Affirmative Covenants and Information-first Monitoring *

Steven Fortney
Yale School of Management

August 13, 2021

Abstract

Using a novel source of data on the originated contracts of syndicated lending agreements matched to their their renegotiations, I examine the role that affirmative covenants play in corporate debt contracts. From the data on originations, I conclude that affirmative covenants constitute a monitoring technology that banks use to keep tabs on their borrowers. Compared to negative covenants which are assumed to be a form of tripwire for lenders, affirmative covenants can be conceptualized as setting the sensitivity of these negative covenant tripwires. Using these observations, I hypothesize that banks monitor loans on an 'information-first' basis, first asking for additional information before imposing more restrictions on firm actions. I test this in a sample of lending renegotiations and find that affirmative covenants are renegotiated first in time, first in default and first after technical defaults which are waived. The results suggest that affirmative covenants are a monitoring tool which is frequently adjusted to help banks manage the information asymmetry that develops over the life of a loan.

*Special Thanks to Stefano Giglio, Gary Gorton, and Heather Tookes for their excellent advice and mentoring contributions on this project. Thanks to Nick Barberis, William Goetzmann, Song Ma, Justin Murfin, Chris Clayton and Kaushik Vasudevan for helpful feedback and suggestions. All errors remain my own.

1 Introduction

Syndicated lending contracts typically contain two broad classes of covenants, negative covenants which restrict the actions the firm can take in some states of the world and affirmative covenants which stipulate actions the firm must take in all states of the world. The importance of negative covenants is relatively well understood. These are commonly presumed to act as 'tripwires' which alert lenders to potential problems with their borrowers. On the other hand, the role that affirmative covenants play in contracts is generally much less understood and written about. In this paper I address this gap in the literature using data on the way that affirmative covenants are included in contracts as well as data on the way in which they are subsequently renegotiated.

The reason this gap in the literature persists can perhaps mostly concisely be attributed to a simple lack of data. LPC DealScan, a commonly used source of data for syndicated lending covenants in the academic literature, does not track affirmative covenants at all. Even papers which hand-collect data on covenants tend to ignore affirmative covenants. Freudenberg, et al. (2011) who attempt to hand collect data on the universe of covenants, note that, "We do not include affirmative covenants such as punctual payment of interest and principal, delivery of financial statements, property and equipment maintenance, compliance to accounting standards, or paying insurance and taxes..." It is not an overstatement to say that papers about lending covenants which even acknowledge the existence of affirmative covenants are in the minority. When affirmative covenants are mentioned, papers typically do so in passing and tend to either de-emphasize their importance or emphasize the similarities with negative covenants.[1]

This ignorance of one entire class of covenants from the entire literature on debt covenants is somewhat surprising. Affirmative and negative covenants each respectively make up about make up about 10% of the text in an average lending contract.[2]. Furthermore, there is great variability in the intensity of affirmative covenant usage in the average contract[3] and this variability is strongly related to the credit quality of the firm issuing the debt.[4] This implies that affirmative covenants are not a perfunctory inclusion into contracts but rather a deliberate feature whose importance increases as the firm gets closer to default.

If affirmative covenants are not a rote or haphazard inclusion into contracts, then it begs the question, what role do affirmative covenants play in the average contract? Do they

[1]Griffin, Nini and Smith (2019) note that,"Affirmative and negative covenants minimize incentive conflicts by contracting directly on certain events, such as the purchase of insurance or the distribution of dividends."

[2]See Figure 8

[3]See Table 1.

[4]See Table 6.

perform the same role as negative covenants or do they play a different role? I use two novel sources of data to answer this question. The first source of data is a comprehensive database of the contents of syndicated lending agreements. This database attempts to categorize all clauses that one might potentially find in a lending contract and is created by applying simple machine learning techniques to original lending contracts scraped from SEC filings. I test this data extensively out-of-sample where it overlaps with existing databases and show that my data matches the moments and co-movements of the existing data quite well. For ease of interpretation, I aggregate this data into ten broad 'supersections' that correspond to the most important sections that one might expect to find in a contract. One of these 10 'supersections' corresponds to negative covenant usage and another corresponds to affirmative covenant usage. The second database is a database of contractual renegotiations which also breaks down the content of the renegotiation into one of these ten 'supersection' categories.

This paper has two main findings, the first is that the main role affirmative covenants play in syndicated lending contracts is that of a monitoring technology which helps banks stay current on the state of their borrowers. Virtually all affirmative covenants can be roughly divided into one of two categories. Affirmative covenants ensure that the information banks have about the borrower is either 1) available in a timely manner to the lender or 2) accurate to the current state of the firm. Taking the popular covenants as a 'tripwire' analogy to heart. Setting the tightness of the negative covenant package can be analogized to determining the *position* of the tripwire while setting the tightness of the affirmative covenant package can be analogized to setting the *sensitivity* of that same tripwire. If the affirmative covenant package is set too loose, firms may be able to significantly cross tripwires without actually triggering a default.

The second main finding of this paper is that bank monitoring of loans happens on an 'information-first' basis. Firms can generally always comply with the terms of affirmative covenants and tightening an affirmative covenant is basically the equivalent of asking for more or better information from the firm. Because of this, I hypothesize that since tightening affirmative covenants does not actually put any additional restrictions on the firm, affirmative covenants have a much lower marginal cost of adjustment than negative covenants (which, given the large literature on how exactly negative covenants trade-off with credit spreads, are typically presumed to have a significant cost of adjustment). I test this theory by examining the way that affirmative and negative covenants are adjusted in renegotiations ex-post of origination. I find evidence of a pecking order in what gets renegotiated or amended first. Relative to negative covenants, affirmative covenants are amended first-in-time, first-in-default and more after minor defaults that do not lead to immediate acceleration/bankruptcy.

These results suggest that affirmative covenants have a lower marginal cost of adjustment and that the first action banks take when they are worried about a borrower is to ask for more information before putting more restrictions on the firm.

In terms of contribution, this paper contributes to the existing literature by filling both a gap in the data and a gap in our understanding of how negative covenant tripwires are actually monitored and enforced. Of value for future papers, I show that affirmative covenant intensity can be used as an effective proxy for the demand for monitoring in a loan contract.

The paper proceeds as follows. Section 2 details the construction of the two novel datasets, one for originations and one for renegotiations. Section 3 uses the data collected in Section 2 to describe the monitoring role that affirmative covenants play in lending contracts. Section 4 lays out the information-first theory of contractual adjustment and tests its testable hypotheses using the data from renegotiations. Section 5 concludes.

2 Data and summary statistics

In this section I describe the process and technique of assembling of two datasets on the contents of loan originations and renegotiations. The primary source for both datasets are syndicated lending contracts and amendments which come attached as exhibits following SEC disclosures. Both datasets are created in a two step process of 1) scraping the text of SEC disclosures for the relevant contract and 2) parsing the text of the contract using a combination of algorithmic text parsing and machine learning to categorize the elements of the text into a manageable dataset. This data is augmented with data from LPC DealScan and Compustat to provide observables of both the loan and the firm around the events of origination and renegotiation. I first describe the way that I scrape and parse lending contracts at origination followed by a description of the way that I scrape and parse renegotiations.

2.1 Original credit agreement data

2.1.1 Scraping original credit agreements

The way that I scrape data on original credit agreements is a modified and improved version of the technique Roberts and Sufi (2008) employed to create their widely-distributed sample. Like Roberts and Sufi (2008), I scrape the appropriate exhibits of 8-K and 10-K filings for documents with titles that identify syndicated credit agreements. For 10-K filings, I search using the pre-cleaned filings available on Bill Macdonald's website.[5] For 8-K filings I download them directly from SEC EDGAR and clean all XML formatting before searching

[5]Website url: https://sraf.nd.edu/data/stage-one-10-x-parse-data/

them. However, compared to Roberts and Sufi (2008), I make four important tweaks to their formula that improve the quality and yield of my collected data:

1. The first change I make is that I consider a slightly wider array of possible search terms. Roberts and Sufi (2008) search for the term ”CREDIT AGREEMENT” in all caps to indicate a loan contract original. I read through a large sample of credit agreements and expand the search to also include terms such as ”LOAN AGREEMENT” and ”FINANCING AGREEMENT” to capture a larger sample of contracts.[6] Similar to Roberts and Sufi (2008), I also ensure that the terms are fully capitalized to avoid false positives.

2. Second, noting work from Nikolaev (2017), I search for contracts in a larger number of exhibits. Instead of searching for credit agreements in exhibits 4 and 10, I search in exhibits 1, 2, 4, 9, 10 and 99.

3. Third, Roberts and Sufi (2008) also require that the term ”TABLE OF CONTENTS” be within 60 lines of the fully capitalized search term, say ”CREDIT AGREEMENT”. This is potentially problematic because (especially in later dated filings that employ more xml formatting) the process of stripping 10-Ks and 8-Ks of their web formatting frequently leaves the entire document as one long string with no line breaks. I amend their technique as follows, instead of searching within 60 lines of ”CREDIT AGREEMENT” for ”TABLE OF CONTENTS”, I search the surrounding 20 words (forward and backwards) for a date in one of the following two example formats, January 18(th), 2008 or 10(th) day of May, 2010. I make this change for two reasons. First, since later filings employ more and more xml formatting (which can affect line counts even when properly stripped), line breaks are an inaccurate measure of distance in a document. Second, while almost all contracts use the all caps standard (for example, ”CREDIT AGREEMENT”) to refer to an original document being disclosed, many deviate from that standard when it comes to the Table of Contents (and many contracts do not have such a title for their table of contents section even if they do have one).

4. Fourth, I employ a flexible scraping script (using Regex in Python) which attempts to correct for errors in formatting. For example, instead of considering just ”CREDIT AGREEMENT”, with one space, my script considers 0 to 8 spaces and/or a line break between these words as a match as well. The same goes for dates.

[6] The full search list is: ’CREDIT AGREEMENT’, ’TERM LOAN’, ’LOAN AGREEMENT’, ’CREDIT FACILITY AGREEMENT’, ’LOAN AND SECURITY AGREEMENT’, ’LOAN & SECURITY AGREEMENT’, ’REVOLVING CREDIT AGREEMENT’, ’FINANCING AND SECURITY AGREEMENT’, ’FINANCING & SECURITY AGREEMENT’, ’CREDIT AND GUARANTEE AGREEMENT’, ’CREDIT & GUARANTEE AGREEMENT’, ’SECURITY AGREEMENT’, ’REVOLVING CREDIT’

Though it is difficult to say how much each of these individual tweaks to the Roberts and Sufi (2008) formula adds to the yield, the overall result gets a far larger sample of contracts than Roberts and Sufi (2008) were able to scrape (even after accounting for the fact that I consider a larger time period).[7]

2.1.2 Organization of credit agreements

Once the corpus of original credit agreements is scraped, I use an intelligent script to determine how to split each credit agreement into its component parts. Much like academic papers, lending contracts are generally hierarchically organized as groups of numbered sections. The following excerpt from a lending agreement gives an example.

- SECTION 5. NEGATIVE COVENANTS OF BORROWER **(Supersection)**
  - 5.1 ASSIGNMENT OF LICENSES AND PERMITS. Assign or... **(Subsection)**
  - 5.2 NO LIENS; EXCEPTIONS. Create, incur, assume or... **(Subsection)**
  - 5.3 MERGER, CONSOLIDATION, ETC. Except as otherwis... **(Subsection)**

In the above example there are three subsections which each represent a covenant inside a broader 'Negative Covenants' section. To ensure that these hierarchical levels are properly disambiguated, I refer to the broader 'Negative Covenants' section grouping as a 'supersection'. It's subsections I simply refer to as 'subsections'.

One final note which is important to stress is that there is a large degree of standardization to these subsections and supersections. The same types of risks need to be addressed by many types of contracts and so lawyers use broadly similar language to accommodate these risks in their contracts. I call the relatively standardized language used to refer to one economic risk as the 'canonical form' of that subsection.

2.1.3 Parsing original credit agreements

Having established that contracts are hierarchically organized as groups of subsections inside supersections, I attempt to construct a database which reflects this organization. The goal is find the canonical forms of each type of subsection and supersection and classify each part of every contract inside these canonical forms. To accomplish this, I turn to machine learning to put each part of a contract into both a subsection bucket as well as a supersection bucket.

The machine learning technique I use to parse the contracts and create a database of the universe of contractual contents is identical to the technique described in Chapter 1. Details

[7] More discussion on this below.

can be found in the Data section of Chapter 1 as well as in Appendix A. The end result of this process is a database with a large number of potential subsections which might be included in a syndicated lending contract and a 1-0 binary variable indicating if the subsection is contained within the given contract. For every subsection, I also note the supersection in which it most commonly appears.

Directly quoting from above, there are three main advantages that my database has compared to other previous datasets. "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) ... 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 ... 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 41K contracts, each containing hundreds of potential covenants."[8]

2.1.4 Originating contracts data collection yield

The above scraping procedure yields a total of 41,758 original lending agreements. I parse these agreements according to the procedure detailed above and match them to DealScan using the Chava-Roberts DealScan linking database. LPC DealScan contains data on loan-level observables such as All-in-Drawn spreads, maturity dates, syndicate size and security levels which my scraping procedure does not capture. This leaves me with a sample of 16,269 agreements. Matching this sample to firm observables from Compustat leaves me with a sample of 10,425 contracts. Finally, after dropping loans to financial firms (SIC code 6000-6999) and utilities (SIC 4900-4999), I am left with a final database of 7,993 original lending contracts with both firm and loan-level observables as well as contractual contents.

2.2 Renegotiations data

I begin with a brief description of the background of how lending contracts are renegotiated followed by a description of how I collect my dataset on renegotiations.

[8]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 covenants in this paper.

2.2.1 Background: How does a contract get renegotiated?

Contractual renegotiations of syndicated lending agreements modify the terms of the original agreement by way of another (typically smaller) contract that both parties mutually agree to. Denis and Wang (2014), note that renegotiations are typically initiated by borrowers and that they are normally used to loosen the terms of the original agreement. The typical renegotiation can be thought of as a form of reprieve for beleaguered borrowers. Lenders typically extract concessions in exchange for offering such reprieves and borrowers are reluctant to ask for them unless needed.

Renegotiation contracts of syndicated loans can take one of two general forms. The first form is that of a fully amended and restated contract. This is a brand new contract which entirely replaces and supersedes the old one. This form of renegotiation is typically preferred when there are a large number of changes to the contract such that it would onerous to detail them all. However, one important complicating fact is this type of contract is also used to effectively issue new debt under an old name.[9] The second form of renegotiation is far more common. It takes the form of a smaller contract which lists in detail the changes both parties wish to mutually make to the contract. Since this second type of contract is far more common, far easier to algorithmically parse and does not come with the ambiguity of possible referring to new debt, this is the principal source of data I will be analyzing in this paper.

2.2.2 Examples of amendments

One renegotiation can (and frequently does) contain multiple amendments. From this point on, to avoid ambiguity, I will refer to the entire renegotiating contract as the renegotiation and the specific changes made to each section as the amendments. The following two examples each show a subsection from an original credit agreement as well as the text of its subsequent amendment. The bolded sections are added by the author and indicate parts of the text which are changed from the original.

[9] For example, many of the contracts listed by LPC DealScan as new loans actually use amended and restated contracts from previous debt issuances.

SECTION 6.28. Additional Debt. Neither of the Borrowers or any of their Subsidiaries shall incur or permit to exist any Debt other than (i) Debt in the amounts listed on Schedule 6.28, (ii) Debt permitted to be secured by Liens permitted by Section 6.18, (iii) Debt of the types described in clause (vii) of the definition of Debt which is incurred in the ordinary course of business in connection with the sale or purchase of goods or to assure performance of any obligation to a utility or a governmental entity or a worker's compensation obligation; (iv) Debt permitted by the FINOVA Intercreditor Agreement; (v) other Debt not to exceed an aggregate amount outstanding at any time of $500,000; (vi) trade payables arising in the ordinary course of business; (vii) Investments in Subsidiaries consisting of Debt excluded under the definition of "Restricted Investment"; and (viii) Debt consisting of a Guarantee by SEDH of SED's obligations to purchase certain equity interests in SED Magna such investment amount permitted under the definition of "Restricted Investment."

(a) Original

(d) Section 6.28 of the Credit Agreement hereby is amended and restated in its entirety as follows:

SECTION 6.28. Additional Debt. Neither of the Borrowers or any of their Subsidiaries shall incur or permit to exist any Debt other than (i) Debt in the amounts listed on Schedule 6.28, (ii) Debt permitted to be secured by Liens permitted by Section 6.18, (iii) Debt of the types described in clause (vii) of the definition of Debt which is incurred in the ordinary course of business in connection with the sale or purchase of goods or to assure performance of any obligation to a utility or a governmental entity or a worker's compensation obligation; (iv) Debt permitted by the FINOVA Intercreditor Agreement; (v) **so long as the same is not Guaranteed by either Borrower, Debt with a maturity date no later than 6 months after the date of issuance incurred by Foreign Subsidiaries not to exceed an aggregate amount outstanding at any time of $6,000,000; (vi) other Debt not to exceed an aggregate amount outstanding at any time equal to the lesser of (A) $500,000 or (B) $6,000,000 minus the outstanding Debt permitted under clause (v) of this Section 6.28;** (vii) trade payables arising in the ordinary course of business; (viii) Investments **permitted by Section 6.17** in Subsidiaries consisting of Debt excluded under the definition of "Restricted Investment"; and (ix) Debt consisting of a Guarantee by SEDH of SED's obligations to purchase certain equity interests in SED Magna such investment amount permitted under the definition of "Restricted Investment."

(b) Amendment

Figure 1: Amendment Example 1

6.12. Dealings with Affiliates. The Borrower shall not, and shall not permit any other Loan Party to, enter into or carry out any transaction with (including, without limitation, purchase or lease property or services from, sell or lease property or services to, loan or advance to, or enter into, suffer to remain in existence or amend any contract, agreement or arrangement with) any Affiliate of the Borrower, directly or indirectly, or agree, become or remain liable (contingently or otherwise) to do any of the foregoing, except:

(a) Execution and performance of contracts, [...]
(b) Directors, officers and employees of a Loan Party may be compensated for services rendered [...]
(c) The SDI Offtake Agreement, the Administration Agreement and the Tax Sharing Agreement.
(d) Other transactions in the ordinary course of the Borrower's business [...]

(a) Original

(f) Dealings With Affiliates. Section 6.12 of the Credit Agreement is hereby amended by adding at the end thereof a new Section 6.12(e) to read as follows:

(e) The IDI Mergers.

(b) Amendment

Figure 2: Amendment Example 2

As can be seen in the above two examples, each amendment inside a larger renegotiation usually has two parts: the preamble which denotes the section in the original contract which is being modified and text itself which is being modified. The preamble generally follows the standard format illustrated above while the included text has no unifying format.

I exploit the relatively standard formating of contractual renegotiations to extract data from them. The standard formatting of the preambles to each amendment allows me to reliably impute the numbering of the subsection in the previous contract which was amended but does not always allow me to determine the subject of the amendment. To determine the subject of the amendment, I turn to the text of the original contract. For instance, in the first example, the preamble specifies that Section 6.28 of the original contract is being amended. From my contractual contents database I know that Section 6.28 of the previous contract falls under the 'Indebtedness' subsection classification. This 'Indebtedness' subsection classification in turn falls under the 'Negative Covenants' supersection. By this way I can classify each amendment by the supersection in the previous contract it adjusts.

2.2.3 Scraping renegotiations

In addition to finding original credit agreements, the above scraping procedure detailed in Section 3.2.1 also captures contractual renegotiations which are disclosed as well. This works because the titles of renegotiations are extremely similar to those of the original contract. A typical amendment or waiver might have a title that looks like the following: "AMENDMENT NO. 2 TO THE CREDIT AGREEMENT", "CONSENT AND WAIVER AGREEMENT AND AMENDMENT NO. 6 TO LOAN AND SECURITY AGREEMENT".

Using data from the title of the renegotiation, I classify renegotiations into three categories. A renegotiation can be a waiver of default, a limited amendment of terms or a complete restatement of the original contract with new terms. Importantly, these categories are non-exclusive. A waiver of default may also include (and frequently does) a limited amendment of the terms of the contract so ensure that the firm does not continue to be in default. The specific terms I search for for each of these categories are 'WAIV' for a waiver,'AMENDMENT' or 'MODIF' for an amendment, and 'RESTAT' for an amended and restated contract.[10]

[10] The distinction between a fully amended and restated contract and a "new" credit agreement that would count as an original contract is an exceedingly nebulous one. In this paper I defer to LPC DealScan to make this distinction for me. I count an amended and restated contract as an original contract if LPC DealScan does as well. Conversations with representatives at LPC DealScan reveal that this categorization is more heuristic than systematic for them as well and that they mostly rely on human judgment to decide if an amended and restated contract should count as a new loan.

2.2.4 Matching renegotiations to original contracts

To identify the original contract which the renegotiation refers to, I search the renegotiation for the date of an original contract. By law, written contractual amendments must refer to the original contract by the date on which it was filed. To identify these previous dates, I first search following the title and grab all text up to the first stated date. I assume this first date is the date of the renegotiation[11] and then search the next 2000 characters for all listed dates attempting to find the date of the original contract. If multiple dates are found, I sort the dates in ascending order (oldest dates first). I then match each renegotiation to an original contract starting with the first date in the list and working backwards from there.

As an illustrated example, consider the following amendment to a credit agreement. The date of the renegotiation is March 29, 2000 and the date of the original contract which it modifies is December 31, 1997. This corresponds to what is recorded in my database for this contract.

> THIS FIFTH AMENDMENT AND WAIVER TO CREDIT AGREEMENT (this "Agreement"), dated as of March 29, 2000, by and among IRON DYNAMICS, INC., an Indiana corporation (the "Borrower"), the lenders listed on the signature pages hereof and MELLON BANK, N.A., a national banking association, as agent for the Lenders under the Credit Agreement referred to below (the "Agent").
> RECITALS:
> WHEREAS the Borrower, certain lenders, the Agent and Mellon Bank, N.A., as Issuing Bank, entered into a Credit Agreement, dated as of December 31, 1997, as amended by the Amendment and Waiver, dated as of June 10, 1998, by the Second Amendment to Credit Agreement, dated as of March 15, 1999, the Third Amendment and Waiver to Credit Agreement, dated as of June 30, 1999 and the Fourth Amendment to Credit Agreement, dated as of December 21, 1999 (as so amended, the "Credit Agreement"), pursuant to which the Lenders have agreed to extend credit to the Borrower;

This technique seems to be successful at matching up renegotiations to original agreements. Of all renegotiations I scrape, 81% of them exactly match to an original contract by the same borrower. Given that I can not collect loan contracts from before 1996 and many of these renegotiations amend loan contracts older than that, I count this statistic as

[11] Practically speaking, the first line which follows the title is virtually always to the effect of "dated as of [date]" and this uniquely identifies the date of the renegotiation.

a successful validation of the technique. The above process yields a total sample of 36,227 renegotiations to 17,769 loans.

2.2.5 When and how often do contracts get renegotiated?

Since one loan may be sequentially renegotiated multiple times, it is interesting to ask what the timing of these sequential renegotiations looks like. Figure 1 shows the timing of renegotiations disaggregated by the number of the renegotiation. This graph serves as a nice initial check on the quality of the scraped renegotiation data. As expected, higher numbered renegotiations tend to be renegotiated at later dates from origination. For the first renegotiation, the average amount of time elapsed since origination is 473 days, or 1.3 years. For the sequentially following renegotiations, the numbers are, 661, 836, 983 and 1120 days, respectively. The average gaps between these renegotiations are about 6-9 months. This can be seen as a confirmation of Roberts (2014)'s finding that, "the typical bank loan is renegotiated five times, or every nine months".

Another interesting dynamic that emerges is a strong preference for renegotiating at yearly intervals. This suggests that perhaps not all renegotiation is driven by salient credit conditions but that some level of renegotiation is baked into the contract at origination.

By combining my data of scraped originations (before merging with DealScan) with my data of scraped renegotiations, I can impute what percent of originations were renegotiated. I find that I am able to unconditionally find renegotiations for some 35% of the originations in my dataset.

The above number might initially seem at odds with the widely quoted finding from Roberts and Sufi (2009) that, *conditionally* (on having a maturity of at least 1 year, and not being censored by their sample period) 90% of debt contracts are renegotiated before maturity. The conditioning of this statement matters for comparing these numbers. Considering the unconditional number reported by Roberts and Sufi (2009), the percentage of loans which are renegotiated falls to 65%. This is still a far cry 35% number I report. So what explains the rest of the difference? The rest of the difference is almost certainly due to the fact that Roberts and Sufi (2009) count fully amended and restated contracts as part of their sample of renegotiations while I do not. I do not count fully Amended and Restated contracts as a renegotiation for my purposes because they are frequently used to issue new debt under an old name. Indeed, Roberts and Sufi (2009) find that 47% of their renegotiations match to new loan packages in DealScan. This means that 53% of Roberts and Sufi's (2008) sample is this smaller form of renegotiation. Multiplying 65% by .53 gives the truly comparable number of 34% for Roberts and Sufi (2009) which is extremely close to the 35% I report above. Far from being contradictory with Roberts and Sufi's (2009) result, my data strongly confirms their findings but emphasizes the importance of considering the nuance of what exactly constitutes a renegotiation.

2.2.6 Algorithmically parsing renegotiations

Once scraped and matched to an original contract, each individual renegotiation is then parsed to find the sections of the previous original contract which it modifies. To do this, I first search for a numbered section title in the text of the renegotiation. An example would be "Section 6.28". I then search the next 20 words for a phrase that indicates some form of contractual modification. An example would be 'amend/amending' or 'delete/deleting'. [12] Finally, I search for a word that indicates that the updated text follows. An example would be 'follows/following' or 'below'.[13]

By using this technique, for each renegotiation, I can cleanly identify the exact sections of the previous document which were modified. Quoting from Included Figure 3.1, the text of such a modification is below:

> (d) Section 6.28 of the Credit Agreement hereby is amended and restated in its entirety as follows:

In this example, I can identify that Section 6.28 of the original document was amended

[12] The full list of words I search for is: amend, delet, substit, add, insert, replac.

[13] The full list of words I search for is: follow, therefor, thereof, thereto, read, below, foregoing.

but the data I collect does not identify the title of clause Section 6.28 refers to.[14] To solve this problem, I use data from the original contract. From the originations database detailed above, I know that Section 6.28 refers to the 'Additional Debt' clause of the original contract. By merging the renegotiations database together with the originations database, I can infer the subject of each clause amended in a renegotiation. Finally, I aggregate this data up to the supersection level for ease of comparison. For example, the 'Additional Debt' subsection[15] falls under the 'Negative Covenants' supersection in my dataset so I simply record that one of the negative covenants was amended.

Since multiple clauses may be amended by a single renegotiation, the final renegotiations dataset records how many clauses from each of the 10 supersections were amended by the renegotiation. For example, in the complete text of the above renegotiation, 4 sections were renegotiated in the 'Negative Covenants' supersection, 1 in 'Affirmative Covenants', 2 in the 'Representations and Warranties', etc.

After scraping and parsing the renegotiations as describe above, I am left with a sample of 4,279 renegotiation contracts containing a total of 15,339 amendments to 2,243 loan facilities. The total number of unique borrowing firms in my sample is 1,685.

2.2.7 Data limitations

The above process yields a dataset of the amendments of the numbered subsections in syndicated lending agreements. For every subsection in an original credit agreement, I can identify two things: the subject of the subsection and if and when the subsection was renegotiated. This data has three important limitations to be aware of.

First, I cannot distinguish between renegotiation towards more restrictive terms vs a renegotiation towards looser terms. However, previous research suggests that most renegotiations loosen restrictions rather than tighten them. Denis and Wang (2014) note that

[14] The amended text itself which follows the preamble only occasionally restates the title of the original text so this is an inconsistent manner of gathering this information.

[15] Which is actually rolled into the 'indebtedness' subsection in my final dataset.

"renegotiations primarily relax existing restrictions". Also supporting this story, Roberts (2015) examines loan originations and conclude that most credit agreements have the terms set too tight ex-ante which would suggest that they are subsequently renegotiated down. Based on this evidence, I will assume in this paper that renegotiations generally loosen terms or at the very least that the proportion of loosening renegotiations does not differ between affirmative and negative covenants. Ultimately, the information-first theory I will present in this paper will be mostly agnostic to the direction of the renegotiation.

Second, I cannot determine the size of the adjustment. To my dataset, an amendment which completely removes a restriction on future indebtedness looks the same as an amendment which only modifies the amount carved-out of the indebtedness restriction. Both are contractual easements of the same direction but different magnitudes.

Third, I cannot impute the subject of amendments to the 'Definitions' supersection (because I impute the subject of the amendment from the title of the subsection). Most contracts have such a subsection, usually numbered Section 1.01 or Section 1, which defines the terms which will be used throughout the contract. Common among these terms are the interest rate and the maturity date of the loan. If one wishes to amend the maturity date or interest rate of the loan, one way they can accomplish this is by amending the definition of this term in the definitions subsection. I only observe such amendments in the most general sense as an amendment to the definitions supersection of the loan. The following excerpt gives an example of such a renegotiation.

(a) Definitions. Section 1.01 of the Credit Agreement is hereby amended by amending the definitions of "Financial Covenant Date" and "Revolving Credit Maturity Date" appearing therein to read, in each case in its entirety, as follows:

As can be seen above, this excerpt modifies the definitions of the maturity date of the loan and the date used to measure compliance with financial covenants. Since these definitions are used variously in multiple parts of the loan, it is difficult to identify all the sections of the contract that might be impacted by this definitional amendment. A modification to ”Financial Covenant Date” might modify all of the covenants subsections while a modification to ”Revolving Credit Maturity Date” might implicitly adjust almost all subsections of the contract.

For this reason, I focus my results on the sections where I can affirmatively identify that only one subsection has been modified and do not attempt to parse definitional amendments. While I think it is quite likely that any supersection categories might potentially be renegotiated via the definitions section, there is little *a priori* reason to think that one type of covenant would be more biased to being implicitly renegotiated via definitions. Thus I view the relative proportions presented in Figure 2 as accurate, especially between covenant classes which is the main focus of this paper.

2.3 Other data sources

Two other data sources used in this paper to supplement the above data are Compustat and LPC DealScan. LPC DealScan is used for loan observables such as the All-in-Drawn credit spread and loan maturity. All originated loans in my originations database are also matched to their corresponding entry in LPC DealScan. Compustat is primarily used for firm observables and for calculating by Bharath and Shumway’s (2008) measure of Distance-to-Default. I primarily use this measure to proxy for the credit quality of the firm. As in their paper, I construct distance to default as,

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

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.[16]

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

2.4 Summary statistics

2.4.1 Originations sample summary statistics

Table 1 describes the characteristics of my sample of the contracts of loan originations. Broadly speaking, my dataset is a sample of syndicated lending contracts from publicly traded firms and this is reflected in the data.[17] In terms of firm and loan observables, the averages look broadly in line with what one would expect of a large, publicly traded firm. Average market capitalization is 2.9 billion dollars. Average distance-to-default (DtD) at origination is 3.88. Thinking of the DtD measure as a z-score of the probability of default within one year, this number seems reasonable for a sample of healthy firms. Average facility amount is about 300 million dollars, average All-in-Drawn spread is 201 basis points and average maturity is close to 5 years. These are all reasonable numbers for a sample of bank loans to public firms and I conclude that the results from using this sample should generalize to loans from most public firms.

Contractual contents are aggregated by the 10 most commonly used supersections. For comparability, within each supersection I find the top 20 most commonly used subsections inside each supersection and the number I report for a supersection is the sum of subsections in the top 20. For example, if I report that a specific contract has a reported value of 5 for Affirmative Covenants, that means that the specific contract in question contained 5 affirmative covenants *in the top 20 most popular affirmative covenants*. For ease of exposition I will generally use this number when describing intensity of use inside a subsection. The reason for reporting this number instead of the raw count is to preserve comparability between supersections. This also ensures (assuming that the top 20 most common clauses are all economically significant) that an extra included subsection is always economically significant. Below I report the averages of these values.

The results in Figure 1 show that the average loan at origination contains 5.12 affirmative

value of debt.

[17] My sample is necessarily public because the source of my credit agreements is from public disclosures in SEC filings.

covenants and 5.92 negative covenants.[18] Other intensively used supersections include the appointments supersection (which describes the syndicate structure and the responsibilities of the lead arranger), the commitments supersection (which describes the lending commitments the bank makes to the borrower), the events of default supersection (which describes all events which constitute a default), the notices supersection (which details the notices that the borrower must provide to the lender) and the representations and warranties supersection (which details warranties that the borrower affirms to the lender before receiving the proceeds of the loan). While these non-covenant supersections are all interesting in their own rights, in this paper I will mainly focus on comparing covenant use between affirmative and negative covenants so I will not focus as much on these supersections going forward.

2.4.2 Renegotiation sample summary statistics

Table 2 describes summary statistics for my sample of renegotiations. One observation is one full renegotiation contract. For every renegotiation I also count the number of amendments aggregated by supersection.

Comparing the sample of originations to the sample of renegotiations I find that the loans which are eventually renegotiated tend to be smaller (313MM vs 223MM) and to much smaller borrowers (2921 MM vs 1268MM). The sample of renegotiated and originated loans are virtually identical in maturity (52 months) and loans which are renegotiated are held (on their books vs. selling off their share) a bit more intensely by banks (46% vs 40%). Compared to the same firm at origination, at renegotiation firms are of slightly lower credit quality (as measured by DtD, 3.88 vs. 3.44). Finally, the average time in days from an origination to a renegotiation (any number) in my sample is 587 days.

Examining the content of these renegotiations, I find that the average renegotiation amends .91 negative covenants and .43 affirmative covenants. The next most common super-

[18] Technically speaking, the results show that the affirmative and negative supersections contain this many *subsections* on average. However, in practice, each subsection in a covenant supersection refers to a unique covenant so the above characterization is accurate.

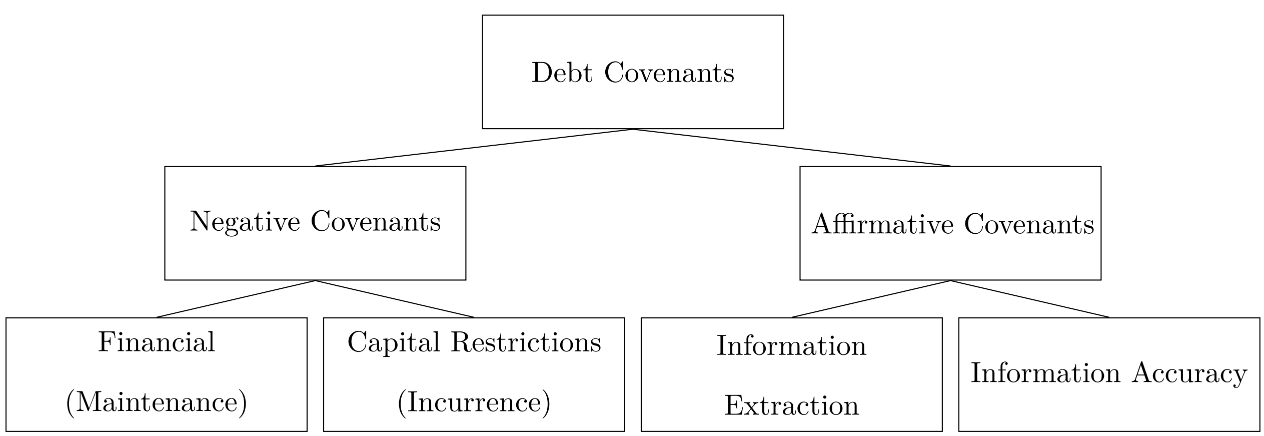
sections to be amended are the commitments (.24), events of default (.23) and representations and warranties (.19). Figure 2 shows this proportionally. About 27.5% of non-definitional amendments are related to negative covenants while about 12.5% of non-definitional amendments are related to affirmative covenants.

3 Affirmative covenants as a monitoring technology

In this section I describe the respective roles that affirmative and negative covenants play in lending contracts. I first discuss the existing literature on negative covenants, specifically financial covenants, and how these types of covenants serve as protective tripwires which alert the lender to any potential problems with the borrower. I then discuss the way that affirmative covenants constitute a monitoring technology used by banks to monitor their creditors. Finally I describe how these results help contextualize the way that affirmative covenants fit into the popular covenants as a tripwire analogy.

The Included Figure 3 previews the basic taxonomy of debt covenants I will describe in this section. Covenants can be divided into the broad categories of affirmative and negative which can then be further subdivided by their specific role in the contract.

Included Figure 3: Classification of Debt Covenants



3.1 Negative covenants

Negative covenants in lending contracts restrict the firm along two main dimensions, the capital actions it might wish to take (capital restrictions covenants) and the financial ratios it must maintain (financial covenants). An example of a capital restrictions covenant might be a restriction on future M&A activity by the borrower to less than a certain dollar amount. Ivashina and Vallee (2019) note that capital restrictions covenants frequently contain 'carve-outs' allowing borrowers to engage in a limited amount of the restricted action. On the other hand, an example of a financial covenant might be a limit on the ratio of total debt to a firm's EBITDA. Becker and Ivashina (2016) point out that this distinction financial and capital restrictions covenants corresponds to the way covenant violation is measured in each category. In financial covenants, violation is typically maintenance-based whereas in capital restrictions covenants violation is incurrence-based. This means that, absent taking any other actions, a firm can find itself in violation of a financial covenant while the same is not true for a capital restrictions covenant.

What both types of covenants have in common is that they act as tripwires which allocate control rights between lenders and borrowers via ex-post renegotiation. Griffin, Nini and Smith (2019) note that financial covenants, "transfer control rights to lenders only when financial ratios drop below contractual thresholds". Control rights are transferred to the lender because violation or imminent violation of a covenant allows (but does not obligate) banks to accelerate the loan and demand immediate payment in full. This threat brings borrowers to the table to renegotiate their loans. This normally happens at less-favorable terms to the borrower. On the other hand, capital restrictions covenants allocate control rights by essentially giving banks a veto power on certain actions of the firm. Imagine a firm with a covenant restriction on mergers or acquisitions above 15 million dollars (the amount of the carve-out). In this case, the same firm wanting to undertake a very large acquisition of, say, 200 million dollars would first have to consult with their lender and renegotiate their loan. In both cases, potential covenant violations bring the borrower to the renegotiation table to amend the terms of their contract. By this way, both classes of negative covenants act as tripwires which let banks know about material changes or potential changes to the ability of the firm to repay its loan.

Table 3 details the top 20 most commonly used negative covenants in syndicated lending contracts along with their frequency of use, if they are also found in DealScan, and the percent of my sample whose text includes any numerical restrictions.[19] Of these 20 covenants, 12 are capital restrictions covenants (indicated below by ‘carve-out’) while 8 are financial covenants (indicated below by ‘limit’).

Figure 3 examines negative covenant usage through time. This figure splits negative covenants into the two categories mentioned above, financial and capital restrictions covenants. I note that using my data, capital restrictions covenant usage has been flat or slightly increasing over time while financial covenant usage has been falling. This is consistent with the cov-lite findings of Becker and Ivashina (2016). They note that cov-lite originations reached peaks at 2015 and 2007. I find the same results below using my data. Another interesting trend that emerges is the growth (especially compared at negative covenants) of affirmative covenant usage in contracts. Affirmative covenant usage grew from an average of 4.7 covenants per contract in 2007 to close to 5.75 in 2016. This closely mirrors the drop in financial covenant usage from 1.5 average covenants per contract to near 0.5 in 2016. In total, these results suggest that both categories of affirmative covenants have been growing in popularity over the sample period. Meanwhile, of the two categories of negative covenants, capital restrictions covenant usage has remained steady while financial covenant usage has fallen sharply since 2007.

3.2 Affirmative covenants

Analysis of the text used by affirmative covenants reveals that affirmative covenants in lending contracts serve as a monitoring technology which helps lenders stay abreast of any

[19] Numerical is the proportion of covenants which contain a numerical restriction in one of the following forms: dollar amount ($100,000), ratio (2:1 or 2 to 1) or percent (50%).

material changes to the borrower's credit condition. Affirmative covenants accomplish this by ensuring that the information that the banks have on the borrower is 1) obtainable and 2) accurate. As seen in Figure 4, of the top 20 most frequently used affirmative covenants I document, 19 fit neatly into one of these two categories. Nine of the top twenty most commonly used affirmative covenants are devoted to helping banks extract information from their borrowers while ten of the top twenty affirmative covenants are devoted to ensuring that information collected by the banks (both with and without the borrowers' help) is accurate. (One miscellaneous covenant deals with reassignment of security interests.) I call the former 'information extraction' covenants and the latter 'information accuracy' covenants

Information extraction covenants help banks extract information from their borrowers either cooperatively or unilaterally. Gustafson, Ivanov and Meisenzahl (2016) note that 50% of loans are monitored on a monthly basis and these covenants are the section of the lending contract that binds borrowers to disclose this information that would otherwise not be disclosed in public filings. Examples of cooperative extraction include the following covenants: 1) other information, 2) certificates; other information, 3) annual financial statements and 4) compliance certificates 5) notice 6) leases. These covenants all require the borrower to send copies of materially important documents (i.e., any public statements, 10-Ks, 8-Ks, new agreements or changes in leases) at some specified frequency to the lender. These are frequently accompanied (moreso in recent years) by a "certificate" from the CFO affirming the accuracy of the statements and explaining the details of the calculations, if any. These covenants are unified in the sense that they require some cooperation on the part of the borrower to extract information. Other examples of information extraction covenants which do not require cooperation include: 7) inspection rights and 8) inspection. These covenants typically allow the lender to unilaterally inspect the firms premises as it desires (usually with a minimum of notice, a few days). Besides perhaps nominally having an agent present open the premises, these do not require the cooperation of the borrower to be effective. Finally, 9) the further assurances covenant ensures that borrowers will "execute any and all further documents that may be required" to execute the loan. This extracts information from the borrower by forcing them to return any needed documents in a timely matter, on the pain of default if they do not. This covenant is similar to the first group in that it depends on borrower some cooperation but it can also be seen as a way of enforcing borrower cooperation.

Examples of information accuracy covenants include the following, 1) insurance, 2) use of proceeds (of the loan), 3) compliance with laws, 4) maintenance of properties, 5) payment of obligations, 6) books and records, 7) compliance with laws, etc, 8) additional subsidiaries, 9) compliance with environmental laws, 10) maintenance of insurance. Each covenant refers (in a largely self-explanatory manner) to a specific information set that the bank want to ensure is always current. It is important to note that these covenants do not represent off-equilibrium paths for the firm but are actions (i.e. maintaining current insurance coverage, complying with laws, keeping good accounting records, not making less-than-arms-length deals with subsidiaries and so forth) that one would typically expect a responsible firm to take. With this in mind, these covenants serve not to change the behavior of the firm but to ensure that the actions of the firm are consistent with what the lender would expect of a good borrower. These covenants also serve the purpose of ensuring that the *borrower* is aware of the state of its own affairs and is not lax or lacking in information about them. Explicit examples of this include the maintenance of properties and the books and records covenants but all of the above covenants perform this function to some extent. By ensuring that the borrower is current on its own information and that it is in compliance with best business practices, these covenants ensure that the information that is subsequently reported to the bank is as accurate and current as possible.

Like capital restrictions covenants, violation of an affirmative covenant is almost entirely incurrence based. This means that if the firm so chooses, they should always be able to comply with such a covenant. Thus the value of affirmative covenants arises not from the potential for violation per-se but from the information the bank gains by knowing the firm is in compliance.

3.2.1 Testing affirmative covenants as a monitoring technology

In this section I test the hypothesis that affirmative covenants serve as a type of monitoring technology in lending contracts. First, I compare how the usage of affirmative covenants co-varies with two popularly accepted proxies of monitoring intensity in contracts. Lee and Mullineaux (2004), Sufi (2006) and François, Missonier-Piera (2007) all negatively associate the size of the syndicate with the demand for monitoring and uncertainty about the loan. The general argument is that smaller, more concentrated syndicates have better incentives to monitor well and that the smaller size of the syndicate makes these highly-monitored loans easier to renegotiate. In a similar vein, Ivashina (2009) associates the percent of the loan which is retained by the lead bank as a proxy for equilibrium monitoring demand in the loan. I test how both of these proxies covary with affirmative covenant usage by estimating the following general regression using my dataset on loan originations.

$$\text{monitoring\_proxy}_{i,t,l,b} = \beta_1 \text{affcov\_orig}_i + \beta_2 \text{negcov\_orig}_i + \beta_3 \text{AiDspread\_orig}_i + \beta_4 \text{maturity\_orig}_i$$

$$+\beta_5 \text{DtD\_orig}_i + \sum_{j=6}^{14} \beta_j \mathbf{O}_{j_i} + l_{i,l} + \tau_{i,t} + \eta_{i,b} + \epsilon_{i,t,l,b}$$

The outcome variable is either the number of members in the syndicate or the percent of the loan which is retained by the lead bank. The key test variable is the number of affirmative covenants included in the lending contract at origination. I also control for the number of negative covenants as well as the other 8 supersections of the contract (captured in the matrix of control variables $\mathbf{O}$), the All-in-Drawn loan spread, the maturity of the loan and the Distance-to-Default of the firm at origination. I include year (τ), lender (l) and borrower (b) fixed effects variously as indicated below. Finally, I cluster all standard errors at the borrower $\times$ year level.

The results in Table 5 show that more affirmative covenant usage is associated more monitoring as measured by both of these proxies. More affirmative covenants in a lending contract imply both smaller syndicates and higher lead arranger shares. This is consistent with the idea that affirmative covenants are a monitoring technology in bank loans.

Table 6 shows the results from running the same regression as above but with the firm's Distance-to-Default at origination as the outcome variable. The results of this regression show that affirmative covenant usage in lending contracts is significantly and negatively correlated with the credit quality of the firm at origination. This is also consistent with the affirmative covenant monitoring hypothesis as lower quality firms would be expected to require more monitoring on their loans.

3.2.2 Interpretation: Affirmative covenants are the sensitivity of the tripwire

Taken together, the two classes of covenant paint a more complete picture of the way that lenders solve the moral hazard problem inherent in lending. Negative covenants attempt to solve the moral hazard problem problem by pre-determining a threshold where control shifts from equityholders to debtholders but affirmative covenants are the means of actually determining if that threshold is crossed. To extend the analogy of covenants as a tripwire, negative covenants determine the line where the tripwire is placed but affirmative covenants determine the sensitivity of the tripwire. If the tripwire is sufficiently insensitive, an object crossing the wire may be able to make it significantly past the specified point without eliciting a response.

Bringing the analogy back to reality, a firm whose loan contains very lax monitoring covenants may be able to spend months below some pre-specified financial ratio before the bank is made aware of any problem. By that point, the firm may have already lost a significant amount of the value that the covenant was supposed to protect. Another way this may work is that loans that do not mandate compliance certificates, or assurances from the CFO that the firm is in compliance with its negative covenants, may be able to rely on bad data or inexperienced employees to report their compliance with their covenant restrictions.

Such a firm might report in a timely manner but report all the wrong numbers, mis-conveying (either intentionally or unintentionally) the true nature of their financial situation.

4 Information-first renegotiation

In this section I use the observations described in the previous section to develop a working theory of how banks actually use these monitoring covenants in practice. Importantly, this working theory will have testable hypotheses relating to the way that loans are renegotiated ex-post of origination.

4.1 Optimal renegotiation

Consider the question of a how a bank should first adjust the lending contract in response to uncertainty about the creditworthiness of the borrower. Under the typical conception of covenants, the only anticipated response would be to tighten negative covenant packages, effectively moving forward the placement of the tripwire. The problem with this strategy is that, as previous literature has shown, tightening covenant packages is costly. No firm enjoys being constrained and banks have to give up some amount of interest margin to achieve this extra level of safety. Another way of achieving the same result is to strengthen enforcement of the already existing covenant protections (assuming there is some existing level of slack in the enforcement). One way the bank can do this is by adjusting the affirmative covenants to increase the frequency, quality or scope of the reporting by the borrower.

Given these two potential dimensions of contractual adjustment–affirmative and negative covenants–which will the bank reach for first when a firm initially gets into trouble? I propose that banks opt for what I will call an 'information-first' policy, choosing to first step up the monitoring of loans before taking any action to tighten the negative covenants themselves. Effectively, when banks sense trouble, they tighten the tripwires they already have before choosing to put new ones in place. This information-first theory cuts both ways as well. If affirmative covenants are really the covenants with the lowest marginal cost of adjustment then one would expect them to also be the first to fall out of contracts when conditions improve. In this way the theory is largely agnostic to the direction of the adjustment. The theory merely suggests that, if there is an adjustment to be made, the adjustment with the lowest marginal cost will be adopted first.

This information-first theory is consistent with the existing theoretical understanding of how affirmative and negative covenants interact. If one thinks of the true state of the firm as something that can only be imperfectly observed by the lender (as well as perhaps the borrower), then affirmative covenants help make this observation process less noisy. Under the conception of Aghion and Bolton (1992), the magnitude of this noise–or the disconnect between the observed signal and the actual state of the world–represents the 'degree of completeness' possible in any ex-ante contract. Thus by reducing the noise in this observation process, affirmative covenants complete contracts but they do so by increasing the accuracy of the contractible signal rather than by pre-specifying action plans in response to uncertain states of the world (as negative covenants do). Assuming the utility of the borrower is not increasing in the incompleteness of the contract[20], the both parties benefit from increased contractual completeness.

To test this information-first theory in the data, I test four hypotheses related how borrowers and lenders renegotiate their loans in practice. For each hypothesis, I compare how affirmative and negative covenants are renegotiated relative to one another. If banks really operate on an information-first basis, then each of the following hypotheses should be true.

[label=**H0:** , wide=0.5em, leftmargin=*]**Affirmative covenants are renegotiated first in time.** By comparing how covenants for the same loan are renegotiated as a function of the time elapsed since origination, I can test if either class of covenant

[20] An example of such a borrower would be one who derives little value from control in the good state of the world and a relatively much higher value from control in the bad state of the world, when the bank should have control.

displays a bias for being renegotiated sooner than the other. If affirmative covenants display this bias for being renegotiated early in time, this would lend evidence to the information-first theory. **Affirmative covenants are renegotiated first in default.** By testing the marginal impact of a change in creditworthiness on renegotiation rates, I can see if changes in creditworthiness elicit differential responses for renegotiation of affirmative and negative covenants. If affirmative covenants are more sensitive to changes in a firm's distance-to-default, this would also lend evidence to the information-first theory. **Affirmative covenants are renegotiated more after technical defaults.** Griffin, Nini and Smith (2019), note that firms frequently experience technical defaults that they refer to as 'false positives'. These are defaults that "occur when a firm is not in danger of financial distress". Such technical defaults are frequently waived by the lender along with a small adjustment to the contract however they also represent a failure of the ex-ante contract. By seeing what types adjustments occur concurrent with such a waiver of default, I can test whether affirmative covenants are renegotiated more after 'false positives'. Assuming that such adjustments relax existing restrictions, this would suggest that affirmative covenants are also the first contents to be loosened if covenants are set too tight. **Affirmative covenants are renegotiated less when firms are very close to bankruptcy.** By examining the content of renegotiations from firms who will declare bankruptcy within 2 years, I can test if firms who are close to bankruptcy renegotiate affirmative covenants or negative more. The analogue to the information-first theory is that more restrictive covenants should be renegotiated second. Firms which are close to declaring bankruptcy represent these firms who are far past the initial stage where information-first would apply. We should expect such firms to renegotiate negative covenants more intensively than affirmative covenants.

4.2 Renegotiation hypothesis testing

In this section I present the results of testing the hypotheses developed above. I find that the results of these tests broadly support the information-first theory of renegotiation.

4.3 Affirmative covenants are renegotiated first in time

For this test, I use the dataset of renegotiations discussed above. I test to see if the content of the renegotiation predicts the timing of the same renegotiation. I measure the timing of the renegotiation in terms of the time elapsed since the loan was originated. The specific regression I estimate is,

$$\begin{aligned}\text{days\_to\_reneg}_{i,t,l,b} &= \beta_1 \text{affcov\_reneg}_i + \beta_2 \text{negcov\_reneg}_i + \beta_3 \text{affcov\_orig}_i + \beta_4 \text{negcov\_orig}_i \\ &\quad + \beta_5 \text{dscov\_orig}_i + \beta_6 \text{DtD\_orig}_i + \sum_{j=7}^{15} \beta_j \mathbf{R}_{j_i} + l_{i,l} + \tau_{i,t} + \eta_{i,b} + \epsilon_{i,t,l,b}\end{aligned}$$

The outcome of the regression is the number of days elapsed from renegotiation until renegotiation. The main test variables of interest are affcov_reneg and negcov_reneg which indicate the number of affirmative and negative covenants amended in the renegotiation.[21] The controls affcov_orig, negcov_orig and dscov_orig control for the number of affirmative, negative and DealScan covenants (financial covenants as reported by LPC DealScan) in the original contract. Also controlled for is the credit quality of the firm at origination, DtD is the Distance-to-Default measure of Bharath and Shumway (2008). The matrix $\mathbf{R}$ is a matrix of control variables which represent the other sections of the contract which are also amended (i.e. representations and warranties, events of default, etc.). I also include year (τ), lender (l) and borrower (b) fixed effects as indicated below. Each of these will capture any systematic propensity that a borrower, lender or year has to renegotiate sooner or later.

[21] Results are also robust to using binary variables indicating if any such covenant was amended in the renegotiation.

Finally, I cluster all standard errors at the borrower $\times$ year level.

Table 7 shows the results from this regression. Coefficients should be interpreted as the marginal impact of amending one covenant on the amount of days it takes for the renegotiation to occur. There are two potential hypotheses being tested by this regression. The first is that the coefficient on the affirmative covenant amendment is negative ($\beta_1 \leq 0$) while the coefficient on the negative covenant amendment is simultaneously positive ($\beta_2 \geq 0$). This implies that, consistent with the information-first theory, affirmative/negative covenant amendments imply that the renegotiation happens sooner/later. The second hypothesis tested is that these effects are statistically different ($\beta_2 \geq \beta_1$). The bottom row of Table 7 gives the p-value for this test for each regression.

What these results show is that, for all specifications of this regression, the estimated coefficient on affirmative covenants is weakly negative while the estimated coefficient on negative covenants is significantly positive. From this, I find partial support for the first hypothesis noted above. For all regressions, $\beta_2 \geq 0$ holds significantly, while $\beta_1 \leq 0$ is generally estimated in the right direction but not significantly so. I also find that these estimates are generally different in a statistical sense. The p-value for the test $\beta_2 \geq \beta_1$ is generally close to 0.01 for all specifications of the regression except the last specification which includes borrower fixed effects. This implies that some of the effect I observe is driven by the fact that borrowers who amend affirmative/negative covenants are the same types of borrowers who renegotiate earlier/later.

In terms of magnitudes, the results above suggest that the average contract which renegotiates an affirmative covenant does so (weakly) about one week earlier while the average contract which renegotiates a negative covenant does so about 1.5-2 weeks later. In total, assuming a counterfactual renegotiation which could only amend one type of covenant, one would expect an affirmative covenant renegotiation to occur anywhere from 1.5 to 3 weeks before a negative covenant renegotiation.

To confirm that the estimated magnitudes in the above results are reasonable in the aggregate, in Figure 4 I plot the cumulative distribution of affirmative and negative covenant renegotiations as a function of time. Considering the difference in days for how long it takes each class of covenant to reach the same level of the empirical CDF, I find that the magnitude of 1.5-3 weeks is broadly consistent with the aggregate results. In the empirical CDF of all amendments, negative covenants lag affirmative covenants by an average of 23 days to reach the same level. With the exception of the first 50 days, negative covenants amendments always lag affirmative covenants.

Both of these sets of results concerning the timing of renegotiations support the theory that renegotiations are information-first. Though I cannot see the direction of the renegotiation (i.e. borrower friendly or creditor friendly), from these results I can conclude that the first aspect of the contract to get renegotiated is the section which concerns information collection. There are two ways to interpret these results. The first interpretation is that the first thing borrowers ask to be removed from their contracts are onerous reporting requirements. Another interpretation is that when banks are concerned about a borrower, they first ask the firm for more information before putting more concrete restrictions on the firm. Unfortunately, my data cannot distinguish between these two stories. They likely both contribute to the effect I observe above. Ultimately though, the direction of the amendment is mostly irrelevant since the information-first theory depends on affirmative covenants having the lowest initial marginal cost of adjustment and both of these stories are consistent with this idea.

4.4 Affirmative covenants are renegotiated first in default

For this test I use an augmented version of my renegotiations dataset which tracks each loan monthly from origination to maturity. The sample of loans and originations used is the same as described above in the summary statistics but I track the progression of each loan monthly in an attempt to see how the creditworthiness of the borrower changes the propensity to renegotiate. One observation in this dataset is a loan-month in which a renegotiation can either occur or not. As before, I disaggregate renegotiations into affirmative covenant amendments and negative covenant amendments.

I estimate the following regression to test how a firm's creditworthiness correlates with the its propensity to renegotiate:

$$\text{reneg}_{i,t,l,b} = \beta_1 \text{DtD\_reneg}_i + \beta_2 \text{days\_to\_reneg} + \beta_3 \text{maturity\_orig} + \beta_4 \text{AiD\_spread\_orig} + \sum_{j=5}^{15} \beta_j \mathbf{O}_{j_i}$$

$$+ l_{i,l} + \tau_{i,t} + \eta_{i,b} + \epsilon_{i,t,l,b}$$

In this regression, the outcome variable is a binary variable indicating if the renegotiation occurred within the loan-month or not. The main test variable is the contemporaneous Distance-to-Default of the firm within the same loan-month. I also control for the amount of time elapsed since origination, the maturity of the loan at origination, the credit spread of the loan at origination and a matrix ($\mathbf{O}$) of the full contents of the originated contract (disaggregated by supersection) at origination. I also include monthly (τ), lender (l) and borrower (b) fixed effects as indicated below. Since the possibility exists that the same borrower might renegotiate multiple loans in the same month and these observations are likely not to be fully independent, I cluster all standard errors at the month $\times$ borrower level.

The regression results detailed in Table 8 are broken down by three different specifications of the outcome variable. The first three columns show results for all types of amendments, the next three show results for just affirmative covenant amendments and the final three columns show results for negative covenant amendments. In the bottom row of the regression table I show the base renegotiation rate for each outcome. This can be interpreted as the chance of a renegotiation happening in any month in which the loan is active.

The results above show that the decision to renegotiate any part of the contract, as well as both the affirmative and negative covenants is heavily correlated with the contemporaneous financial health of the firm. In terms of magnitude, the point estimate of the marginal effect of distance-to-default is about twice as high for negative covenants across all regressions. However, this is to be expected since negative covenants are unconditionally renegotiated more than twice as often as affirmative covenants. The bottom row of the table gives the unconditionally (monthly) rate of renegotiation for affirmative and negative covenants. This is about 0.3% in any month for affirmative covenants and 0.8% in any month for affirmative covenants. Multiplying the point estimates by the appropriate base rates, I find that a one unit increase in Distance-to-Default leads to a -4.8% reduction in the propensity to renegotiate an affirmative covenant.[22] Similarly, I find that a one unit increase in Distance-to-Default leads to a -3.5% reduction in the propensity to renegotiate a negative covenant.[23] This supports the information-first theory since the same change in Distance-to-Default has a larger impact on the conditional probability of renegotiating an affirmative covenant than it does for a negative covenant.

Interestingly, the point estimate for the marginal effect of distance-to-default flips for all three classes of renegotiation when considering within-loan variation in the propensity to renegotiate. The correct way to interpret this flip is that when loans are renegotiated, it is by firms that are worse relative to their peers but better relative to the loan itself at all points of the time from origination until maturity. Another way of restating this is that renegotiations anticipate worsening credit conditions for the same borrower going forward.

To confirm this intuition is correct, in Figure 5 I plot an event study of the distance-to-default of renegotiating firms ± 2 years around the event of renegotiation (left axis). I also plot this number but relative to the prevailing average distance-to-default of the whole market (right axis). Consistent with the regression results above, firms who renegotiate are of significantly lower credit quality than the market as a whole (right axis). Around the event of renegotiation, they are on average 2 units of distance-to-default lower than the prevailing market. This roughly corresponds to being 2 standard deviations closer to

[22] -.00017/.0035 = -.0485
[23] -.00029/.0081 = -.0354

declaring bankruptcy (within one year) than the average firm. The fact that both lines closely track one another shows that these renegotiations mostly happen when there is no trend to the average prevailing creditworthiness of the market. Finally, Figure 5 also confirms the within-loan results of the above regression. Distance-to-Default of renegotiating firms falls about twice as much in the 2 years after a renegotiation as it does in the 2 years preceding.

4.5 Covenant renegotiation around credit events

To test the third hypothesis I consider the how the composition of a renegotiation changes after a default. The vast majority of such defaults are waived and many represent what Griffin, Nini and Smith (2019) call 'false positives' where a default occurs "when a firm is not in danger of financial distress". If the information-first theory is correct, then the first reaction for banks upon seeing a default should be to either increase monitoring of the loan if the default was a 'true positive' or to make monitoring less stringent if the default was a 'false positive'. In Figure 6 I examine renegotiations that occur near a default (using three definitions) and consider how the composition of these default renegotiations differ from renegotiations in the general sample. I cannot observe if the default is a true or false positive but in either case, the information-first theory suggests that the first aspect of the contract to be adjusted will be the monitoring of the loan.

The results in Figure 6 show that no matter how one defines a default, affirmative covenants are renegotiated much more than negative covenants after a default. The graph below compares two samples, the first sample is renegotiations by firms which have recently experienced a default and the second sample is the remainder of renegotiations. For robustness, I use three types of default events. The first type of default event comes from searching the titles of my scraped renegotiations for waivers of default. This indicates that the renegotiation is occurring concurrent with a waiver. The second and third types of default event I note are defaults which occur within one year of a default as noted by either S&P or the covenant violation database from Roberts and Sufi (2009). The numbers reported below are the average amendment composition of the default sample minus the average amendment composition of the remainder sample. For example, if the number below is positive, it implies that this part of the contract is amended more after default than in the general population of renegotiations.

In terms of magnitudes, compared to the average non-default renegotiation, default renegotiations amend about 0.065 more affirmative covenants. While this number may seem small, the average unconditional number of affirmative covenants amended in a renegotiation is 0.43 so this represents a 15% higher likelihood of amendment for affirmative covenants. On the other hand, negative covenants are renegotiated about 6% less in default. This pattern of affirmative covenants being renegotiated more (and negative covenants being renegotiated less) in default is remarkably consistent no matter how one defines a default. In all three columns, the default sample amends anywhere from 0.05 to 0.1 more affirmative covenants while also amending between 0.05 to 0.1 fewer negative covenants. This is consistent with the information-first theory as this implies that after a default, especially one which is waived, the first thing to be adjusted is the monitoring of the loan.

Finally, in Figure 7, I repeat the same exercise but I compare the renegotiations of firms that are about to enter bankruptcy (within the next two years) with the rest of the population. Consistent with the information-first theory, I find that such firms renegotiate relatively weakly *more* negative covenants. This is consistent with the theory since bankruptcy represents a state in which the firm is likely to have already had multiple rounds in which they would have already adjusted the monitoring covenants. Thus by the time bankruptcy is imminent, the majority of what is left to adjust is the negative covenants. Finally, it should be noted that–most likely because the sample of firms who declare bankruptcy is quite small–these effects are not statistically significant for the covenant categories. Because of this, these bankruptcy Results should be viewed as mostly complimentary to the results presented above.

5 Conclusion

In this paper I use two novel sources of data to shed light on an under-appreciated class of covenants commonly used in syndicated lending contracts. Affirmative covenants are frequently neglected or ignored in the academic treatment of covenants and this paper aims to fill that gap in the literature.

Using a novel dataset which records the intensity of affirmative covenant usage at origination, I document the role of affirmative covenants in debt contracts as a monitoring technology. This monitoring technology has two parts, ensuring information is 1) available in a timely manner and 2) factually accurate for lenders. I document that the inclusion of affirmative covenants is highly variable and heavily correlated with 2 popular proxies of monitoring demand (as well as credit quality). In total, the results suggest that the monitoring hypothesis is correct and setting the tightness of affirmative covenants at origination can be analogized to setting the sensitivity of the negative covenant tripwires.

Using another novel database of the timing and content of contractual renegotiations, I show that the way affirmative covenants are renegotiated is consistent with this monitoring story. I theorize that since tightening affirmative covenants provides some benefit to the lender without actually putting any more meaningful restrictions on the borrower, that these covenants have a lower marginal cost of adjustment and so should be renegotiated first, if possible. I call this idea the "information-first" theory of contractual adjustment. I test it in the data and find that affirmative covenants are renegotiated first in time, first in default and first after technical or waived defaults. The frequent adjustments of affirmative covenants I document in this paper almost certainly reflects a response of banks to the evolving information asymmetry that develops over the life of the loan.

In total, the results suggest that this frequently-overlooked aspect of contracts has an important role to play in syndicated lending contracts. By better understanding the technology that banks use to monitor their loans, we can better understand how they fulfill one of their most important functions. For future papers, these results suggest that affirmative covenant intensity might be a useful proxy used for measuring the monitoring demand of a loan. Future papers might also consider the intensive margin of affirmative covenant usage and the specific directions in which they are amended in the data.

References

[1] Aghion, P., and Bolton, P. (1992). An Incomplete Contracts Approach to Financial Contracting. The Review of Economic Studies, 59(3), 473-494.

[2] Anthony, S., Steffen, S., Freudenberg, F. and Imbierowicz, B. (2012). Covenant Violations, Loan Contracting, and Default Risk of Bank Borrowers. NYU Working Paper No. 2451/31417.

[3] Becker, B., and Ivashina, V., (2016). "Covenant-Light Contracts and Creditor Coordination." Swedish House of Finance Research Paper, No. 16-09.

[4] Bharath, S. and Shumway, T. (2008). Forecasting Default with the Merton Distance to Default Model. The Review of Financial Studies, Volume 21, Issue 3 Pages 1339–1369.

[5] Godlewski, C. (2016). Debt Renegotiation and the Design of Financial Contracts. Available at SSRN.

[6] Griffin, T., Nini, G., and Smith, D. (2019). Losing Control? The 20-Year Decline in Loan Covenant Restrictions.

[7] Gustafson, M., Ivanov, I., and Meisenzahl, R., (2020). Bank Monitoring: Evidence from Syndicated Loans (January 7, 2020). Journal of Financial Economics (JFE), Forthcoming.

[8] Ivashina, V. (2009). Asymmetric Information Effects on Loan Spreads. Journal of Financial Economics 92, pp. 300-319.

[9] Ivashina, V., and Vallée, B., (2020). "Weak Credit Covenants." NBER Working Paper Series, No. 27316.

[10] Lee, S., and Mullineaux, D. (2004). Monitoring, Financial Distress, and the Structure of Commercial Lending Syndicates. Financial Management, vol. 33, no. 3, 2004, pp. 107–130.

[11] Loughran, T., and McDonald, B. (2016). Textual Analysis in Accounting and Finance: A Survey. Available at SSRN: http://dx.doi.org/10.2139/ssrn.2504147.

[12] Missonier-Piera, F. and Francois, P. (2007). The Agency Structure of Loan Syndicates. Financial Review, Vol. 42, No. 2, pp. 227-245.

[13] Nikolaev, V. (2016). Scope for Renegotiation in Private Debt Contracts. Chicago Booth Research Paper Series.

[14] Roberts, M. (2015). The role of dynamic renegotiation and asymmetric information in financial contracting. Journal of Financial Economics, Volume 116, Issue 1, Pages 61-81. ISSN 0304-405X.

[15] Roberts, M., and Chava, S. (2008). How does Financing Impact Investment? The Role of Debt Covenants. Journal of Finance, 63, 2085 - 2121.

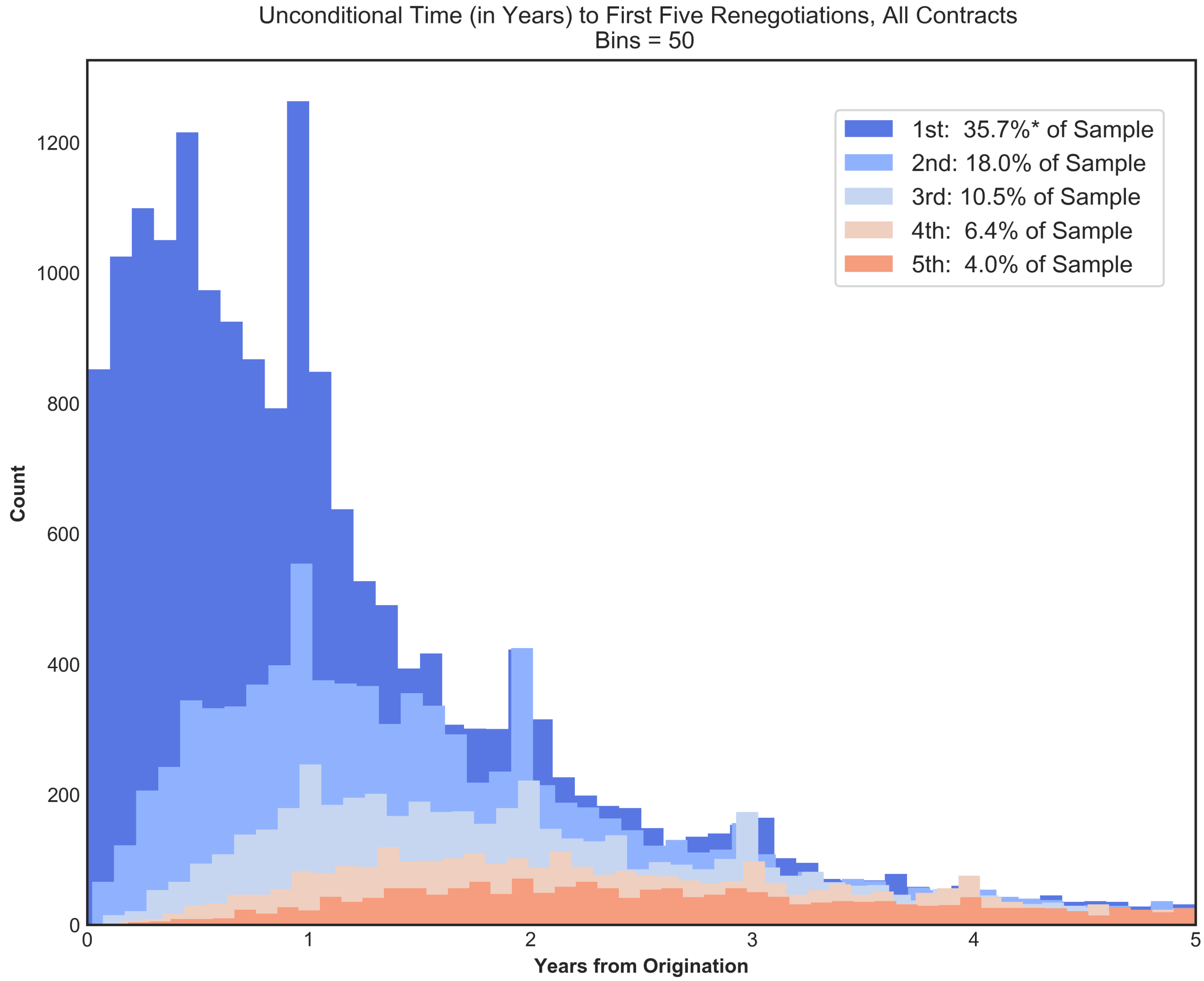
[16] Roberts, M., and Sufi, A. (2009a). Control Rights and Capital Structure: An Empirical Investigation. The Journal of Finance, 64: 1657-1695.

[17] Roberts, M., and Sufi, A. (2009b). Renegotiation of financial contracts: Evidence from private credit agreements, Journal of Financial Economics, 93, issue 2, p. 159-184.

[18] Sufi, A. (2006). Information Asymmetry and Financing Arrangements: Evidence from Syndicated Loans. Journal of Finance.

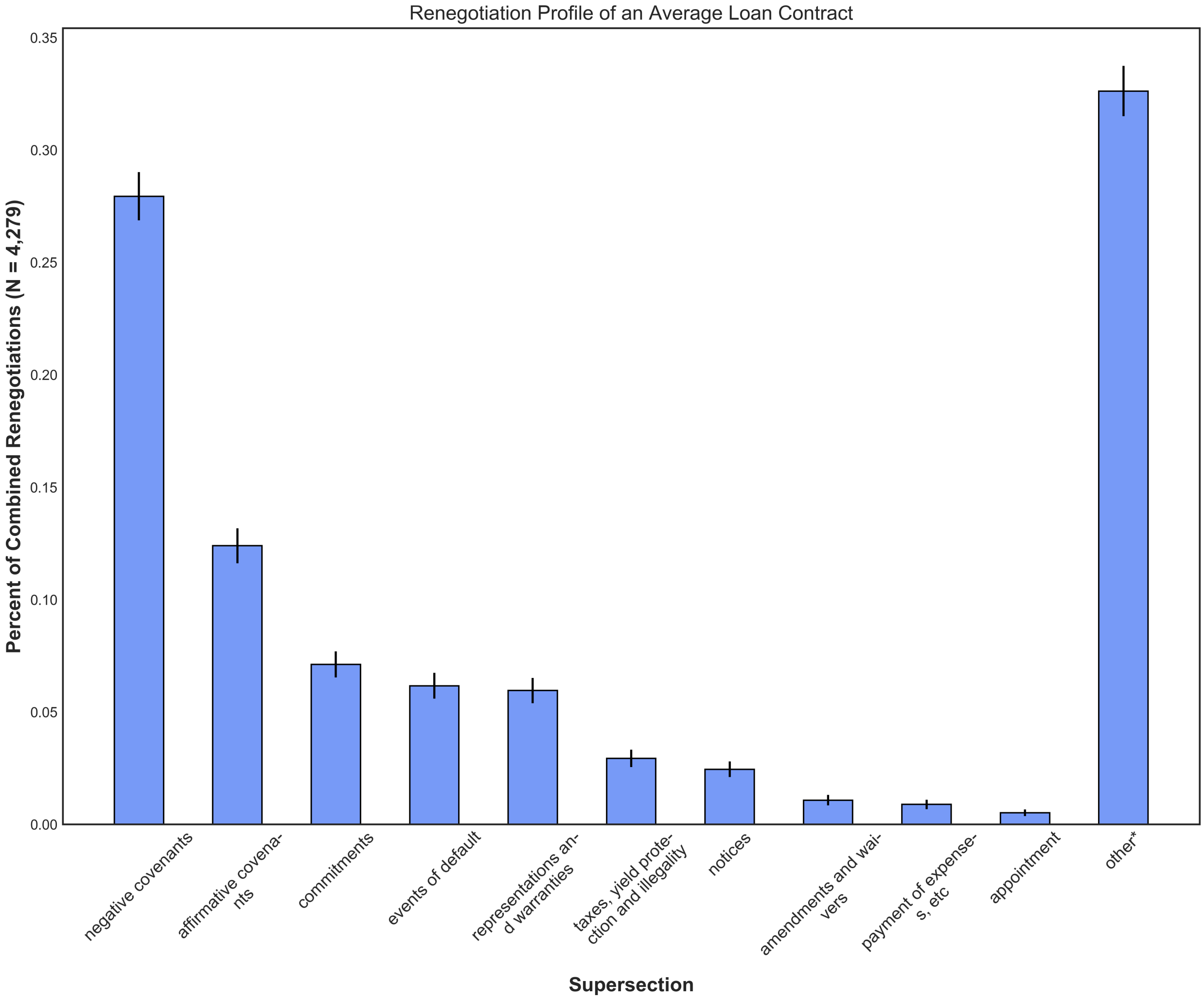
Figures:

Figure 1: Unconditional time to renegotiation



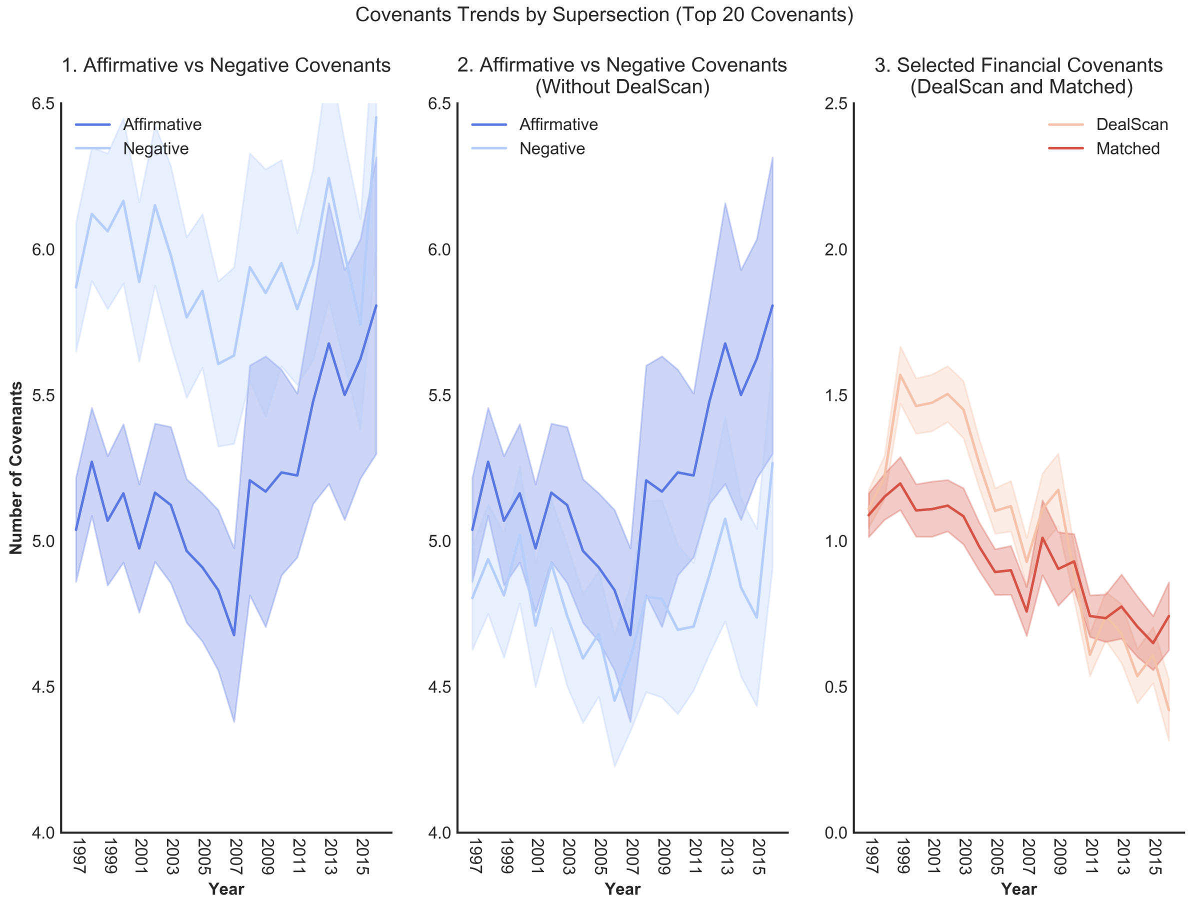
* To rationalize this result in the context of Roberts and Sufi (2009), it is important to remember that the 90% renegotiation rate reported by Roberts and Sufi is a conditional mean and uses a more generous definition of renegotiation than I do here. Both of these choices increase the reported rate. The relevant imputed number for comparison from their sample when considering unconditional renegotiations that exclude fully amended and restated contracts is 34%. This is very close to the number reported above. See paper for details of this calculation.

Figure 2: Renegotiation Composition by Amendment Type



Note: Renegotiation profile of an average contract. One observation is one complete recorded renegotiation path for one contract. One observation might include data from multiple renegotiations, i.e. 3 negative covenants and 1 affirmative covenant. In this case the renegotiation profile would have a value of 0.75 for negative covenants, 0.25 for affirmative covenants and 0 for all else. Standard errors clustered at the original contract level. Black bars indicate 95% confidence interval of point estimate. Data does not include renegotiations of 'Definitions' supersections as these cannot be matched cleanly to a specific subsection. Other* supersection is the composite of the 23 identified supersections that are not in the top ten supersections by length in a contract. Data from 15,339 individual renegotiations to 4,279 contracts.

Figure 3: Growth in Affirmative Covenant Usage



Note: Each graph shows the average number of covenants included in one contract per year, broken down by supersection. To ensure that this graph reflects economically meaningful covenants, covenants used for each supersection are drawn from the top twenty most frequently used covenants from that supersection. Graph 1 shows unconditional average covenant usage broken down by supersection. Graph 2 is similar but excludes covenants also found in DealScan (i.e. Current Ratio which is a covenant contained in both DealScan and my database). Removing covenants also found in DealScan disproportionately affects the negative covenants. Graph 3 shows the time trend of the DealScan covenants removed in Graph 2. This is measured by using both DealScan data and the matched complements of the removed DealScan covenants in my dataset. For clarity, this graph excludes all forms of DealScan leverage ratio covenants because of the double-counting problem noted earlier in the paper. Shaded areas indicate 95% confidence intervals.

Figure 4: CDF of total renegotiations by covenant type

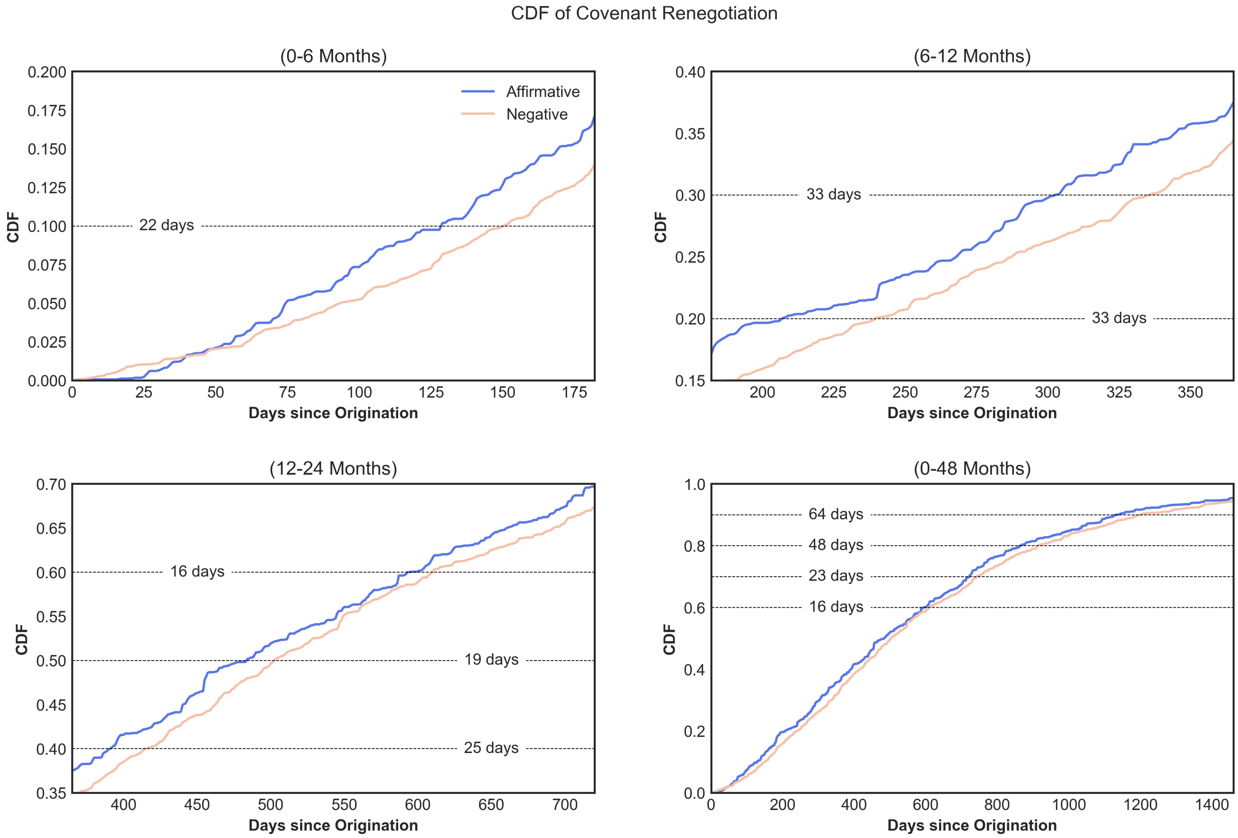
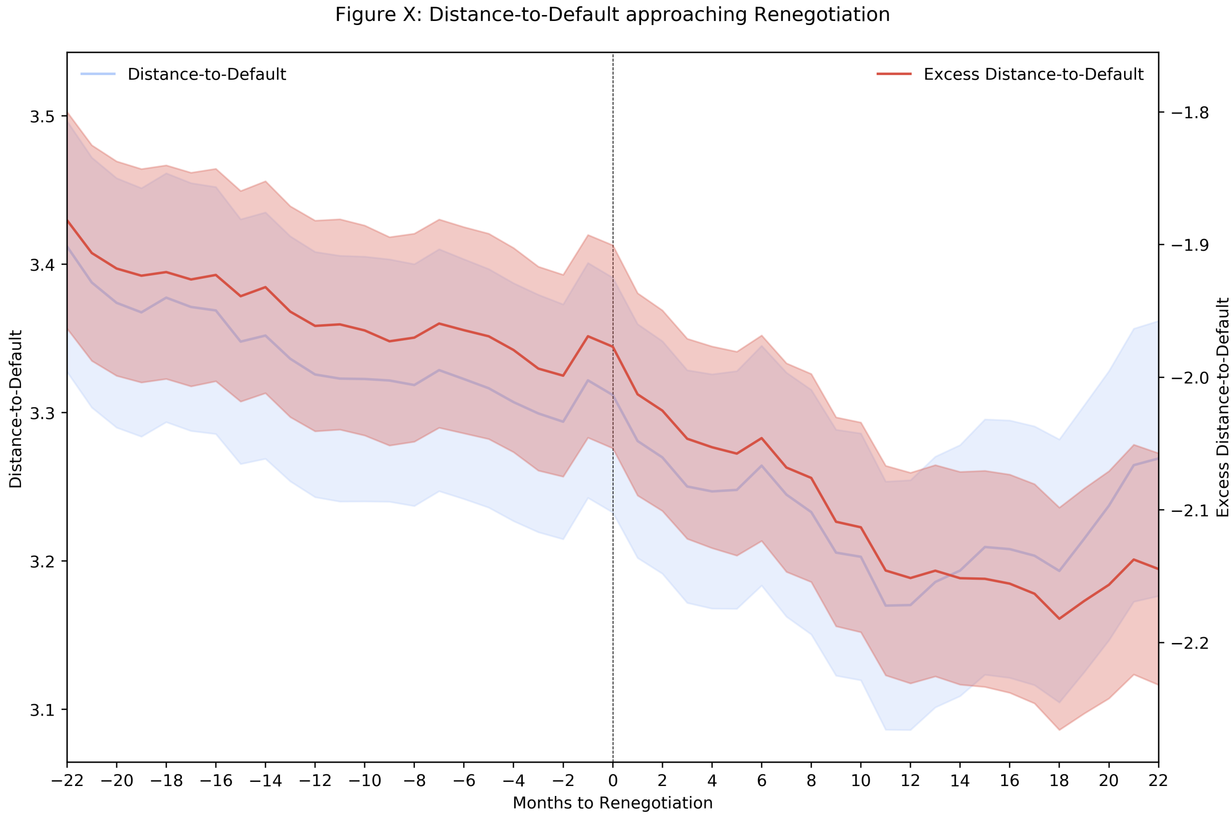
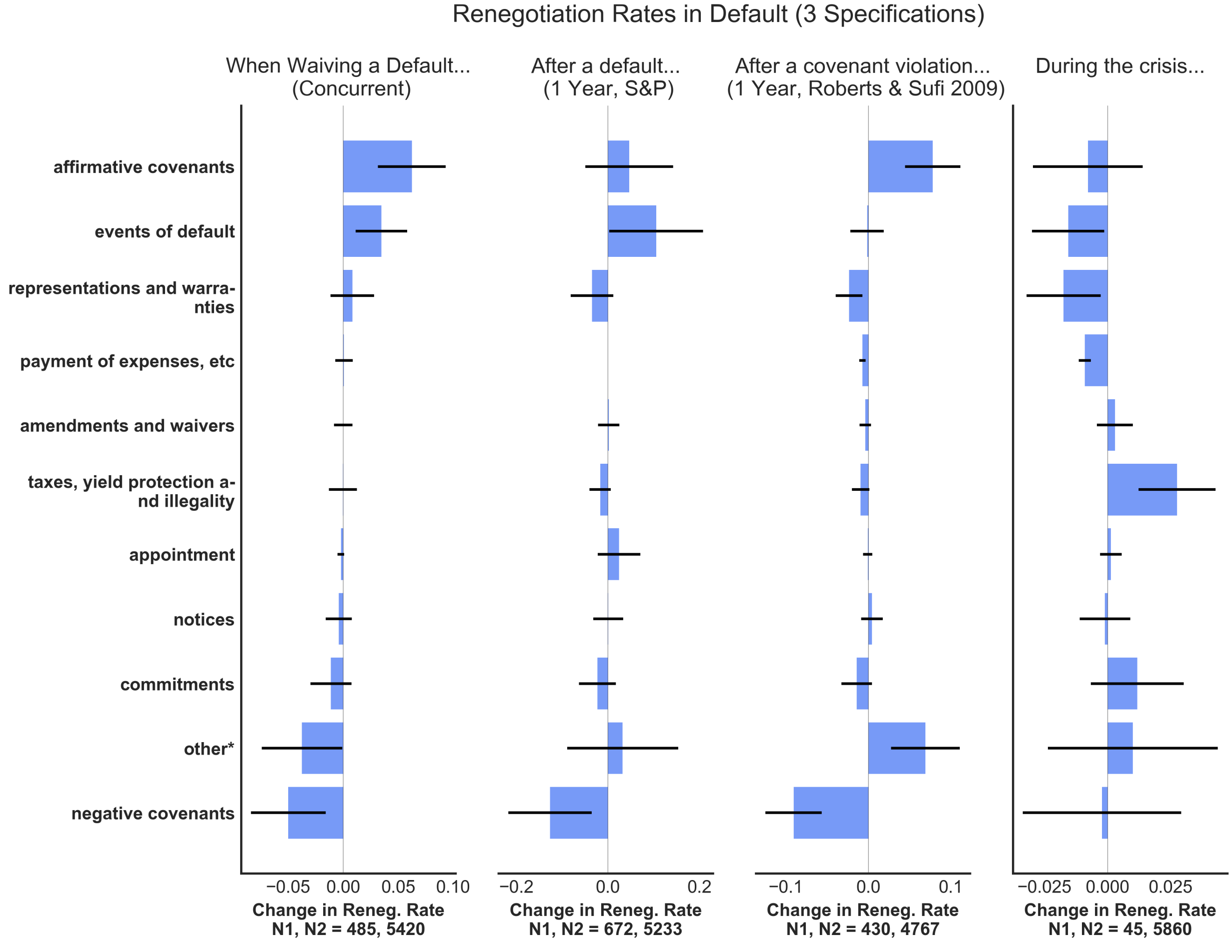


Figure 5: Firm Distance-to-Default around renegotiation event



Note: This graph shows distance-to-default for an average firm +/-2 years around a contractual renegotiation of a loan. Blue is raw average distance-to-default. Red is average distance-to-default of a renegotiating firm minus the distance-to-default of the (market capitalization weighted) average firm in the market. Shaded regions are 95% confidence intervals. Distance-to-default measure used is constructed as described in Barath and Shumway (2008). N = 4279.

Figure 6: Covenant renegotiation by category around credit events



Note: This graph shows changes in renegotiation rates after borrower default (3 different specifications). Stardard errors computed by estimating standard errors for difference in two means. N1 is the number of renegotiations where the stated condition is met and N2 is the number of observations where it is not. Bars indicate 95% confidence interval of point estimate. Standard errors clustered at the level of the original contract for each renegotiation. Time sample differs for the Roberts and Sufi dataset (1996-2012) and the crisis dataset (2008-2009), all others 1996-2017.

Figure 7: Covenant renegotiation for firms that will declare bankruptcy within 2 years

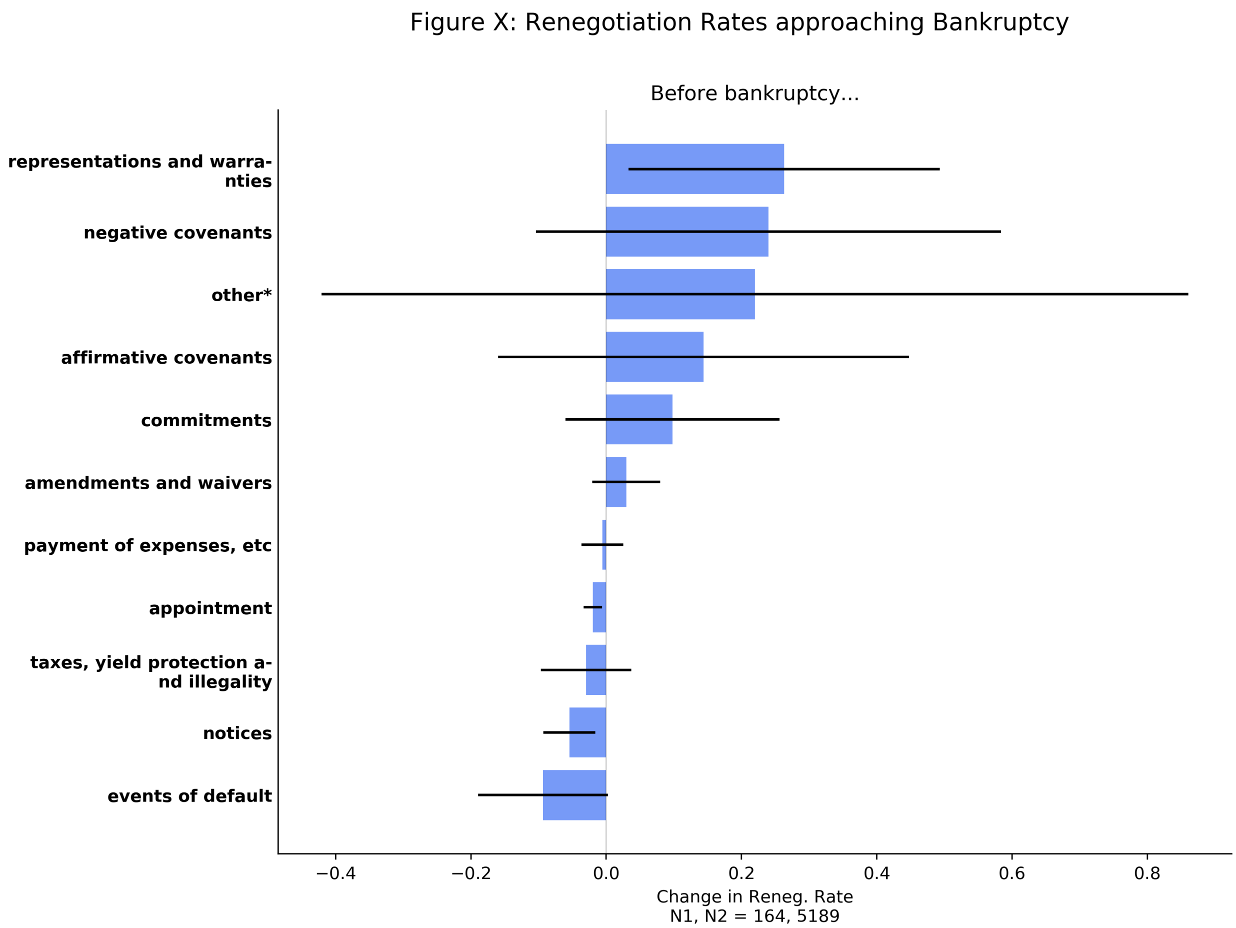
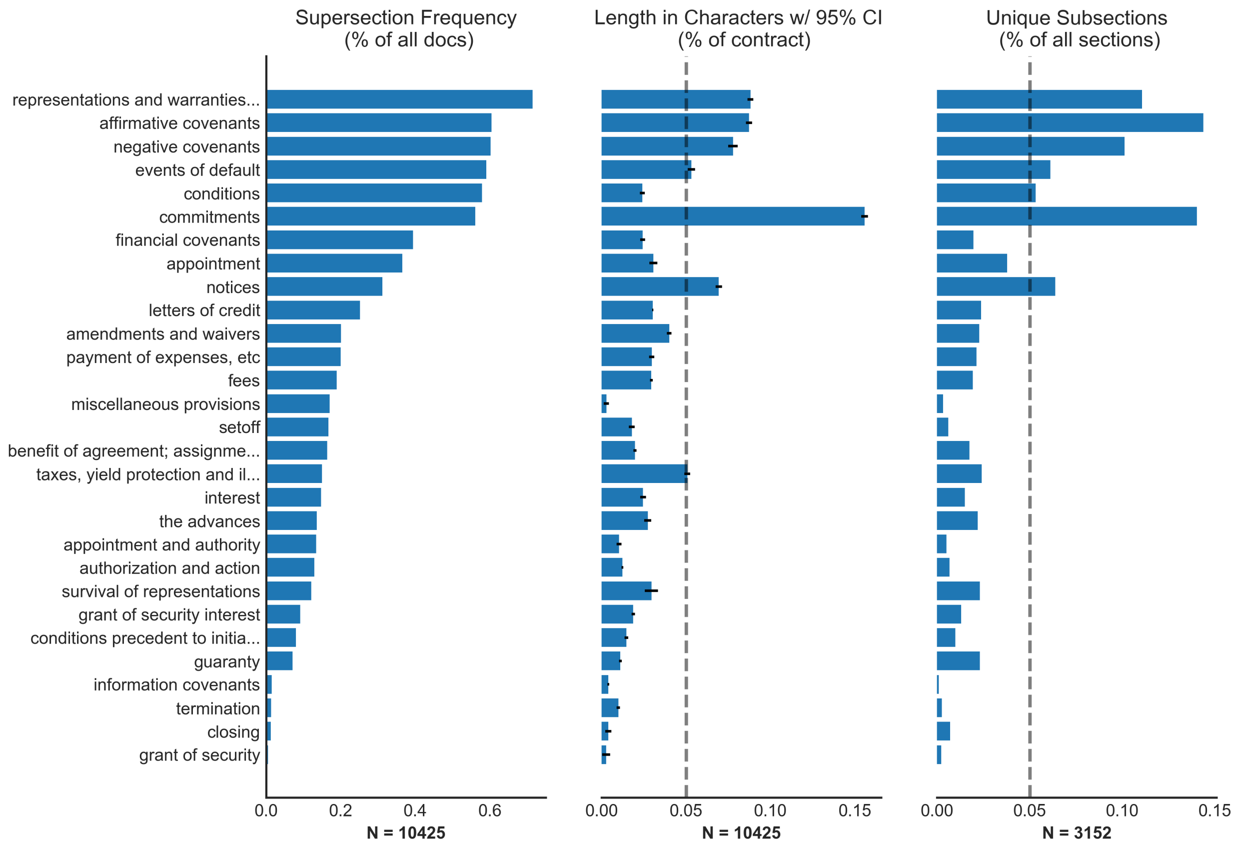


Figure 8: Visualizing Supersection Composition



Tables:

Table 1: Origination Data Summary Statistics

	Mean	Std	10%	50%	90%	Obs.
Firm Details:						
-Distance-to-Default	3.88	2.92	0.73	3.51	7.64	7282
-Market Cap (MM)	2921	10521	30	488	5908	7671
Loan Details:						
-Facility Amount (MM)	313	580	12	125	750	7993
-All-in-Drawn Spread (bp)	201	132	60	175	350	7822
-Maturity (Months)	52	20	29	60	74	7993
-Bank Allocation (Pct.)	0.40	0.36	0.08	0.24	1.00	7647
-Syndicate Members (Count)	3.40	6.40	0.00	0.00	12	7647
Contents by Supersection (Count/Top 20):						
-Affirmative Covenants	5.12	2.65	2.00	5.00	9.00	7993
-Amendments and Waivers	1.08	1.73	0.00	0.00	3.00	7993
-Appointment	2.77	2.47	0.00	2.00	6.00	7993
-Commitments	5.09	2.98	1.00	5.00	9.00	7993
-Events of Default	2.76	2.49	0.00	2.00	6.00	7993
-Negative Covenants	5.92	2.92	2.00	6.00	10	7993
-Notices	6.10	3.14	2.00	6.00	10	7993
-Payment of Expenses, etc	0.92	1.33	0.00	1.00	2.00	7993
-Representations and Warranties	6.75	3.13	2.00	7.00	11	7993
-Taxes, Yield Protection and Illegality	1.66	3.59	0.00	0.00	4.00	7993

Table 2: Renegotiation Data Summary Statistics

	Mean	Std	10%	50%	90%	Obs.
Renegotiated Sections (Count):						
-Affirmative Covenants	0.43	1.19	0.00	0.00	1.00	4279
-Amendments and Waivers	0.04	0.34	0.00	0.00	0.00	4279
-Appointment	0.02	0.20	0.00	0.00	0.00	4279
-Commitments	0.24	0.83	0.00	0.00	1.00	4279
-Events of Default	0.23	0.95	0.00	0.00	1.00	4279
-Negative Covenants	0.91	1.65	0.00	0.00	3.00	4279
-Notices	0.09	0.47	0.00	0.00	0.00	4279
-Definitions and Other*	1.27	2.30	0.00	0.00	4.00	4279
-Payment of Expenses, etc	0.03	0.30	0.00	0.00	0.00	4279
-Representations and Warranties	0.19	0.77	0.00	0.00	1.00	4279
-Taxes, Yield Protection and Illegality	0.13	0.69	0.00	0.00	0.00	4279
-Sum Total	3.58	3.79	1.00	2.00	8.00	4279
At Renegotiation:						
-Distance-to-Default	3.43	2.66	0.56	3.13	6.65	3871
-Days to Renegotiation	587	471	122	471	1184	4279
At Origination:						
-Distance-to-Default (Orig.)	3.31	2.55	0.59	3.02	6.27	3976
-Facility Amount (MM)	223	410	12	100	525	4279
-All-in-Drawn Spread (bp)	221	119	80	200	350	4202
-Maturity (Months)	52	20	33	58	82	4279
-Market Cap (MM)	1268	4052	25	288	2643	4096
-Bank Allocation (Pct.)	0.46	0.37	0.08	0.32	1.00	4140

Table 3: Top 20 Most Commonly Used Negative Covenants

Summary of the top 20 most common negative covenants in syndicated lending contracts (1996-2017). Sample is from 8426 syndicated lending contracts to 3662 borrowers. Borrowers exclude utilities and financial firms. Frequency is the proportion of all contracts that contain a covenant. DS identifies if the given covenant is also found in LPC's DealScan database. Numerical is the proportion of covenants which contain a numerical restriction in one of the following forms: dollar amount ($100,000), ratio (2:1 or 2 to 1) or percent (50%). Type is the type of numerical restriction. Description provides a brief description of the covenant, if possible, in the text's own words.

Summary of Top 20 most Common Negative Covenants

Name	Freq	DS	% Num	Type	Description
liens	0.767	No	0.286	carve-out	Restrictions on additional liens
indebtedness	0.662	No	0.397	carve-out	Restrictions on additional indebtedness
transactions with affiliates	0.587	No	0.156	carve-out	Restrictions on affiliate transactions with "terms less favorable than would be obtained in an arm's length transaction"
investments	0.520	No	0.496	carve-out	Restrictions on investments (typically includes a long list of restricted investments)
leverage ratio	0.336	Yes	0.629	limit	"The Borrower shall not, at any time, permit the Leverage Ratio to be greater than..."
restricted payments	0.324	No	0.528	carve-out	Restrictions on payments to equity holders (frequently includes dividends)
interest coverage ratio	0.280	Yes	0.577	limit	"Borrower shall not permit the Interest Coverage Ratio to be less than..."
fixed charge coverage ratio	0.260	Yes	0.674	limit	"Borrower shall maintain a Fixed Charge Coverage Ratio of at least..."
capital expenditures	0.259	Yes	0.621	carve-out	"Borrower...may make Capital Expenditures in an aggregate amount not exceeding..."
acquisitions	0.205	No	0.360	carve-out	Restrictions on acquisitions
fundamental changes	0.200	No	0.155	carve-out	"Enter into any merger, consolidation or amalgamation, or liquidate, wind up or dissolve itself..except that:"
debt	0.169	No	0.440	carve-out	Restrictions on additional indebtedness
sale of assets	0.167	No	0.477	carve-out	"Borrower shall not sell, lease, transfer, or otherwise dispose of any of its Properties without the prior written consent of Lender except for:"
net worth	0.156	No	0.837	limit	"Borrower will maintain at all times a Consolidated Net Worth of at least the sum of..."
tangible net worth	0.149	No	0.839	limit	"Borrower will at all times maintain its Consolidated Tangible Net Worth at not less than..."
mergers, etc	0.146	No	0.111	carve-out	Restrictions on mergers
financial covenants	0.146	No	0.131	limit	"Borrower shall at all times maintain the following financial ratios and covenants"
conduct of business	0.140	No	0.076	N/A	"At all times engage only in the business described in SECTION..."
dividends	0.138	No	0.297	carve-out	Restriction on paying dividends
dispositions	0.123	No	0.494	carve-out	Restictions on dispositions (sales) of assets

Table 4: Top 20 Most Commonly Used Affirmative Covenants

Summary of the top 20 most common affirmative covenants in syndicated lending contracts (1996-2017). Sample is from 8426 syndicated lending contracts to 3662 borrowers. Borrowers exclude utilities and financial firms. Frequency is the proportion of all contracts that contain a covenant. DS identifies if the given covenant is also found in LPC's DealScan database. Numerical is the proportion of covenants which contain a numerical restriction in one of the following forms: dollar amount ($100,000), ratio (2:1 or 2 to 1) or percent (50%). Type is the type of numerical restriction. Description provides a brief description of the covenant, if possible, in the text's own words.

Summary of Top 20 most Common Affirmative Covenants

Name	Freq	DS	% Num	Type	Description
insurance	0.692	No	0.139	specific	Maintain insurance on property. *Specific: Frequently 100% of value
use of proceeds	0.647	No	0.078	N/A	Specifies how borrower will use proceeds of loan
compliance with laws	0.512	No	0.009	N/A	Borrower will comply with laws when "not complying would...have a material adverse effect".
further assurances	0.357	No	0.068	N/A	"Execute any and all further documents that may be required... in order to effectuate the transactions contemplated by the Loan"
maintenance of properties	0.273	No	0.011	N/A	"Maintain and keep its property in good repair, working order and condition"
payment of obligations	0.260	No	0.040	N/A	Pay and discharge taxes and other obligations which might incur a lien
other information	0.252	No	0.041	N/A	Borrower sends lender copies of all publicly availible statements
certificates; other information	0.223	No	0.125	specific	Similar to above but includes certificate from CFO affirming accuracy and detailing calculations. *Specific: Financial states in which CFO has to certificate
books and records	0.206	No	0.005	N/A	"Maintain books of record and account...in conformity with GAAP...of all financial transactions"
annual financial statements	0.180	No	0.018	N/A	Submit current corporate balance sheets to lender once a year
leases	0.153	No	0.175	limit	Lender notified of any changes in leases. Restrictions on leases and assumed leases
inspection rights	0.143	No	0.117	specific	"Permit representatives...of either Agent to visit and inspect any of its properties"
inspection	0.138	No	0.041	N/A	"Permit the Lender ... to examine the Borrower's files, books and records and make and take away copies"
compliance with laws, etc	0.135	No	0.006	N/A	Borrower and subsid. will comply with laws and other contractual obligations when not complying would have a material
compliance certificate	0.124	No	0.026	N/A	Financial statements delivered to lender include certificate from CFO affirming accuracy
additional subsidiaries	0.119	No	0.392	specific	Stipulations re. subsidiaries. *Specific: Occasionaly requires subsidiaries to become loan partners if large enough.
notice	0.113	No	0.219	specific	Defines events under which borrower has to notify lender. *Specific: Refers to financial events for notifying
compliance with environmental laws	0.107	No	0.041	N/A	Borrower will not use...Real Estate...for the handling, processing, storage or disposal of Hazardous Substances", etc
[delegation of security interest]	0.105	No	0.039	N/A	"Lender may at any time create a security interest in all or any portion of its rights under this Agreement"
maintenance of insurance	0.102	No	0.019	N/A	Borrower will maintain insurance for usual business risks

Table 5: Bank Monitoring Proxies and Affirmative Covenant Usage

This regression shows how covenant usage co-varies with two popular proxies for bank monitoring. Outcome variable is either syndicate size or lead arranger share. Syndicate size is the total number of banks in the syndicate for one credit facility. Lead arranger share is the percent of the loan retained on the lead arranger bank's balance sheet at origination (averaged for loans with more than one Lead Arranger). One unit of observation is one credit facility and its corresponding contract. Standard errors robust to clustering at the Lender × Year level. Sample time period is 1996-2017.

Bank Monitoring Proxies and Affirmative Covenant Usage

	Syndicate Size			**Lead Arranger Share**		
	(1)	(2)	(3)	(4)	(5)	(6)
Affirmative Covenants	-0.2194***	-0.1266**	-0.1786**	0.0105***	0.0065**	0.0056*
	(0.0372)	(0.0442)	(0.0580)	(0.0020)	(0.0023)	(0.0024)
Negative Covenants	-0.1152***	-0.1010**	0.0427	-0.0080***	-0.0033	-0.0055**
	(0.0316)	(0.0362)	(0.0495)	(0.0016)	(0.0017)	(0.0020)
Loan Spread (bp)	-0.0135***	-0.0112***	-0.0074***	0.0008***	0.0005***	0.0003***
	(0.0008)	(0.0009)	(0.0010)	(0.0000)	(0.0001)	(0.0000)
Maturity	0.0193***	0.0135**	-0.0013	-0.0054***	-0.0031***	-0.0018***
	(0.0043)	(0.0046)	(0.0078)	(0.0003)	(0.0003)	(0.0004)
Distance-to-Default	-0.0386	-0.0595	-0.0428	0.0036*	0.0031*	-0.0029
	(0.0294)	(0.0314)	(0.0502)	(0.0015)	(0.0015)	(0.0018)
Full Contract Contents	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Lender FE		✓			✓	
Borrower FE			✓			✓
N	6911	5747	5338	6911	5747	5338
adj. R^2	0.112	0.183	0.253	0.323	0.489	0.596

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

Table 6: Covenant Usage and Distance-to-Default around Origination

This regression shows how borrower Distance-to-Default varies with the price and non-price terms of a contract. Outcome variable is Distance-to-Default (as found in Bharath and Shumway, 2008) measured at origination and +/- 1 year from origination. The main test variables of interest are the covenants used in the originated contract. Controls include loan observables as well as year, lender and borrower fixed effects as indicated. One observation is one loan (also matched to Compustat and LPC DealScan) originated between 1996-2017. Standard errors robust to clustering at the Lender × Year level.

Distance-to-Default around Origination

	DTD at Origination				DTD -1 Year		DTD +1 Year	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Affirmative Covenants	-0.0521**	-0.0419*	-0.0460*	-0.0237	-0.0605**	-0.0335	-0.0330	-0.0312
	(0.0163)	(0.0197)	(0.0208)	(0.0267)	(0.0196)	(0.0207)	(0.0178)	(0.0180)
DealScan Covenants	-0.1057*	-0.1169*	-0.0567	-0.0825	-0.1358*	-0.0515	-0.1487***	-0.0801
	(0.0416)	(0.0563)	(0.0491)	(0.0642)	(0.0579)	(0.0501)	(0.0407)	(0.0460)
Negative Covenants (w/o DS)	-0.0265	-0.0377	-0.0345	-0.0214	-0.0318	-0.0175	-0.0224	-0.0122
	(0.0183)	(0.0224)	(0.0213)	(0.0295)	(0.0243)	(0.0226)	(0.0184)	(0.0201)
Amendments and Waivers	-0.0110	0.0043	0.0168	0.0245	-0.0009	-0.0233	-0.0007	0.0227
	(0.0155)	(0.0189)	(0.0222)	(0.0278)	(0.0214)	(0.0218)	(0.0174)	(0.0205)
Appointment	-0.0361***	-0.0335**	-0.0038	-0.0121	-0.0257*	0.0133	-0.0268**	0.0023
	(0.0089)	(0.0104)	(0.0108)	(0.0142)	(0.0116)	(0.0114)	(0.0093)	(0.0109)
Commitments	0.0074	0.0072	0.0080	0.0088	0.0065	0.0052	0.0015	0.0027
	(0.0039)	(0.0054)	(0.0047)	(0.0063)	(0.0061)	(0.0049)	(0.0045)	(0.0045)
Events of Default	0.0062	0.0010	-0.0027	-0.0093	0.0044	0.0066	0.0177	0.0130
	(0.0075)	(0.0108)	(0.0095)	(0.0128)	(0.0107)	(0.0095)	(0.0091)	(0.0089)
Notices	-0.0094	-0.0021	-0.0019	0.0114	-0.0039	-0.0067	-0.0023	-0.0039
	(0.0060)	(0.0072)	(0.0078)	(0.0108)	(0.0082)	(0.0078)	(0.0074)	(0.0076)
Payment of Expenses	0.0432*	0.0331	0.0135	0.0085	0.0411	-0.0271	0.0237	0.0116
	(0.0173)	(0.0220)	(0.0233)	(0.0326)	(0.0239)	(0.0237)	(0.0193)	(0.0217)
Taxes, Yield Protection...	0.0304***	0.0317***	0.0237**	0.0196	0.0226*	0.0112	0.0224**	0.0122
	(0.0060)	(0.0082)	(0.0082)	(0.0120)	(0.0089)	(0.0078)	(0.0078)	(0.0080)
Loan Spread (bp)	-0.0080***	-0.0087***	-0.0044***	-0.0050***	-0.0072***	-0.0015***	-0.0092***	-0.0059***
	(0.0004)	(0.0005)	(0.0004)	(0.0006)	(0.0005)	(0.0004)	(0.0005)	(0.0004)
Maturity	-0.0018	-0.0002	0.0093***	0.0139***	0.0007	0.0030	0.0000	0.0073**
	(0.0020)	(0.0024)	(0.0025)	(0.0033)	(0.0026)	(0.0024)	(0.0019)	(0.0023)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE		✓		✓	✓		✓	
Borrower FE			✓	✓		✓		✓
N	6911	5747	5338	4089	5464	5145	5439	5056
adj. R^2	0.255	0.279	0.592	0.591	0.234	0.564	0.344	0.599

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

Table 7: Days to Renegotiation and Renegotiation Contents

This regression shows the relation between renegotiating an affirmative/negative covenant and the timing of the renegotiation. Outcome variable is number of calender days between origination and renegotiation. Main test variables are the number of disaggregated covenants amended in the renegotiation. P-value in the bottom row is the p-value from the test of the hypothesis that the coefficient estimate for affirmative and negative covenants are the same. Controls include the the covenants included in the contract at origination, the Distance-to-Default of the firm at the time of renegotiation, the full contents of the renegotiation (i.e. if a renegotiation also amended the Events of Default supersection, etc.) as well as year, lender and borrower fixed effects where indicated. One observation is one renegotiation of a loan originated between 1996-2017. Standard errors robust to clustering at the Lender × Year level.

	(1)	(2)	(3)	(4)	(5)
Affirmative Covenants (Reneg)	-7.332	-5.998	-7.309	-5.887	0.570
	(5.607)	(5.434)	(5.687)	(5.518)	(5.891)
Negative Covenants (Reneg)	12.00**	14.22**	11.41**	13.47**	10.95*
	(4.380)	(4.403)	(4.421)	(4.459)	(5.037)
Affirmative Covenants (Orig)		-9.726*		-9.619*	4.989
		(4.682)		(4.717)	(19.22)
Negative Covenants (Orig)		-15.44**		-15.67**	-10.54
		(5.558)		(5.553)	(20.04)
DealScan Covenants (Orig)		6.226		6.061	-13.62
		(10.98)		(10.94)	(49.37)
Distance-to-Default	10.60*	9.460*	11.03*	9.794*	6.037
	(4.736)	(4.757)	(4.750)	(4.770)	(7.085)
Full Contents			✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓	✓
Borrower FE					✓
N	3582	3582	3582	3582	3111
R2	0.379	0.386	0.383	0.389	0.782
p-val: $H_0(\beta_{\text{AffCov(reneg)}} - \beta_{\text{NegCov(reneg)}} = 0)$	0.0117	0.00718	0.0142	0.00979	0.199

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Distance-to-Default and renegotiation by covenant type

This regression shows how monthly changes in borrower Distance-to-Default measure, as described in Bharath and Shumway (2008), correlate with the monthly propensity to renegotiate. Outcome variable is an indicator variable which is one if there was a monthly renegotiation of the stated category and zero if there was no monthly renegotiation of the stated category. Loan Spread and Maturity are also determined at origination and attempt to help control for borrower quality at origination. Duration is the length of time (in months) at which the renegotiation occurs. Origination Controls account for the non-price composition of contract at origination. Regressions 1, 2, 4, 5, 7 and 8 are between-borrower regressions while regressions 3, 6 and 9 are within-borrower/loan regressions. One observation is one loan-month in which the loan is active. Sample time period is 1996-2017. To avoid double counting firms which might have multiple concurrent loans outstanding, standard errors robust to clustering at the borrower × month level.

What drives the choice to renegotiate...

	All (N = 7637)			**Affirmative Cov (N = 1513)**			**Negative Cov (N = 3428)**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Distance-to-Default	-0.00074***	-0.00063***	0.00035*	-0.00014**	-0.00017**	0.00029**	-0.00041***	-0.00029*	0.00056*
	(-9.336)	(-7.106)	(2.445)	(-2.583)	(-2.714)	(2.721)	(-4.070)	(-2.564)	(2.532)
Duration	-0.00038***	-0.00040***	0.00017	-0.00008***	-0.00009***	0.00007	-0.00018***	-0.00020***	-0.00003
	(-31.477)	(-29.211)	(0.646)	(-9.607)	(-8.728)	(0.434)	(-11.339)	(-10.923)	(-0.111)
Maturity	0.00002	0.00004*		-0.00002	-0.00001		0.00006**	0.00006*	
	(1.371)	(2.248)		(-1.456)	(-0.510)		(2.830)	(2.456)	
Loan Spread (bp)	0.00004***	0.00003***		0.00001***	0.00001***		0.00001***	0.00002***	
	(16.376)	(9.938)		(6.040)	(4.190)		(6.192)	(5.144)	
Origination Controls	✓	✓	(subsumed)	✓	✓	(subsumed)	✓	✓	(subsumed)
LoanType FE	✓	✓	(subsumed)	✓	✓	(subsumed)	✓	✓	(subsumed)
Year-Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE		✓	(subsumed)		✓	(subsumed)		✓	(subsumed)
Loan FE			✓			✓			✓
N	4.161e+05	4.161e+05	4.212e+05	4.161e+05	4.161e+05	4.212e+05	4.161e+05	4.161e+05	4.212e+05
R2	0.00696	0.02123	0.07633	0.00137	0.00735	0.04228	0.00214	0.01015	0.04190
Base Rate	0.01807	0.01807	0.01796	0.00357	0.00357	0.00355	0.00819	0.00819	0.00811

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$