Proxy) on Distance-to-Default

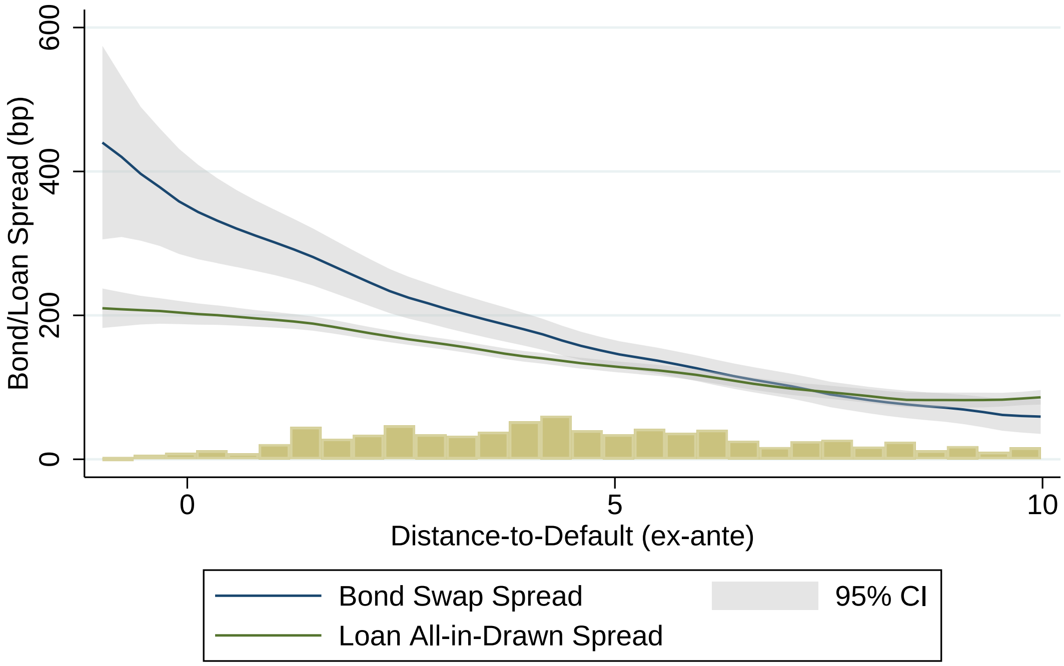
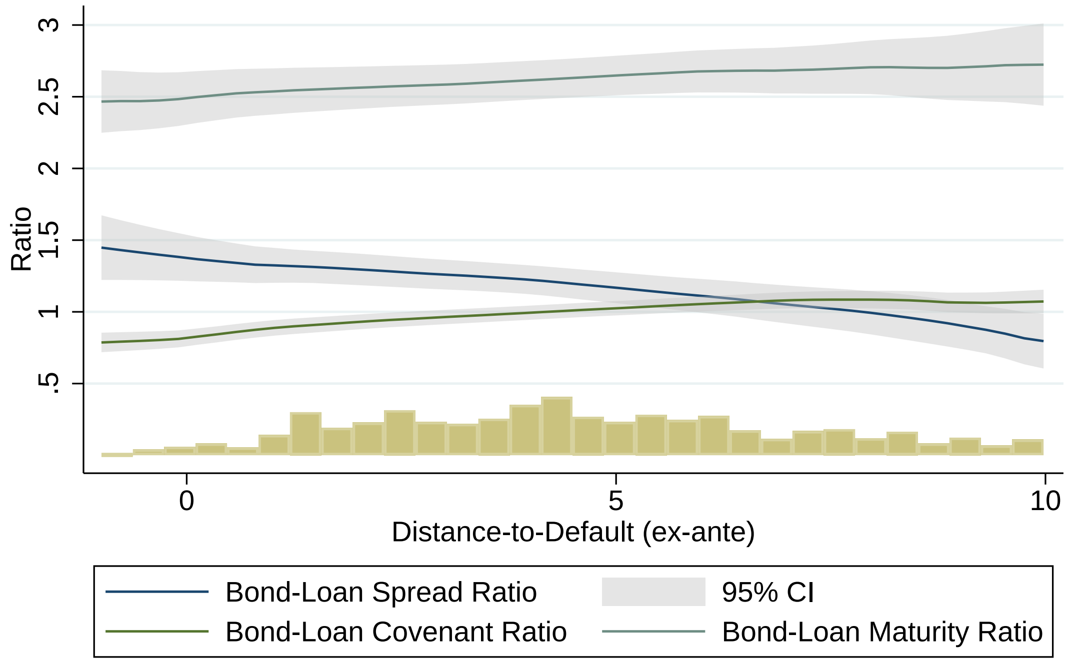


Figure 6: Negative Relation between Relative Protections and Relative Spreads

Panel A: Non-Parametric Regression of Relative Covenant Protections and Relative Credit Spreads on Distance-to-Default



Panel A: Non-Parametric Regression of Relative Covenant Protections and Relative Credit Spreads on Bank Debt Share

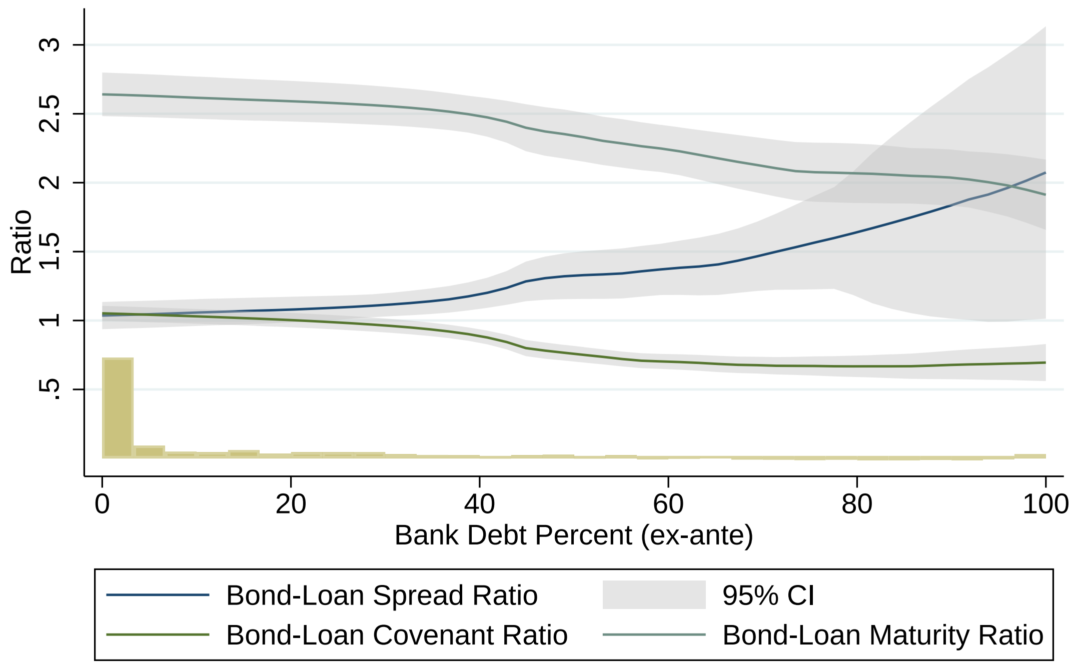
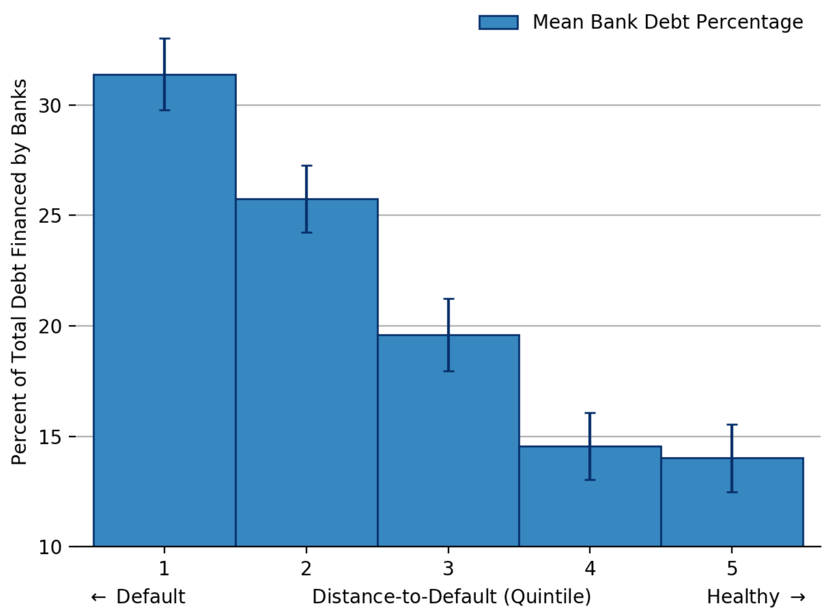


Figure 7: Debt Capital Structure and Credit Quality

Panel A: In-sample Bank Debt Usage by Quintile of Distance-to-Default
(In-sample: Public Firms Close to Issuing both a Bond and Loan)



Panel B: Out-of-Sample Bank Debt Usage by Quintile of Distance-to-Default
(Out-of-Sample: Any Firm with Access to Bond and Loan Markets)

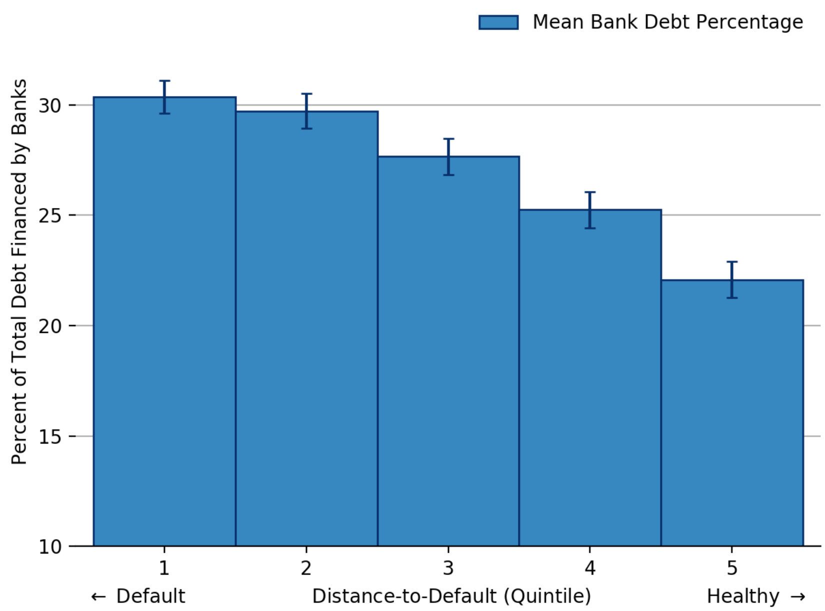


Figure 8: Expected Recovery Rates as a Function of Covenant Intensity

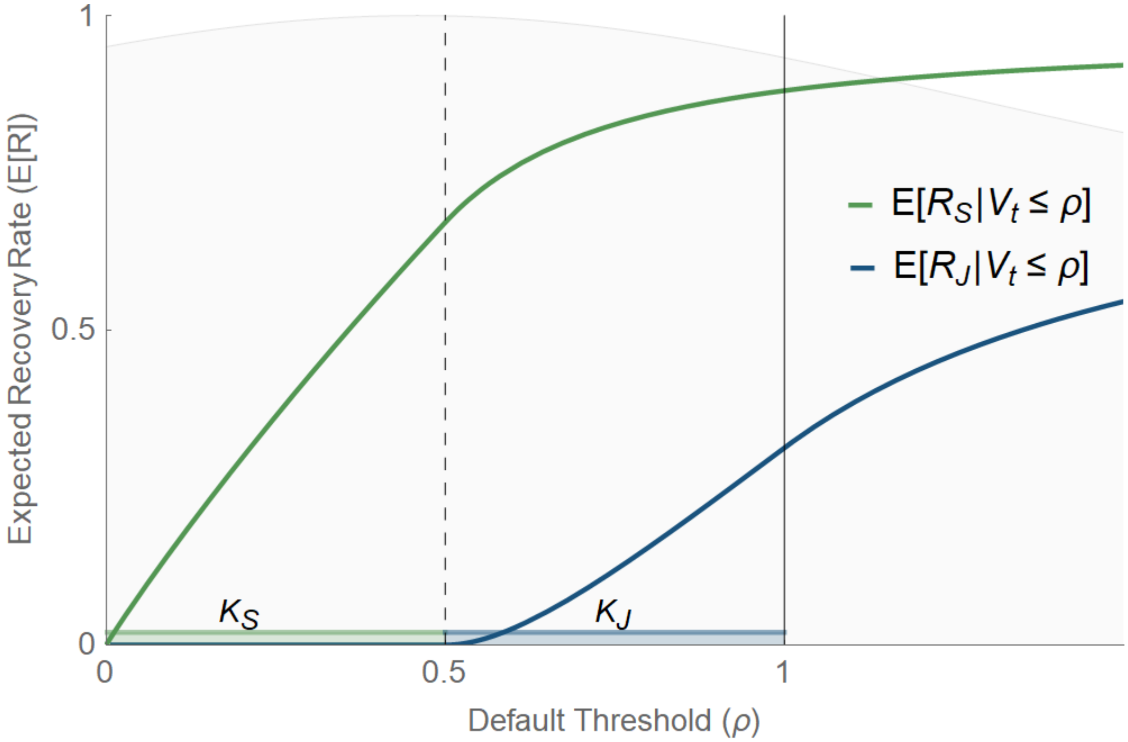
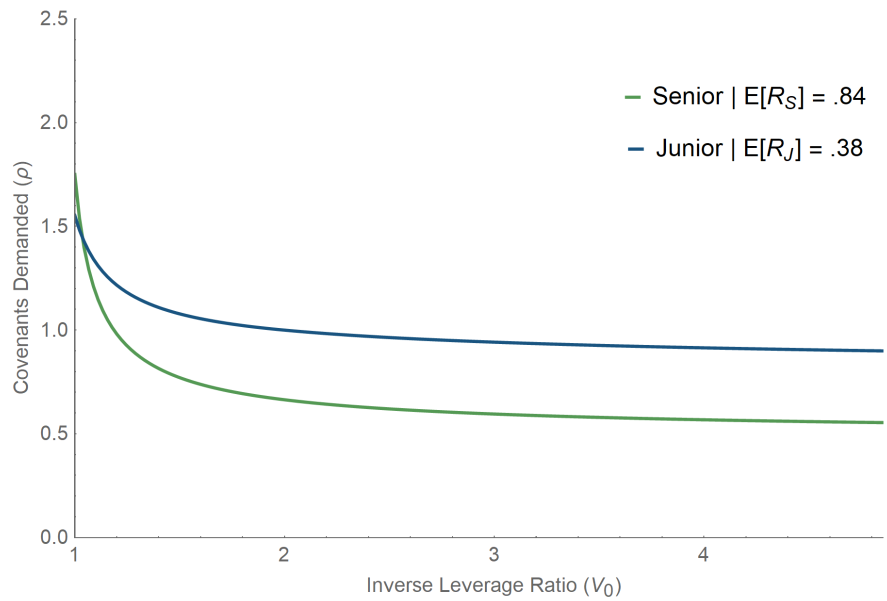


Figure 9: Comparative Statics - How does changing leverage change relative protections? (Assuming Historical Recovery Rates)

Panel A: Comparative Statics of Absolute Protections



Panel B: Comparative Statics of Relative Protections

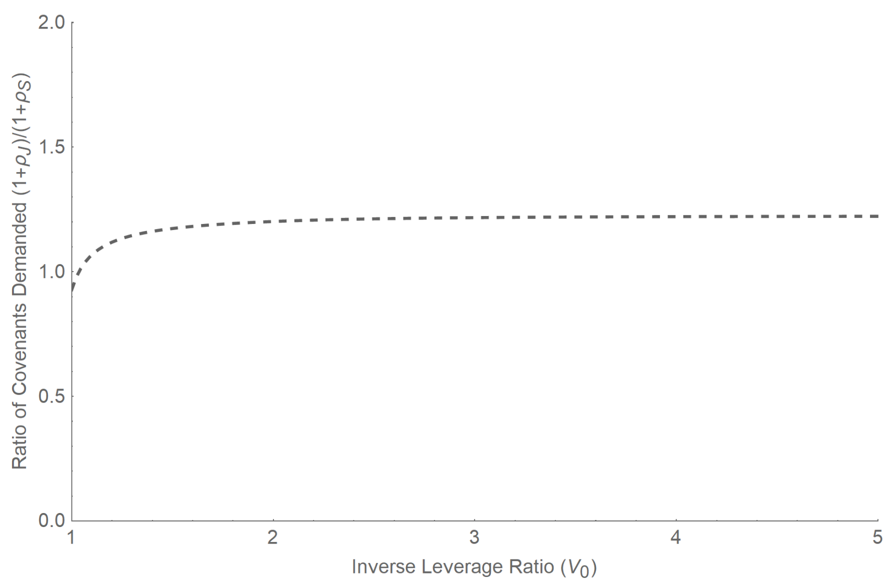
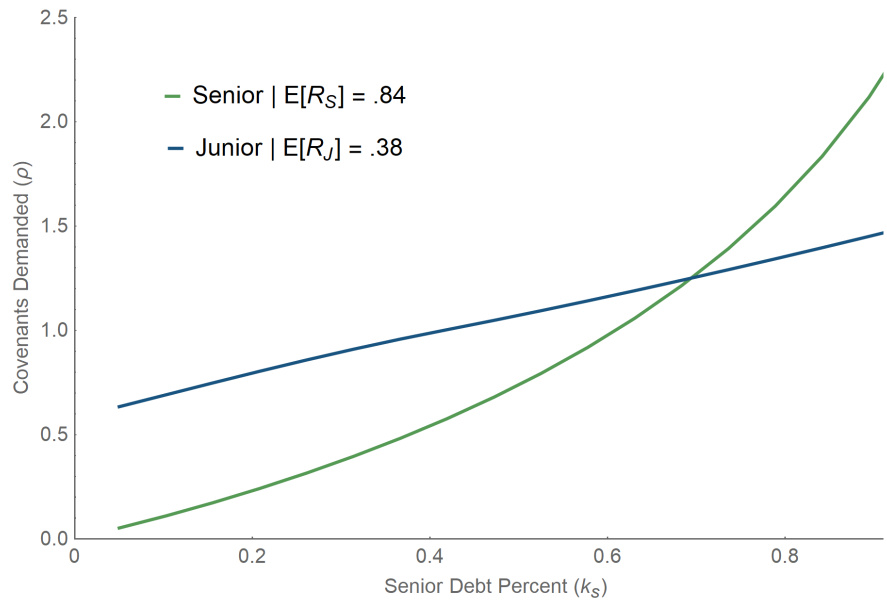


Figure 10: Comparative Statics - How does changing debt capital structure change relative protections? (Assuming Historical Recovery Rates)

Panel A: Comparative Statics of Absolute Protections



Panel B: Comparative Statics of Relative Protections

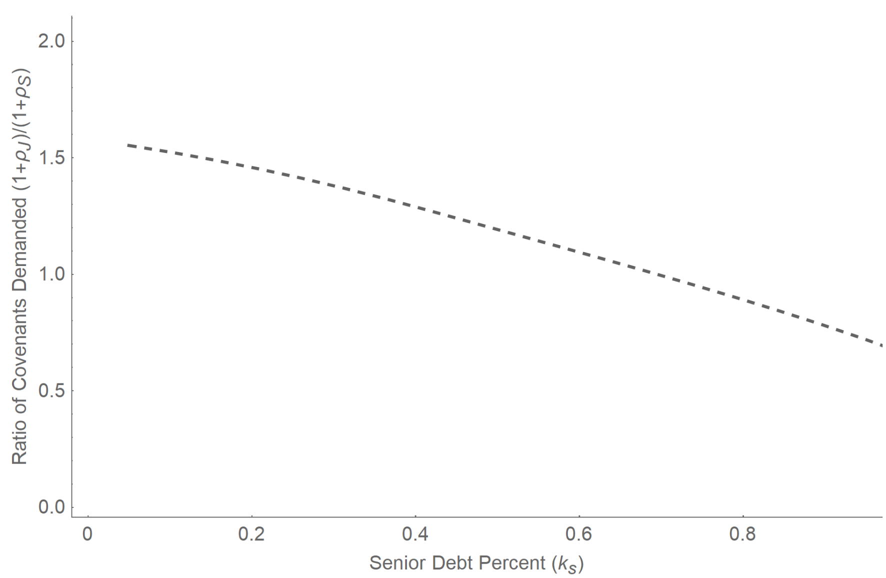
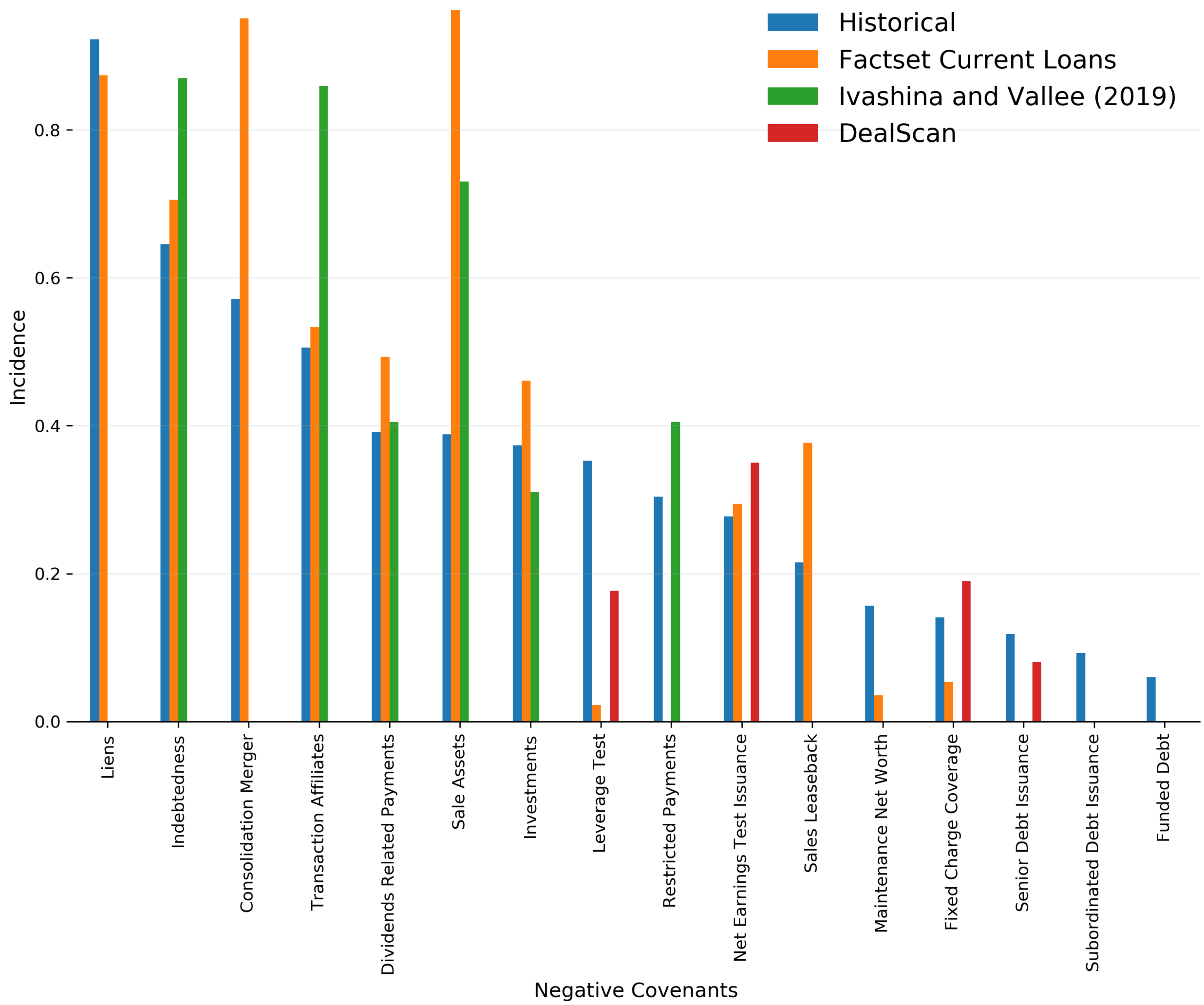


Figure 11: Loan Covenant Incidence by DataSource

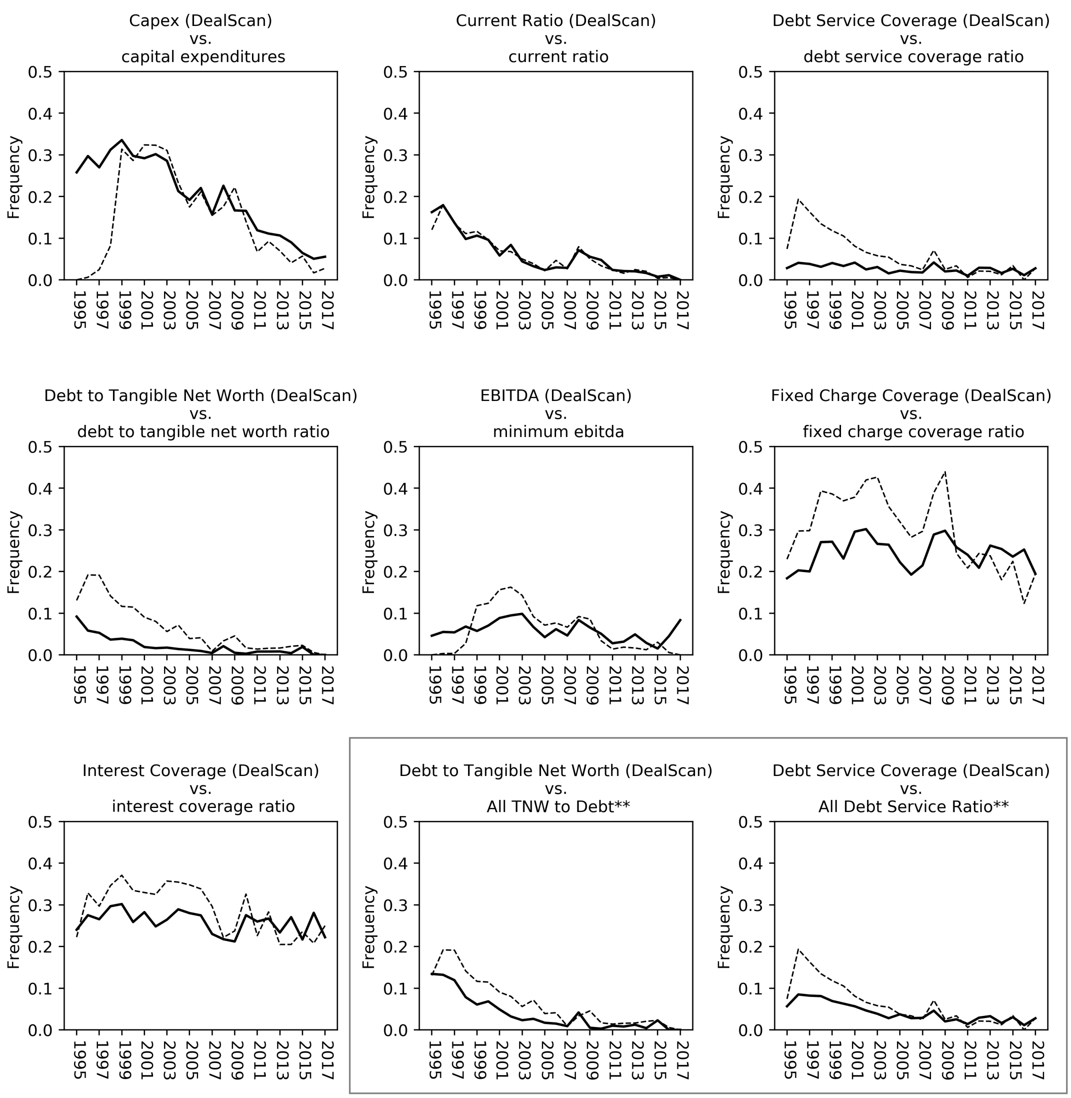
This figure shows incidence of 16 classes of loan covenants as reported by 4 data sources. Incidence is measured as the percentage of loan contracts in each respective database containing a given covenant. With the exception of the Historical database, not all covenants appear in all databases. Historical denotes a historical database of the universe of loan covenants constructed as described in Section 2. Factset Current Loans denotes a sample of loans taken from the data provider Factset. This includes a sample of currently active loans issued to firms (excluding financials and utilities) from the years 2012-2020 (with most of the observations being in the later years). Ivashina and Vallee (2019) mirrors data as reported in Figure 1 of their 2019 "Weak Credit Covenants" paper. Their data is from a sample of highly leveraged loans obtained from the industry source Street Diligence. My sample of loans is toward the safer end of the spectrum. This as well as difference in aggregation* explain some of the large discrepancies seen by Ivashina and Vallee (2019) in a minority of covenant classes. DealScan includes covenant data as reported in DealScan and matched to the same set of loans as my Historical database. Classes of covenants are hand matched between each set of data as described in Table 12.



*Because Ivashina and Vallee's covenant classes are slightly more aggregated than what is reported in my Historical data, FactSet Current Loans and Mergent FISD, a bit of care needs to be taken to compare these covenant classes. Where possible, and supported by their own words, I split their categories between two of my own to better match the classes used by most datasets.

Figure 12: Comparing Historical Loan Covenant Dataset with DealScan

This figure shows yearly incidence of seven classes of financial loan covenants* which are common to both my Historical dataset and LPC DealScan for the same set of loan contracts. Incidence is measured as the yearly percentage of loan contracts in each respective database containing a given covenant. For each covenant in DealScan, its covariance with every covenant in my historical database is measured, and the covenant in my database with the highest correlation is chosen as its match. This shows how much of the covariance of the DealScan covenants can be explained with just the first best match in my database. The boxed graphs show that this exercise can be improved by hand-matching and considering potentially multiple covenants in my database which might match to the same DealScan covenant.



*Only ten covenants appear with any regular frequency in DealScan (>.5%). Of those, there are seven DealScan covenants (plotted) which are not obvious amalgams of multiple covenants. Excluded are the DealScan Leverage Ratio, Debt to EBITDA and Senior Debt to EBITDA covenants. Berlin, Nini and Yu (2017) also document deficiencies in early DealScan data which could account for large gaps in DealScan data seen early in the sample (Capex and EBITDA).

**These are hand-matched composite variables which are the sum of all subsection clusters which mention any sort of net worth to debt ratio/debt service coverage ratio. This suggests that some discrepancies with DealScan may not be due to missing data but simply found in multiple subsections.

Tables:

Table 1: Matched Bond-Loan Sample Construction

This table explains the details of my dataset construction and the amount of available observations at step. I begin with two sets of data, a dataset of bonds from Mergent FISD and loans from my own historical dataset which is merged with LPC DealScan. I use these two datasets to match up bond-loan pairs which meet two criteria, 1) from the same borrower and 2) concurrently active. Before this point, an observation is a single bond or loan. After this point, an observation is a matched bond-loan pair. To make sure that the bond and loan are truly comparable, for my results I only consider bonds and loans which are issued within one year of each other. The statistics of this restricted sample are in the left column while the statistics of the complete sample are in the right column.

Step 1: Preparing Bond and Loan Data	**Bonds:**	**FISD**	**Loans:**	**Historical**
	Obs	Firms	Obs	Firms
Starting count	434810	13301	10204	4535
Dropping observations with no covenant data	33865	8767	10204	4535
Sample period: 1996-2016	28047	7820	9586	4353
Dropping financials and utilities	18305	5158	7705	3615
Step 2: Matching Bond and Loan Pairs	**Sample:**	**$\leq$ 1 Year**	**Sample:**	**All**
	Obs	Firms	Obs	Firms
Matching bonds and loans (same firm and concurrently active)	2392	721	10904	1053
Step 3: Cleaning Merged Bond-Loan Pairs	**Sample:**	**$\leq$ 1 Year**	**Sample:**	**All**
	Obs	Firms	Obs	Firms
Dropping with 0 Loan Covenants (3% of sample)	2320	709	10558	1036
Merge with CapitalIQ	1696	523	6913	779
Dropping secured bonds	1622	501	6708	753
Dropping convertible bonds	1390	402	5748	595
Dropping non-public issued bonds	1340	393	5480	586
Dropping micro-cap firms ($\leq$ 300 MM)	1283	359	5227	526
Final Data Set	**1283**	**359**	**5227**	**526**
Step 4: Adding Optional Extra Data	**Sample:**	**$\leq$ 1 Year**	**Sample:**	**All**
	Obs	Firms	Obs	Firms
Matches to a bond swap spread (public proxy)	970	320	3911	469

Table 2: Summary Statistics from Matched Bond-Loan Sample

Matched Bond-Loan Sample is a dataset of matched bonds and loans issued by the same firm, active at the same time and issued within one year of each other. Dataset excludes financials and utilities and only includes firms which match to the CRSP/Compustat merged dataset. Sample period covers the years 1996 - 2016. Firm characteristics data obtained from CRSP/Compustat Merged database and matched within the one year previous to the minimum of the bond and loan offering dates.

Matched Bond-Loan Sample Summary Statistics

	Mean	Std	10%	50%	90%	Obs.
Loan Credit Agreement:						
-Facility Amount (MM)	1441	1821	200	1000	2790	1283
-All-in-Drawn Spread (bp)	137	101	40	112	275	1283
-Loan Maturity (months)	57	12	36	60	60	1283
-DealScan Covenants (count)	1.32	1.07	0.00	1.00	3.00	1283
-Affirmative Covenants (count)	4.47	2.56	1.00	4.00	8.00	1283
-Matched Loan Covenants (count)	5.24	3.09	2.00	4.00	10	1283
Bond Prospectus:						
-Offering Amount (MM)	557	454	200	425	1000	1283
-Offering Yield (bp)	485	193	230	496	704	884
-Coupon (bp)	522	216	230	530	787	1283
-Bond Maturity (months)	139	109	60	120	360	1283
-Matched Bond Covenants (count)	3.67	1.55	2.00	3.00	6.00	1283
Firm Characteristics:						
-Market Cap. (MM)	25429	42478	1211	8770	62030	1281
-Total Debt (LT + ST, MM)	8560	19107	485	2632	14847	1214
-M/B	1.32	0.75	0.69	1.08	2.27	977
-Sales	0.26	0.20	0.09	0.21	0.48	1283
-Profitability	0.04	0.04	0.02	0.04	0.06	1254
-Cash Holdings	0.08	0.10	0.01	0.05	0.18	1283
-Uniqueness	0.20	0.40	0.00	0.00	1.00	1283
-Market Leverage	0.27	0.17	0.09	0.23	0.51	1213
-Book Leverage	0.31	0.16	0.14	0.30	0.51	1214
-Cash Flow Volatility	0.01	0.02	0.00	0.01	0.02	1266
-Capex	0.03	0.05	0.00	0.02	0.07	1282
-Advertising	0.04	0.04	0.01	0.03	0.09	1195
-R and D	0.01	0.01	0.00	0.01	0.02	508
-Tangible	0.32	0.25	0.05	0.26	0.73	1255
-Dividends Flag (-1 year)	0.75	0.43	0.00	1.00	1.00	1283
-Firm Age (months)	178	97	62	158	289	465

Table 3: Comparing Sample Means from Matched Bond-Loan Dataset with Component Datasets

Comparison of sample means from 4 datasets. All datasets exclude financials and utilities and only include firms which match to the CRSP/Compustat merged dataset. Sample period covers the years 1996 - 2016. FISD Bonds contains bond data obtained from Mergent FISD. DealScan Data contains loan data obtained from LPC DealScan. DS+Historical Loans is the subset of DealScan loans for which complete contract data is available is available from the Historical database. Bond-Loan Matched a dataset of matched bonds and loans issued by the same firm and active at the same time. Firm characteristics data obtained from CRSP/Compustat Merged database and matched within one year previous to the offering date (bonds), first deal active date (loans) or the minimum of both (bond-loan merged).

Sample Means Comparison: Component Datasets

	FISD Bonds	DealScan Loans	DS + Hist. Loans	Bond-Loan Matched
Loan Credit Agreement:				
-Facility Amount (MM)		391	320	1441
-All-in-Drawn Spread (bp)		215	200	137
-Loan Maturity (months)		47	52	57
-DealScan Covenants (count)		1.40	1.90	1.32
-Affirmative Covenants (count)			5.13	4.47
-Matched Loan Covenants (count)			7.07	5.24
Bond Prospectus:				
-Offering Amount (MM)	592			557
-Offering Yield (bp)	512			485
-Coupon (bp)	538			522
-Bond Maturity (months)	135			139
-Matched Bond Covenants (count)	3.11			3.67
Firm Characteristics:				
-Market Cap. (MM)	31299	5486	3028	25429
-Total Debt (LT + ST, MM)	7554	3416	888	8560
-M/B	1.69	2.12	1.53	1.32
-Sales	0.22	0.26	0.33	0.26
-Profitability	0.03	0.03	0.03	0.04
-Cash Holdings	0.12	0.08	0.09	0.08
-Uniqueness	0.20	0.18	0.23	0.20
-Market Leverage	0.28	0.31	0.26	0.27
-Book Leverage	0.35	0.35	0.28	0.31
-Cash Flow Volatility	0.01	0.02	0.02	0.01
-Capex	0.04	0.03	0.04	0.03
-Advertising	0.05	0.06	0.07	0.04
-R and D	0.02	0.01	0.01	0.01
-Tangible	0.33	0.31	0.30	0.32
-Dividends Flag (-1 year)	0.61	0.44	0.36	0.75
-Firm Age (months)	138	98	100	178
N	8841	45419	7705	1283

Table 4: Covenant Frequency by Industry Classification

Frequency of covenant usage for sample of 1283 matched bonds and loans broken down by industry. Sample of loans and bonds from firms in CRSP/Compustat in the US 1996-2016. Loan covenant data collected in this paper as described in Appendix A. Bond covenant data collected from Mergent FISD. Financial, utilities and micro-cap (<300MM) issuers excluded. 1-digit SIC Industry Codes. 0 : Agriculture, Forestry and Fishing, 1 : Mining and Construction, 2-3: Manufacturing, 4 : Transportation and Communications, 5 : Wholesale Trade and Retail, 7-8 : Services, 9: Public Administration and Non-Classifiable.

Panel A: Loan Covenants

		First Digit of SIC Code						
	Total	0	1	2-3	4	5	7-8	9
Financial Covenants:								
-Fixed Charge Coverage	0.13	0.4	0.10	0.08	0.13	0.21	0.24	0.0
-Leverage Test	0.33	0.6	0.41	0.31	0.19	0.28	0.58	0.0
-Maintenance Net Worth	0.15	0.2	0.49	0.11	0.04	0.11	0.09	0.0
-Net Earnings Test	0.27	0.2	0.31	0.30	0.20	0.15	0.39	0.0
Capital Restriction Covenants:								
-Consolidation Merger	0.57	1.0	0.65	0.46	0.67	0.63	0.61	1.0
-Dividends Related Payments	0.36	0.6	0.50	0.25	0.31	0.38	0.62	0.0
-Funded Debt	0.06	0.0	0.04	0.04	0.07	0.11	0.11	0.0
-Indebtedness	0.61	0.6	0.69	0.63	0.53	0.57	0.68	0.0
-Investments	0.33	1.0	0.60	0.26	0.26	0.23	0.50	0.0
-Liens	0.92	1.0	0.95	0.90	0.93	0.95	0.93	1.0
-Restricted Payments	0.27	0.2	0.29	0.20	0.27	0.31	0.50	0.0
-Sale Assets	0.36	1.0	0.38	0.33	0.19	0.42	0.55	0.0
-Sales Leaseback	0.20	0.2	0.27	0.21	0.19	0.10	0.30	0.0
-Senior Debt Issuance	0.11	0.4	0.13	0.09	0.03	0.13	0.24	0.0
-Subordinated Debt Issuance	0.08	0.0	0.18	0.05	0.03	0.11	0.11	0.0
-Transaction Affiliates	0.48	1.0	0.64	0.45	0.42	0.43	0.55	0.0
Obs.	1283	5.0	188	554	182	208	135	11

Panel B: Bond Covenants

		First Digit of SIC Code						
	Total	0	1	2-3	4	5	7-8	9
Financial Covenants:								
-Fixed Charge Coverage	0.29	0.0	0.18	0.35	0.23	0.34	0.21	0.0
-Leverage Test	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.0
-Maintenance Net Worth	0.01	0.0	0.05	0.00	0.02	0.00	0.01	0.0
-Net Earnings Test	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.0
Capital Restriction Covenants:								
-Consolidation Merger	0.93	1.0	0.91	0.92	0.93	0.96	0.99	1.0
-Dividends Related Payments	0.06	0.0	0.09	0.08	0.02	0.02	0.07	0.0
-Funded Debt	0.02	0.0	0.00	0.00	0.04	0.07	0.00	0.0
-Indebtedness	0.26	1.0	0.41	0.19	0.29	0.18	0.41	0.0
-Investments	0.00	0.0	0.01	0.01	0.00	0.00	0.01	0.0
-Liens	0.05	0.0	0.00	0.05	0.13	0.04	0.03	0.0
-Restricted Payments	0.20	1.0	0.37	0.17	0.16	0.11	0.30	0.0
-Sale Assets	0.93	1.0	0.91	0.91	0.92	0.95	0.99	1.0
-Sales Leaseback	0.69	1.0	0.74	0.84	0.24	0.70	0.56	1.0
-Senior Debt Issuance	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.0
-Subordinated Debt Issuance	0.01	0.0	0.02	0.01	0.01	0.01	0.04	0.0
-Transaction Affiliates	0.20	1.0	0.34	0.16	0.16	0.11	0.35	0.0
Obs.	1283	5.0	188	554	182	208	135	11

Table 5: Regression of Covenant Intensity on Measures of Composition Risk and Traditional Credit Risk

Cross-sectional regressions of covenant intensity for 16 classes of covenants on the debt structure of the firm as well as the distance-to-default score of the firm. Dependent variable is a binary variable indicating 1 if the individual covenant (16 total) is present in the contract and 0 if not. Loan covenant data collected in this paper as described in Appendix A. Loan type, year, industry and firm-level fixed effects are included as indicated. All standard errors robust to heteroskedasticity.

Panel A: Covenants (1-8)

	Covenant							
	Mergers	Dividends	Funded Debt	Indebtedness	Investments	Liens	Restr. Payments	Maint. Net Worth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bank Debt Percent	0.000	0.002^{***}	0.000	0.001^{***}	0.002^{***}	-0.000	0.002^{***}	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Distance-to-Default	-0.002	-0.005^{*}	0.002	-0.000	-0.008^{**}	0.001	-0.006^{*}	0.002
	(0.003)	(0.003)	(0.001)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
4-Digit SIC FE	✓	✓	✓	✓	✓	✓	✓	✓
Loantype FE	✓	✓	✓	✓	✓	✓	✓	✓
N	2552	2552	2552	2552	2552	2552	2552	2552
R2	0.212	0.238	0.171	0.227	0.246	0.151	0.250	0.340

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Panel B: Covenants (9-16)

	Covenant							
	Sales LB	Sales Assets	Sen. Debt Iss.	Sub. Debt Iss.	Trans. w/ Aff.	Net Earn. Test	Fixed Charge	Lev. Test
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bank Debt Percent	0.001^{**}	0.002^{***}	-0.000^{*}	0.001^{**}	0.001^{**}	0.000	0.001^{*}	0.001^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Distance-to-Default	-0.005^{*}	-0.003	-0.012^{***}	-0.008^{***}	-0.001	0.002	-0.004	-0.000
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
4-Digit SIC FE	✓	✓	✓	✓	✓	✓	✓	✓
Loantype FE	✓	✓	✓	✓	✓	✓	✓	✓
N	2552	2552	2552	2552	2552	2552	2552	2552
R2	0.210	0.238	0.219	0.230	0.180	0.221	0.290	0.219

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Bond-Loan Covenant Ratio and Composition Risk

Regression of the bond-loan covenant ratio on the debt structure of the firm which measures composition risk. One observation of the outcome variable represents the bond-loan covenant ratio for a comparable bond-loan pair issued by the same firm at about the same time (less than one year difference). Higher values of this variable can be interpreted as better protections for the bond as compared to the loan. This variable is defined as the number of covenants in the bond (max 16) divided by the number of covenants in the matched loan. The main explanatory variable is the firm's debt capital structure as measured by the percentage of the firms' total debt which is financed by bank loans (prior to issuance) as reported by CapitalIQ. Sample period covers the years 1996 - 2016 and is constructed as described in Table 1. Also included are controls for the specifics of the loan and bond being considered, additional controls for credit quality as well as controls for the matching procedure to account for any systematic bias this might introduce. Loan type, year, industry and firm-level fixed effects are included as indicated. All standard errors are clustered at the loan level.

	Bond-Loan Covenant Ratio				
	(1)	(2)	(3)	(4)	(5)
Bank Debt Percent	-0.006***	-0.004***	-0.004**	-0.004*	-0.010**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)
Distance-to-Default	0.013	0.005	0.009	-0.007	0.014
	(0.008)	(0.009)	(0.009)	(0.010)	(0.018)
Bond Controls:					
-log(Bond Offering Amount)		0.046	0.020	-0.067	-0.112
		(0.067)	(0.073)	(0.074)	(0.060)
-Bond Maturity (months)		0.000	0.000	0.000	-0.000
		(0.000)	(0.000)	(0.000)	(0.000)
-Bond Coupon (bp)		-0.000**	-0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)	(0.000)
Loan Controls:					
-log(Loan Package Amount)		0.057	0.078*	0.146***	0.103
		(0.040)	(0.036)	(0.043)	(0.077)
-Loan Maturity (months)		-0.003	-0.002	-0.005	-0.013**
		(0.004)	(0.004)	(0.004)	(0.005)
-Loan All-in-Drawn Spread (bp)		0.001	0.001	0.001	-0.000
		(0.001)	(0.001)	(0.000)	(0.001)
log(Market Cap.)					-0.207
					(0.125)
S&P Instituional Credit Rating					-0.052
					(0.050)
Match Controls	✓	✓	✓	✓	✓
Loantype FE		✓	✓	✓	✓
Year FE			✓	✓	✓
2-Digit SIC FE				✓	
Firm FE					✓
N	1108	1106	1106	1101	943
R2	0.047	0.079	0.143	0.274	0.683

Cluster-robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Bond and Loan Covenant Intensity and Composition Risk

Regression of covenant intensity for both bonds and loans on Bank Debt Percent. One observation of the outcome variable represents the unweighted sum of covenant protections in either a bond or loan (in my sample of matched bonds and loans). A total of 16 potential covenants are hand matched between the bond and loan databases to ensure that covenants cover the same set of risks. The main explanatory variable is the firm's debt capital structure as measured by the percentage of the firms total debt which is financed by bank loans (prior to issuance) as reported by CapitalIQ. Sample period covers the years 1996 - 2016 and is constructed as described in Table 1. Also included are controls for the specifics of the loan and bond being considered, additional controls for credit quality as well as controls for the matching procedure to account for any systematic bias this might introduce. Loan type, year, industry and firm-level fixed effects are included as indicated. All standard errors are clustered at the loan level.

	Bond Covenant Intensity			**Loan Covenant Intensity**		
	(1)	(2)	(3)	(4)	(5)	(6)
Bank Debt Percent	0.006*	0.007*	0.006	0.029***	0.024***	0.022*
	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.011)
Distance-to-Default	-0.091***	-0.121***	-0.019	-0.160***	-0.130***	-0.087
	(0.021)	(0.023)	(0.027)	(0.037)	(0.039)	(0.052)
Bond Controls:						
-log(Bond Offering Amount)	-0.293*	-0.204	-0.110			
	(0.117)	(0.109)	(0.092)			
-Bond Maturity (months)	-0.001**	-0.001**	-0.001			
	(0.000)	(0.000)	(0.000)			
-Bond Swap Spread (bp)	0.002**	0.002***	0.001			
	(0.001)	(0.001)	(0.000)			
Loan Controls:						
-log(Loan Package Amount)				-0.689***	-0.701***	0.008
				(0.131)	(0.149)	(0.201)
-Loan Maturity (months)				0.026*	0.033**	0.039**
				(0.012)	(0.012)	(0.013)
-Loan All-in-Drawn Spread (bp)				0.003	0.002	-0.001
				(0.002)	(0.003)	(0.001)
Match Controls	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
2-Digit SIC FE		✓			✓	
Loantype FE				✓	✓	✓
Firm FE			✓			✓
N	847	843	720	1106	1101	965
R2	0.316	0.425	0.797	0.392	0.483	0.855

Cluster-robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Testing for Endogeneity with 14 Additional Measures of Credit Risk

Regression of the bond-loan covenant ratio on debt structure including 14 potential controls which proxy for credit risk. All other controls are the same as Table 6. One observation of the outcome variable represents the bond-loan covenant ratio for a comparable bond-loan pair issued by the same firm at about the same time (less than one year difference). Higher values of this variable can be interpreted as better protections for the bond as compared to the loan. This variable is defined as the number of covenants in the bond (max 16) divided by the number of covenants in the matched loan. The main explanatory variable is the firm's debt capital structure as measured by the percentage of the firms' total debt which is financed by bank loans (prior to issuance) as reported by CapitalIQ. Sample period covers the years 1996 - 2016 and is constructed as described in Table 1. Also included are controls for the specifics of the loan and bond being considered, additional controls for credit quality as well as controls for the matching procedure to account for any systematic bias this might introduce. Loan type, year, industry and firm-level fixed effects are included as indicated. All standard errors are clustered at the loan level.

	Bond-Loan Covenant Ratio														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Bank Debt Percent	-0.010**	-0.010**	-0.011**	-0.011**	-0.011**	-0.010**	-0.011**	-0.010**	-0.010*	-0.010*	-0.010**	-0.010**	-0.010**	-0.010**	-0.009*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Distance-to-Default	0.027	0.016	0.016	0.015	0.014	0.016	0.014	0.020	0.005	0.005	0.004	0.012	0.015	0.020	0.030
	(0.019)	(0.019)	(0.018)	(0.017)	(0.018)	(0.018)	(0.017)	(0.018)	(0.018)	(0.021)	(0.018)	(0.018)	(0.018)	(0.018)	(0.026)
Advertising	-1.157														5.363
	(3.266)														(7.040)
Asset Maturity		0.008													0.011
		(0.007)													(0.009)
Capex			-1.739*												-2.694***
			(0.817)												(0.724)
Cash Flow Volatility				-1.636											-1.958
				(3.490)											(3.934)
Cash Holdings					-2.183										-2.983*
					(1.183)										(1.355)
Disposition of Assets						-5.034									-8.272
						(5.223)									(6.994)
$1_{\text{Dividends Paid}}$							0.055								0.069
							(0.176)								(0.224)
Firm Age in Compustat								-0.019*							-0.014
								(0.009)							(0.012)
Market to Book									0.086						0.070
									(0.083)						(0.096)
Book Leverage										-0.281					0.189
										(0.638)					(1.025)
Market Leverage											-0.516				-0.819
											(0.666)				(0.991)
R&D												8.536			6.452
												(6.934)			(6.766)
Sales													-0.735		-1.290
													(0.613)		(1.198)
Tangibility														-0.032	-1.761
														(0.767)	(1.199)
Loan Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Bond Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Loantype FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	874	821	943	943	943	943	943	943	896	896	896	943	943	915	763
R2	0.689	0.697	0.685	0.683	0.687	0.683	0.683	0.686	0.703	0.702	0.702	0.684	0.684	0.697	0.727

Robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Bond-Loan Spread Ratio and Bond-Loan Covenant Ratio

Regression of bond-loan spread ratio on bond-loan covenant ratio. One observation of the outcome variable represents the ratio of credit spreads (above LIBOR) for a bond and a loan of a comparable bond-loan pair issued by the same firm at about the same time (less than one year difference). Credit spreads for the loan are defined as the All-In-Drawn spread as reported by LPC DealScan. Credit spreads for the bond are defined as $BSS\_Proxy_T = YieldToMaturity_T - Treasury\_Swap_T - TED\_Spread_3$ or the bond's yield-to-maturity in basis points (of maturity T months) minus the rate of a maturity matched treasury swap minus the 3 month TED Spread. This credit spread is a public approximation of the proprietary bond swap spread data (from Bank of America Merrill-Lynch) used by Schwert (2020). Bond-loan spread ratio is defined as the bond swap spread (measured as close as possible to the loan's issuance date) divided by the loan's all-in-drawn credit spread. The main explanatory variable is relative covenant protections of the bond which is defined as the unweighted sum of covenants in the bond (max 16) divided by the number of covenants in the matched loan. Sample period covers the years 1996 - 2016 and is constructed as described in Table 1. Also included are controls for the specifics of the loan and bond being considered, additional controls for credit quality as well as controls for the matching procedure to account for any systematic bias this might introduce. Loan type, year, industry and firm-level fixed effects are included as indicated. All standard errors are clustered at the loan level.

	Bond-Loan Spread Ratio				
	(1)	(2)	(3)	(4)	(5)
Bond-Loan Covenant Ratio	-0.187**	-0.173*	-0.189**	-0.198***	-0.241**
	(0.069)	(0.067)	(0.062)	(0.057)	(0.086)
Bank Debt Percent	0.006	0.005	0.003	0.002	-0.001
	(0.004)	(0.005)	(0.002)	(0.002)	(0.005)
Distance-to-Default	-0.075***	-0.066***	-0.087***	-0.080***	0.007
	(0.017)	(0.017)	(0.012)	(0.012)	(0.025)
Bond-Loan Maturity Ratio		0.108***	0.100***	0.113***	0.130***
		(0.027)	(0.023)	(0.024)	(0.024)
log(Bond Offering Amount)		-0.034	-0.158*	-0.274***	-0.111
		(0.093)	(0.078)	(0.080)	(0.105)
log(Loan Package Amount)		-0.114	-0.072	-0.048	0.023
		(0.069)	(0.042)	(0.046)	(0.065)
log(Market Cap.)					-0.043
					(0.164)
S&P Instituional Credit Rating					-0.144*
					(0.065)
Match Controls	✓	✓	✓	✓	✓
Loantype FE		✓	✓	✓	✓
Year FE			✓	✓	✓
2-Digit SIC FE				✓	
Firm FE					✓
N	849	848	846	842	703
R2	0.068	0.104	0.370	0.461	0.654

Cluster-robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Bond Swap Spread and Bond-Loan Covenant Ratio

Regression of bond swap spread on relative bond covenant intensity. One observation of the outcome variable represents the relative credit spreads (above LIBOR) of a comparable bond-loan pair issued by the same firm at about the same time (less than one year difference). Credit spreads for the loan are defined as the All-In-Drawn spread as reported by LPC DealScan. Credit spreads for the bond are defined as $BSS\_Proxy_T = YieldToMaturity_T - Treasury\_Swap_T - TED\_Spread_3$ or the bond's yield-to-maturity in basis points (of maturity T months) minus the rate of a maturity matched treasury swap minus the 3 month TED Spread. This credit spread is a public approximation of the proprietary bond swap spread data (from Bank of America Merrill-Lynch) used by Schwert (2020). Relative bond spreads are defined as the ratio of these two credit spreads as measured on the date of the loan's issuance. The main explanatory variable is relative covenant protections of the bond which is defined as the unweighted sum of covenants in the bond (max 16) divided by the number of covenants in the matched loan. Sample period covers the years 1996 - 2016 and is constructed as described in Table 1. Also included are controls for the specifics of the loan and bond being considered, additional controls for credit quality as well as controls for the matching procedure to account for any systematic bias this might introduce. Loan type, year, industry and firm-level fixed effects are included as indicated. All standard errors are clustered at the loan level.

	Bond Swap Spread				
	(1)	(2)	(3)	(4)	(5)
Bond-Loan Covenant Ratio	-44.378***	-27.176**	-25.280***	-21.249**	-20.048*
	(11.701)	(8.952)	(7.479)	(7.958)	(8.065)
Bond Controls:					
-log(Bond Offering Amount)		-5.947	-32.346**	-43.466***	-42.564***
		(13.661)	(10.557)	(10.484)	(10.455)
-Bond Maturity (months)		0.104*	0.087*	0.144***	0.145***
		(0.048)	(0.039)	(0.035)	(0.035)
Loan Controls:					
-log(Loan Package Amount)		-48.679***	-37.385***	-41.184***	-41.265***
		(10.367)	(7.198)	(7.169)	(7.161)
-Loan Maturity (months)		-1.944	-2.163*	-1.390	-1.463
		(1.379)	(0.980)	(0.785)	(0.785)
Match Controls	✓	✓	✓	✓	✓
Loantype FE		✓	✓	✓	✓
Year FE			✓	✓	✓
2-Digit SIC FE				✓	
Firm FE					✓
N	971	970	967	962	962
R2	0.016	0.148	0.583	0.667	0.668

Cluster-robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Correlation between Bond Covenant Intensity and Loan Covenant Intensity (3 measures)

This regression shows the degree of correlation between bond covenant intensity and three measures of loan covenant intensity. One observation of the outcome variable represents the unweighted sum of covenant protections in either a bond (in my sample of matched bonds and loans). A total of 16 potential covenants are hand matched between the bond and loan databases to ensure that covenants cover the same set of risks. Potential explanatory variables include, the analogous unweighted sum of 16 loan covenants, the unweighted sum of financial covenants as recorded by LPC DealScan and the unweighted sum of affirmative covenants (which relate to monitoring) which are features of loans but are typically excluded by bonds. Sample period covers the years 1996 - 2016 and is constructed as described in Table 1. Loan type, year, and industry-level fixed effects are included as indicated. All standard errors are clustered at the loan level.

	Bond Covenants Measure			
	(1)	(2)	(3)	(4)
Loan Covenants Measure	0.179***			0.170***
	(0.022)			(0.026)
Dealscan Covenants (Count)		0.265***		0.122
		(0.065)		(0.066)
Affirmative Covenants (Count)			0.0688**	-0.00915
			(0.025)	(0.027)
Match Diff. (Days)	-0.000762*	-0.000645	-0.000642	-0.000727
	(0.000)	(0.000)	(0.000)	(0.000)
Loan Before	-0.0444	-0.0250	-0.0388	-0.0441
	(0.080)	(0.082)	(0.084)	(0.080)
Year FE	✓	✓	✓	✓
Loantype FE	✓	✓	✓	✓
2-Digit SIC FE	✓	✓	✓	✓
N	1276	1276	1276	1276
R2	0.377	0.318	0.307	0.381

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Summary Statistics for Moody's Defaulted Debt Instruments by Collateral Rank

Summary statistics of defaulted debt instruments by collateral rank. One observation is one defaulted debt instrument issued by a non-financial/utility issuer as reported by Moody's Ultimate Recovery Database. Panel A reports recovery rates, interest rates, maturity details, debt structure and various flags indicating the nature/outcome of the default for debt instruments reporting the highest level of collateral ranking. These represent the most senior creditors in the priority structure. Panel B reports the same data for debt instruments reporting the second highest collateral ranking. These represent the junior creditors in the priority structure. Though further subordinated debt tranches are also reported, they make up the small minority of observations.

Panel A: Summary Statistics for Defaulted Debt Instruments where Collateral Rank = 1

	Mean	Std	10%	50%	90%	Obs.
Recovery Rate (%)	78.89	30.73	23.54	100.00	100.00	1598.0
Size of Senior Debt Tranche (%)	53.57	30.22	12.81	52.52	100.00	1598.0
Pre-Packaged Flag	0.21	0.41	0.00	0.00	1.00	1598.0
Bankruptcy Flag	0.83	0.37	0.00	1.00	1.00	1598.0
Emerged Flag	0.80	0.40	0.00	1.00	1.00	1598.0
Maturity at Origination (months)	78.91	62.02	33.23	70.00	121.88	1438.0
Maturity Remaining (months)	42.82	53.13	5.11	33.47	78.73	1309.0
Effective Interest (%)	6.40	3.80	0.00	6.60	11.00	1597.0

Panel B: Summary Statistics for Defaulted Debt Instruments where Collateral Rank = 2

	Mean	Std	10%	50%	90%	Obs.
Recovery Rate (%)	48.46	37.63	0.96	40.23	100.00	1293.0
Size of Senior Debt Tranche (%)	33.66	24.66	6.96	29.03	70.30	1293.0
Pre-Packaged Flag	0.20	0.40	0.00	0.00	1.00	1293.0
Bankruptcy Flag	0.77	0.42	0.00	1.00	1.00	1293.0
Emerged Flag	0.85	0.35	0.00	1.00	1.00	1293.0
Maturity at Origination (months)	133.03	92.95	60.87	120.87	255.80	1209.0
Maturity Remaining (months)	65.94	53.18	13.18	59.35	110.20	1146.0
Effective Interest (%)	8.72	3.83	1.28	9.50	12.85	1293.0

Table 13: Size of the Senior Debt Tranche and Recovery Rates by Collateral Rank

Regression of debt instrument recovery rates in default on the size of the senior tranche as reported by Moody's ultimate recovery database. One observation is one debt instrument sorted by its collateral ranking. A collateral rank of 1 denotes the most senior tranche of debt and a collateral rank of 2 denotes the second-most senior tranche of debt. Recovery rates reported in percent. Size of the highest priority tranche is the proportion of debt financed by instruments with collateral rank = 1 also reported in percent. Three flags denote if the bankruptcy was pre-packaged, a distressed debt exchange, or if the firm emerged from default as going concern. Maturity at origination denotes the maturity of the debt when it was originated (in months) and remaining maturity denotes the remaining maturity (in months) at the time of firm default. Heteroskedasticity-robust standard errors reported in parentheses.

Panel A: Defaulted Senior Debt Instruments (Collateral Rank = 1)

	Recovery Rate (%)				
	(1)	(2)	(3)	(4)	(5)
Size of Highest Priority Tranche	-0.542***	-0.520***	-0.498***	-0.501***	-0.429***
	(0.021)	(0.028)	(0.030)	(0.031)	(0.044)
log(Principal Amount at Default)		-0.555	-0.498	-0.441	-0.169
		(0.554)	(0.571)	(0.573)	(0.595)
Pre-Packaged Flag		5.450***	4.244*	3.914*	3.444
		(1.570)	(1.705)	(1.677)	(2.248)
Bankrupcty Flag		-19.693***	-19.945***	-22.740***	-27.759***
		(3.667)	(3.591)	(3.593)	(4.860)
Emerged Flag		7.019***	6.274**	4.617*	6.093*
		(2.031)	(2.052)	(2.110)	(2.891)
Maturity at Origination		-0.091***	-0.052	-0.042	0.012
		(0.025)	(0.027)	(0.028)	(0.032)
Remaining Maturity		0.049	0.023	0.027	-0.010
		(0.031)	(0.032)	(0.033)	(0.037)
Effective Interest (bps)		-1.765***	-1.871***	-1.948***	-2.059***
		(0.264)	(0.326)	(0.339)	(0.412)
Year FE			✓	✓	✓
2-Digit SIC FE				✓	
4-Digit SIC FE					✓
N	1597	1225	1224	1220	1163
R2	0.285	0.371	0.423	0.524	0.714

Robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13 (cont.): Size of the Senior Debt Tranche and Recovery Rates by Collateral Rank

Panel B: Defaulted Junior Debt Instruments (Collateral Rank = 2)

	Recovery Rate (%)				
	(1)	(2)	(3)	(4)	(5)
Size of Highest Priority Tranche	-0.219***	-0.139**	-0.241***	-0.224***	-0.192**
	(0.043)	(0.045)	(0.044)	(0.049)	(0.064)
log(Principal Amount at Default)		-0.221	-1.127	-1.193	-0.625
		(0.763)	(0.669)	(0.691)	(0.641)
Pre-Packaged Flag		1.541	-0.975	-1.574	-1.104
		(2.673)	(2.561)	(2.848)	(3.512)
Bankrupcty Flag		-12.665***	-11.822***	-14.450***	-21.217***
		(2.954)	(3.098)	(3.359)	(4.524)
Emerged Flag		18.358***	10.966***	8.468**	5.144
		(2.850)	(2.835)	(3.139)	(3.895)
Maturity at Origination		0.009	-0.064**	-0.054*	-0.071**
		(0.029)	(0.023)	(0.025)	(0.027)
Remaining Maturity		-0.045	0.027	0.016	0.045
		(0.035)	(0.029)	(0.029)	(0.030)
Effective Interest (bps)		-1.570***	-1.407**	-1.039*	-1.154*
		(0.417)	(0.429)	(0.431)	(0.549)
Year FE			✓	✓	✓
2-Digit SIC FE				✓	
4-Digit SIC FE					✓
N	1293	1041	1041	1034	921
R2	0.021	0.094	0.333	0.406	0.593

Robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: Additional Placebo Test: Covenant Intensity around First Bond IPO

Regression of financial covenant intensity (as reported by LPC DealScan) on a flag which indicates whether or not the loan was issued ex-ante or ex-post of the firms' first bond IPO. One observation is one loan issued within ±1 year of the first bond IPO. Controls include package amounts, maturities and all-in-drawn spreads.

	Loan Covenant Intensity (DealScan)					
	(1)	(2)	(3)	(4)	(5)	(6)
First Bond Market Entry	-0.210**	-0.212**	-0.192**	-0.185**	-0.207**	-0.123
	(0.071)	(0.071)	(0.071)	(0.070)	(0.071)	(0.111)
Loan Controls:						
-log(Loan Package Amount)		0.052*	0.061*	0.053*	0.075**	0.174***
		(0.025)	(0.025)	(0.026)	(0.027)	(0.027)
-Loan Maturity (months)		0.004	0.003	0.004*	0.004	0.004
		(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
-Loan All-in-Drawn Spread (bp)		0.001***	0.001***	0.001***	0.001***	-0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Loantype FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
2-Digit SIC FE			✓			
3-Digit SIC FE				✓		
4-Digit SIC FE					✓	
Firm FE						✓
N	2486	2450	2450	2439	2427	2127
R2	0.177	0.192	0.245	0.335	0.396	0.746

Robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: Cross-Default/Acceleration Protections and Covenant Intensity

This table shows how the inclusion of cross-default/acceleration clauses in the bond impacts the number of covenants used by the bond, the loan and the relative covenant protections of the bonds. One observation of the outcome variable represents the absolute or relative bond protections of a comparable bond-loan pair issued by the same firm at about the same time (less than one year difference). Cross-default or cross-acceleration is a binary indicator variable which denotes the presence of such a clause in the bond. Sample period covers the years 1996 - 2016 and is constructed as described in Table 1. Loan type and year-level fixed effects are included as indicated. All standard errors are clustered at the loan level.

	Bond Cov.			Loan Cov.			B-L Cov. Ratio		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Bond Cross-acceleration Clause	1.045***	1.093***	0.675*	1.022*	0.863*	0.074	0.077	0.137	0.257
	(0.188)	(0.197)	(0.327)	(0.435)	(0.405)	(0.272)	(0.109)	(0.104)	(0.170)
Bond Cross-default Clause	-0.099	-0.042	0.331	-0.765*	-0.589	-0.337	0.275	0.272	0.189
	(0.192)	(0.192)	(0.338)	(0.382)	(0.386)	(0.248)	(0.150)	(0.168)	(0.205)
log(Market Cap.)			-0.366*			-0.630			0.089
			(0.184)			(0.357)			(0.155)
S&P Instituional Credit Rating			-0.150			-0.290			-0.024
			(0.084)			(0.187)			(0.060)
Distance-to-Default			-0.068			-0.041			
			(0.055)			(0.099)			
Loan Controls			✓			✓			✓
Bond Controls			✓			✓			✓
Match Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Loantype FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
2-Digit SIC FE		✓			✓			✓	
Firm FE			✓			✓			✓
N	717	711	571	717	711	571	717	711	571
R2	0.258	0.376	0.836	0.223	0.411	0.883	0.142	0.305	0.754

Cluster-robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16: Cross-Default/Acceleration Protections and Overlapping Covenant Intensity

This table shows how the inclusion of cross-default/acceleration clauses in the bond impacts the number of overlapping covenants used by the bond, the loan and the relative covenant protections of the bonds. The outcome variable counts the number of overlapping or scaled overlapping protections in a bond-loan pair (issued by the same firm within one year of one another). An example might be a capital expenditures clause found in both contracts. If this was the only class of covenant which simultaneously appeared in both contracts then the overlapping covenants measure would be 1. The scaled overlapping measure just divides this number by the total unweighted sum of covenants used by both contracts. Cross-default or cross-acceleration is a binary indicator variable which denotes the presence of such a clause in the bond. Sample period covers the years 1996 - 2016 and is constructed as described in Table 1. Loan type and year-level fixed effects are included as indicated. All standard errors are clustered at the loan level.

	Overlapping Cov.				**Overlapping Cov. (scaled)**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bond Cross-acceleration Clause	0.831***	0.863***	0.781***	0.322	0.063***	0.068***	0.060***	0.033
	(0.196)	(0.199)	(0.187)	(0.232)	(0.018)	(0.018)	(0.017)	(0.023)
Bond Cross-default Clause	-0.531**	-0.164	-0.012	0.046	-0.021	-0.001	0.007	0.003
	(0.183)	(0.204)	(0.204)	(0.204)	(0.022)	(0.025)	(0.025)	(0.039)
log(Market Cap.)				-0.234				-0.004
				(0.206)				(0.021)
S&P Instituional Credit Rating				-0.201*				-0.007
				(0.082)				(0.006)
Distance-to-Default				-0.097				-0.006
				(0.059)				(0.005)
Bond-Loan Controls		✓	✓	✓		✓	✓	✓
Match Controls	✓	✓	✓	✓	✓	✓	✓	✓
Year FE		✓	✓	✓		✓	✓	✓
Loantype FE		✓	✓	✓		✓	✓	✓
2-Digit SIC FE			✓				✓	
Firm FE				✓				✓
N	719	717	711	571	719	717	711	571
R2	0.043	0.227	0.375	0.850	0.035	0.144	0.295	0.782

Cluster-robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 17: Bond and Loan Covenant Matching by Hand Glossary

This table shows 16 bond covenants from Mergent FISD and their hand-matched loan covenant counterparts from two data sources, FactSet Current Bank Loans (as of Aug. 2020) and a Historical database of loan covenants created for this paper. The Historical database is significantly more granular than either Factset or Mergent FISD, so it is possible for many Historical loan covenants to match to the same bond covenant. For example, both 'mergers, etc' and 'aquisitions' match to the "Consolidation Merger' covenant in Mergent FISD. Also, since one type of Historical covenant might refer to two different risks as identified by Mergent FISD, it is possible that the same Historical covenant matches to multiple Mergent FISD covenants. As an example, the Historical covenant "consolidation, merger, purchase or sale of assets, etc", matches to both the "Consolidation Merger" and 'Sale Assets" covenants in Mergent FISD. Historical covenants listed in order of the frequency with which they appear in the corpus.

<table>
<tr><th>Bonds</th><th colspan="2">Loans</th></tr>
<tr><th>Mergent FISD</th><th>FactSet Current Loans</th><th>Historical</th></tr>
<tr><td>Consolidation Merger</td><td>Consld Merger</td><td>mergers, etc | acquisitions | consolidation, merger, purchase or sale of assets, etc | dissolution; merger or consolidation | merger, consolidation | consolidation, merger, etc | mergers, consolidations, sales | mergers or acquisitions | consolidations and mergers | mergers | mergers, consolidations, sales of assets and acquisitions | consolidation and merger | consolidation; merger | merger | merger, consolidation, acquisition and sale of assets | merger, consolidation, transfer of assets | consolidation, merger, purchase or sale of assets, etc | dissolution; merger or consolidation | investments, loans, advances, guarantees and acquisitions | acquisitions | permitted acquisitions | make acquisitions | notices of asset sales and/or acquisitions | investments and acquisitions | acquisition of property | restrictions on intercompany transfers</td></tr>
<tr><td>Dividends Related Payments</td><td>Div Payment</td><td>dividends | dividends and distributions | limitation on dividends | dividends, distributions | distributions; investments | distributions; | distributions; capital change; restricted investments | clauses restricting subsidiary distributions | distributions | restricted payments; certain payments of indebtedness | restricted payments</td></tr>
<tr><td>Funded Debt</td><td>Funded Debt Issuance</td><td>funded debt | funded debt to ebitda ratio | funded debt to cash flow ratio</td></tr>
<tr><td>Indebtedness</td><td>Indebt</td><td>indebtedness | debt | restrictions on indebtedness | indebtedness to total capitalization</td></tr>
<tr><td>Investments</td><td>Invest</td><td>investments | advances, investments and loans | investments and acquisitions | investments, loans, advances, guarantees and acquisitions | loans and investments | limitation on investments, loans and advances | restricted investment</td></tr>
<tr><td>Liens</td><td>Lien</td><td>liens | liens and encumbrances | limitation on liens | liens, etc | liens securing | liens pursuant to any loan document; | restrictions on liens | prohibition on liens | liens securing indebtedness permitted under</td></tr>
<tr><td>Maintenance Net Worth</td><td>Net Worth | Tangible Net Worth</td><td>net worth | tangible net worth | minimum net worth</td></tr>
<tr><td>Restricted Payments</td><td>N/A</td><td>restricted payments | restricted junior payments | restricted payments; certain payments of indebtedness | restrictions on intercompany transfers | merger, consolidation, transfer of assets | payment of subordinated obligations</td></tr>
<tr><td>Sales Leaseback</td><td>Sale Leaseback Trans</td><td>sale leasebacks | sale and leaseback | sales and leasebacks | limitation on sales and leasebacks | sale and leaseback transactions | leases, | sale or lease of assets | lease obligations | sale and lease-back transactions | sales and leasebacks | capitalized lease obligations | payment of subordinated obligations</td></tr>
<tr><td>Sale Assets</td><td>Asset Sales</td><td>sale of assets | limitation on sales and leasebacks | sales, etc | merger, consolidation, acquisition and sale of assets | notices of asset sales and/or acquisitions | consolidation, merger, purchase or sale of assets, etc | sales, | mergers, consolidations, sales | mergers, consolidations, sales of assets and acquisitions | asset sales | limitation on sale of assets | disposition of collateral | disposition of property | dispositions | disposition of assets | dispositions permitted by | asset dispositions | sale and leaseback transactions | sale or lease of assets | restrictions on intercompany transfers | merger, consolidation, transfer of assets</td></tr>
<tr><td>Senior Debt Issuance</td><td>Senior Debt Issuance</td><td>senior indebtedness | designation as senior debt | senior notes | senior debt ratio | designated senior indebtedness | senior debt to capital base</td></tr>
<tr><td>Subordinated Debt Issuance</td><td>Subord Debt Issue</td><td>subordinated debt | subordinated notes | subordinated indebtedness</td></tr>
<tr><td>Transaction Affiliates</td><td>Trans w/ Affiliates</td><td>transactions with affiliates | affiliates | unrestricted subsidiaries | restricted investment</td></tr>
<tr><td>Net Earnings Test Issuance</td><td>Interest Coverage</td><td>interest coverage ratio</td></tr>
<tr><td>Fixed Charge Coverage</td><td>Fixed Charge Coverage</td><td>fixed charge coverage ratio | fixed charges ratio | fixed charge coverage</td></tr>
<tr><td>Leverage Test</td><td>Leverage</td><td>leverage ratio | total leverage ratio | maximum leverage</td></tr>
</table>

Appendix A:

Title Recombination K-Means Methodology Description (TRKM)

To facilitate the explanation of the TRKM methodology, I divide the process into 5 steps which I detail below.

1. I scrape the universe of available lending credit agreements from SEC EDGAR from 1996-2016. These are frequently included as materially relevant information as exhibits at the end of 8K and 10K filings. With small exceptions, the scraping procedure is virtually identical to the technique used by Roberts and Sufi in their papers. The output of this step is a corpus of about 30K text documents, each one a credit agreement contract from a bank loan given to a public corporation.

2. I algorithmically parse the text of the contracts to separate each contract into its component parts. To explain how this works, it is important to take a quick detour and explain the hierarchical organization of a typical lending agreement. The typical contract is organized into two hierarchical levels, I call these the 'supersection' and the 'subsection'. As the names suggest, each supersection typically contains a number of subsections. For example, the 'Negative Covenants' supersection might contain the 'Liens', 'Investments' and 'Mergers and Acquisitions' subsections. As a helpful analogy, the structure is roughly analogous to that typically employed academic papers. Since each contract might have its own way of designating subsections and supersections, I write an adaptive script which intelligently parses each contract and divides it along these two dimensions. First each contract is divided into a number of supersections which are then further subdivided into a number of subsections. Though the exact details of how this parsing script functions are beyond the scope and length of this paper, the guiding principle for defining subsections is finding clauses that have the

following basic format.

Section 6.2 Capital Expenditures Restriction [Body of text]

The three important pieces of a subsection are 1) a section numbering of any sort, 2) a title and 3) a body of text (longer than some cutoff threshold). This is by far the most common paradigm of contract construction found in the data (though others exist). The guiding principle of the parsing algorithm is that, if a subsection meets these three criteria, it should be designated as a separate subsection. One final note is that algorithm also tracks what part of the subsection is the number/title/body, a detail that will be important in the fifth step.

3. The text subsections are vectorized. Vectorization follows the commonly used bag-of-words methodology first popularized in finance by Hanley and Hoberg (2012). Effectively, each snippet of text is transformed into a numerical vector, where each element of a vector represents intensity of use for a specific word. I also consider bi-grams and tri-grams of words which both massively increase the dimensionality of the vectors. Since these numerical vectors can frequently be quite large, multiple tricks are used to cut down the size of the vectors. The most common tricks include eliminating so-called 'stop-words' as well as eliminating words which are either overly common or rarely seen in the corpus. Finally, once all subsections have been parsed and vectorized, a transformation is applied to the entire vector space which re-weights vector elements proportional with their inverse frequency. Effectively, the more uncommon a word is in the entire corpus, the more weight it gets.

4. Vectors are clustered together using an off-the-shelf implementation of the K-Means algorithm. In machine learning nomenclature, the K-Means algorithm is classified as an unsupervised learning technique. The advantage of this unsupervised technique is that, as opposed to other commonly used machine learning techniques (for example

neural nets), the researcher does not need to pre-train the algorithm with 'supervised' or labeled data showing what a good cluster looks like. Clusters are approximately chosen by finding a set of clusters for the subsections such that the (euclidean) distance between vectors inside a cluster is minimized. The main drawback of K-Means clustering is that it is far from obvious what the choice of K, or the number of clusters should be. Though some heuristic methods exist for solving this 'choosing K' problem, I exploit the extra data available to me to sidestep this problem entirely. My method relies on deliberately over-clustering the data and then exploiting the extra data available to me to recombine the overly-small clusters ex-post. For this method, I choose a 'K' of 10,000, or 10,000 clusters. This value of K should hopefully be larger than any reasonable prior of the true total number of types of clauses included in lending contracts.

One final note for the details of the clustering is that I define distance between two clauses in terms of euclidean distance instead of the popularly used cosine similarity. Intuitively, what this means is that I am placing a premium on clauses not only having the same proportional distribution of words, but also the same absolute numbers of words as well. Such a premium might be undesirable in a setting (i.e. news) where one wants to connect clauses with the same types of words or topics, regardless of length. However in a contracting setting, where language is relatively standardized, it makes more sense to demand that the lengths be the similar amongst clauses in the same cluster. Mathematically, difference can be roughly thought of as the difference between taking the covariance (euclidean) and correlation (cosine) of two vectors.[72]

5. I use the previously collected data on the title of the subsections to assess which clusters are overly-small and need to be recombined with another cluster. I call this part title-recombination. The process is relatively straightforward. For each cluster I find the

[72] Another added advantage of using euclidean distance is that it speeds up the convergence of K-means algorithm.

modal, or most common, title in the cluster. This is set as the title of that cluster. If another cluster has the same modal title, I combine the clusters together. In this way I am exploiting the extra data available to to me to double-check the accuracy of the clusters. Finally, these recombined and named clusters are mapped back to each contract. If the contract contains a subsection which is in a the cluster titled X, then the contract is said to contain X. In this way I establish a universe of about 3K potential subsections which may or may not be in a contract and assign binary 1-0 variables to each to indicate if the subsection is in a given contract. As a final step, subsection clusters are assigned a supersection by seeing which supersection the elements of the cluster most commonly fall into.

Comparison with Topic-Modeling Techniques

One could reasonably argue that the above approach is much more suited to the task of classifying contractual data than an approach based on topic modeling techniques. Topic models work best in settings such as news (Kelly, et al (2019)) where there are a small number of fundamental topics and each article has a distribution of words which cover these topics. Legal clauses in contracts are almost the exact opposite of this. There are a large number of potential topics and each clause typically only deals with only one topic. When a clause does contain multiple topics, these typically have their own subsections inside the clause and they can be easily picked up by an intelligent scraping script (as I do in my paper). Generally speaking, in contracts, the tendency of lawyers to taxonomize their thoughts obviates the need for a machine learning technique to do so.

Ganglmair and Wardlaw (2017) use topic modeling techniques to create a covenant database similar in spirit to the one I create in this paper, however their approach and resultant data suffers from some key drawbacks compared to my technique and data. First, my data is more precise. My technique generates unique labels for each cluster which directly correspond to the covenant names that one would search for in public databases. This is valuable because allows me to verify the quality of my data out of sample. This is something Ganglmair and Wardlaw do not because their technique does not allow them to be confident that their clusters only represent one covenant.[73] Second, my dataset is larger in scope. While Ganglmair and Wardlaw use 50 topics in their topic model which they hope each capture a unique class of covenant, my technique finds hundreds of distinct clusters of covenants which are uniquely identified and easily comparable with other covenant databases. Where it overlaps, I compare my covenant data against publicly available sources and find that my results compare well with the publicly available data.[74] Third, my database is also simply larger in the number of observations available and covers a longer time period. For their sample of contracts, Ganglmair and Wardlaw mainly use the same sample of about 3,000 contracts scraped by Nini et al (2009). I scrape my more than 30,000 contracts directly from EDGAR and consider about 10,000 contracts which all match to LPC DealScan.

[73] As an example of this, Ganglmair and Wardlaw implicitly define clusters in terms of the most common words used in that cluster. Accordingly, they only use the top ten best clusters (according to psuedo-R^2) for their results.

[74] As mentioned, Ganglmair and Wardlaw do not provide data on the composition of their covenant clusters and I cannot compare my data against theirs.

Appendix B: Bond Swap Spread Approximation

In this appendix I consider the size and directions of potential errors introduced by my approximation of bond swap spreads using non-proprietary data. My proxy for bonds swap spreads is defined as,

$BSS\_Proxy_T = YieldToMaturity_T - Treasury\_Swap_T - TED\_Spread_3$

Since, in theory and assuming no arbitrage, the price for a Libor swap of maturity T would equal,

$Libor\_Swap_T = Treasury\_Swap_T - TED\_Spread_T$

Then the usage of the 3 month Ted Spread instead of a T month Ted spread is the primary source of error in this calculation. This would affect the results most there if is a strong term structure to the TED spread.

As data from the St. Louis Federal Reserve shows[75], before 2009 there is no discernible term structure (for tenors ranging from 3 months to 12 months, the longest maturity for which LIBOR is available) to the TED spread. After 2009 there develops a monotonic term structure in the TED spread that persists before disappearing again in 2018. In the period from 2009 to 2018, the average difference between a 12-Month TED spread and a 3-Month Ted Spread is about 25 bps. In the period outside of this time range, it is close to 0. Only about 30 percent of my data falls within this period in which there exists discernible term structure to the TED spread. Thus, I conclude that there is a small but negligible bias that comes from using the 3-Month TED spread in my calculations.

As an additional check, when I compare my approximated spreads with Schwert's, I find that my proxy exhibits the same general dynamics of Schwert's variable (at least along the cross-section of distance to default). The main noticeable bias is that my relative spreads variable is slightly attenuated compared to Schwert's and exhibits less variance over the cross-section of credit quality. To test this, I split my data (as Schwert does in his paper) on the dimension of distance-to-default and see how my proxied variable compares to Schwert's

[75] https://fred.stlouisfed.org/series/TEDRATE contains data on Ted Spreads of multiple tenors.

actual data for different levels of distance-to-default. Schwert finds that when firms are extremely close to default, bonds have spreads that are 2-2.5 times the spreads of loans. As firms get further away from default, this difference shrinks before achieving parity about where distance-to-default equals 10. As Figure 4 shows, when firms (in my data) are very close to default, bonds have spreads that are a little more than 2 times those of loans. As firms get further away from default, the difference exhibits the same shrinking pattern before reaching parity about where distance-to-default equals 6. From this, I conclude that my proxy exhibits the same general dynamics of Schwert's variable (at least along the cross-section of distance to default). This means that my relative spread variable will tend to understate the actual magnitude of the spread differential which would be a bias against finding any results as compared with the true data.

Appendix C: Derivation of Expected Recovery Rates

This appendix describes the derivation expected recovery rates for junior and senior creditors as a function of the default threshold ρ. I also discuss the assumption for an average firm that I use to calibrate the model.

Probabilities of Impairment and Being Made Whole in Bankruptcy

Given a realization of default ($V_T \leq \rho K_{total}$ or D), there are only two possible states of the world (with respective probabilities) for the firm; the state in which the creditor is made whole (W) and the state in which the creditor is impaired and loses money (I). These will be different for each class of creditor. For senior debt, they will be impaired if the terminal value of the firm at maturity is less than the face value of senior debt ($0 \leq V_T \leq K_S$ or I_S) and they will be made whole in the complementary state where the terminal value of the firm at maturity is greater than the face value of senior debt ($K_S \leq V_T \leq \rho K_{total}$ or W_S). For junior debt, they will be impaired if the terminal value of the firm at maturity is less than the face value of total debt ($0 \leq V_T \leq K_{total}$ or I_J) and they will be made whole in the complementary state where the terminal value of the firm at maturity is greater than the face value of total debt ($K_{total} \leq V_T \leq \rho K_{total}$ or W_J).

Probability that senior debt is impaired is,

$$P(0 \leq V_t \leq \min\left[\rho K_{total}, K_S\right]) = P(0 < V_t \leq \rho K_{total}) - P(K_S \leq V_t \leq \max\left[\rho K_{total}, K_S\right])$$

or,

$$P(I_S) = P(D) - P(W_S)$$

And the probability that junior debt is impaired and has a non-zero payoff is,

$$P(\min[K_S, \rho K_{total}] \leq V_t \leq \min[\rho K_{total}, K_{total}]) = P(0 < V_t \leq \rho K_{total})$$

$$-P(K_{total} < V_t \leq \max\left[\rho K_{total}, K_{total}\right]) - P(0 < V_t \leq \min\left[K_S, \rho K_{total}\right])$$

or,

$$P(I_J) = P(D) - P(W_J) - P(I0_J)$$

Though the max functions slightly complicate the above notation, it is necessitated by the variable default threshold to ensure that these probabilities are never negative. Note that the First probability is equal to 0 if $\rho \leq \frac{K_S}{K_{total}}$. And the second probability is equal to 0 if $\rho \leq 1$.

Expected Recovery Rate for Senior Debt

The expected raw payoff to senior debt conditional on the firm defaulting and senior debt being impaired is,

$$E[\pi_S^t | I_S \equiv (V_t \leq \min\left[\rho K_{total}, K_S\right])] = \frac{e^{\ln(V_0)+(r-\delta)t}\Phi\left(\frac{\ln(\min[\rho K_{total}, K_S]) - \ln(V_0) - \left(r-\delta+\frac{\sigma^2}{2}\right)t}{\sigma\sqrt{t}}\right)}{P(0 \leq V_t \leq \min\left[\rho K_{total}, K_S\right])}$$

And the expected recovery rate of senior debt conditional on the firm defaulting is,

$$E[R_S^t | D] = \frac{P(I_S) \cdot E[\pi_S^t | I_S] + P(W_S) \cdot K_S}{P(D) \cdot K_S}$$

Expected Recovery Rate for Junior Debt

The expected raw payoff to junior debt conditional on senior debt being made whole and junior debt being impaired is,

$$E\left[\pi_J^t | I_J \equiv (\min[K_S, \rho K_{total}] \leq V_t \leq \min[\rho K_{total}, K_{total}])\right] =$$

$$\frac{e^{\ln(V_0)+(r-\delta)t}\left[\Phi\left(\frac{\ln(\min[\rho K_{total}, K_{total}])-\ln(V_0)-\left(r-\delta+\frac{\sigma^2}{2}\right)t}{\sigma\sqrt{t}}\right)-\Phi\left(\frac{\ln(\min[K_S, \rho K_{total}])-\ln(V_0)-\left(r-\delta+\frac{\sigma^2}{2}\right)t}{\sigma\sqrt{t}}\right)\right]}{P(\min[K_S, \rho K_{total}] \leq V_t \leq \min[\rho K_{total}, K_{total}])} - K_S$$

And the expected recovery rate for junior debt, conditional on the firm defaulting is,

$$E[R_J^t|D] = \frac{P(I0_J)\cdot 0 + P\left(I_J\right)\cdot E\left[\pi_J^t | I_J\right] + P(W_J)\cdot K_J}{P(D)\cdot K_J}$$

Model Calibration

I calibrate the model as follows:

- $T = 7.5$, Average Bond/Loan Maturity $\approx$ 10/5 years
- $r = .05$, Average market risk premium 2011-2020 $\approx 5.6\%$
- $\delta = .02$, Average All-in-Drawn Loan Spread = 164 bps, Bond Swap Spread = 214 bps
- $\sigma = .35$, Average yearly asset volatility in data = .32
- Variables of interest
  - Leverage: $V_0 = 2$. If $K_J + K_S = 1$, equal to inverse leverage ratio, historically $V_0 \approx 3$
  - Senior Debt Percent: $K_S = .5$. For firms entering bankruptcy $K_S = .48$. Average in matched sample $K_S = .21$
- ρ, Left as free variable to generate predictions about covenant usage

Appendix D: Additional Figures And Tables

D1: De-facto Seniority and Debt Type

Panel A: Most Common Collateral Backing by Debt Type

Bonds		Loans	
Collateral Type	Freq.	Collateral Type	Freq.
Unsecured	76.7%	All Assets	64.52%
Equipment	5.7%	Inventory and Accounts Receivable	6.08%
Second Lien	5.06%	**Unsecured**	5.36%
PP&E	3.65%	Capital Stock	5.29%
Capital Stock	2.83%	Second Lien	4.08%
All Assets	2.64%	All Non-current Assets	3.29%
All Non-current Assets	1.69%	All Current Assets	2.79%
Third Lien	0.87%	PP&E	2.58%
Most Assets	0.23%	Accounts Receivable	1.29%
Guarantees	0.14%	Most Assets	1.14%
Intellectual Property	0.09%	Real Estate	1.0%
Inventory	0.09%	Guarantees	0.64%
Other	0.09%	Inventory	0.57%
Accounts Receivable	0.05%	Oil and Gas Properties	0.5%
All Current Assets	0.05%	Cash	0.43%
Cash	0.05%	Third Lien	0.36%
Inventory and Accounts Receivable	0.05%	Equipment	0.07%
Oil and Gas Properties	0.05%	Other	0.00%

N = 3591 Defaulted Debt Instruments, Source: Moody's Ultimate Recovery Database

Panel B: Collateral rank and Debt Type - Two most senior debt tranches

Sub. ↓ / Sen. →	Bond	Loan	Both	Total
Bond	7.4%	73.7%	3.3%	84.3%
Loan	0.7%	13.9%	0.3%	14.9%
Both	0.0%	0.8%	0.0%	0.8%
Total	8.0%	88.4%	3.6%	100.0%

N = 687, Source: Moody's Ultimate Recovery Database

D2: Absolute Bond and Loan Covenant Intensity and Distance-to-Default

Regression of absolute covenant intensity for both bonds and loans on debt capital structure. One observation of the outcome variable represents the unweighted sum of covenant protections in either a bond or loan in my sample of matched bonds and loans. A total of 16 potential covenants are hand matched between the bond and loan databases to ensure that covenants cover the same set of risks. The main explanatory variable is Distance-to-Default (prior to issuance) as defined in Bharath and Shumway (2008). Sample period covers the years 1996 - 2016 and is constructed as described in Table 1. Also included are controls for the specifics of the loan and bond being considered, additional controls for credit quality as well as controls for the matching procedure to account for any systematic bias this might introduce. Loan type, year, industry and firm-level fixed effects are included as indicated. All standard errors are clustered at the loan level.

	Bond Covenants			**Loan Covenants**		
	(1)	(2)	(3)	(4)	(5)	(6)
Distance-to-Default	-0.067***	-0.109***	-0.040	-0.210***	-0.197***	-0.104
	(0.020)	(0.022)	(0.026)	(0.047)	(0.047)	(0.054)
Bond Controls:						
-Senior Bond	-0.715***	-0.572**	0.009			
	(0.181)	(0.200)	(0.346)			
-log(Bond Offering Amount)	-0.292**	-0.300***	-0.110			
	(0.090)	(0.076)	(0.067)			
-Bond Maturity (months)	-0.003***	-0.003***	-0.001*			
	(0.000)	(0.000)	(0.000)			
-Bond Coupon (bp)	0.003***	0.003***	0.000			
	(0.000)	(0.000)	(0.000)			
Loan Controls:						
-log(Loan Package Amount)				-0.786***	-0.718***	0.161
				(0.126)	(0.139)	(0.190)
-Loan Maturity (months)				0.032*	0.041***	0.038**
				(0.012)	(0.011)	(0.012)
-Loan All-in-Drawn Spread (bp)				0.004	0.002	0.001
				(0.003)	(0.003)	(0.001)
Match Controls	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
2-Digit SIC FE		✓			✓	
Loantype FE				✓	✓	✓
Firm FE			✓			✓
N	1279	1273	1133	1277	1271	1130
R2	0.362	0.444	0.787	0.341	0.453	0.846

Cluster-robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

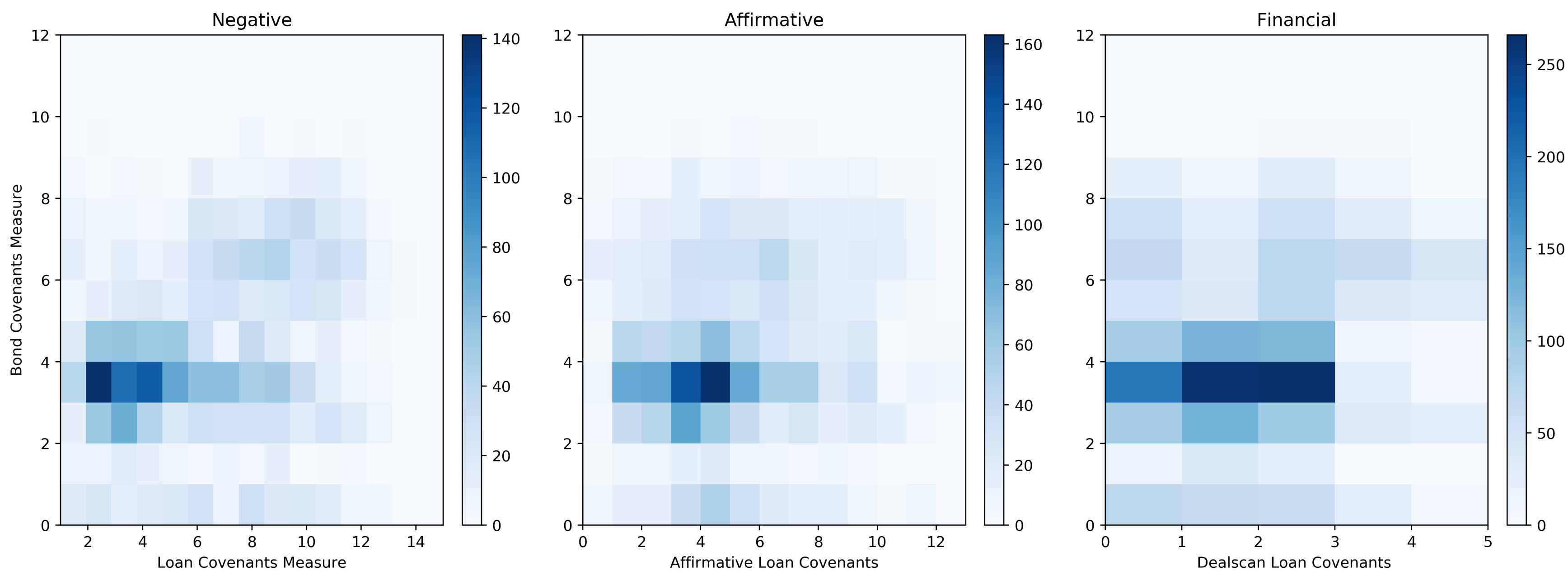
D3: Determinants of Debt Structure

Regression of debt structure on 14 measures of firm credit quality. One observation of the outcome variable represents one firm-quarter observation of the debt structure of the firm. Columns 1-3 are the entire sample of firms from Capital IQ. Columns 4-6 test with a sub-sample firms who also have current access to public bond markets (as measured by having a concurrent percentage of total senior bonds and notes greater than 0). Year, industry and firm-level fixed effects are included as indicated. All standard errors are clustered at the firm level.

	Sample: Any			**Sample: Bond Market Access**		
	Bank Debt Percent			**Bank Debt Percent**		
	(1)	(2)	(3)	(4)	(5)	(6)
Advertising	73.49*	91.54	13.64	52.82***	60.76***	13.00
	(30.224)	(47.306)	(12.615)	(10.349)	(11.945)	(12.765)
Asset Maturity	0.00197	0.00161	674	0.00192	0.00162	0.00109
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Capex	-3.170	-13.64	-7.612	2.487	1.907	-2.060
	(9.971)	(18.152)	(8.337)	(6.528)	(5.594)	(4.425)
Cash Flow	-24.57**	-24.01*	-22.95	-12.56*	-12.42*	-4.564
	(8.450)	(11.227)	(15.787)	(6.217)	(6.170)	(3.469)
Cash Flow Volatility	3.296	4.260	2.737	4.596	5.700*	-0.300
	(4.304)	(4.681)	(3.412)	(2.780)	(2.863)	(2.708)
Cash Holdings	-55.14***	-53.81**	-41.01*	-45.21***	-47.47***	-51.94***
	(15.480)	(16.380)	(16.238)	(5.700)	(5.729)	(4.199)
Disposition of Assets	18.11	-3.387	-13.34	23.83*	2.703	-4.668
	(11.458)	(12.159)	(7.237)	(11.793)	(9.672)	(7.065)
$1_{\text{Dividends Paid}}$	-16.25***	-16.98***	0.287	-10.93***	-9.642***	0.157
	(3.261)	(4.237)	(1.328)	(1.034)	(0.997)	(1.113)
Distance-to-Default	0.322	0.0819	0.599	-0.325*	-0.342**	0.136
	(0.457)	(0.534)	(0.701)	(0.132)	(0.130)	(0.130)
Firm Age in Compustat	-0.106***	-0.0918***	-0.146	-0.104***	-0.0940***	-0.0335
	(0.012)	(0.015)	(0.127)	(0.007)	(0.008)	(0.021)
Market to Book	0.212	-0.449	0.688	0.276	0.315	0.299
	(0.982)	(0.914)	(1.153)	(0.366)	(0.355)	(0.357)
Book Leverage	-17.53**	-15.44**	-16.58	-15.46***	-14.89***	-7.783**
	(5.353)	(4.855)	(10.191)	(2.661)	(2.632)	(2.574)
Market Leverage	-5.619	-14.64	-5.486	1.299	0.240	3.393
	(4.086)	(11.770)	(5.112)	(2.796)	(2.710)	(2.256)
R&D	-72.96	-84.60	8.501	-1.760	-47.99	-27.65
	(70.390)	(62.114)	(35.551)	(28.369)	(30.322)	(22.550)
Sales	19.06	16.14*	24.13	7.237**	11.46***	10.95***
	(12.574)	(7.503)	(20.389)	(2.725)	(2.828)	(2.588)
Tangibility	-7.185*	-12.25	-19.06	-6.716*	-2.933	-20.99***
	(3.200)	(11.560)	(19.308)	(2.696)	(3.678)	(4.716)
Year FE	✓	✓	✓	✓	✓	✓
4-Digit SIC FE		✓			✓	
Firm FE			✓			✓
N	138613	138613	138526	112331	112331	112217
R2	0.00341	0.0267	0.195	0.0675	0.128	0.540

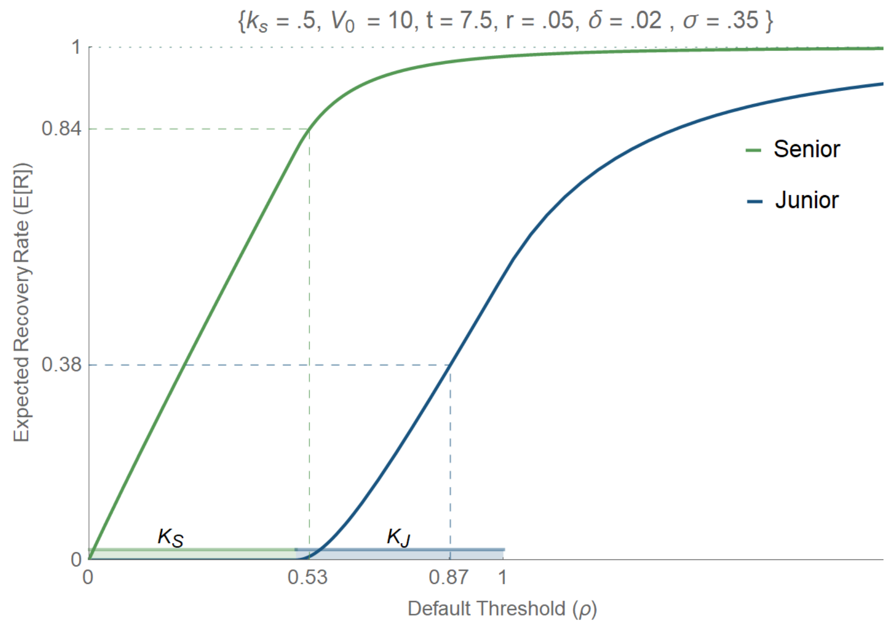
Cluster-Robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

D4: Correlations between Bond Covenants and 3 Types of Loan Covenants

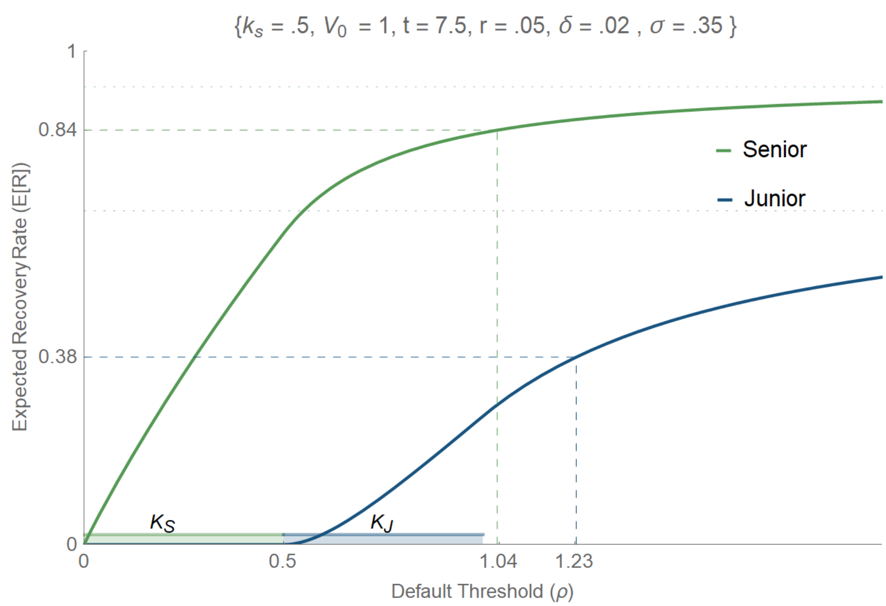


D5: Recovery Rates Under Two Leverage Scenarios

Panel A: Scenario 1 - Levered 1-10

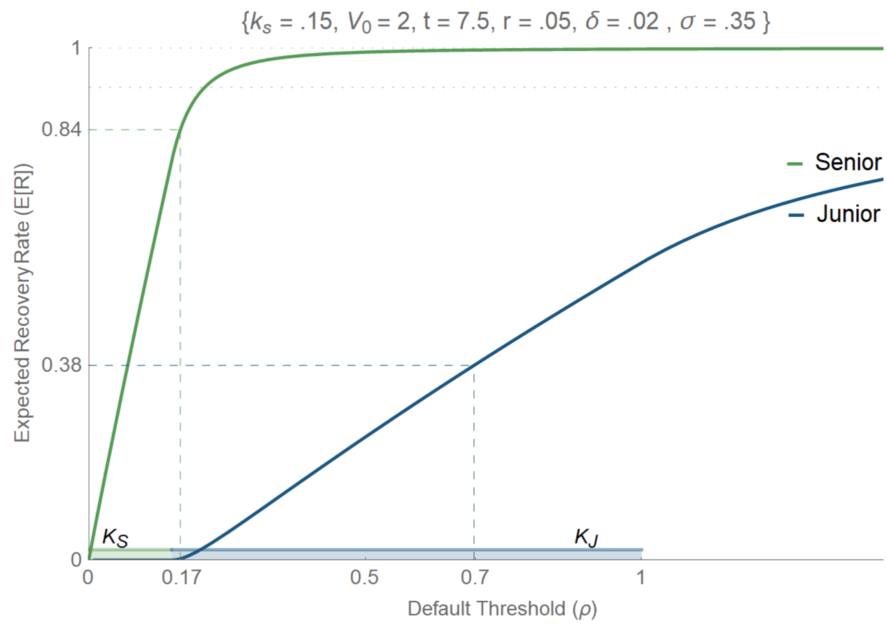


Panel B: Scenario 2 - Levered 1-1



D6: Recovery Rates Under Two Debt Structure Scenarios

Panel A: Scenario 1 - 15% Bank Debt



Panel B: Scenario 2 - 85% Bank Debt