Bank Monitoring: Evidence from Syndicated Loans*

Matthew T. Gustafson† Ivan T. Ivanov‡ Ralf R. Meisenzahl§

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Abstract

We directly measure banks' monitoring of syndicated loans. Banks typically demand borrower information on at least a monthly basis. About 20% of loans involve active monitoring (i.e., site visits or third-party appraisals). Monitoring increases with the lead bank's incentives and the value of information and is negatively associated with loan spreads and maturity. The monitoring captured by our measures can either complement or substitute for covenant-based monitoring, depending on whether the monitoring informs covenant compliance. Banks increase monitoring following deteriorations in borrower financial condition and credit line drawdowns. Finally, monitoring is positively related to future covenant violations and loan renegotiations.

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†Smeal College of Business, Penn State University, State College, PA 16801, USA; +1-814-867-4042; mtg15@psu.edu.

‡Federal Reserve Board, 20th Street and Constitution Avenue NW, Washington, DC 20551; 202-452-2987; ivan.t.ivanov@frb.gov.

§Federal Reserve Bank of Chicago, 230 S LaSalle St, Chicago, IL 60604; 312-322-4804; ralf.meisenzahl@chi.frb.org.

1 Introduction

To what extent do banks monitor borrowers when they only retain a fraction of the loan? Although banks have a comparative advantage in monitoring (see e.g., Diamond, 1984; Fama, 1985; James, 1987; Focarelli, Pozzolo, and Casolaro, 2008; Addoum and Murfin, 2018), their incentives to monitor are important determinants of the extent to which monitoring occurs. For instance, Keys et al. (2010) find that mortgage securitization adversely affected the screening incentives of subprime lenders leading up to the 2009 financial crisis. One market in which the moral hazard-in-monitoring problem is particularly relevant is the $4.7 trillion global syndicated loan market. Lead arrangers of syndicated loans bear the majority of monitoring costs, such as acquisition and analysis of the borrower's information or site visits to value a loan's underlying collateral. Yet, lead arrangers retain only 20% of the loan on average and so share the benefits to monitoring with their syndicate.

In this paper, we examine the empirical questions of how banks monitor syndicated loans, what factors determine banks' monitoring efforts, and how monitoring relates to other features of the loan contract and loan outcomes. Despite a large theoretical literature relying on a financial intermediary having a unique monitoring technology, there is little empirical evidence on these questions.[1] To fill this void, we use the Shared National Credit (SNC) database to construct two new measures of bank monitoring activity. Our first measure is an indicator for the presence of active monitoring, which includes borrower site visits or the use of third party appraisers. Our second measure captures the frequency with which banks demand loan-specific information, such as borrower financial statements or information on inventories. These measures directly capture two important components of how banks monitor that have not been explored before in the academic literature. These measures capture aspects of both soft and hard information (Liberti and Petersen, forthcoming), with active

[1] Existing studies on this topic present only indirect evidence based on the examination of the determinants of syndicate structure, loan covenants, or banks' risk management systems. See, for example, Lee and Mullineaux (2004) and Sufi (2007) regarding syndicate structure, Sufi (2009) and Wang and Xia (2014) regarding covenants, and Plosser and Santos (2018) on banks' risk management systems.

monitoring likely to produce soft information and monitoring frequency indicating how often hard information is updated. However, these measures do not directly capture other aspects of bank monitoring, such as banks' screening efforts, the intensity with which banks analyze information, or the extent to which banks employ covenant-based monitoring.

We first document a number of new empirical facts about bank monitoring. We show that 20 percent of syndicated loans are monitored actively, meaning that the lender or a third-party visits the borrower on a regular basis. Banks also demand information on borrowers frequently and there is substantial cross-sectional heterogeneity in such demand for information. For approximately 50 percent of syndicated loans, borrowers provide information to the lender at least on a monthly basis, 5 percent provide daily updates, while 29 percent are only required to provide annual updates. Additionally, we show that a significant portion of the variation in bank monitoring could be attributed to lead arranger preferences on how to monitor a given loan. For instance, even after controlling for a variety of loan, borrower, and macroeconomic characteristics, approximately 40% of lenders have a fixed effects estimate that shifts the probability of active monitoring by over 25 percentage points.[2]

To gain insights into the most economically relevant determinants of monitoring, we investigate several theoretically predicted equilibrium relations regarding how banks trade off monitoring with other features of the loan contract. Our first set of tests investigates the theoretical prediction that banks retain a larger stake in loans that require more monitoring in order to credibly commit to monitoring on behalf of the syndicate. In the data, we observe the loan share held by the administrative agent at the end of the year in which monitoring is measured, which we denote as the lead share. Regression estimates indicate an economically and statistically significant positive association between lead share and both monitoring measures. Controlling for credit quality and a rich set of loan characteristics, we estimate that a one standard deviation increase in the lead bank's share is associated with a 2.4 percentage point (or 12 percent) increase in the likelihood of active monitoring and an 8

[2]Notably, this supply side variation in monitoring does not materially affect our findings as our empirical results are qualitatively similar whether or not we include lead bank fixed effects.

percent increase in monitoring frequency. Subsequent tests again indicate a positive relation between our monitoring measures and lead share using variation in lead share triggered by mergers between lenders.

This evidence that banks adjust monitoring with changes in lead share corroborates an important theoretical construct in the bank monitoring literature and supports lead share as a proxy for monitoring (Lee and Mullineaux, 2004; Sufi, 2007). A benefit to our novel empirical measures is that we can examine heterogeneity in their positive correlation with lead share, which in turn can guide the use of lead share as a proxy for bank monitoring in future studies. We find that lead share is more positively associated with both active monitoring and monitoring frequency for private borrowers and long maturity loans, consistent with lead arrangers needing to credibly commit to monitoring via larger lead shares when the information environment is more opaque or the investment horizon is longer-term. We also find that the relation between lead share and active monitoring becomes significantly more positive as borrowers become riskier. These findings suggest that lead share is a better proxy for the dimensions of bank monitoring captured by our empirical measures when information is scarce or the investment is risky.

Another benefit to not relying on lead share as a proxy for monitoring is that we can examine the conditional correlation between monitoring and its theoretical determinants, after controlling for the stake of the lead arranger. Although we stop short of establishing causal relations, our findings are consistent with the theoretical prediction that monitoring will trade off with other borrower and loan characteristics such that monitoring is more frequent when it produces valuable information. We find that monitoring is more frequent for private borrowers, for which the lack of public disclosures makes the information obtained from monitoring more valuable. We also find that short maturity loans are monitored more frequently. This is consistent with Rajan and Winton (1995) who argue that banks specialize in relatively small, lesser known, firms for which shortening loan maturity will increase monitoring incentives, since shorter maturities give banks more flexibility to use any information

garnered via monitoring in subsequent negotiations.[3]

We next examine whether borrowers trade monitoring requirements off with the loan's price or quantity. Consistent with borrowers' capital demands being primarily determined by factors outside the banking relationship, the conditional association between monitoring and loan amount is statistically insignificant (with t-statistics ranging from 0.4 to 1.9). We do, however, find a robust and significant negative relation between loan spreads and active monitoring within the approximately two-thirds of our sample with available loan spread data. This is consistent with borrowers trading off reductions in monitoring for higher loan spreads. However, this conclusion appears particular to active monitoring as we find no such relation between loan spreads and monitoring frequency.

We also examine whether our active monitoring and monitoring frequency measures are complements or substitutes with covenant-based monitoring. Ex-ante it is possible that covenants are sufficient for all monitoring and the types of monitoring we measure are simply a form of enforcing covenant-based monitoring. In this scenario, we would expect a positive relation between our monitoring measures and the use of financial covenants. We find such a relation when examining balance sheet and loan-to-value covenants and active monitoring, suggesting that active monitoring complements covenant-based monitoring when it can inform covenant compliance.[4] This is consistent with the models of Rajan and Winton (1995) and Park (2000) that show the information garnered via monitoring becomes more valuable when it can be used to trigger covenants. However, we also find evidence that covenant-based monitoring substitutes for monitoring when monitoring is less likely to inform the lender of covenant compliance. For instance, we find a negative relation between cash flow-based covenants and both of our monitoring measures. This result supports the predictions of large literatures arguing that covenant-based monitoring can reduce the need for other forms of monitoring either because covenant-based monitoring is already in place

[3]Barclay and Smith (1995) and Park (2000) also provide arguments as to why monitoring incentives are decreasing in loan maturity.

[4]The violation of loan-to-value and balance sheet covenants can be affected by information obtained via active monitoring. In contrast, the violation of cash flow or capital expenditure covenants cannot.

to allocate control rights to the lender when borrower financial condition deteriorates (see e.g., Smith and Warner, 1979; Smith, 1993; Garleanu and Zwiebel, 2009; Roberts and Sufi, 2009) or because covenants discipline firm activity such that additional monitoring is less necessary (see e.g., Chava and Roberts, 2008; Nini, Smith, and Sufi, 2009). More generally, these findings indicate complex trade-offs between different types of monitoring that are important for testing monitoring theories, but have been largely ignored by existing empirical research in part due to a lack of data on bank monitoring activity.

Having established that bank monitoring is strongly related to lender incentives and the value of information in the cross-section, we next examine whether banks adjust their monitoring activity following changes in a borrower's financial condition or large credit line drawdowns. Regressing our monitoring measures on indicators for lender rating upgrades and downgrades during the previous year, we find that banks demand more (less) frequent information on borrowers following ratings downgrades (upgrades). We find no relation between ratings changes and active monitoring, but do find that the probability of active monitoring increases when borrowers draw heavily on their credit lines. These findings further support the idea that banks monitor more as information on the borrower becomes more valuable.

Finally, we investigate the relation between monitoring activity and subsequent covenant violations or loan renegotiations. We find that (conditional on the use of at least one covenant) active monitoring is positively associated with future covenant violations, as well as future renegotiations. For instance, actively monitored loans are 12 percentage points (or 27%) more likely to have a covenant violation in the following year. This finding is consistent with banks validating the value of collateral when anticipating future loan renegotiations.

We contribute to the literature by studying two distinct and important dimensions of bank monitoring—active monitoring and the frequency with which banks demand information from the borrower. Although data limitations continue to preclude exploration of many interesting dimensions of bank monitoring, such as the intensity of each monitoring engagement, to our knowledge we are the first study to provide direct empirical evidence on

the extent to (and method by) which US banks conduct non-covenant-based monitoring of syndicated loans. One limitation to our setting is that our monitoring measures are only available for a selected sample of bank loans, which over represents risky loans. Thus, our evidence should be interpreted as a reasonable characterization of monitoring activity and its determinants within a sample of loans deemed to be large and complex.

Our study is related to recent work that investigates the relation between collateral value and monitoring (see, Cerqueiro, Ongena, and Roszbach, 2016; Ono and Uesugi, 2009; Manove, Padilla, and Pagano, 2001). Other studies have examined covenants as a form of monitoring (see e.g., Sufi, 2009; Wang and Xia, 2014), while Plosser and Santos (2018) uses banks' internally-generated quarterly probability of default estimates to assess bank risk models and incentives. We investigate a wide range of determinants of bank monitoring using less coarse measures of bank monitoring. We document that banks often demand information considerably more often than on a quarterly basis and often actively monitor borrower assets to collect information themselves. We also show that lenders dynamically adjust their monitoring over the life of the loan and provide evidence on how our new measures of monitoring trade off with other features of the loan contract, such as loan maturity, loan spreads, and covenant-based monitoring. Taken together, our findings are consistent with monitoring playing an economically meaningful role in today's syndicated lending market, although our evidence that the monitoring of syndicated loans is decreasing in the lead's loan share suggests that this may cease to be the case if the trend toward more aggressive syndication practices continues.

2 Measuring Bank Monitoring

2.1 Background and Motivation

Since the seminal work of Diamond (1984) and Fama (1985), an extensive theoretical literature has investigated the unique features of banks that give them a comparative ad-

vantage in information production and make them a natural choice to monitor borrowers on behalf of depositors and other investors. Despite the large theoretical literature that assumes there exists a financial intermediary with a unique monitoring technology (see e.g., Diamond, 1991), empirical studies have yet to capture much of the texture in banks' decision to monitor. Rather, empirical studies have proxied for monitoring with stock returns (see e.g., James, 1987; Focarelli, Pozzolo, and Casolaro, 2008; Addoum and Murfin, 2018), debt yields (see e.g., Datta, Iskandar-Datta, and Patel, 1999), financial covenants (see e.g., Wang and Xia, 2014), syndicate structure (see e.g., Lee and Mullineaux, 2004; Sufi, 2007), or the lenders' risk management systems (see e.g., Plosser and Santos, 2018).

These coarse measures used in the academic literature gloss over many specifics of the bank monitoring process. Monitoring costs vary by the type of monitoring, but often involve direct costs related to collateral appraisals, field examinations, or collateral protection.[5] Often monitoring also entails lenders requesting and analyzing information on the borrower. This information acquisition and analysis can range from annual updates of financial statements to daily updates of accounts receivables; sometimes lenders will even demand initial possession of all receivables so that they can monitor the loan on a daily basis. In addition to the time spent on these tasks, bank employees also monitor borrowers/loans throughout the life of the loan in several other ways. Conversations with industry experts indicate that the typical syndicated loan begins with a junior investment banker working with the loan officer and other experts to determine collateral value and the structure of the initial contract. As the loan progresses, bank employees and third-party auditors often spend several days per quarter assessing the loan and the borrower. Finally, bankers also typically meet with the borrower's management one to three times per quarter.

Despite the limited empirical evidence on bank monitoring, understanding the extent and type of bank monitoring remains an important empirical question with implications for both economic policy and financial intermediation theory. The recent rise of the syndicated loan

[5]See for example Section 9.03 in ABL's 2007 credit agreement. Another example of this language is on page 88 of the following contract.

market, which now totals approximately $4.7 trillion worldwide, reinforces the importance of this issue. Ex-ante, it is unclear how or if banks monitor syndicated loans (see e.g., Berlin, Nini, and Yu, 2018). As with bilateral bank loans, lead arrangers of syndicated loans bear the majority of monitoring costs. However, syndicated loan lead arrangers typically retain only 20% of the loan and hence benefit less from monitoring.[6] The purpose of this paper is to provide new evidence on how banks monitor syndicated loans, what determines the extent of bank monitoring, and how monitoring efforts relate to other features of the loan contract and loan outcomes.

2.2 Sample Description

The primary reason for the dearth of empirical evidence on questions relating to bank monitoring is the lack of available data. In this paper, we employ a new dataset to examine several dimensions of bank monitoring that are new to the academic literature.

Our sample comes from the Shared National Credit (SNC) database. The SNC is a credit register of syndicated loans maintained by the Board of Governors of the Federal Reserve System, the Federal Deposit Insurance Corporation (FDIC), the Office of the Comptroller of the Currency, and, prior to 2011, the now-defunct Office of Thrift Supervision. The administrative agent banks are required to provide confidential information for all syndicated loan commitments larger than $20 million that are either shared by three or more unaffiliated federally supervised institutions or sold to two or more such institutions.[7] All new and outstanding loans meeting these criteria are surveyed on December 31 each year.

Bank examiners from the three Federal agencies collect more information on a subset of these loans "to review and assess risk in the largest and most complex credits shared

[6]See also Parlour and Plantin (2008). Irani and Meisenzahl (2017) provide for evidence on an active secondary market for syndicated loans. The Global Syndicated Loans Review (http://dmi.thomsonreuters.com) provides for statistics on the size of the syndicated lending market. Irani et al. (2018) show that about 75 percent of syndicated term loan shares are held by non-banks.

[7]This includes loan packages containing two or more facilities issued by a borrower on the same date where the sum exceeds $20 million.

by multiple financial institutions."[8] Typically these exams are based on information as of December 31^{st} of the previous calendar year, although occasionally banks provide information as of March 31^{st} of the current year. During our sample period, which runs from 2007 through 2015, the fraction of the SNC portfolio that was sampled in annual exams ranges from 27% (in 2013) to 41% (in 2009), with the sample being tilted toward non-investment grade credits.[9] We refer to the loans that are sampled as the exam sample.

2.3 Active Monitoring Measure

Within the exam sample we observe a textual discussion that allows us to discern whether a loan is actively monitored. The example below is an excerpt from the monitoring requirements description of one of the typical loans in our sample:

> *""This senior credit facility is secured by A/R, inventory and RE. The bank receives and uses a quarterly borrowing base certificate, generated by the company, to monitor collateral values. The bank performs periodic field examinations conducted by independent contractors. The most recent onsite inspection was conducted in March 2006 by [Auditing Company]. It covered accounts receivable audit, inventory testing at several of the company's manufacturing facilities, accounts payable and cash verifications, and borrowing base calculation validation."*

This excerpt provides an example of what we refer to as active monitoring. The bank hires an auditing company to conduct field inspections to certify the company's reports that are submitted quarterly.

Our first measure of monitoring activity, *Active Monitoring*, is an indicator variable for whether or not a lead bank actively monitors a loan. Specifically, we define active monitoring as field exams of the borrowers that are initiated or conducted by the lender (see Appendix A for formal definitions of all variables). We include field exams or audits conducted by the lead bank as well as third-party appraisals conducted by external firms hired by the lender.

[8] Please see the Shared National Credit Joint Press Release dated November 7^{th}, 2014: http://www.federalreserve.gov/newsevents/press/bcreg/20141107a.htm.

[9] http://www.federalreserve.gov/bankinforeg/snc.htm

The third-party appraisers would most frequently be valuation consulting firms that conduct a thorough exam to estimate collateral values or appraise operations.

Banks actively monitor approximately 20% of loans in the sample. Figure I, panel (a) shows the share of loans that is actively monitored partitioned by the type of collateral. Loans with real estate and fixed asset collateral are actively monitored in 80% and 30% of cases, respectively. This is considerably more often than loans collateralized by other types of collateral. A likely explanation for this is that active monitoring is more useful when the collateral involves assets that need to be directly appraised.

Figure I, panel (b) shows that there is also substantial cross-lender variation in the propensity to actively monitor loans. About 17% of lead arrangers rarely actively monitor, while approximately 15% actively monitor almost all loans in their portfolio. Given the descriptive nature of the figure we cannot say the extent to which this cross-lender variation is due to the types of loans a lead arranger originates or differential preferences regarding how to monitor a given loan. We present our main empirical analyses with and without lead arranger fixed effects to transparently present evidence on the extent to which our findings are due to cross- and within-lender variation in the decision to monitor. We reexamine this idea in the context of our regression framework in Section 4.

2.4 Monitoring Frequency Measure

During the exam, examiners can provide additional information about monitoring activity in text fields. This information details the frequency with which banks demand information from the borrower. The following excerpt illustrates that monitoring activities can occur at different frequencies.

> *"The Revolving credit facility amounts to $250 million... The facility provides for 85% advance of eligible Domestic A/R's, 50% for eligible Foreign A/R's and Inventory advances are confined to [operating sub] and are calculated at the lower of 65% or 85% of NOLV of eligible inventory. [Bank] maintains dominion over cash receipts. [Bank] receives a monthly Borrowing Base Certificate and inventory is*

appraised quarterly on site subject to borrower maintaining excess availability of $50 million."

We construct our second monitoring measure from text such as the above excerpt. Specifically, we define *Monitoring Frequency* as the maximum number of times a given loan is monitored within a year. Daily (365 times) is the highest frequency and annually (1 time) is the lowest frequency.

Unlike our active monitoring measure, which is available for the entire SNC exam database, *Monitoring Frequency* is only available for a subset of loans within the SNC exam database. The reason for this is that although examiners always collect information on covenants, collateral, and monitoring, they do not always provide the frequency with which a loan is monitored. We are able to compute *Monitoring Frequency* for 2,210 loan-years (or 12.3% of the exam sample). We refer to this subsample as the monitoring frequency sample. To ensure that selection into this smaller sample does not compromise the generalizability of our findings, we show that our results are similar using a Heckman selection correction in which we instrument for non-missing monitoring frequency with examiner fixed effects. See Appendix B for a discussion of these analyses.

Figure II, panel (a) shows the distribution of *Monitoring Frequency* across all loans. There is large variation in *Monitoring Frequency*. For instance, while approximately 29% of loans are monitored only on an annual basis, 35% are monitored monthly, and 14% are monitored at least on a weekly basis. In addition, over half of loans are monitored more frequently than once per quarter, which suggests that even though financial statements are a useful source of information for lenders, lenders typically require more frequently updated information. Panel (b) of the figure further shows that, as with our active monitoring measure, there is considerable variation in monitoring frequency across banks. In the case of monitoring frequency, the cross-bank distribution is right skewed with a few banks demanding information at a well above average frequency.

We find that 105 loans in our sample that are monitored at least at a daily frequency. For

approximately half of these loans some other aspects of the collateral or the borrower are also monitored at other frequencies, with the most common other frequencies being monthly and annually. Moreover, 212 loans have a weekly maximum monitoring frequency. More than one half of these loans are also evaluated at the monthly frequency with respect to different aspects of the collateral/the borrower. This evidence aligns with the above excerpt in suggesting that a large fraction of loans are monitored at frequencies other than the maximum frequency.[10]

2.5 Sample Comparisons

Table I provides descriptive statistics on the full SNC sample relative to the exam sample and to the monitoring frequency sample. We start by comparing the full sample (columns 1 and 2) to the exam sample (columns 3 and 4). Lead arrangers retain approximately 23% of loans in the full sample and 19% of loans over the exam sample. The average (median) loan amount in the full sample is $328 ($127) million compared to $320 ($125) million in the exam sample. Similarly, the average (median) loan maturity is 2,055 (1,826) days in the full sample compared to 1,988 (1,827) days in the exam sample. Consistent with stated goal of SNC to examine non-investment grade loans more frequently, terms loans and heavily drawn credit lines, which are riskier on average, are more common in the exam sample. In general the loan characteristics in our sample are qualitatively similar to those in the DealScan syndicated loan origination database. For example, the average (median) loan amount and maturity in the DealScan database during our sample period are $280 ($86) and 1,768 (1,826) days, respectively, and Sufi (2007) reports average (median) lead shares of 28.5% (23.5%)

The differences between the full and exam samples, shown in column 7, are generally economically small, but statistically significant. The economically significant differences that do exist reflect the tendency for riskier loans to be examined. Although this overweighting of risky loans mitigates our ability to speak to the broader population of syndicated loans,

[10]For details, see Internet Appendix Table IA.I showing all monitoring frequencies in our sample conditional on the maximum monitoring frequencies being daily, weekly, etc. (in the rows).

it offers an opportunity to examine monitoring and its determinants in a sample of loans in which one would expect monitoring to be economically meaningful.

When we compare the exam sample with the 12.3% subsample for which we compute monitoring frequency, shown in columns 5 and 6, we again observe differences in the loan characteristics. For instance, the exam sample has a lower lead share (19%) than the monitoring frequency sample (24%) and more term loans.[11]

One benefit to the SNC database is that it provides detailed information on collateral and loan covenants for the examined loans. Within the SNC exam sample, approximately 93% of loans are secured. Approximately 60% are secured only by fixed asset collateral, such as property, plant, and equipment. Another 13% of loans are secured only by more liquid collateral, such as accounts receivable or inventories. The remaining secured loans are secured by both fixed and liquid assets. We also present descriptive statistics on the number of covenant types in each loan. We classify covenants into the following nine broad categories: capital expenditures, cash flow leverage, net worth, debt-to-assets, cash, current ratio, interest coverage, debt-to-capitalization, and distributions. The average (median) loan contains 1.74 (2) types of covenants. See Appendix A for formal definitions of all variables used throughout the analysis.

3 Empirical Predictions and Descriptive Evidence

As we discuss in Section 2.1, there are costs and benefits to monitoring that banks trade off when determining their monitoring effort. Many theories highlight the importance of this trade-off for the capital raising process. For instance, Holmstrom (1979) and Holmstrom and Tirole (1997) both introduce a moral hazard framework whereby informed investors must conduct due diligence and monitoring before uninformed investors are willing to invest. In this section, we discuss several predictions from the theoretical literature regarding the

[11] We address potential sample selection concerns relating to the monitoring frequency sample in Appendix B.

monitoring of syndicated bank loans. We provide descriptive evidence for these predictions.

3.1 Lead Bank Incentives

As pointed out by Dennis and Mullineaux (2000), syndicated loans are an intermediate step between the bilateral bank lending and public debt markets. Similar to the bilateral bank lending market, the lead arranger is responsible for most of the monitoring effort. Unlike the bilateral bank lending market, the lead arranger only retains a fraction of the loan. Because the lead arranger bears all costs and captures only some of the benefits to monitoring, syndication creates a moral hazard problem between the lead bank and other syndicate members, which could result in sub-optimal monitoring.[12]

An intuitive prediction is that the lead arranger can mitigate this moral hazard problem by retaining a sufficiently large stake in the loan. Park (2000) shows that a bank's monitoring incentives are largest when they are the sole senior claimant. Based on arguments such as this, the empirical literature has assumed that the lead's stake in the loan is a plausible empirical proxy for monitoring (see e.g., Sufi, 2007). Using the SNC data, we can measure both monitoring and the lead share, which allows us to test the extent to which this established proxy for monitoring correlates with our empirical measures of bank monitoring. Specifically, we define lead share as the loan share held by the administrative agent at the end of the year in which monitoring is measured. Thus, our measure accounts for the possibility that lead banks may have already sold part of their share after origination.[13]

We predict that there will be a positive relation between the lead bank's loan share and monitoring. We descriptively investigate this prediction using our two measures of monitoring—active monitoring and monitoring frequency. Table II shows that loans that are actively monitored exhibit a significantly larger mean and median lead share. The mean

[12]All financing costs are ultimately born by the borrower so monitoring effort of the lead arranger is compensated for by the borrower in terms of loan fees. This does not change the nature of the moral hazard problem between the lead bank and the syndicate members.

[13]This measures also mitigates the problem discussed in Ivashina and Scharfstein (2010) and Bruche, Malherbe, and Meisenzahl (2017) whereby the lead share at the time of loan origination can reflect demand factors.

lead share for actively monitored loans is 28 percent (median: 27 percent) while the mean lead share for not actively monitored loans is 17 percent (median 13 percent).

To investigate the descriptive relation between monitoring frequency and lead share, Figure III, Panel (a) plots the cumulative density functions (CDF) of monitoring frequency partitioned by whether or not the lead share is above the median. Each point on the CDF can be interpreted as the percentage of loans that are monitored at least as frequently as the interval reported on the x-axis. The marked line shows the density of monitoring frequency for loans in which the lead arranger share exceeds the median lead share of 22.2%. The unmarked line reports a similar CDF for loans in which the lead bank retains less than a median stake. At each point the CDF of the above-median lead share subsample is above the CDF of the below-median lead share subsample. Approximately 60% of lead arrangers retaining an above-median stake monitor the loan at least on a monthly basis, compared to only 40% of lead arrangers retaining a below-median stake. There are similar differences at the weekly, quarterly, and semi-annual frequencies. For example, lenders retaining above median stakes are almost twice as likely to monitor on at least a weekly basis.

An alternative mechanism that could mitigate the moral hazard problem between the lead and other syndicate members is the lead bank's reputation. Paravisini and Lin (2013) provide empirical evidence on the value of lender reputation by showing that a bank's lending business suffers after one of their borrowers commits fraud. Chemmanur and Fulghieri (1994) and Pichler and Wilhelm (2001) formalize this argument in the investment banking industry, where reputation plays a similar role. It then follows that because syndicated lending is a repeated game, lenders may monitor, in part, to protect their reputation. Using the bank's market share as a measure of reputation (as in Lee and Mullineaux, 2004; Sufi, 2007), Table II provides descriptive evidence that more reputable lead managers conduct less active monitoring. However, Figure III, panel (b) provides little support for this idea using our monitoring frequency measure. Thus, there is mixed descriptive evidence on the extent to which banks trade off their reputation with monitoring commitments. We cannot

rule out the possibility that a more powerful measure of bank reputation or a sample that includes smaller banks, leading to more variation in bank market share, would provide more evidence of a link between bank reputation and their monitoring activity. However, given these findings, it is unlikely that bank reputation is a first-order driving of bank monitoring in our sample.

3.2 Value of information production

Monitoring should be increasing in the expected value of information that monitoring will produce. Our primary proxy for the amount of information that monitoring is likely to produce is whether the borrower is publicly traded or not. The motivation behind this prediction builds off the idea in Sufi (2007) that, unlike public firms, private firms are not required to disclose their financial statements, making them more informationally opaque to outside investors.

In Table II, a univariate comparison of loans that are actively monitored to loans that are not actively monitored shows that public firms make up a smaller percentage of the actively monitored sample (18%) than of the not actively monitored sample (43%). Figure IV provides additional descriptive evidence using our monitoring frequency measure. Public and private borrowers are similarly likely to be monitored on at least a daily, weekly, or bi-weekly basis. However, private borrowers are over 30% (20%) more likely to be monitored on at least a monthly (quarterly) basis compared to annual monitoring. Thus, both monitoring measures indicate that lenders conduct more monitoring for private borrowers compared to their publicly traded counterparts.

3.3 Trade off with other loan provisions

We next consider the extent to which borrowers trade monitoring off with other loan provisions. We begin with the possibility that borrowers trade off monitoring requirements with the loan's quantity or price. It is reasonable to expect such a trade off if borrowers

view monitoring as an economically meaningful cost to taking out a loan. Alternatively, if borrowers view monitoring as low-cost or even beneficial (if for example it enhances the certification benefits of borrowing) then there may be no relation between monitoring and loan amount or loan spreads. Moreover, to the extent that borrowers demand for capital is primarily determined by investment opportunities loan amounts may be insensitive to monitoring requirements.

Table II provides little descriptive support for a trade off between monitoring and loan amount. In fact, loans that are not actively monitored are almost twice as large as loans that are actively monitored. Within the sample of loans with available information on loan spreads we do find some descriptive support for the idea that firms trade off monitoring and loan spreads, although the estimates are statistically insignificant. Loans that are actively monitored pay about 22 bps less in spreads than loans that are not.[14]

We next examine how monitoring trades off with loan maturity. Loan maturity is a likely proxy for the value of information, however the direction of the relation is theoretically ambiguous. Rajan and Winton (1995), Barclay and Smith (1995), and Park (2000) argue that loans with a short maturity maximize the value the bank receives from any information gathered from monitoring efforts. The reason for this is that short maturities provide the bank more frequent opportunities to use their information to strengthen their bargaining position in loan renegotiations. Rajan and Winton (1995) note that it does not necessarily follow that there will be a negative relation between monitoring and loan maturity because shorter maturities may not maximize the difference between the value of public information and the information obtained via monitoring. Despite this complexity, however, Rajan and Winton (1995) still conclude that there is likely to be a negative relation between maturity and monitoring within the sample of bank loans because the bank lending market specializes in small, lesser known, borrowers. A notable complicating factor in the relation between maturity and monitoring, however, is that banks may be less likely to monitor shortly after

[14]However, these is little evidence of a significant tradeoff between our monitoring frequency measure and either loan amount or loan spreads, see Internet Appendix Figures IA.I and IA.II.

the loan is renegotiated because not much new information is likely to exist. Thus, loans with short maturities may actually represent cases in which monitoring is not valuable and therefore they may be monitored less frequently.

Here, we descriptively examine which of these forces dominates on average. Table II shows that loans with shorter original maturity are more likely to be monitored actively. The average maturity of actively monitored loans is 1700 days whereas the average maturity of the not actively monitored loans is 2100 days. Figure V provides additional evidence for this negative relation between monitoring and loan maturity using our monitoring frequency measure as every point on the monitoring frequency CDF of the below-median remaining maturity subsample, the marked line, is above the corresponding point for the above-median maturity subsample (the unmarked line).

3.4 Covenant-based monitoring

Rajan and Winton (1995) and Park (2000) extend their argument that the information garnered from monitoring is more valuable for short maturity loans to the covenant structure of the loan. Specifically, they argue that covenant-based monitoring increases the bank's incentive to gather information via other forms of monitoring because covenants allow the bank to force renegotiation more often. This argument would predict that covenant-based monitoring is complementary to other forms of monitoring, including the aspects of monitoring captured by our active monitoring and monitoring frequency measures.[15] There is, however, a competing view. Because covenant violations allocate control rights to the lender when a borrower's financial condition deteriorates (see, e.g., (Smith and Warner, 1979); (Smith, 1993); (Garleanu and Zwiebel, 2009); (Roberts and Sufi, 2009)), covenant-based monitoring may instead substitute for other forms of monitoring – a lender can either wait to monitor until an adverse shock triggers a covenant violation or continuously monitor the loan. In

[15]Murfin (2012) argues that covenant tightness at origination varies with lenders' financial conditions, pointing to complementarities. Griffin, Nini, and Smith (2018) argue that over the last 20 years covenants have become less strict, reflecting fundamental changes in the cost and benefits of covenants.

addition, the evidence in Chava and Roberts (2008) and Nini, Smith, and Sufi (2009) suggest that covenants mitigate borrower moral hazard problems by influencing the firm's operations outside of default. This enhanced efficiency of covenant monitored firms may require less monitoring, leading to a substitution between covenant-based monitoring and other forms of monitoring.

We descriptively investigate this empirical question. Table II shows that loans that are actively monitored tend have less covenants types (average: 1.4) than loans that are not actively monitored (average: 1.8). Similarly, Figure VI shows that banks demand more information from loans with a below-median number of covenant types (the marked line) compared to loans with an above-median number of covenant types (the unmarked line).

Additionally, we show that the incidence of active monitoring decreases almost monotonically with the number of covenants in the contract. Figure VII indicates that the lead lender monitors actively over 36% of the loans without financial covenants. In contrast, the incidence of active monitoring decrease to 21%, 14%, 14%, and 22% for loans with 1, 2, 3, and 4 covenant types, respectively. Panel B of this figure shows a similar association for monitoring frequency.[16]

This descriptive evidence points to monitoring and covenants being substitutes, on average. However, the relation between covenant-based monitoring and other forms of monitoring is complex, and may depend on the type of covenant or form of monitoring under examination. Moreover, Figure VIII suggests that covenant use may be sensitive to supply side factors as over 20% of banks use over two covenants per loan on average, while over 25% use less than one-half a covenant per loan. In our regression analysis we examine how important these supply side factors are in a regression framework that includes lead bank fixed effects in some specifications. Section 4.4 contains a more detailed investigation of the relation between covenant-based monitoring and our monitoring measures.

[16]Figure VII also shows supervisory rating by number of covenants to illustrate that part of the relation between covenants and monitoring is driven by risk. For example, supervisory ratings tend to be better for loans with more covenants, while the monitoring measures tend to decline with more covenants.

4 Regression Analysis

To more formally examine the determinants of monitoring, we employ a series of regression specifications with either an indicator for the presence of active monitoring or the natural log of the annual monitoring frequency as the dependent variable.[17] Due to the large number of fixed effects, we estimate a linear probability model specification for active monitoring and linear specification for monitoring frequency. Logisitic regressions excluding the fixed effects yield comparable results for active monitoring, our dichotomous outcome. Specifically, we estimate:

$$Monitoring\ Measure_{ijt} = c_t + \alpha_1 Lead\ Share_{ijt} + \alpha_2 Public\ Borrower_{jt} + \alpha_3 Log(Maturity)_{ijt} + \alpha_4 Number\ of\ Covenants_{ijt} + \beta X_{ijt} + \epsilon_{ijt} \quad (1)$$

We present several specifications, which include various sets of control variables. In addition to controlling for the loan amount, the loan type, and whether the loan is secured and with what type of collateral, we include a variety of fixed effects to control for other potentially unobservable factors. To control for inter-temporal variation in monitoring incentives we include year fixed effects for the year associated with each observation as well as year-quarter fixed effects for the loan origination date.

We also include industry and lead bank fixed effects in some specifications. This mitigates the possibility that our findings are attributable to differences in monitoring practices that are common to certain industries or banks. For example, in Figure IX we show that a significant portion of the variation in active bank monitoring could be attributed to lead arranger preferences, even after controlling for loan and borrower characteristics. Approximately 40% of lenders have a fixed effects estimate that shifts the probability of active monitoring by

[17] We take the natural log of monitoring frequency because doing so generates economically interesting variation in monitoring frequency when used in an OLS framework. With this transformation, our dependent variable ranges from 0 for annual monitoring to 5.9 for daily monitoring and the increase going from annual to quarterly monitoring is similar to the jump from monthly to weekly monitoring.

over 25 percentage points. Comparing our regression analyses with lead bank fixed effects to those without the lead bank fixed effects will identify the extent to which these supply side factors influence our estimates. We cluster standard errors at the bank-year level when active monitoring is the dependent variable. We do not cluster the standard errors when monitoring frequency is the dependent variable due to the considerable smaller sample size.[18]

In some specifications we also use loan rating fixed effects to control for loan quality. The data provide lead lender internal ratings and examiner ratings both of which can be converted to the same five-grade scale. However, as explained in Carey and Hrycay (2001), judgmental mappings from banks' internal ratings scales to external scales common for all banks could result in loss of information or biases as internal scales could be subjective and incompatible with external scales (see also Treacy and Carey, 2000). To avoid concerns about concordance mapping, we control for loan quality using lead bank internal rating dummies based on the internal rating scales of the 24 largest lead arrangers by total dollar amount of outstanding loans.[19]

4.1 Lead bank incentives

We begin by investigating the relation between monitoring activity and the share of the loan that the lead arrangers retains. As we discuss in Section 3.1, we expect a positive relation, leading α_1 in Equation 1 to be positive.

Columns 1 through 3 of Table III regress an indicator for active monitoring on lead share and a variety of control variables. Consistent with the descriptive evidence in Section 3, we find a positive relation between lead share and the probability of active monitoring. The point estimates, which range from 0.15 to 0.31 suggest that a one standard deviation (i.e., a 0.18 point) increase in lead share is associated with a 2.7 to 5.6 percentage point (or 14 to

[18] All variables are defined in Appendix A.

[19] Given that internal-risk metrics of banks are also used for regulatory monitoring, banks might have incentives to manipulate and potentially not update these metrics (see, Treacy and Carey, 2000; Carey and Hrycay, 2001). For example, Plosser and Santos (2014) find that internal risk estimates of low-capital banks may not only be biased downward but also not incorporate as much information as those of high capital banks.

28 percent) increase in the probability of active monitoring. The largest of these estimates is in Column 1, before the inclusion of lead bank fixed effects. Thus, a portion, but not all, of the relation between lead share and monitoring may be due to a supply side effect whereby some banks tend to both monitor more and retain a larger stake in loans. However, columns 2 and 3 demonstrate a statistically and economically significant relation between lead share and monitoring even after controlling for this possibility.

In columns 4 through 6 we conduct a similar set of analyses using *Monitoring Frequency* as the dependent variable. Again, we find a significantly positive relation between monitoring and the percentage of the loan retained by the lead arranger. In terms of economic significance, multiplying the lead share coefficient, which is approximately 0.45 when controlling for banks' own ratings in column (6), by the standard deviation of lead share of 0.18, suggests that a one standard deviation increase in lead share is associated with a 0.08 increase in monitoring frequency, corresponding to an approximately 8% increase. In unreported tests we find no evidence that a banks reputation (proxied for with several measures of lending market share) predicts monitoring, however we cannot rule out the possibility that this null result is do to our imperfect empirical proxies for a lender's reputational incentives or our sample that may lack substantial variation in reputation due to a concentration of large lenders.

We next examine heterogeneity in the relation between lead share and our measures of bank monitoring. The motivation for this analysis is that understanding the cases in which bank monitoring is more or less positively correlated with lead share can help guide the use of lead share as a proxy for bank monitoring in future studies. To examine cross-sectional variation in the relation between monitoring and lead share, we add interactions between lead share and other variables of interest to the analysis in Columns 1 and 4 of Table III. We present the estimates for these interactions in Table IV. Columns 1 and 5 indicate that the relation between lead share and both of our monitoring measures is more positive for private borrowers. The interactions have t-statistics of 1.70 and 1.63 for the active monitoring and

monitoring frequency measures, respectively. This is consistent with lead share being a more credible means of committing to monitor when information is limited (as is the case with private firms with no public filings).

Columns 2 and 6 indicate that the relation between both monitoring measures and lead shares is more positive for loans with longer maturity. This could be because lead share is a better proxy around the time of loan origination or because lead share is a better proxy for monitoring when considering riskier investments. Columns 4 and 8 provide more direct evidence that the relation between monitoring and lead share strengthens as borrower risk increases (although this increase is statistically insignificant in Column 8 using our Monitoring frequency measure). We find no evidence that the relation between lead share and monitoring depends on loan amount. Primarily in unreported analyses, we also examine how the relation between lead share and our monitoring measures varies over time during our sample period. Although the coefficient on lead share in the Active monitoring regression is largest during the 2009 financial crisis, we find no statistically significant year-by-year variation in the relation between monitoring and lead share. However, this lack of intertemporal variation should be interpreted with caution due to our relatively short time series.[20]

In sum, we provide suggestive evidence that lead share is a better proxy for the dimensions of bank monitoring captured by our empirical measures when information is scarce or the investment is risky. More generally, the positive association between the stake of the lead arranger and monitoring activity confirms the approach of prior empirical research that uses the lead share to understand monitoring incentives (see e.g., Lee and Mullineaux, 2004; Sufi, 2007). It also corroborates an important theoretical construct in the bank monitoring literature (see Park, 2000). Importantly, because we do not use the lead's share to proxy for monitoring we are able to extend the literature by identifying additional determinants of monitoring frequency after controlling for the stake of the lead arranger.

[20]For details, see Internet Appendix Figure IA.III.

4.2 Value of information production

We now turn to the relation between monitoring and the expected value of the information that monitoring will produce. Monitoring should be increasing in the value of information. As discussed in Section 3.2, our primary proxy for the value of information is whether or not the borrower is a private firm.

We predict that monitoring will be higher when the borrower is not publicly traded as information production is more valuable for privately held firms. Hence, we expect α_2, the coefficient on the public firm dummy, to be negative. Columns 1 through 3 of Table III support our prediction using our *Active Monitoring* measure. The point estimates, which range from -0.037 to -0.055, are all significant at the 1% level and suggest that the probability of actively monitoring a private borrower is 3.7 to 5.5 percentage points (or approximately 20% to 30%) higher than the probability of monitoring a publicly traded borrower.

In columns 4 through 6 we conduct similar analyses using our *Monitoring Frequency* measure. We find a similar relation, however the coefficient becomes statistically insignificant and smaller in magnitude once lead bank fixed effects are added as controls. In sum, we find strong evidence that banks are more likely to actively monitor private borrowers, but mixed evidence that they demand more frequent information from private borrowers.

Taken together, our findings corroborate the descriptive evidence in Section 3 and support our empirical prediction that banks will monitor more when the expected information benefits to monitoring are the largest.

4.3 Trade off with other loan provisions

A corollary of the results in Section 4.2 is that lenders have incentives to demand monitoring when such activity is likely to produce actionable information. In turn, borrowers may pre-commit to being monitored if this allows them to save on borrowing costs. We next examine these tradeoffs by estimating the equilibrium relation between monitoring activity and a loan's price or quantity.

The coefficient on Log(Committed) in Table III generally supports this idea, but is statistically insignificant with t-statistics ranging from 0.4 to 1.9 across the six columns. One reason for this could be that the amount firms borrow is predominantly determined by their capital demands and not something they are likely to actively trade off with the extent of monitoring.

Our main regressions do not include interest rate spreads as an explanatory variable because doing so reduces our sample by approximately 40%. To examine how firms trade off monitoring and loan price we re-run our main set of tests on the sample with available loan spread data. Table V presents these results. In columns (1) through (3), we show that after controlling for other loan and borrower characteristics there is a negative association between loan spreads and active monitoring. We do not find evidence that loan spreads are significantly related to the frequency with which lenders demand information.[21]

Taken together, there is some evidence that borrowers trade off monitoring with the price or quantity of their bank debt. This tradeoff appears to be strongest when considering loan price and active monitoring — some borrowers accept increased monitoring in exchange for reduce spreads.

We next examine how monitoring trades off with loan maturity, which is an alternate proxy for the value of information. Indeed, the descriptive evidence in Section 3.3 is consistent with Rajan and Winton (1995)'s theoretical argument that there will be a negative relation between loan maturity and bank loan monitoring because short maturities provide the bank more frequent opportunities to use any information garnered from monitoring. The significantly negative coefficients on the natural log of maturity in Table III further support this idea. In columns 1 through 3, which use *Active Monitoring* as the dependent variable, the highly significant coefficients range from -0.09 to -0.12. In columns 4 through 6, the coefficients on *Monitoring Frequency* are also statistically significant and range from -0.30 to -0.32, suggesting that a 10% increase in maturity leads to between a 3% and 4% decrease

[21]This is not driven by differential effect of the control variables. Specifically, in the Internet Appendix (Table IA.II) we show that the coefficients of the control variables are very similar to those in Table III.

in monitoring frequency.

4.4 Covenant-based monitoring

We next examine whether the aspects of monitoring captured by our empirical measures are complements or substitutes with monitoring via financial covenants. As we discuss in Section 3.4, these forms of monitoring will be complements to the extent that covenants make it more likely that the information gathered through monitoring can be immediately useful, either in triggering default or during subsequent renegotiations (Rajan and Winton, 1995). Put differently, it is possible that covenants are sufficient for all monitoring and the monitoring contained in our measures is simply used to inform covenant compliance. Alternatively, the forms of monitoring we capture may substitute for covenant-based monitoring. Covenant violations reallocate control rights to lenders after adverse shocks and covenants themselves can discipline firm activity (see e.g., Chava and Roberts, 2008; Nini, Smith, and Sufi, 2009), either of which may reduce the need for other forms of monitoring.

Section 3.4 indicates a negative univariate relation between both of our monitoring measures and covenant use. In Table III we corroborate this result using multiple regressions. The coefficients in columns 1 through 3 of Table III are -0.023, suggesting that each additional covenant type reduces the probability of active monitoring by between two and three percentage points on average. Notably, the inclusion of lender fixed effects has little effect on the estimates, suggesting that the substitutability between covenants and the forms of monitoring captured by our measures is not primarily determined by supply side factors.

In columns 4 through 6, which use *Monitoring Frequency* as the dependent variable, the coefficient estimates range from -0.08 to -0.12. Thus, each additional covenant type is associated with approximately 10% less *Monitoring Frequency*.[22]

These findings suggest that on average covenants substitute for monitoring. However, it is reasonable to expect that the relation depends on the type of covenant and the type of

[22]In the Internet Appendix we further show that our inferences are largely unchanged using indicators for each number of covenants bin as opposed to a continuous measure (see Table IA.III).

monitoring. In particular, complementarities between covenant-based monitoring and other forms of monitoring can be higher when these other forms of monitoring are likely to inform covenant compliance. For instance, visiting a firm's plant may provide information relevant to a firm's loan-to-value covenant. Substitutability between covenants and monitoring is likely to arise when both covenants and monitoring rely on metrics directly related to the ability to repay the loan. For instance, sufficiently tight cash flow covenants can allocate control rights to lenders before a borrower's financial condition deteriorates too much, making banks less inclined to monitor.

To investigate whether the relation between monitoring and covenant use depends on the type of covenant, Table VI replicates columns 2, 3, 5, and 6 of Table III using a series of indicators for six different covenant types. In columns 1 and 2 the dependent variable is *Active Monitoring*. Four of the six covenant types are significantly related to active monitoring. Monitoring with balance sheet and loan-to-value covenants positively predicts active monitoring. This result is consistent with active monitoring complementing covenant-based monitoring when it provides additional information useful for covenant compliance or covenant renegotiations.

Not all types of covenant compliance can be inferred from active monitoring. For instance, compliance with cash flow-based covenants is not something that can be understood by visiting a firm's production site. The negative and significant relation between cash flow covenants and both of our monitoring measures suggests that when monitoring is not informative about covenants compliance, covenant-based monitoring is a substitute for other forms of monitoring. Indeed, the negative relation between covenants and active monitoring over the full sample is driven primarily by cash flow covenants, although there is also a marginally significant negative relation between active monitoring and capital expenditure covenants (compliance with which also cannot be easily inferred from active monitoring).

In columns 3 and 4 we conduct a similar analysis using *Monitoring Frequency* as the dependent variable. Here, we find that the entire negative relation between *Monitoring Fre-*

quency (i.e, the demand for a borrower's information) and covenant use is driven by cash flow covenants. Again, this finding is consistent with lenders monitoring less when doing so is likely to yield information that is already taken into account via covenants.

Overall, the evidence in this section is consistent with covenant-based monitoring being a complement with other forms of monitoring when such monitoring results in information production that is informative for covenant structure. In other cases, covenant-based monitoring acts as a substitute for other forms of monitoring.

5 Do banks dynamically adjust monitoring over the life of a loan?

In this section we conduct several tests to provide evidence on whether banks dynamically adjust their monitoring behavior over the life of a loan. We begin by examining how lenders adjust monitoring as the risk of the loan changes followed by an examination of whether changes in lead share due to acquisitions affect monitoring activity.

5.1 Monitoring and Borrower Financial Condition

Changes in the borrower's financial condition affect a bank's incentives to monitor for at least two reasons. First, a deterioration of the borrower's financial condition increases the likelihood of loan renegotiation, making information about the borrower more valuable. Second, given that lenders bear downside risk and have little upside potential, their investment becomes more sensitive to the borrower's value as the borrower's financial health deteriorates. Thus, we predict that monitoring will increase as borrowers' financial conditions deteriorates.

Empirically, we measure changes in borrower financial condition using changes in the lender's own ratings of the borrower because this is the measure of financial health that is most likely to affect the lender's behavior. Using these internal rating changes, we test

whether bank dynamically adjust monitoring over the lifetime of the loan. This test requires that loans are in our sample for at least two years prior to each observation year, reducing the sample size. Figure X illustrates the monitoring frequency CDFs of upgraded loans (the marked line) and downgraded loans (the unmarked line). Recently downgraded loans are approximately 50% more likely to be monitored on at least a monthly frequency, compared to recently upgraded loans. Unreported results further show that the group of loans that have not been upgraded or downgraded falls between the marked and unmarked lines.

To formally test whether a change in financial condition is related to monitoring we regress our two monitoring measures on indicators for lender rating upgrades and downgrades during the previous year. The aforementioned sample restrictions reduce our sample sizes to 4,907 and 682 observations for our active monitoring and monitoring frequency samples, respectively. This restriction also weights our sample toward longer maturity loans.[23] We estimate the following regression:

$$Monitoring\ Measure_{ijt} = c_t + \alpha_1 Rating\ Change_{jt} + \beta X_{ijt} + \epsilon_{ijt} \tag{2}$$

We expect that banks monitor more (less) when information becomes more (less) valuable. Hence, α_1 is expected to be positive in the case of a rating downgrade and negative in the case of a rating upgrade.

Table VII shows the results of estimating the relation between rating changes and monitoring (equation (2)). Columns 1 through 3 of provide no evidence of a significant relation between active monitoring and recent changes in borrower financial health. However, columns 4 through 6 indicate that lenders demand more frequent information when a borrower's financial health deteriorates. This finding is consistent with bank's dynamically adjusting monitoring in response to changes in the value of information.

A second measure of the deterioration of the borrower's financial health is an increase

[23]We do not necessarily have monitoring data for previous years, which precludes a traditional change specification.

in the credit line usage. Since credit lines are often used as liquidity insurance, firms tend to draw on them when financial condition deteriorates (Jimenez, Lopez, and Saurina, 2009). Norden and Weber (2010) show that increased credit line usage predicts bankruptcy. Hence, information about the borrower becomes more valuable to the bank when credit line usage increases. We therefore expect banks to dynamically adjust monitoring in response to changes in credit line usage.

Here, we restrict the sample to credit lines that we observe in the exam year and in the year before the exam. This restriction reduces the sample to 6,894 observations for active monitoring and to 1,011 for the monitoring frequency. We then measure the change in credit line usage from date $t-1$ to date t as the change in the ratio of amount drawn to total commitment. We estimate the following regression:

$$Monitoring\ Measure_{ijt} = c_t + \alpha_1 \Delta\ Utilization_{jt} + \beta X_{ijt} + \epsilon_{ijt} \tag{3}$$

Table VIII presents the results of estimating the effect of changes in credit line usage on monitoring (equation (3)). Active monitoring is the outcome in columns 1 and 2. An increase in the credit line utilization is positively related to active monitoring. A drawdown of 50 percent of a credit line increases the probability of active monitoring by 1.7 to 2.6 percentage points. This finding is consistent with banks collecting additional information on asset values in anticipation of potential loan restructuring or bankruptcy. However, we do not find a significant relation between a change in utilization rates and monitoring frequency (columns 3 and 4). In sum, the results presented in the section suggest that bank dynamically adjust monitoring to changes in the borrower's financial condition.

5.2 Merger-Induced Changes in Lead Share

We provide complementary evidence by examining how bank monitoring changes in response to merger-induced changes in lead share. These changes shed light on the extent to which banks adjust their monitoring behavior over the life of a loan and how banks respond when they are suddenly exposed to a loan.

We focus this analysis on large bank mergers that introduce considerable variation in the lead shares. Specifically, we study how acquiring banks respond to new exposures—that is, we distinguish between loans in which acquiring banks had a positive share and loan in which the acquiring bank had no share before the merger. To be clear, this includes loans for which the acquiring bank becomes the lead arranger and the target shares are "new" exposures for the acquiring banks. Instead of the lead share of the acquiring bank in the current year, we use the target share prior to the merger that was arguably beyond the control of the acquiring bank. We study whether these increased or new exposures that change the acquiring bank's lead share result in more monitoring.[24] By doing so, we provide complementary evidence showing how banks dynamically adjust monitoring when facing increased or new exposures.

The key explanatory variable, $Target\ Share_{ikt-1}$, is the share of acquired bank k in loan i in the year before the merger $(t-1)$. We estimate following regression:

$$Active\ Monitoring_{ijt} = c_t + \alpha Target\ Share_{ikt-1} + \delta X_{ijt} + \epsilon_{ijt} \tag{4}$$

where *Active Monitoring* is that by the acquiring bank j in period t and X_{ijt} is a vector of control variables that includes the other equilibrium outcomes and fixed effects similar to

[24] We study bank mergers in the wake of the 2007-09 financial crisis, which were primarily driven by bank liquidity needs. Second, commercial and industrial (C&I) loans, of which syndicated loans are a considerable fraction, account for only 18% percent of U.S. bank balance sheets, making C&I lending activity an unlikely M&A driver. The banks involved in the mergers we study do not exhibit an unusually large C&I portfolio. While a merger will also affect lender concentration in the syndicate, this change will be driven by a change in the lead share.

the main specification in section 4.1.[25]

Table IX shows the results from estimating equation 4. Column 1 reports that the point estimate on the target's share is positive, statistically significant, and about three times the estimated effect in column (2) of Table III. The estimated effect suggest that a 5 percentage point increase in lead share increase in the probability of active monitoring by almost 3 percent.[26] There are two possible interpretations of the increase in the point estimate. One is that loans to which the acquiring bank had no prior exposure necessitate increased monitoring. The other is that the results shown in Table III suffer from attenuation bias as they are estimated on equilibrium relationships.

We test the first proposed interpretation by first including an interaction of $Target\ Share_{ikt-1}$ with an indicator of $Prior\ Exposure_{ijt-1}$ of the acquiring bank. Column 2 shows the results. The point estimate of the interaction term is negative and almost as large as the main effect, suggesting that only loans in which the acquirer had no pre-merger exposure are monitored more after the merger. However, the interaction term is not statistically significant.[27]

We then drop the loans for which the acquiring bank had prior exposure and estimate the effect of the target share on the sample of loans for which the acquiring bank had no prior exposure.[28] We find that a positive and significant coefficient on the target share for the sample of loans for which the acquiring bank had no prior exposure (column 3).[29]

We argue that the target share estimates are substantially larger than those presented in section 4 because in the latter case banks have already gathered information during the loan origination process and have established information gathering procedures. In other words, our main results reflect post-origination equilibrium relations that are based on the infor-

[25]This is a reduced-form specification of an instrumental variable regression. In unreported results, we estimated the relation between the target's pre-merger share and the post-merger lead share and found a large and significant point estimate.

[26]Dropping time and loan quality fixed effects does not change our result.

[27]The size of the sample for which the acquiring bank had prior exposure is fairly small, reducing the power of this test.

[28]Due to small sample size, we do not perform estimate the relation between active monitoring and target share for loans for which the acquiring bank had prior exposure.

[29]We obtain similar results for when dropping loans for which the target was the lead bank.

mation acquisition during the origination process. In contrast, the merger analysis shows dynamic adjustments to "new" exposures. The acquiring bank has to start the information acquisition process, thereby resulting in higher observed monitoring. The larger this new exposure, the stronger the bank's incentives to gather information about a "new" loan in the portfolio. Since the nature of the information gathering process in merger analysis differs substantially from the post-origination information gathering, the respective point estimates cannot be compared directly but should be seen as complementary evidence on the determinants of monitoring.

Overall, the merger analysis provides complementary evidence on the relationship between lead share and our measures of monitoring. An implication of this result is that monitoring incentives have been crucially affected by the presence of a secondary market for loans that allow lead banks to reduce their share in a loan (Parlour and Plantin, 2008; Irani and Meisenzahl, 2017). However, our collection of results still suggests that there is an economically meaningful amount of bank monitoring going on in today's syndicated lending market.

6 Monitoring and Loan Outcomes

In our final set of tests, we study the relation between monitoring and future loan contracting outcomes. First, we investigate the relation between monitoring and covenant violations and waivers, restricting the sample to loans with at least one covenant type. We then examine how monitoring in a given year relates to the likelihood of loan renegotiations (proxied by changes in loan amount or maturity) in the subsequent year.

To this end, we estimate the following regression:

$$Outcome_{ijt+1} = c_t + \alpha_1 Monitoring\ Measure_{ijt} + \beta X_{ijt} + \epsilon_{ijt} \tag{5}$$

X_{ijt} includes year, origination quarter, examiner and lead bank rating, as well as lead bank FEs. In some specifications, we include lead share as a control variable to examine how the predictability of our monitoring measures compares to that of the lead share. For ease of interpretation, we do not include other firm-level control variables, although the results are qualitatively similar after the inclusion of the control variables used in prior analyses.

Table X shows the results of estimating Equation 5. In panel A the explanatory variable of interest is our active monitoring indicator. Column 1 shows that conditional on the loan contract having financial covenants, active monitoring in a given year is positively associated with the probability of a covenant violation in the following year. The point estimate of 0.12 suggests that loans with active monitoring have an approximately 12 percentage point higher probability of violating a covenant in the following year. Given that 45% of borrowers violate covenants each year in our sample, this represents an approximately 27% increase in the probability of a subsequent covenant violation. This positive relation is consistent with our previous finding suggesting that active monitoring can complement covenants and provides information about the value of collateral, which is valuable information in loan restructuring or renegotiation. This finding is also consistent with increased monitoring when the value of information is high. Banks monitor more in anticipation of covenant breaches and the subsequent negotiations.

In column 2, we investigate whether the relation between active monitoring and future covenant violations continues to hold after controlling for lead share, a common proxy for monitoring in the existing literature. We find a significantly positive relation between future covenant violations and both lead share and active monitoring. Interestingly, the coefficient on active monitoring is virtually unchanged, suggesting that lead share and active monitoring capture distinct components of monitoring, with respect to predicting future covenant violations. In columns 3 and 4 we find that active monitoring is unrelated to waivers, conditional on covenant violations.

In columns 5 and 6 we conduct similar analyses using an indicator for loan renegotiations

(proxied by changes in loan amount or maturity) during the next year as the dependent variable. Under this interpretation, we find a consistently positive relation between active monitoring this period and subsequent loan renegotiations. Again this is consistent with active monitoring providing valuable information about collateral values, which in turn facilitates future renegotiations. In contrast, we find a negative relation between the lead share retained and future renegotiations. One interpretation of this findings is that when lead banks hold a large stake in the loan already they are less likely to increase loan amount or lengthen loan maturity.

Private firms are on average more opaque than public firms and as a result the value of information obtained from monitoring is likely to be higher for private firms. To better understand how the information obtained from monitoring is used in future loan contracting, we also conduct this analysis for private and public firms, separately. In unreported results we find that while the effects of active monitoring on future covenant violations are similar between the two types of firms, the renegotiation results are driven by private firms. The latter result confirms our hypothesis that the value of information generated by active monitoring is greater for more opaque, privately-held, borrowers.[30] This idea is further reinforced by the finding that conditional on covenant violation, active monitoring is positively correlated with covenant violation waivers for public firms. Thus, less opaque borrowers are more likely to obtain covenant violation waivers if lenders are already monitoring the loan actively.

In panel B of Table X we replicate the analysis with *Monitoring Frequency* as the explanatory variable of interest. This results in a substantially smaller sample, ranging from 331 to 1,262 observations, so we interpret these findings with caution. We do not find monitoring frequency to be related to future covenant violations or renegotiations, indicating that it is the lenders' decision to collect actionable information rather the frequency of information that matters for future renegotiation. However, borrowers are more likely to obtain

[30]See Internet Appendix Table IA.IV.

waivers conditional on covenant violations if lenders have been monitoring the loan more frequently. One explanation for this finding is that lenders are less likely to enforce covenant compliance when they are already collecting detailed information about the financial health of the borrower.

The evidence presented in this section, while only suggestive, points to some potential benefits of monitoring to the borrower that have not been discussed in the literature. Borrowers actively monitored by banks may find it easier to renegotiate their loans, while frequently monitored borrowers may receive frequent guidance from banks, which helps them receive covenant violation waiver and therefore avoid costly loan renegotiations.

7 Concluding Remarks

In this paper, we provide direct empirical evidence on bank monitoring activity in a large sample of US syndicated loans. The totality of our evidence suggests that monitoring plays an economically meaningful role in today's syndicated loan market. Approximately 20% of loan agreements also involve active monitoring, such as site visits or the hiring of third party appraisers. Half of lenders require the borrowers to provide information at least on a monthly basis, 5% require such information every day, while 29% require information only on an annual basis.

Primary drivers of monitoring activity are the share of the loan retained by the lead arranger and the value of information to the lender. Borrowers appear to trade off monitoring in the form of site visits and required information provision with monitoring via financial covenants and the loan's maturity. We find little evidence that monitoring is traded off against loan size, and mixed evidence of a tradeoff between monitoring and loan spreads. In sum, our findings highlight the importance of ensuring that banks continue to be properly incentivized to monitor syndicated loans and suggest that the lead share is a good proxy for monitoring when loans become very risky or the borrower is informational opaque.

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Appendix A - Variable Definitions

Active Monitoring: is defined as a dummy variable for whether or not a lead bank actively monitors a loan. Specifically, we define active monitoring as field exams of the borrowers conducted by the lead bank as well as third-party appraisals.

Balance Sheet Covenant: is an indicator variable that takes the value of one when a net worth covenant is present.

CAPEX Covenant: is an indicator variable that takes the value of one when a covenant restricting investment is present.

Cash Flow Covenant: is an indicator variable that takes the value of one when a cash flow covenant is present.

Δ *Amount*: is an indicator variable that takes the value of one when the total loan amount changed between period t and $t+1$.

Δ *Maturity*: is an indicator variable that takes the value of one when the loan maturity changed between period t and $t+1$.

Distributions Covenant: is an indicator variable that takes the value of one when a covenant restricting distributions is present.

Downgrade: is an indicator variable that takes the value of one if the loan rating decreased.

$Examiner-Scale\ Credit\ Ratings$: The SNC database includes information on credit facility risk both in terms of the risk ratings assigned by the examiners and the internal risk rating assigned by the lead lender. Each year the lead lenders' internal risk rating scales are converted by the Federal supervisors to a 5-grade scale using a concordance mapping provided by the lead lenders. The supervisory 5-grade scale is defined as follows: 1) Pass—a loan facility defined to be in a good credit standing, 2) Special Mention—a loan facility with some credit weaknesses that could result in deterioration of loan repayment prospects, 3) Substandard—a loan facility with well-defined credit weaknesses that could result in some losses for the bank if these weaknesses are not corrected, 4) Doubtful—a loan facility with

the problems described in the Substandard category with additional deficiencies that make successful collection highly unlikely, and 5) Loss—a loan facility that is considered uncollectable and should be charged-off. For details, see
http://www.federalreserve.gov/newsevents/press/bcreg/20141107a.htm.

Fraction Used: is defined as the loan amount that has been utilized by the borrower divided by the loan commitment amount. This variable always takes the value of one for term loans.

High Volatility Collateral: is an indicator variable that takes the value of one when the loan is secured by accounts receivable, inventories, and securities.

Industry Fixed Effects: these are indicators for 24 industry groups defined in the SNC collection.

Market Cap. Covenant: is an indicator variable that takes the value of one when a market capitalization covenant is present.

Lead Bank Fixed Effects: these are indicators for the different lead banks in our sample defined by the top holder RSSD ID.

Lead Bank Internal Credit Ratings Fixed Effects: these are indicators for the internal credit ratings grades of each lead bank for which we have consistent internal ratings information.

Lead Share: is defined as the share of a loan held by the lead bank.

Lender Herfindahl: is defined as the Herfindahl index constructed from all lender shares excluding that of the lead bank.

$Loan-to-Value\ Covenant$: is an indicator variable that takes the value of one when a covenant restricting leverage is present.

Low Volatility Collateral: is an indicator variable that takes the value of one when the loan is secured by fixed assets (such as property, plant, and equipment) and real estate, and zero otherwise.

$Log(Committed)$: is defined as the natural logarithm of the loan commitment amount

in US dollars.

$Log(Maturity)$: is defined as the natural logarithm of the loan maturity in days.

$Monitoring\ Frequency$: is defined as the maximum number of times a given loan is monitored within a year. More specifically, daily (365 times) is the highest frequency and annually (1 time) is the lowest frequency.

$Number\ of\ Covenants$: is equal to the total number of covenant types included in a credit facility, the different types are defined as a function of the following variables: Capital Expenditures, Cash Flow Leverage, Net Worth, Debt to Assets (Loan to Value), Cash, Current Ratio, Interest Coverage, Debt to Capitalization, Distributions.

$Origination\ Year-Quarter\ Fixed\ Effects$: these are indicators for the year-quarter of loan origination for each loan observation.

$Public$: is an indicator variable that takes the value of one when the borrower is public, and zero elsewhere.

$Term\ Loan$: is an indicator variable that takes the value of one when the loan is a term loan, and zero elsewhere.

$Unsecured$: is an indicator variable that takes the value of one when the loan is secured, and zero otherwise.

$Upgrade$: is an indicator variable that takes the value of one if the loan rating increased.

$Violation$: is an indicator variable that takes the value of one if a loan covenant was violated.

$Year\ Fixed\ Effects$: are indicators for the year of each loan observation.

Appendix B - Addressing selection

As discussed in section 2.5, our second measure of bank monitoring, *Monitoring Frequency*, is reported for only a subset of the SNC database. While the sample is similar to the full SNC sample on observable dimensions (Table I), loans for which the monitoring information is collected may not be chosen at random. The monitoring frequency sample consists of 2,210 loan-years with sufficient data, which is only 12.3% of the exam sample.

To examine the extent to which we can generalize our findings to the entire exam sample we employ a Heckman selection model. Our first stage exploits examiners' differential propensities to collect monitoring information as exogenous variation in the likelihood of a given loan in the SNC database ending up in our monitoring frequency sample.[31] This identification strategy is similar to Sampat and Williams (2019) who use patent examiner fixed effects as an instrument for a patent being granted. Our second stage replicates the analysis in Table III, using the inverse Mills-ratio from the first stage to control for unobservables that may result in a given loan ending up in the monitoring frequency sample. Formally, our second stage can be written as:

$$\begin{aligned} Monitoring\ Frequency_{ijt} = c_t + \alpha_1 Lead\ Share_{ijt} + \alpha_2 Public\ Borrower_{jt} + \\ \alpha_3 Log(Maturity)_{ijt} + \alpha_4 Number\ of\ Covenants_{ijt} + \\ \delta\phi_{ijt} + \beta X_{ijt} + \epsilon_{ijt}, \end{aligned} \tag{B.1}$$

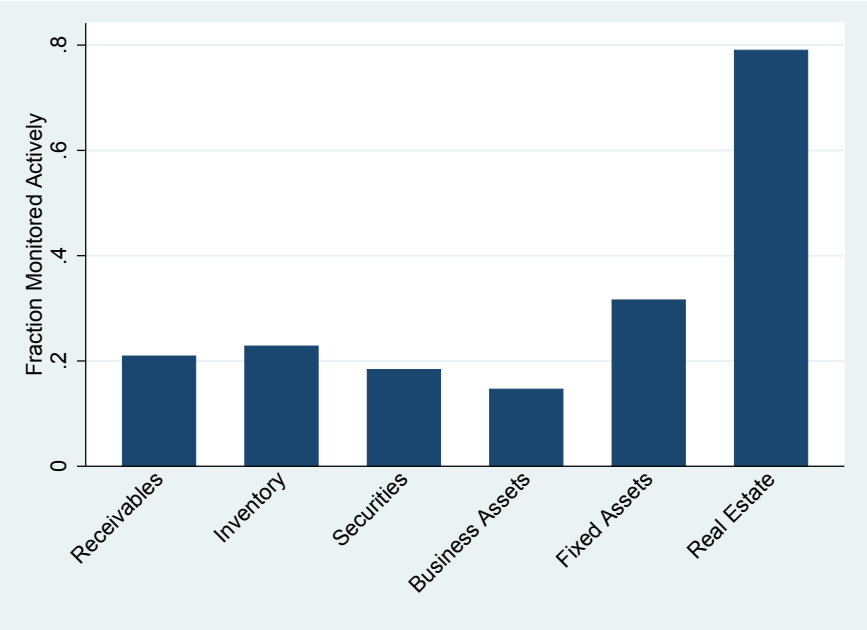
where all variables are as defined in Appendix A and the ϕ_{ijt} is the inverse Mills-ratio for loan i is evaluated by lead bank j within a given year t.

Table B.I reports the second-stage results of our Heckman specification (equation B.1),

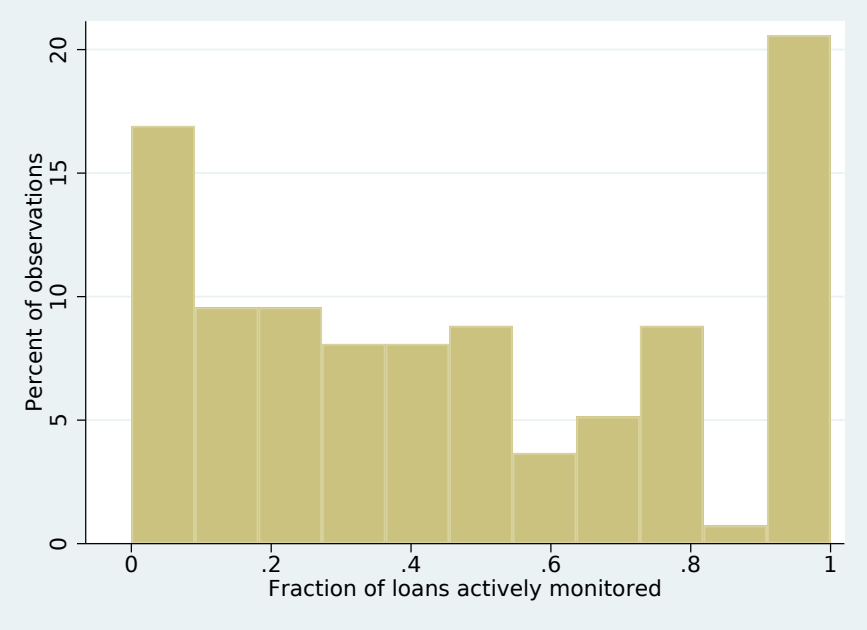
[31] For parsimonious considerations, we use the examiner fixed effect whenever the examiner has rated at least 50 loans in the SNC exams, otherwise we use the identity of the agency affiliation of the examiner. It is plausible that idiosyncratic differences in loan examiner could translate to different probabilities in recording the monitoring frequency for each loan. In unreported tests we indeed find that the examiner fixed effects are jointly highly statistically significant in predicting whether a loan would have the frequency of monitoring recorded in the examiner report.

including the same controls as columns 4-6 of Table III. We find that the results in Table B.I for our main variables of interest are very similar and generally statistically indistinguishable from those in Table III. The inverse Mills-ratio is statistically insignificant after the inclusion of lead bank fixed effects.[32] This indicates that unobservables driving the selection decision (to include monitoring frequency in the exam report) are not correlated with monitoring frequency. We conclude that the subset of loans with information on monitoring frequency do not appear to differ materially from the loans in the exam sample along uncontrolled for dimensions.

[32]Due to the large number of examiner fixed effects in the first stage, we cannot include fixed effects for the lead bank's internal rating.

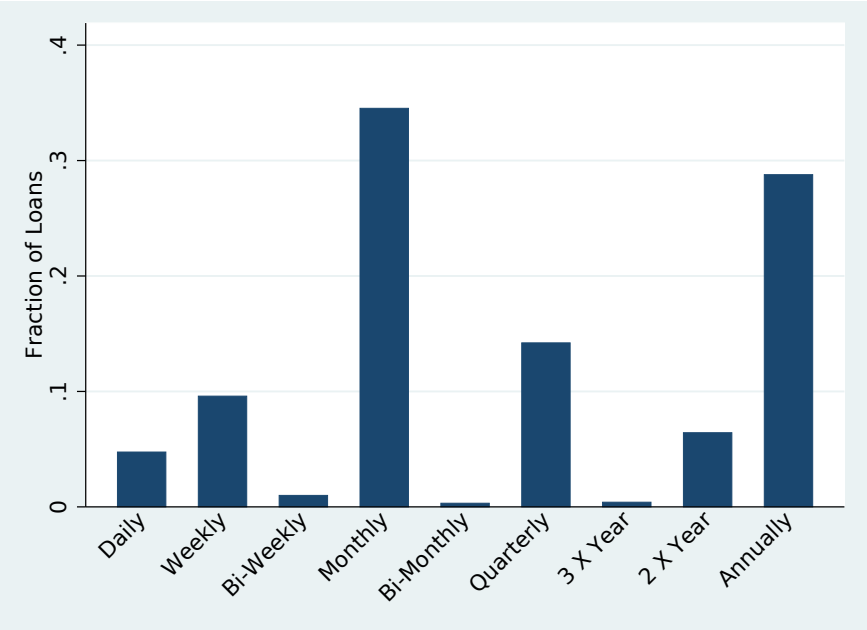


(a) *Active Monitoring & Collateral Type*

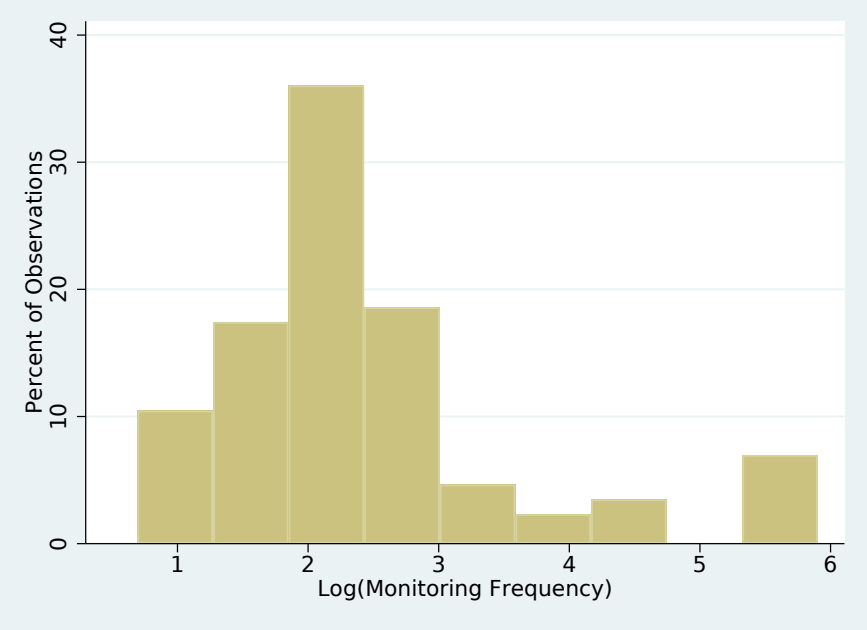


(b) Cross Lender Variation in *Active Monitoring*

Figure I: Active Monitoring Panel (a) of this figure plots the fraction of loans that are actively monitored partitioned by collateral type. Panel (b) shows the distribution of average active monitoring across lenders. Specifically, for each lender we compute the number of loans that are monitored actively as a fraction of the total number of loans in a lender's portfolio over our sample period; we then present the resulting distribution across lenders.

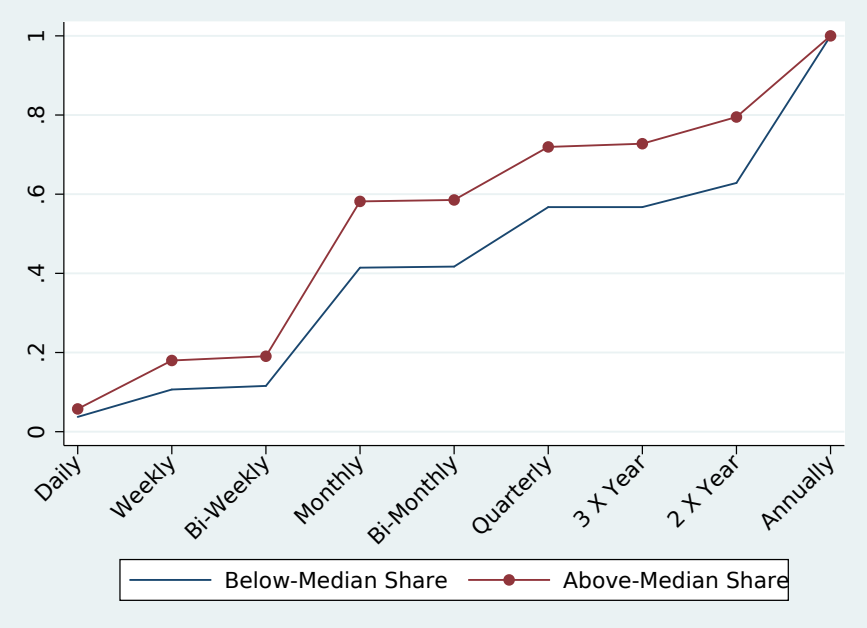


(a) *Monitoring Frequency* histogram

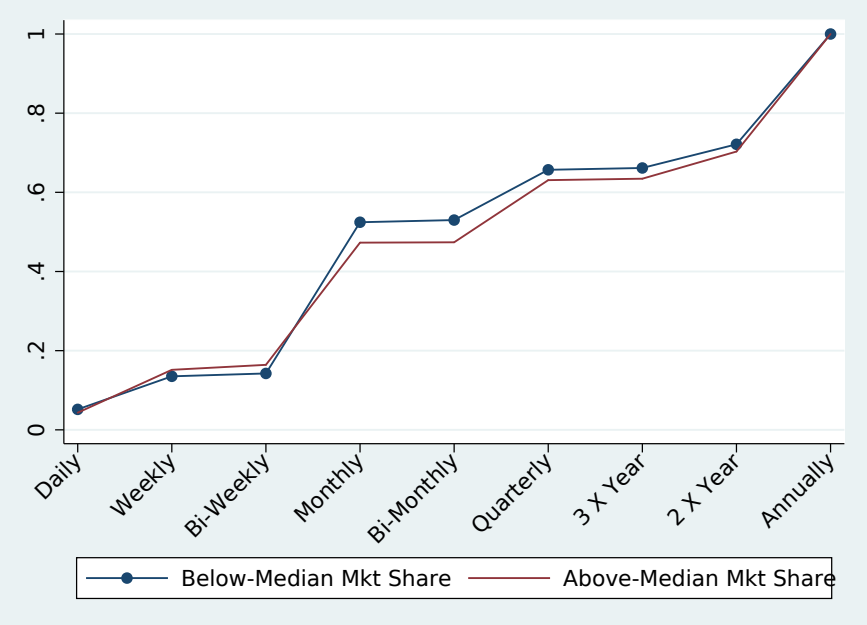


(b) Cross Lender Variation in *Monitoring Frequency*

Figure II: Monitoring Frequency Panel (a) plots the distribution of monitoring frequency for our monitoring frequency sample (2,210 loans). Panel (b) shows the distribution of monitoring frequency across lenders. Specifically, for each lender we compute the simple average Log(Monitoring Frequency) across all loans in a lender's portfolio over our sample period; we then present the resulting distribution across lenders.



(a) *Monitoring Frequency and Lead Share*



(b) *Monitoring Frequency and Lead Market Share*

Figure III: Monitoring Frequency and Lead Bank Variables Panel (a) plots the cumulative density function (CDF) of monitoring frequency for loans in which the lead arranger share is either above or below the median lead share of 21.1%. The x-axis plots monitoring frequency, thus a point on the figure corresponds to the percentage of loans that are monitored at least as frequently as the interval listed on the x-axis. Panel (b) is the same as Panel (a) except that the sample is partitioned on the lender's market share in the syndicated lending market.

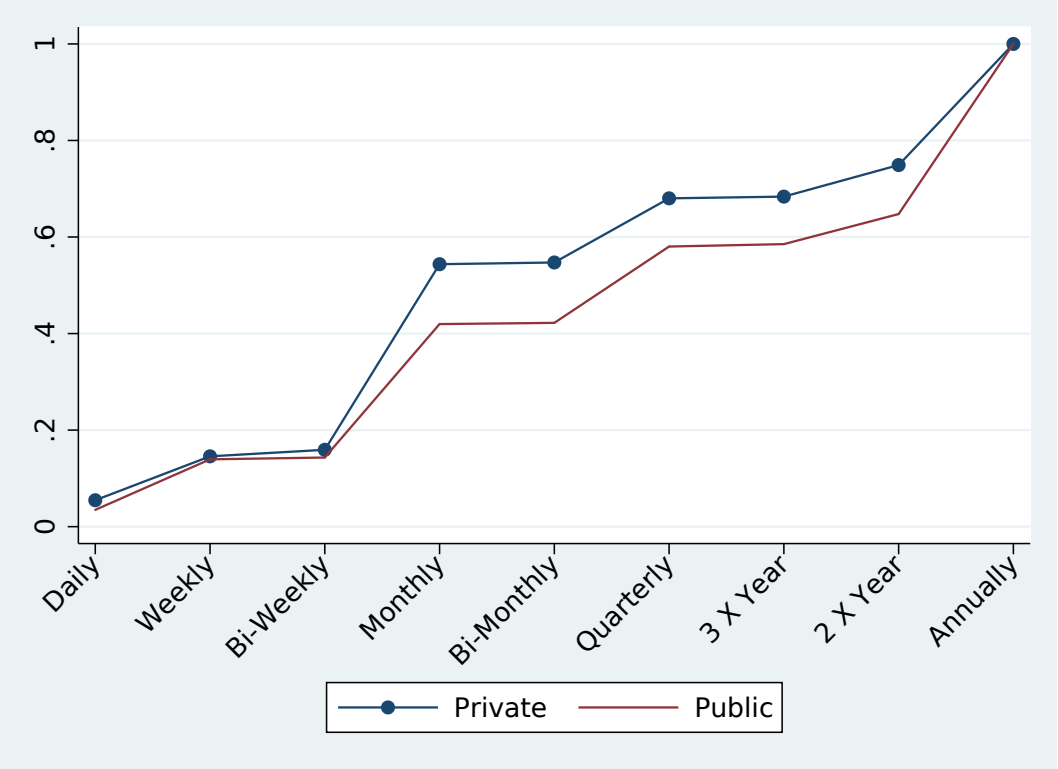


Figure IV: Monitoring Frequency and Public Status This figure plots the cumulative density function (CDF) of monitoring frequency partitioned by whether the loans are extended to public or private companies. The x-axis plots monitoring frequency, thus a point on the figure corresponds to the percentage of loans that are monitored at least as frequently as the interval listed on the x-axis.

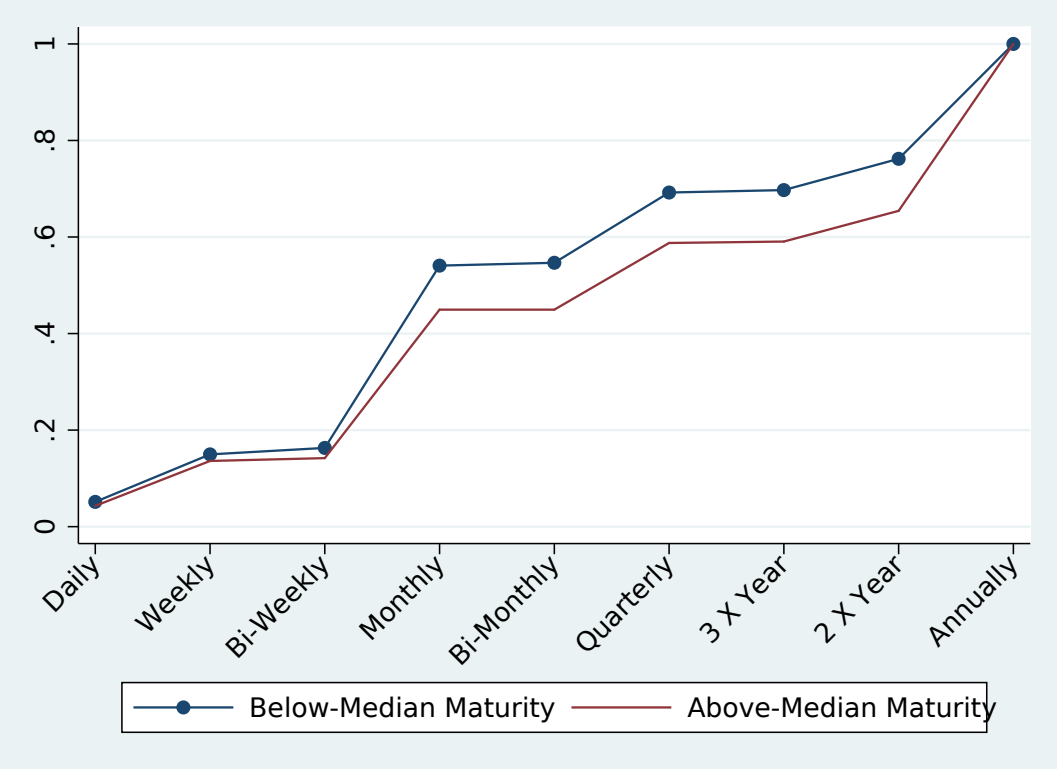


Figure V: Monitoring Frequency and Loan Maturity This figure plots the cumulative density function (CDF) of monitoring frequency partitioned by whether the loans are above or below median in stated maturity. The x-axis plots monitoring frequency, thus a point on the figure corresponds to the percentage of loans that are monitored at least as frequently as the interval listed on the x-axis.

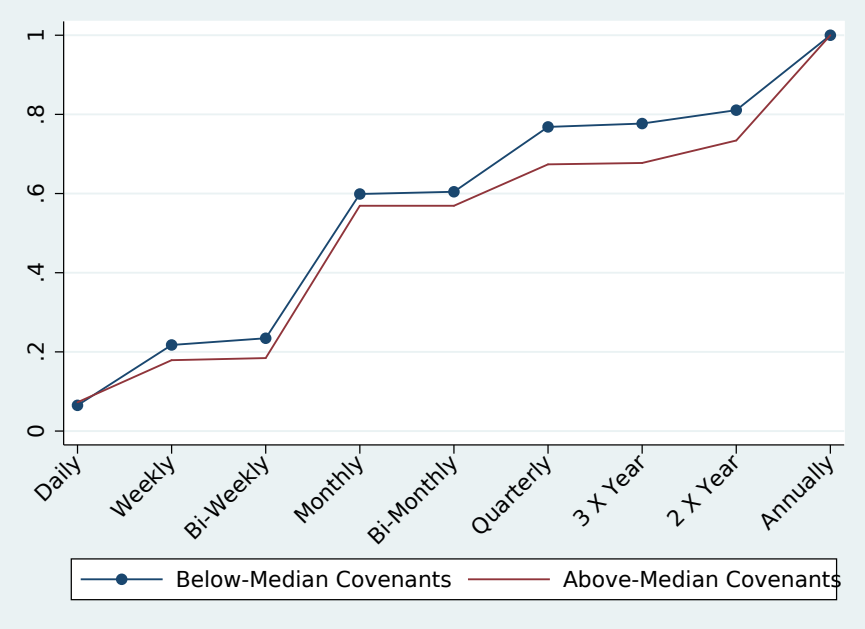
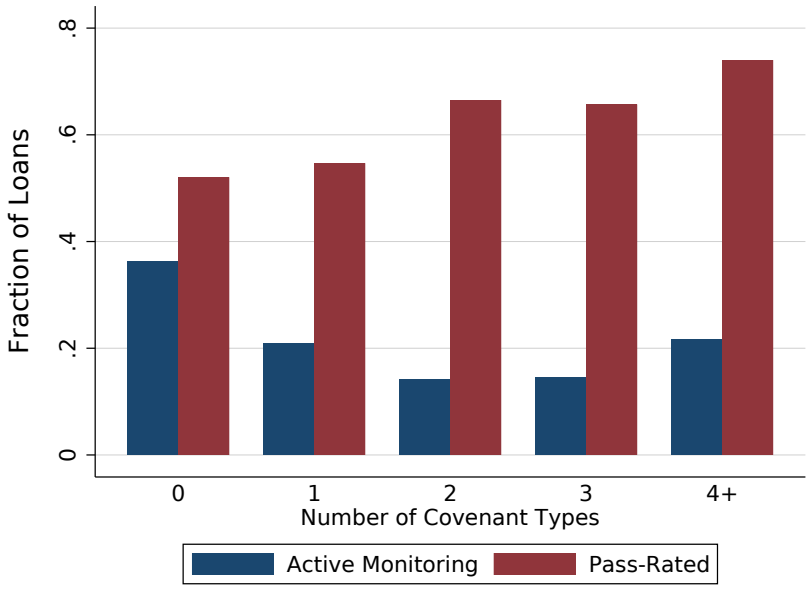
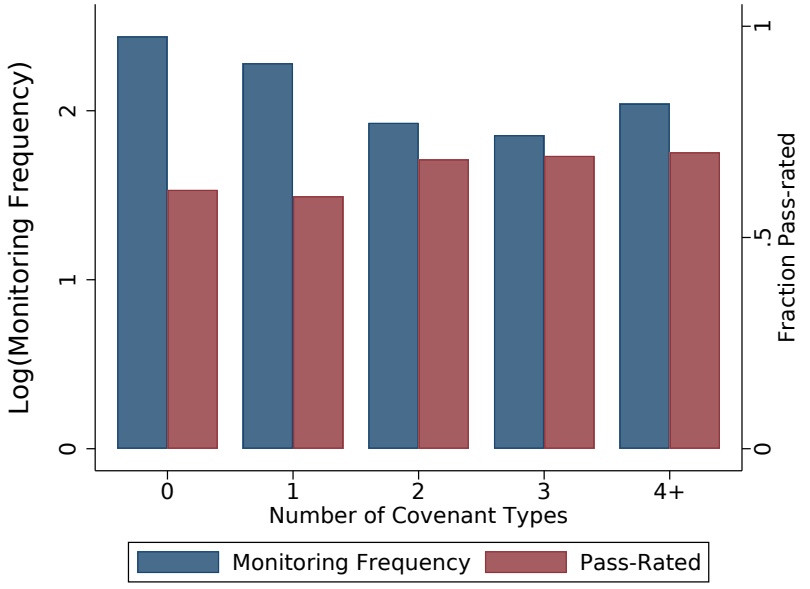


Figure VI: Monitoring Frequency and Covenant Use. This figure plots the cumulative density function (CDF) of monitoring frequency partitioned by whether the loans have above-median or below-median number of covenants. The x-axis plots monitoring frequency, thus a point on the figure corresponds to the percentage of loans that are monitored at least as frequently as the interval listed on the x-axis.



(a) *Active Monitoring*



(b) *Monitoring Frequency*

Figure VII: Bank Monitoring and the Number of Covenant Types. This figure presents the fraction of active monitoring and average monitoring frequency (y-axis) split by the number of covenant types in a loan contract (x-axis). Pass-rated is a binary variable that takes the value of one whenever a loan is rated "Pass" (the best supervisory rating category) by the Shared National Credit Program.

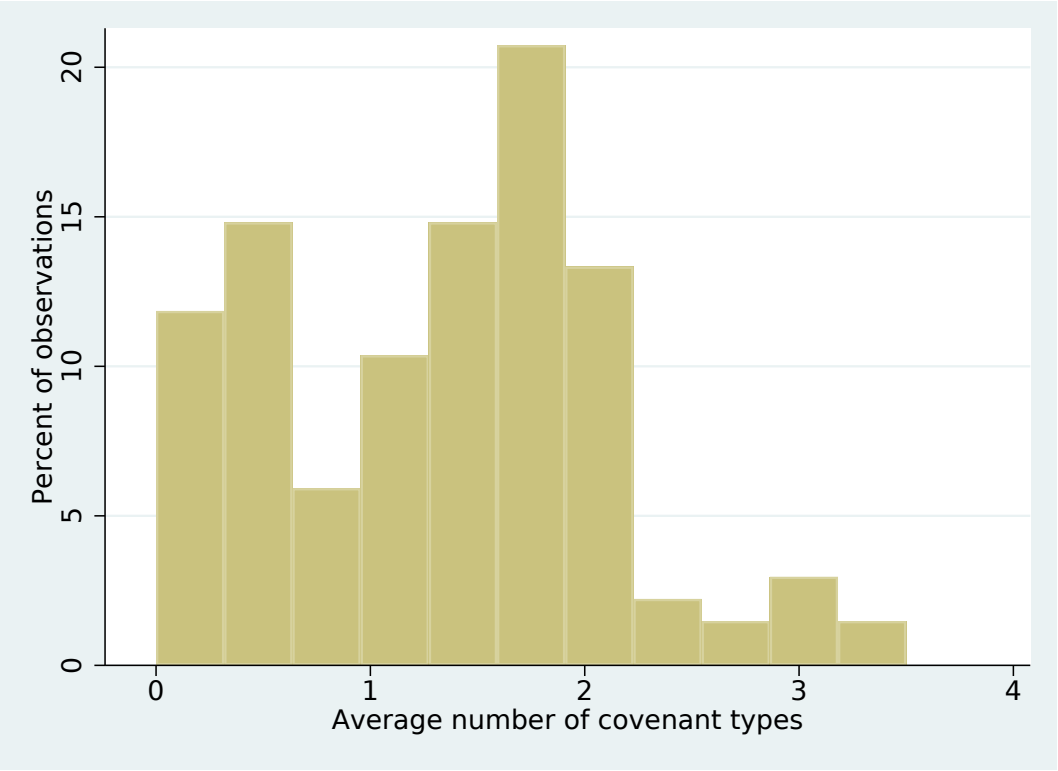
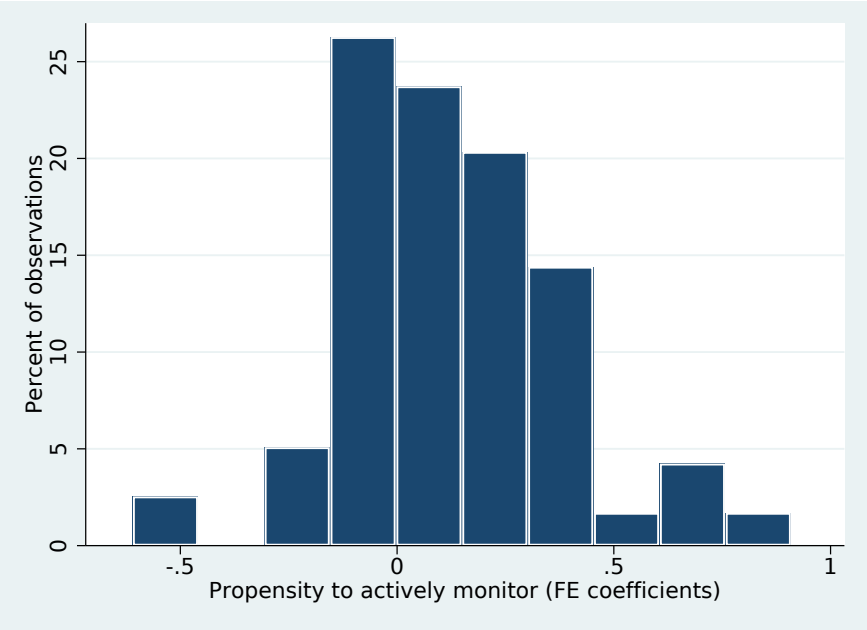
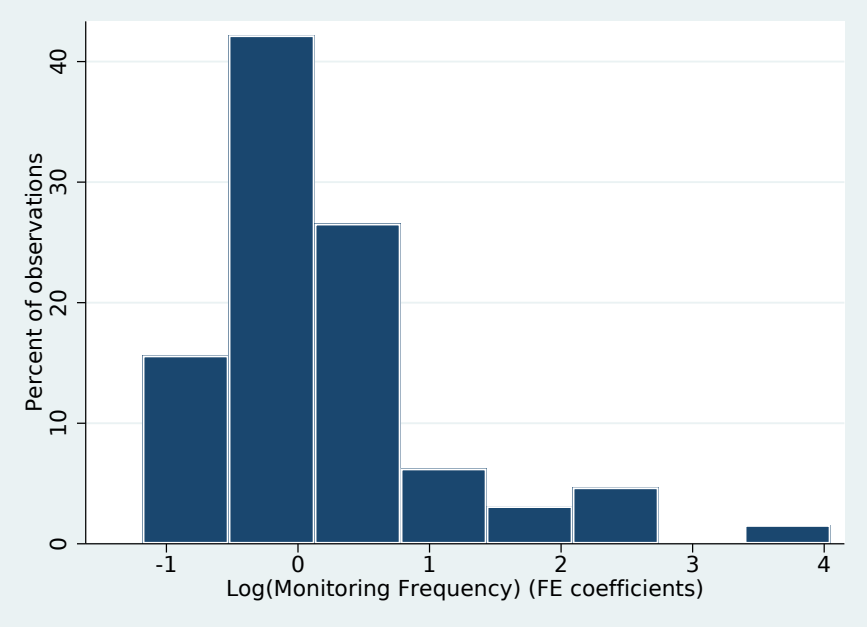


Figure VIII: The Distribution of the Number of Covenant Types Across Banks. This figure shows the distribution of the number of covenant types across banks.



(a) *Active Monitoring*



(b) *Monitoring Frequency*

Figure IX: Monitoring Preferences Panel (a) of this figure shows the distribution of the lead arranger fixed effects in the active monitoring regression from Equation 1. Panel (b) presents the fixed effects coeffcients in the monitoring frequency regression.

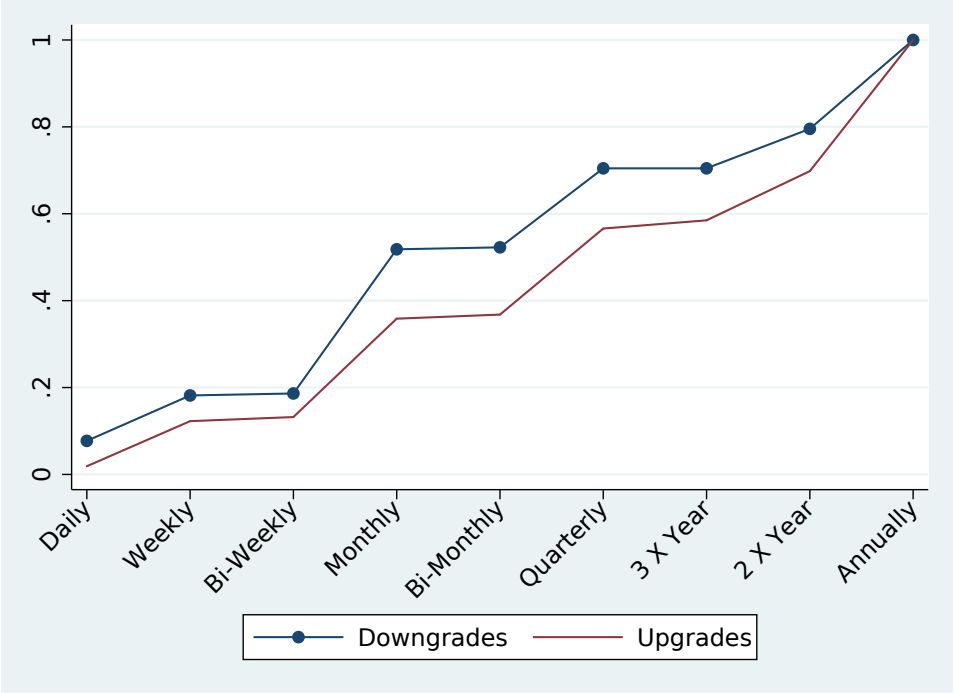


Figure X: Monitoring Frequency and Internal Ratings Changes. This figure plots the cumulative density function (CDF) of monitoring frequency partitioned by whether the loans are upgraded or downgraded. The x-axis plots monitoring frequency, thus a point on the figure corresponds to the percentage of loans that are monitored at least as frequently as the interval listed on the x-axis.

Table I: Summary Statistics: Comparison. Columns 1 and 2 describe the entire SNC database from the May 2007 collection to the May 2015 collection (N = 79,402), while Columns 3 and 4 provide descriptive statistics for the exam sample for which we have covenant and collateral information (N = 19,729). Columns 5 and 6 provide descriptive statistics for the sample with available information on monitoring frequency (N = 2,210). Finally, Columns 7-9 present differences in means between each pair of samples. *, **, and *** correspond to differences that are significant at the 10%, 5%, and 1% levels respectively, according to a t-statistic for differences in means.

	Full Sample (I)		Exam Sample (II)		Monitoring Frequency Sample (III)		Difference		
	Mean	*Median*	*Mean*	*Median*	*Mean*	*Median*	(I)-(II)	(I)-(III)	(II)-(III)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Loan Amount	328	127	320	125	309	125	7.700	18.366	10.667
Loan Maturity	2,055	1,826	1,988	1,827	1,895	1,826	66.318	159.092	92.775***
Loan Spread	231	200	292	275	260	250	-60.701***	-28.820***	31.881***
Lead Share	0.228	0.200	0.193	0.160	0.241	0.222	0.034***	-0.013***	-0.048***
Public	0.393	0.000	0.378	0.000	0.363	0.000	0.015***	0.030***	0.015
Lender Herfindahl	0.124	0.106	0.120	0.100	0.127	0.108	0.004***	-0.003	-0.007***
Fraction Used	0.550	0.603	0.657	0.894	0.616	0.690	-0.107***	-0.066***	0.041***
Δ*Fraction Used*	0.022	0.000	0.033	0.000	0.033	0.000	-0.011***	-0.011*	0.001
Term Loan	0.270	0.000	0.344	0.000	0.242	0.000	-0.074***	0.028***	0.102***
Upgrade	0.166	0.000	0.117	0.000	0.155	0.000	0.052***	0.012	-0.039***
Downgrade	0.197	0.000	0.324	0.000	0.323	0.000	-0.126***	-0.124***	0.001
Unsecured			0.067	0.000	0.026	0.000			0.041***
Low Volatility Collateral			0.605	1.000	0.401	0.000			-0.082***
High Volatility Collateral			0.128	0.000	0.211	0.000			0.204***
Number of Covenants			1.735	2.000	1.822	2.000			-0.087***
				Future Outcomes					
$Violation_{it+1}$	0.430	0.000	0.463	0.000	0.523	1.000	-0.032***	-0.093***	-0.060***
$Waiver_{it+1}$	0.839	1.000	0.856	1.000	0.858	1.000	-0.017*	-0.020***	0.003
$Renegotiation_{it+1}$	0.571	1.000	0.631	1.000	0.620	1.000	-0.060***	-0.049***	0.012

Table II: Summary Statistics: Comparisons. This table presents comparisons of loan characteristics on whether loans are monitored actively. All variables are defined in Appendix A. Statistical significance is denoted as follows: $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Active Monitoring		Passive Monitoring		
	Mean	*Median*	*Mean*	*Median*	*Diff Means*
Lead Share	0.282	0.273	0.172	0.133	0.110***
Mkt. Share	0.080	0.004	0.114	0.027	−0.034***
Public	0.176	0.000	0.430	0.000	−0.254***
Loan Amount	193	80	355	150	−162***
Loan Spread	272	250	294	275	−21.635
Loan Maturity	1,700	1,821	2,068	1,827	−367***
Number of Covenants	1.423	1.000	1.814	2.000	−0.391***

Table III: Main Results: Determinants of Bank Monitoring OLS regression estimates are reported for the relation between an indicator for some active monitoring (columns (1) through (3)) and the log of monitoring frequency (columns (4) through (6)) and key loan, lender, and borrower characteristics. The fixed effects structure for each regression is presented at the bottom of the table. All variables are defined in Appendix A. Standard errors in columns 1-3 are clustered on the bank-year level. P-values are presented in parentheses and statistical significance is denoted as follows: $^*p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Active Monitoring			*Log(Monitoring Frequency)*		
	(1)	(2)	(3)	(4)	(5)	(6)
Lead Share	0.309***	0.187***	0.148***	0.718***	0.418**	0.455*
	(0.037)	(0.036)	(0.040)	(0.181)	(0.185)	(0.242)
Public	−0.055***	−0.037***	−0.040***	−0.134**	−0.075	−0.105
	(0.009)	(0.008)	(0.009)	(0.061)	(0.062)	(0.073)
Log(Committed)	0.002	0.006	0.002	0.020	0.028	0.060*
	(0.005)	(0.004)	(0.004)	(0.023)	(0.025)	(0.031)
Log(Maturity)	−0.124***	−0.092***	−0.091***	−0.312***	−0.299***	−0.320***
	(0.015)	(0.014)	(0.018)	(0.087)	(0.087)	(0.113)
Number of Covenants	−0.023***	−0.023***	−0.023***	−0.123***	−0.111***	−0.080***
	(0.004)	(0.004)	(0.005)	(0.023)	(0.024)	(0.028)
High Volatility Collateral	−0.163***	−0.172***	−0.159***	0.440***	0.450***	0.519***
	(0.019)	(0.020)	(0.023)	(0.083)	(0.083)	(0.101)
Low Volatility Collateral	−0.052***	−0.042***	−0.035*	−0.225***	−0.153**	−0.158**
	(0.015)	(0.015)	(0.018)	(0.062)	(0.063)	(0.077)
Lender Herfindahl	0.035	0.052	0.041	0.308	0.397*	0.556**
	(0.037)	(0.036)	(0.038)	(0.301)	(0.241)	(0.253)
Term Loan	0.021**	0.014**	0.017**	−0.100	−0.070	−0.143**
	(0.009)	(0.007)	(0.007)	(0.065)	(0.063)	(0.073)
Unsecured	−0.069***	−0.065**	−0.068**	−0.511***	−0.539***	−0.713***
	(0.022)	(0.026)	(0.028)	(0.183)	(0.184)	(0.215)
Adjusted R-Squared	0.299	0.349	0.327	0.174	0.270	0.326
Observations	19,729	19,729	14,539	2,210	2,210	1,713
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Origination Year-Quarter Fixed Effects	YES	YES	YES	YES	YES	YES
Industry Fixed Effects	YES	YES	YES	YES	YES	YES
Examiner Ratings	YES	YES	YES	YES	YES	YES
Examiner-Scale Lead Bank Ratings	YES	YES	NO	YES	YES	NO
Lead Bank Fixed Effects	NO	YES	YES	NO	YES	YES
Lead Bank Internal Ratings	NO	NO	YES	NO	NO	YES

Table IV: Lead Share Interaction Effects OLS regression estimates are reported for the relation between an indicator for some active monitoring (columns (1) through (4)) and the log of monitoring frequency (columns (5) through (8)) and the lead arranger's loan share interacted with other explanatory variables of interest. The fixed effects structure for each regression is presented at the bottom of the table. All variables are defined in Appendix A. Standard errors in columns 1-4 are clustered on the bank-year level. P-values are presented in parentheses and statistical significance is denoted as follows: $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Active Monitoring				*Log(Monitoring Frequency)*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lead Share	0.342***	− 0.678	0.716***	0.000	0.981***	−5.771**	0.199	0.000
	(0.047)	(0.458)	(0.339)	(0.000)	(0.314)	(2.526)	(2.219)	(0.000)
Lead Share X Public	−0.131*				−0.757			
	(0.077)				(0.463)			
Lead Share X Log(Maturity)		0.132**				0.874**		
		(0.061)				(0.347)		
Lead Share X Log(Committed)			−0.023				0.029	
			(0.018)				(0.120)	
Lead Share X High Risk				0.143***				0.318
				(0.047)				(0.430)
Adjusted R-Squared	0.300	0.300	0.299	0.296	0.176	0.177	0.174	0.163
Observations	19,729	19,729	19,729	19,729	2,210	2,210	2,210	2,210
Table III Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Origination Year-Quarter Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Industry Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Examiner Ratings	YES	YES	YES	YES	YES	YES	YES	YES
Examiner-Scale Lead Bank Ratings	YES	YES	YES	NO	YES	YES	YES	NO

Table V: Bank Monitoring and Spreads. This table reports OLS regression estimates for the relation between *Active Monitoring* or *Log(Monitoring Frequency)* and the natural log of loan spreads. Controls are the same as in table III. The fixed effects structure for each regression is presented at the bottom of the table. All variables are described in Appendix A. Standard errors in columns 1-3 are clustered on the bank-year level. P-values are presented in parentheses and statistical significance is denoted as follows: $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Active Monitoring			*Log(Monitoring Frequency)*		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Spread)	−0.043***	−0.032***	−0.027**	0.149	0.179*	0.100
	(0.012)	(0.011)	(0.012)	(0.099)	(0.104)	(0.122)
Adjusted R-Squared	0.224	0.262	0.281	0.194	0.275	0.308
Observations	12,685	12,685	10,314	1,407	1,407	1,195
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Origination Year-Quarter Fixed Effects	YES	YES	YES	YES	YES	YES
Industry Fixed Effects	YES	YES	YES	YES	YES	YES
Examiner Ratings	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES
Examiner-Scale Lead Bank Ratings	YES	YES	NO	YES	YES	NO
Lead Bank Fixed Effects	NO	YES	YES	NO	YES	YES
Lead Bank Internal Ratings	NO	NO	YES	NO	NO	YES

Table VI: Bank Monitoring and Covenants. This table reports OLS regression estimates for the relation between *Active Monitoring* or *Log(Monitoring Frequency)* and indicators for different covenants types. Controls are the same as in table III. All variables are described in Appendix A. Standard errors in columns 1-3 are clustered on the bank-year level. P-values are presented in parentheses and statistical significance is denoted as follows: $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Active Monitoring		*Log(Monitoring Frequency)*	
	(1)	(2)	(3)	(4)
Balance Sheet Covenant	0.062***	0.058***	−0.005	−0.040
	(0.011)	(0.013)	(0.068)	(0.083)
Cash Flow Covenant	−0.093***	−0.088***	−0.311***	−0.219***
	(0.014)	(0.022)	(0.066)	(0.078)
CAPEX Covenant	−0.018*	−0.026*	0.004	0.036
	(0.010)	(0.013)	(0.066)	(0.077)
Distributions Covenant	0.002	0.018	0.023	−0.013
	(0.011)	(0.012)	(0.071)	(0.086)
Market Cap. Covenant	−0.005	0.004	−0.334	−0.192
	(0.046)	(0.051)	(0.350)	(0.319)
$Loan-to-Value$ *Covenant*	0.143***	0.117**	−0.287	−0.313
	(0.038)	(0.048)	(0.192)	(0.245)
Adjusted R-Squared	0.360	0.337	0.270	0.325
Observations	19,729	14,539	2,210	1,713
Controls	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Origination Year-Quarter Fixed Effects	YES	YES	YES	YES
Industry Fixed Effects	YES	YES	YES	YES
Examiner Ratings	YES	YES	YES	YES
Examiner-Scale Lead Bank Ratings	YES	NO	YES	NO
Lead Bank Fixed Effects	YES	YES	YES	YES
Lead Bank Internal Ratings	NO	YES	NO	YES

Table VII: Bank Monitoring and Bank Internal Ratings Upgrades and Downgrades. This table reports OLS regression estimates for the relation between *Active Monitoring* or *Log(Monitoring Frequency)* and bank internal ratings downgrades and upgrades as well as key loan, lender, and borrower characteristics. All variables are defined in Appendix A. Standard errors in columns 1-3 are clustered on the bank-year level. P-values are presented in parentheses and statistical significance is denoted as follows: $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Active Monitoring			*Log(Monitoring Freq)*		
	(1)	(2)	(3)	(4)	(5)	(6)
Upgrade	0.029			−0.289*		
	(0.020)			(0.160)		
Downgrade		0.003			0.241*	
		(0.012)			(0.124)	
Δ*Rating*			−0.007			0.202**
			(0.010)			(0.085)
Adjusted R-Squared	0.329	0.329	0.329	0.278	0.278	0.281
Observations	4,907	4,907	4,907	682	682	682
Controls	YES	YES	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES	YES	YES
Orig. Year-Quarter FEs	YES	YES	YES	YES	YES	YES
Industry FEs	YES	YES	YES	YES	YES	YES
Examiner Ratings	YES	YES	YES	YES	YES	YES
Examiner-Scale Lead Ratings	YES	YES	YES	YES	YES	YES
Lead Bank FEs	YES	YES	YES	YES	YES	YES

Table VIII: Bank Monitoring and Credit Line Utilization. This table reports OLS regression estimates for the relation between *Active Monitoring* or *Log(Monitoring Frequency)* and changes in credit line utilization as well as key loan, lender, and borrower characteristics for the credit lines in our sample. All variables are defined in Appendix A. Standard errors in columns 1 and 2 are clustered on the bank-year level. P-values are presented in parentheses and statistical significance is denoted as follows: $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Active Monitoring		*Log(Monitoring Freq)*	
	(1)	(2)	(3)	(4)
$\Delta Utilization$	0.052***	0.033**	−0.047	−0.016
	(0.015)	(0.014)	(0.164)	(0.150)
Adjusted R-Squared	0.162	0.298	0.126	0.256
Observations	6,894	6,894	1,011	1,011
Controls	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES
Orig. Year-Quarter FEs	YES	YES	YES	YES
Industry FEs	YES	YES	YES	YES
Examiner Ratings	YES	YES	YES	YES
Examiner-Scale Lead Ratings	YES	YES	YES	YES
Lead Bank FEs	YES	YES	YES	YES

Table IX: Merger Analysis This table reports OLS regression estimates for the relation between *Active Monitoring* and the lead share proxied by the target's loan share in the previous year. Controls are the covenant types and loan characteristics in shown in table III. Column 3 only uses loans for which the acquiring bank's share was positive. All variables are described in Appendix A. P-values are presented in parentheses and statistical significance is denoted as follows: $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)
		Active Monitoring	
	All Loans	All Loans	No Prior Exposure
Target Share	0.562***	0.659***	0.587**
	(0.207)	(0.229)	(0.242)
Prior Exposure		-0.028	
		(0.032)	
Target Share × Prior Exposure		-0.502	
		(0.381)	
Adjusted R-Squared	0.382	0.383	0.409
N	934	934	700
Controls	YES	YES	YES
Industry FEs	YES	YES	YES
Year Fixed Effects	YES	YES	YES
Origination Year-Quarter Fixed Effects	YES	YES	YES
Examiner Ratings	YES	YES	YES
Examiner-Scale Lead Bank Ratings	YES	YES	YES
Lead Bank Fixed Effects	YES	YES	YES

Table X: Bank Monitoring and Loan Outcomes This table presents OLS regression estimates of future loan outcomes (at time $t+1$) on indicators for active bank monitoring (Panels A) and monitoring frequency (Panel B) at time t . The regression specifications include year, origination quarter, industry, examiner and lead bank rating, as well as lead bank FEs. All variables are defined in Appendix A. P-values are presented in parentheses and statistical significance is denoted as follows: $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: *Active Monitoring*

	$Violation_{it+1}$		Waiver$_{it+1}$		Renegotiation$_{it+1}$	
Active Monitoring	0.123***	0.119***	−0.009	−0.009	0.036**	0.055***
	(0.030)	(0.030)	(0.027)	(0.027)	(0.017)	(0.018)
Lead Share		0.195***		0.037		−0.499***
		(0.057)		(0.048)		(0.097)
Adjusted R-Squared	0.193	0.196	0.201	0.201	0.038	0.059
Observations	4,983	4,983	2,274	2,274	11,090	11,090

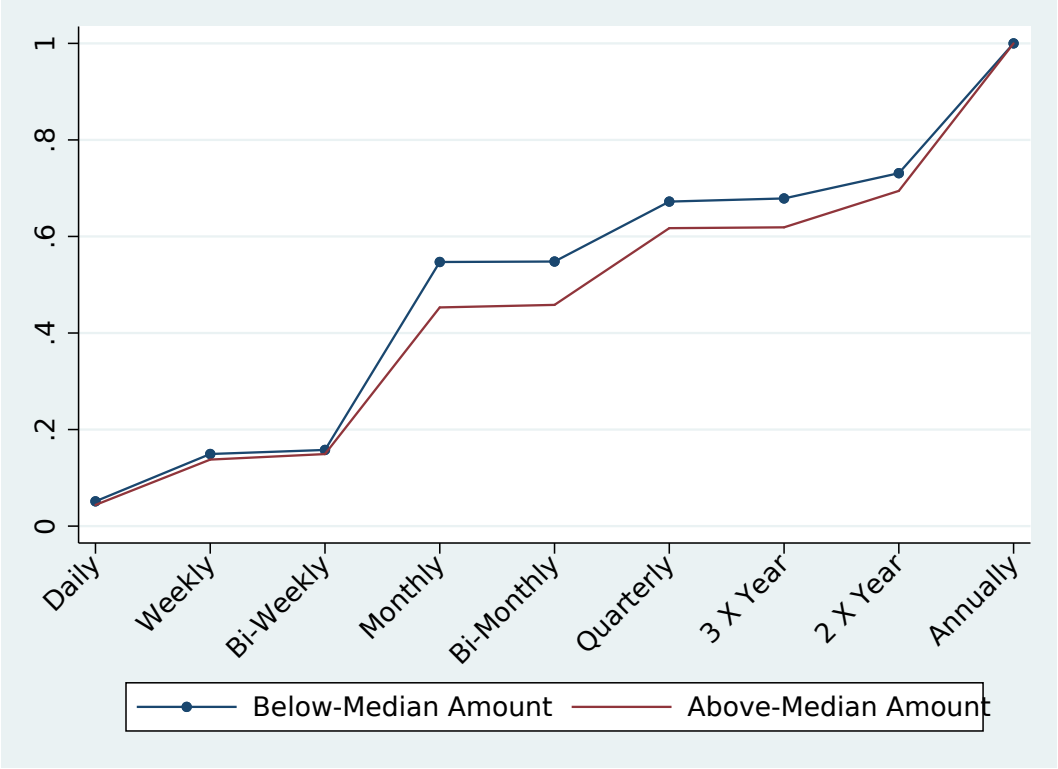
Panel B: *Log(Monitoring Frequency)*

	$Violation_{it+1}$		Waiver$_{it+1}$		Renegotiation$_{it+1}$	
Log(Monitoring Frequency)	−0.008	−0.009	0.044**	0.044**	−0.016	−0.013
	(0.024)	(0.024)	(0.022)	(0.022)	(0.013)	(0.013)
Lead Share		0.151		0.023		−0.290***
		(0.167)		(0.114)		(0.109)
Adjusted R-Squared	0.324	0.324	0.517	0.515	0.088	0.094
Observations	553	553	289	289	1,262	1,262

Table B.I: Heckman Selection Model Heckman regression estimates are reported for the relation between the log of monitoring frequency (dependent variable) and key loan, lender, and borrower characteristics. The exclusion restriction in the first-stage equation is the fixed effects associated with the loan examiners that are assigned to each SNC loan. All variables are defined in Appendix A. P-values are presented in parentheses and statistical significance is denoted as follows: $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

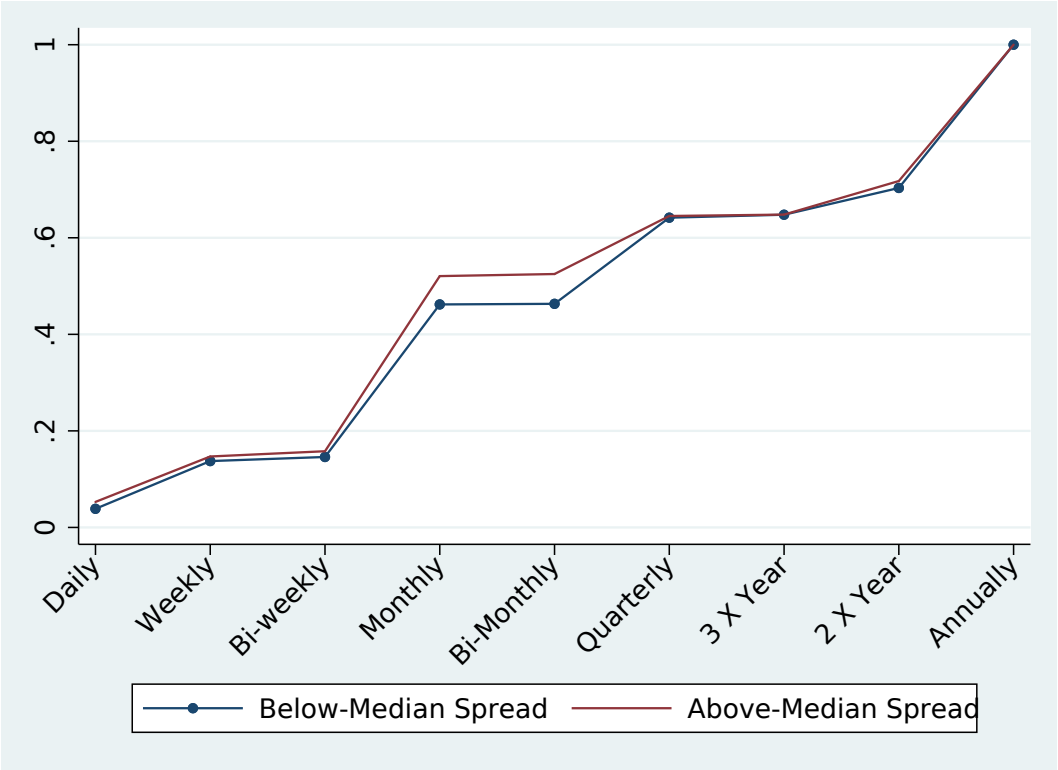
	$Log(Monitoring\ Frequency)$		
	(1)	(2)	(3)
Lead Share	0.921^{***}	0.853^{***}	0.466^{**}
	(0.185)	(0.184)	(0.192)
Number of Covenants	-0.114^{***}	-0.114^{***}	-0.107^{***}
	(0.023)	(0.023)	(0.023)
Log(Maturity)	-0.378^{***}	-0.364^{***}	-0.319^{***}
	(0.082)	(0.083)	(0.080)
Public	-0.137^{**}	-0.120^{*}	-0.071
	(0.062)	(0.062)	(0.061)
High Volatility Collateral	0.528^{***}	0.546^{***}	0.493^{***}
	(0.090)	(0.090)	(0.089)
Low Volatility Collateral	-0.259^{***}	-0.276^{***}	-0.171^{***}
	(0.066)	(0.066)	(0.064)
Lender Herfindahl	0.468^{*}	0.425^{*}	0.441^{*}
	(0.254)	(0.254)	(0.243)
Log(Committed)	0.017	0.032	0.034
	(0.026)	(0.026)	(0.026)
Term Loan	-0.143^{*}	-0.155^{**}	-0.082
	(0.077)	(0.078)	(0.074)
Unsecured	-0.770^{***}	-0.748^{***}	-0.642^{***}
	(0.216)	(0.216)	(0.213)
λ	0.283^{**}	0.289^{**}	0.117
	(0.129)	(0.130)	(0.130)
Observations, second-stage	2,210	2,210	2,210
Observations, selection equation	18,798	18,786	18,786
Year Fixed Effects	YES	YES	YES
Origination Year-Quarter Fixed Effects	YES	YES	YES
Industry Fixed Effects	YES	YES	YES
Examiner Ratings	NO	YES	YES
Examiner-Scale Lead Bank Ratings	NO	YES	YES
Lead Bank Fixed Effects	NO	NO	YES

Internet Appendix



(a) *Monitoring Frequency and Loan Amount*

Figure IA.I: Monitoring Frequency and Loan Amount This figure plots the cumulative density function (CDF) of monitoring frequency partitioned by whether the loans are above or below median in loan amount. The x-axis plots monitoring frequency, thus a point on the figure corresponds to the percentage of loans that are monitored at least as frequently as the interval listed on the x-axis.



(a) *Monitoring Frequency and Loan Spread*

Figure IA.II: Monitoring Frequency and Loan Spread This figure plots the cumulative density function (CDF) of monitoring frequency partitioned by whether the loans are above or below median in loan spread. The x-axis plots monitoring frequency, thus a point on the figure corresponds to the percentage of loans that are monitored at least as frequently as the interval listed on the x-axis.

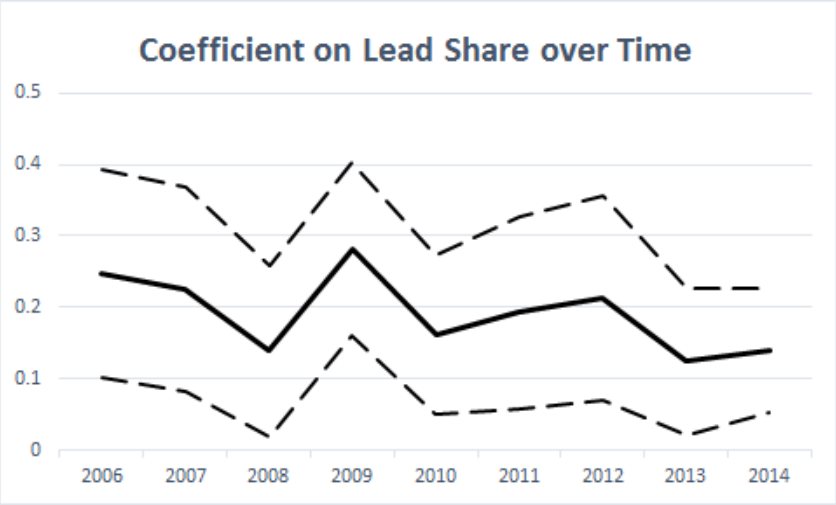


Figure IA.III: Monitoring over Time. This figure plots the year-by-year coefficients from a regression of lead share on active monitoring.

Table IA.I: Monitoring Matrix. This table presents a complete breakdown of bank monitoring frequencies (see column entries) conditional on a loan being monitored at the maximum frequencies indicated in each row. Loans in our sample are monitored daily, weekly, bi-weekly, monthly, bi-monthly, quarterly, three times a year, semi-annually, and annually.

	N	Daily	Weekly	Bi-Weekly	Monthly	Bi-Monthly	Quarterly	3 X Year	2 X Year	Annually
Daily	105	100.00%	15.24%	2.86%	27.62%	0.95%	11.43%	5.71%	5.71%	16.19%
Weekly	212		100.00%	0.00%	57.08%	0.00%	10.38%	6.60%	23.11%	36.32%
Bi-Weekly	22			100.00%	31.82%	0.00%	0.00%	0.00%	4.55%	9.09%
Monthly	763				100.00%	0.00%	8.39%	1.31%	6.29%	19.66%
Bi-Monthly	7					100.00%	0.00%	0.00%	0.00%	57.14%
Quarterly	314						100.00%	0.00%	2.55%	8.60%
3 X Year	9							100.00%	22.22%	0.00%
2 X Year	142								100.00%	61.97%
Annually	636									100.00%

Table IA.II: Bank Monitoring and Spreads. This table reports OLS regression estimates for the relation between *Active Monitoring* or *Log(Monitoring Frequency)* and the natural log of loan spreads. Controls are the same as in table III. The fixed effects structure for each regression is presented at the bottom of the table. All variables are described in Appendix A. Standard errors in columns 1-3 are clustered on the bank-year level. P-values are presented in parentheses and statistical significance is denoted as follows: $*p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

	Active Monitoring			*Log(Monitoring Frequency)*		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Spread)	−0.043***	−0.032***	−0.027**	0.149	0.179*	0.100
	(0.012)	(0.011)	(0.012)	(0.099)	(0.104)	(0.122)
Lead Share	0.276***	0.175***	0.146***	0.921***	0.292	0.620
	(0.043)	(0.040)	(0.048)	(0.280)	(0.364)	(0.487)
Public	−0.040***	−0.033***	−0.040***	−0.126	−0.051	−0.078
	(0.008)	(0.008)	(0.008)	(0.101)	(0.084)	(0.105)
Log(Maturity)	−0.115***	−0.090***	−0.075***	−0.222*	−0.307**	−0.324
	(0.017)	(0.017)	(0.020)	(0.128)	(0.144)	(0.191)
Number of Covenants	−0.013***	−0.016***	−0.016***	−0.116***	−0.114***	−0.096*
	(0.004)	(0.004)	(0.005)	(0.040)	(0.039)	(0.050)
High Volatility Collateral	−0.134***	−0.141***	−0.133***	0.390***	0.414***	0.438***
	(0.025)	(0.026)	(0.028)	(0.130)	(0.100)	(0.105)
Low Volatility Collateral	−0.051***	−0.039**	−0.029	−0.266***	−0.200**	−0.197*
	(0.017)	(0.019)	(0.021)	(0.081)	(0.088)	(0.109)
Lender Herfindahl	0.044	0.062	0.078	0.011	0.295	0.223
	(0.041)	(0.044)	(0.048)	(0.345)	(0.270)	(0.456)
Log(Committed)	0.007	0.009*	0.010**	0.007	0.018	0.072
	(0.005)	(0.005)	(0.004)	(0.048)	(0.049)	(0.048)
Term Loan	0.022*	0.016	0.017*	−0.116**	−0.112**	−0.207***
	(0.011)	(0.010)	(0.010)	(0.055)	(0.055)	(0.072)
Unsecured	−0.083***	−0.080***	−0.087***	−0.484*	−0.520*	−0.727***
	(0.024)	(0.029)	(0.030)	(0.285)	(0.266)	(0.225)
Adjusted R-Squared	0.224	0.262	0.281	0.194	0.275	0.308
Observations	12,685	12,685	10,314	1,407	1,407	1,195
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Origination Year-Quarter Fixed Effects	YES	YES	YES	YES	YES	YES
Industry Fixed Effects	YES	YES	YES	YES	YES	YES
Examiner Ratings	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES
Examiner-Scale Lead Bank Ratings	YES	YES	NO	YES	YES	NO
Lead Bank Fixed Effects	NO	YES	YES	NO	YES	YES
Lead Bank Internal Ratings	NO	NO	YES	NO	NO	YES

Table IA.III: Bank Monitoring and Covenant Intensity. This table reports OLS regression estimates for the relation between *Active Monitoring* or *Log(Monitoring Frequency)* and covenant intensity as defined by the number of covenant types. Controls are the same as in table III. All variables are described in Appendix A. Standard errors in columns 1-3 are clustered on the bank level. P-values are presented in parentheses and statistical significance is denoted as follows: $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Log(Monitoring Frequency)				*Active Monitoring*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cov. Types = 1	−0.159	−0.087	−0.093	−0.059	−0.155***	−0.081***	−0.043***	−0.048***
	(0.109)	(0.121)	(0.093)	(0.112)	(0.023)	(0.013)	(0.009)	(0.012)
Cov. Types = 2	−0.511***	−0.491**	−0.377**	−0.330	−0.222***	−0.150***	−0.084***	−0.080***
	(0.147)	(0.172)	(0.147)	(0.195)	(0.028)	(0.021)	(0.013)	(0.018)
Cov. Types = 3	−0.585***	−0.553***	−0.438***	−0.358*	−0.218***	−0.152***	−0.089***	−0.085***
	(0.165)	(0.179)	(0.164)	(0.209)	(0.032)	(0.021)	(0.015)	(0.020)
Cov. Types = 4+	−0.398***	−0.352***	−0.274**	−0.131	−0.147***	−0.117***	−0.068***	−0.083***
	(0.128)	(0.124)	(0.116)	(0.093)	(0.034)	(0.024)	(0.022)	(0.022)
Adjusted R-Squared	0.025	0.161	0.274	0.330	0.038	0.193	0.351	0.328
Observations	2,210	2,210	2,210	1,713	19,729	19,729	19,729	14,539
Lead Bank Fixed Effects	NO	YES	YES	YES	NO	YES	YES	YES
Year Fixed Effects	NO	YES	YES	YES	NO	YES	YES	YES
Risk & Opacity Controls	NO	NO	YES	YES	NO	NO	YES	YES
Banks' Internal Ratings (Own Scale)	NO	NO	NO	YES	NO	NO	NO	YES

Table IA.IV: Bank Monitoring and Loan Outcomes: Private and Public Firms This table presents OLS regression estimates of future loan outcomes (at time $t+1$) on indicators for active bank monitoring for private and public firms at time t. The regressions include year, origination quarter, industry, examiner and lead bank rating, as well as lead bank FEs. All variables are defined in Appendix A. P-values are presented in parentheses and statistical significance is denoted as follows: $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Private Companies

	$Violation_{it+1}$		$Waiver_{it+1}$		$Renegotiation_{it+1}$	
Active Monitoring	0.096***	0.096***	-0.027	-0.026	0.037**	0.047***
	(0.034)	(0.034)	(0.040)	(0.040)	(0.017)	(0.017)
Lead Share		0.129		0.049		-0.394***
		(0.079)		(0.051)		(0.079)
Adjusted R-Squared	0.213	0.214	0.262	0.262	0.051	0.067
Observations	2,930	2,930	1,515	1,515	6,832	6,832

Panel B: Public Companies

	$Violation_{it+1}$		$Waiver_{it+1}$		$Renegotiation_{it+1}$	
Active Monitoring	0.127**	0.124**	0.054*	0.054*	-0.006	0.025
	(0.053)	(0.053)	(0.029)	(0.030)	(0.033)	(0.034)
Lead Share		0.201		0.028		-0.929***
		(0.127)		(0.059)		(0.158)
Adjusted R-Squared	0.209	0.211	0.222	0.221	0.032	0.080
Observations	2,053	2,053	759	759	4,258	4,258

Table IA.V: Bank Monitoring and Covenant Types. This table reports OLS regression estimates for the relation between *Active Monitoring* or *Log*(*Monitoring Frequency*) and specific covenant types and interactions with the lead share. P-values are presented in parentheses and statistical significance is denoted as follows: $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)
	Monitoring Frequency		*Active Monitoring*	
Lead Share	0.410	0.127	0.166***	0.288***
	(0.263)	(0.342)	(0.034)	(0.058)
CAPEX	0.023	0.118	-0.014	-0.010
	(0.100)	(0.083)	(0.010)	(0.012)
Cash Flow	-0.397***	-0.508***	-0.101***	-0.069***
	(0.079)	(0.112)	(0.013)	(0.013)
Net Worth	-0.050	0.106	0.038***	0.038
	(0.126)	(0.203)	(0.014)	(0.027)
DA	-0.347*	-0.488	0.139***	0.161**
	(0.185)	(0.382)	(0.037)	(0.062)
BB	0.170	0.205	-0.013	0.000
	(0.105)	(0.148)	(0.025)	(0.031)
CASH	0.095	0.416*	0.067***	0.030
	(0.135)	(0.215)	(0.024)	(0.041)
CURRENT	-0.147	-0.166	0.057**	0.174***
	(0.166)	(0.221)	(0.023)	(0.035)
COV	-0.079	-0.203*	-0.014	-0.011
	(0.096)	(0.109)	(0.009)	(0.010)
DCAP	-0.310	-0.257	-0.022	0.018
	(0.269)	(0.714)	(0.049)	(0.063)
DIST	0.002	-0.202	-0.001	0.005
	(0.108)	(0.159)	(0.012)	(0.021)
CAPEX × Lead Share		-0.459		-0.017
		(0.342)		(0.044)
Cash Flow × Lead Share		0.480		-0.162***
		(0.378)		(0.058)
Net Worth × Lead Share		-0.625		0.008
		(0.433)		(0.085)
DA × Lead Share		0.527		-0.081
		(1.438)		(0.142)
BB × Lead Share		-0.190		-0.058
		(0.483)		(0.124)
CASH × Lead Share		-1.295*		0.141
		(0.730)		(0.147)
CURRENT × Lead Share		0.091		-0.518***
		(0.827)		(0.138)
COV × Lead Share		0.491		-0.021
		(0.317)		(0.045)
DCAP × Lead Share		-0.461		-0.208
		(2.990)		(0.246)
DIST × Lead Share		0.813*		-0.023
		(0.421)		(0.075)
Adjusted R-squared	0.283	0.286	0.364	0.366
Oberservations	2,210	2,210	19,729	19,729