# Bank Monitoring: Evidence from Syndicated Loans*

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**Abstract**

The rise in popularity of syndicated lending raises questions about the incentives of banks to actively monitor borrowers. We empirically investigate these incentives using a novel dataset that includes the frequency with which banks monitor borrowers' financial condition and the collateral underlying syndicated bank loans. We find that banks monitor frequently with approximately 50% of loans being monitored at least on a monthly basis. Monitoring frequency is increasing in the lead arranger's loan share for private borrowers and the lead bank's reputation for public borrowers. These results are consistent with lender reputation mitigating moral hazard only to the extent that monitoring effort is verifiable. Lead banks also monitor more when monitoring is likely to produce new information and when information is more valuable, such as when borrower financial health deteriorates. Overall, our results suggest that banks actively monitor the average syndicated loan in a manner consistent with theoretical predictions in the literature.

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# 1 Introduction

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 advantage in information production and make them a natural choice to monitor borrowers on behalf of depositors and other investors. However, the incentive for banks to monitor has become less clear with the rise of syndicated lending, which now totals approximately \$4.7 trillion in proceeds worldwide,[1] and the propensity of lenders to securitize and resell loans.[2] Yet, there is little direct evidence on how frequently banks monitor syndicated loans or which theoretical predictions regarding the determinants of monitoring intensity are most empirically relevant. Due to the lack of publicly available data, existing studies on this topic rely on indirect evidence based on the examination of the determinants of syndicate structure or loan covenants.[3]

The purpose of this paper is to provide direct empirical evidence on how banks monitor syndicated loans. To do so, we use a novel dataset that includes information on the frequency with which bank engages in monitoring activity such as scrutinizing borrower financial statements, checking the inventory or receivables pledged as collateral, or revaluing real estate and other fixed assets securing the loan.[4] Our sample comes from the Shared National Credit (SNC) program, which includes all syndicated deals exceeding \$20 million and that are held by three or more Federally-supervised institutions. Starting with the 2007 annual SNC exam, we observe detailed information on loan collateral and financial covenants for the subset of examined loans.

We first document that banks monitor the average syndicated loan frequently and that

[1]See Global Syndicated Loans Review for year 2015 at http://dmi.thomsonreuters.com.

[2]Parlour and Plantin (2008) show that the presence of a secondary market for loans reduces monitoring incentives. Irani and Meisenzahl (2015) document that U.S. bank holding companies sell, on average, 10 percent of their syndicated loan portfolio each year.

[3]See, for example, Lee and Mullineaux (2004) and Sufi (2007) regarding syndicate structure, and Sufi (2009) and Wang and Xia (2014) regarding covenants.

[4]In this paper, we only consider monitoring of pre-existing loans and not initial screening of borrowers or projects as in Holmstrom and Tirole (1997).

there is substantial variation in monitoring frequency. For instance, approximately 50 percent of loans are monitored at least on a monthly basis, 5 percent of loans are monitored daily, while 29 percent are monitored only once per year. We exploit this significant dispersion in monitoring frequency to understand the relative importance of factors theorized to effect the monitoring frequency of syndicated loans.

Theory suggests that bank monitoring benefits borrowers and their stakeholders, (see, Diamond (1991) and Von Thadden (1995)), however the structure of the loan contract critically affects the bank's incentive to monitor (see, Rajan and Winton (1995); Park (2000); Gorton and Kahn (2000)). This is particularly relevant in the syndicated lending market. Monitoring is unobservable and the lead arranger conducts most of the monitoring after loan origination, but it is only a partial stakeholder in the loan. This creates a moral hazard problem (as in Holmstrom (1979)) between the lead arranger and the rest of the syndicate.Our first set of tests investigates the theoretical prediction that banks will retain a larger stake in loans likely to require intensive monitoring to alleviate this moral hazard problem and credibly commit to monitoring on behalf of the syndicate.

We find a positive association between the retained lead's share and monitoring frequency.[5] The median (average) stake the lead arranger retains is 22% (24%). Approximately 59% of loans in which lead arrangers retain an above-median share in the loan are monitored at least on a monthly basis, compared to only 40% of loans in which lead arrangers retain a below-median stake. Regression estimates confirm an economically and statistically significant positive association between lead share and monitoring frequency. After controlling for credit quality, loan characteristics, as well as lender, industry, and year fixed effects, we estimate that a one standard deviation increase in the lead bank's share is associated with a 10% increase in monitoring frequency.

This positive association between the stake of the lead arranger and monitoring frequency

[5] In the data, we only observe the lead share as of year-end, not at origination. Lead banks may have already sold part of their share after originations. Ivashina and Scharfstein (2010) suggest that the lead share can also reflect demand factors at the time of loan origination.

corroborates an important theoretical construct in the bank monitoring literature (see Park (2000)). Moreover, it supports the approach of prior empirical research that uses the lead share to understand monitoring incentives (Lee and Mullineaux (2004); Sufi (2007)). Perhaps most importantly, however, 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.

Reputation is a second mechanism through which lead arrangers can mitigate moral hazard within the syndicate. Because syndication is a repeated game, a reputable lender may have the incentive to monitor to protect its reputation (Chemmanur and Fulghieri (1994); Paravisini and Lin (2013)). We find some empirical support for this mechanism, as a lead lender's share of annual syndicate interactions, which is our proxy for reputation, is positively associated with monitoring intensity. Interestingly, a stake in the loan and reputational considerations are associated with increased monitoring for different types of borrowers. For public borrowers, where public filings and disclosures make monitoring effort more verifiable ex-post, there is no significant association between monitoring frequency and the lead's loan share, but a strong positive association between reputational concerns and monitoring frequency. For private borrowers, we find the opposite. This is consistent with lead arrangers preferring to commit to monitoring via reputation, but having to retain a large stake to the extent that monitoring effort is more costly to verify.

We also find some evidence that private borrowers are monitored more frequently, which is consistent with our prediction that monitoring will be most frequent when it produces new information. We find the strongest support for this prediction when applying it to the relation between monitoring frequency and the volatility of the value of the collateral securing the loan. We predict that monitoring will be increasing in the volatility of collateral because monitoring is more likely to produce new information in these instances. We find support for this prediction as the 40% of loans secured only by fixed assets, including real estate, are monitored significantly less frequently than loans secured by assets with more volatile value, such as accounts receivable and inventories. For instance, banks monitor only 38% of loans secured by fixed assets at least at a monthly frequency compared to approximately 70% of loans secured by volatile collateral. In fact, almost a quarter of loans secured by volatile assets are monitored at least every week. This suggests that the common assumption that collateral substitutes for monitoring (see, e.g., Holmstrom and Tirole (1997)) is most applicable to collateral with low volatility, otherwise an important part of monitoring becomes monitoring the collateral itself.

Banks are likely to take into account not only how much information monitoring will produce, but also the value of that information. Information is particularly valuable is when it is likely to become immediately actionable. This idea underlies the arguments in Barclay and Smith (1995), Rajan and Winton (1995), and Park (2000) that shortening a loan's maturity makes monitoring more useful because it provides the bank more frequent opportunities to use their information in renegotiation. We find empirical support for this argument as shorter maturity loans are monitored more frequently.

Rajan and Winton (1995) extend this argument and suggest that loan covenants on longer term loans create similar incentives and thus should also increase monitoring frequency—in other words, covenants and monitoring are complements. However, a competing prediction is that because covenant violations 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)), a lender may wait to monitor until an adverse shock causes a likely covenant violation—covenants may substitute for frequent monitoring. Our empirical tests suggest that on average covenants substitute for active monitoring as there is a significant negative association between the number of covenant types in a loan and monitoring frequency.

One limitation to our data is that because almost two-thirds of our sample is non-public firms we are unable to include many firm-level control variables. Although this precludes us from investigating firm-level determinants of monitoring, it is unlikely to bias our analysis because of the rich set of loan-level characteristics we observe. For example, we include both the bank examiner's and the lender's own loan ratings, which is an ideal set of controls for financial condition of a firm because it captures the regulators' and the lenders' assessments of loan quality. However, because each lender uses their own rating scale, it is difficult to directly test the intuitive prediction that banks monitor financially riskier borrowers more often.

Instead, we test the related prediction that a change in financial condition affects monitoring frequency by regressing monitoring frequency on separate indicators for lender rating upgrades and downgrades during the previous year.[6] We find that banks monitor firms significantly more (less) frequently following ratings downgrades (upgrades). This result is consistent with our prediction that banks will monitor more frequently as information on the borrower becomes more valuable. Indeed, as borrower health deteriorates tighter covenants make information more actionable and the syndicate's stake in the loan becomes more sensitive to the value of the borrower and the loan's collateral. Thus, our findings suggest that banks dynamically adjust their monitoring frequency over the course of the loan according to the expected benefits of monitoring.

One concern with our data set is that Federal supervisors collect information on monitoring frequency only for a subset of examined loans. Although the loan characteristics of this subset are comparable to the exam sample and the full SNC sample, the availability of information on monitoring frequency could be correlated with unobserved loan-quality. To address this concern, we use the propensities of different bank examiners to collect monitoring frequency information as an instrument for whether monitoring frequency is available for a given loan.[7] We find that the examiners' fixed effects are highly significant predictors of the likelihood that we observe monitoring frequency and all of our results are robust to the use of a Heckman two-stage selection model.

[6]This reduces our sample size by approximately 60% because the ratings change is only defined for loans with two post-origination annual filings that have not been renegotiated or terminated.

[7]Sampat and Williams (2015) use a similar approach for patent approvals.

The strength of this paper is our novel measure of bank monitoring frequency. Although we cannot explore other dimensions of bank monitoring quality, such as the intensity of each monitoring engagement, to our knowledge we are the first study to provide direct empirical evidence on how US banks monitor syndicated loans. 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)). Unlike these studies, we investigate a wide range of determinants of bank monitoring using a direct measure – the frequency with which banks monitor borrowers. Perhaps, the paper closest to ours is Plosser and Santos (2016) that uses bank internally-generated risk probability of default estimates to understand bank monitoring activity. Their study complements ours by providing new evidence on the incremental information banks have as compared to outside markets on a quarterly frequency. We find that banks receive such information considerably more frequently as about half of loans are monitored at least on a monthly frequency.[8]

Overall, our findings suggest that syndicate structure and lender reputation serve to mitigate intra-syndicate moral hazard, leading to active monitoring in a manner that is consistent with theoretical predictions.

# 2 Sample Description

## 2.1 The Share National Credit Database

Our sample comes from the Shared National Credit (SNC) database. The SNC database is collected by the Board of Governors of the Federal Reserve System, the Federal Deposit Insurance Corporation (FDIC), and the Office of the Comptroller of the Currency (OCC) and includes all syndicated deals exceeding $20 million and held by three or more Federally

[8]In addition, 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) and 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.

supervised institutions. At the beginning of each year, examiners from the three Federal agencies select a subsample of loans from the entire SNC portfolio "to review and assess risk in the largest and most complex credits shared by multiple financial institutions."[9] These sampled loans are weighted toward non-investment grade credits based on the loan credit quality information submitted by each Federally-supervised institution.[10] During our sample period, which runs from 2007 through 2015, the fraction of total lending volume that was sampled in the annual SNC exams ranges from 27% (in 2013) to 41% (in 2009) of the entire SNC portfolio.

The annual reviews of the sampled loans are conducted in May of each year. The information examiners collect and analyze during the field exams is typically as of December $31^{st}$ of the previous calendar year, although occasionally banks provide information as of March $31^{st}$ of the current year. For example, SNC reviews conducted in May of 2014 are based on borrower and loan information as of December of 2013 or March of 2014.

Starting with the 2007 annual SNC exam, we observe detailed information on the financial covenants and collateral of each examined loan. As part of this process, examiners collect information on the frequency with which the lead bank monitors various aspects of the loan, including financial statements and collateral. Often examiners report only the date of the most recent monitoring event, however in many cases they also report the frequency with which monitoring events occur. Because the annual frequency of the data makes it difficult to infer monitoring frequency from the date of the most recent monitoring event, we restrict our analysis to loans of U.S. based borrowers for which we can identify the number of monitoring events throughout the year. Our final sample consists of a total of 2,210 loan-years with sufficient data.

Another advantage of the SNC database is that it contains detailed data on covenants and collateral. The covenant data includes information on the types of covenants in each

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

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

credit facility such as restrictions on accounting ratios and capital expenditures, the current levels at which the financial covenants are set, and whenever available, the current level of the borrower-specific accounting variables underlying the covenants. The collateral data includes information on whether the loan is secured, the type of collateral securing each loan, the collateral valuation, as well as a detailed description of the collateral, including valuation methods and any relevant monitoring activity by the lead bank.

## 2.2 Descriptive Statistics

In this section, we provide descriptive statistics regarding the explanatory variables used throughout our analysis. Table I shows that the average (median) *Lead Share*, defined as the fraction of the total loan amount retained by the lead lender, is equal to 24.1% (22.2%),[11] the average (median) loan amount is $309 ($125) million and the average (median) loan maturity is 1,895 (1,826) days. Table I also shows that the loan facilities in our sample have an average (median) of 1.82 (2) types of covenants and 36.3% of the borrowers are public companies.[12] In addition, approximately 21% of the loans in our sample are secured only by collateral with high volatility of asset value such as accounts receivable or inventories. Another 40% are secured only by collateral with low volatility of asset value such as property, plant, and equipment. Most other loans are secured by both fixed and liquid assets as only 3% of loans are unsecured. See Appendix A for detailed variable definitions.

Table II extends these descriptive statistics by comparing our test sample to the SNC database. This comparison is important because it speaks to whether our test sample's selection criteria are likely to affect the generalizability of our results. Columns 1 and 2 of II replicate the mean and median statistics from Table I for our test sample. Columns 3 and 4 of II present similar statistics from the full sample of examined loans, for which we have

[11] This is also similar to the average (median) of 28.5% (23.5%) reported in Sufi (2007).

[12] The *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, Cash, Current Ratio, Interest Coverage, Debt to Capitalization, Distributions.

collateral and covenant data, while Columns 5 and 6 describe the full SNC database over our sample period.

Overall, our test sample appears economically similar to both comparison samples on most dimensions. For example, loan amount and maturity are almost in terms of both means and medians identical across the three samples. The average and median *Lead Shares* in the test sample are very similar to those in the full SNC sample, but somewhat larger than those in the sample of examined loans. All three samples have between 36% and 39% public borrowers. Most of the economically meaningful differences between the three samples relate to the stated goal of examining non-investment grade quality loans more frequently. For example, sampled firms tend to have used a larger fraction of the loan commitment.

Table II also shows that loans in the test sample are more likely to be secured than those in the entire exam sample, suggesting that our requirement that annual monitoring frequency be reported affects sample composition. Specifically, we are more likely to have loans that are secured by volatile assets. Although this difference is statistically and economically significant, we have a large fraction of loans that are secured by only fixed assets that should allow us to examine monitoring across the entire cross-section of secured loans.

Finally, it is worth noting that our sample is similar to the DealScan database on the dimensions across which we have comparable data. For example, during our sample period the average (median) loan amount and maturity in the DealScan database are $280 ($86) and 1,768 (1,826) days, respectively. Overall, although there are some small differences, our test sample is similar to the universe of bank loans in both the SNC and DealScan databases. While it is reassuring that there are only minor differences between the subsample with monitoring information and the full SNC sample and Dealscan, loans for which the monitoring information was collected may not have been chosen at random. In Section 7 we we employ a Heckman selection model to directly address any biases that may emerge from the fact that our test sample is selected, possibly based on unobservable characteristics.

# 3 Bank Monitoring Frequency

In this section, we provide a detailed description of our measure of bank monitoring as well as novel descriptive evidence on how frequently banks monitor borrowers.

Our monitoring measure comes from the loan examination reports of the Federal Supervisors conducting the SNC exam. As an example, below is an excerpt from the collateral description of one of the typical loans for which we have monitoring frequencies information:

> *"Collateral on the operating line consists of accounts receivable and inventory. The term loan is secured with a 2nd lien on accounts receivable and inventory and 1st liens on PP&E, intangibles, and stock of subsidiaries. Borrower does not have the ability to substitute collateral. Controls: springing cash dominion, annual plant visits, quarterly client visits, monthly financial statements, monthly borrowing base certifications, accounts receivable aging, and inventory reports, field audits and inventory appraisals twice a year, and daily accounts receivable and inventory monitoring. Accounts Receivable Field Audit dated 03/29/10 was satisfactory overall. There were minor discrepancies in the borrower's BBC calculations, but nothing that resulted in an overadvance."*

This excerpt demonstrates the complexity of the bank monitoring process.[13] The lead lender conducts comprehensive audits of the borrower at frequencies that range from annual plant visits and quarterly client visits to daily accounts receivable and inventory monitoring. Not only is there significant within-loan variation in the type of monitoring that the bank performs, but the bank also conducts each type of monitoring at different frequencies.

To aggregate this complex monitoring process into a statistically tractable form, we define our primary variable of interest, $Monitoring\ Frequency$, as the maximum number of times a given loan is monitored within a year. As such, daily (365 times) is the highest frequency and annually (1 time) is the lowest frequency. Although, we undoubtedly lose some information through this aggregation, the maximum monitoring frequency is an informative measure of bank monitoring activity as it is closely related to monitoring costs. Notably, we do not claim to measure other dimensions of bank monitoring quality such as monitoring

[13]The examination reports we draw from also typically contain the examiner assessment of each loan. As this information is privileged, we are unable to present the additional detail from these descriptions.

effort or expertise.

Figure 1 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.

Table III summarizes *Monitoring Frequency* and shows all monitoring frequencies in our sample conditional on the maximum monitoring frequencies being daily, weekly, etc. (in the rows). The first row presents descriptive statistics on the 105 loans in our sample that are monitored at a daily frequency. Approximately half of these loans are also monitored at other frequencies, with the most common other frequencies being monthly and annually. The second row provides similar statistics for the 212 loans with a weekly maximum monitoring frequency. Most of these loans are also monitored on a monthly basis. This evidence aligns with the above excerpt in suggesting that a large fraction of loans are monitored at frequencies other than the maximum frequency.

Although we provide descriptive evidence using this untransformed measure of monitoring frequency, we take the natural log in our empirical tests. 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. Thus, the transformed variable generates economically interesting variation in monitoring frequency when used in an OLS framework.

# 4 Empirical Predictions and Descriptive Evidence

In this section, we derive predictions on the determinants of the variation in bank monitoring frequency based on the theoretical literature in financial intermediation. Three results highlighted in this literature are that monitoring should be increasing in (1) the bank's incentive to monitor, (2) the expected information produced from monitoring, and (3) the value the bank places on that information.

## 4.1 Lead Bank Incentives

Banks need to be incentivized to monitor. 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. This idea uniquely manifests itself in the syndicated loan market, which can be thought of as an intermediate step between the bank lending and public debt markets (see, e.g., Dennis and Mullineaux (2000)). Similar to the traditional bank lending market, the lead arranger is responsible for most monitoring effort. Unlike the traditional 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 suboptimal monitoring.[14]

Given this moral hazard problem rooted in the syndication process, an intuitive prediction is that the lead arranger can mitigate the 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 this result, the empirical literature has assumed that the lead's stake in the loan is a plausible empirical proxy for monitoring intensity.[15] Using the SNC data, we can measure both monitoring frequency and the lead share, which allows us to test this assumption. Our first empirical prediction, prediction I, is a positive relationship between the lead bank's loan share and monitoring frequency.

Figure 2 Panel (a) plots cumulative density functions (CDF) of monitoring frequency to

[14]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.

[15]See, e.g., Sufi (2007).

provide descriptive evidence on this prediction. 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.

In line with prediction I, there is a strong positive association between the lead arranger's stake and monitoring frequency—that is, 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. To our knowledge, we are the first to directly document the link between the loan share the lead retains and monitoring frequency.

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. We proxy for lender reputation using the lead arrangers share of syndicate member interactions. This measure is similar to market share based reputation measures used by Lee and Mullineaux (2004) and Sufi (2007), but more directly captures the size of the lender's network of business partners.

Empirical prediction II is a positive association between monitoring frequency and lender reputation. Panel (b) of Figure 2 descriptively investigates this by presenting separate monitoring frequency CDFs for lenders with above- and below-median values of our reputation measure. The figure reveals little relation between reputation and monitoring frequency. One explanation for this null result is that non-reputable banks tend to service riskier borrowers, which require more frequent monitoring. In Section 5, we revisit the relation between lender reputation and monitoring frequency after controlling for other determinants of monitoring frequency, such as credit risk.

## 4.2 Expected Information Production

Monitoring should be increasing in the expected amount of information monitoring will produce. We first apply this general prediction to the loan's collateral value. Empirical prediction III is that monitoring will be increasing in the volatility of collateral value because monitoring is likely to produce new information in these instances. Panel (a) of Figure 3 investigates this prediction by plotting the CDF of monitoring frequencies split by collateral type. Banks conduct weekly monitoring on only approximately 9% of loans secured by non-volatile collateral (the unmarked line) compared to over 24% of loans secured exclusively by volatile collateral (the marked line). In fact, approximately 8% of loans secured only by volatile collateral are monitored every day and roughly 67% are monitored at least on a monthly basis. Therefore, consistent with prediction III, the figure indicates that loans with volatile collateral are monitored at a considerably higher frequency than loans secured with less volatile assets.

Another measure that proxies for information produced by monitoring is whether the firm is publicly traded or privately held. Different from publicly traded firms, private firms are not required to disclose their financial statements. Private firms are therefore more informationally opaque to outside investors. Prediction IV is that banks will monitor private, informationally opaque borrowers more frequently because doing so is more likely to produce new information. Panel (b) of Figure 3 provides some descriptive evidence for this prediction as private borrowers are over 30% more likely to be monitored on at least a monthly basis.

## 4.3 The Value of Information

We also expect monitoring frequency to be increasing in the expected value of loan specific information. Barclay and Smith (1995), Rajan and Winton (1995) and Park (2000) all argue that shortening a loan's maturity makes monitoring more valuable because it provides the bank more frequent opportunities to use their information. Following these arguments, prediction V is that loans with a short maturity are likely to be monitored more frequently. Consistent with this prediction, Figure 4 panel (a) shows that every point on the monitoring frequency CDF of the below-median maturity subsample, the marked line, is above the corresponding point for the above-median maturity subsample (the unmarked line).

Rajan and Winton (1995) extend this argument to show that loan covenants in long-term loans create similar incentives to monitor, suggesting that covenants may increase monitoring frequency. 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)), covenants may instead substitute for frequent monitoring – a lender can either wait to monitor until an adverse shock triggers a covenant violation or continuously monitor the loan. In 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. Thus, it is possible that covenants act as a substitute for frequent monitoring. It therefore is an empirical question whether covenants and monitoring are complements or substitutes.

Panel (b) of Figure 4 descriptively investigates this empirical question. We find banks monitor loans with a below-median number of covenants (the marked line) more than loans with above-median number of covenant (the unmarked line). The figure therefore suggests that on average covenants substitute for active monitoring.

### 4.3.1 Borrower Financial Condition

Finally, a particularly interesting example of a time when information becomes more valuable to a lender is when a borrower's financial health deteriorates. There are at least two reasons why this event will make the information obtained from monitoring more valuable. First, because lenders bear downside risk and little upside potential, their investment becomes more sensitive to the borrower's value as the borrower's financial health deteriorates. Second, covenants are likely to become tighter as financial health deteriorates. Both reasons increase the value of information. Empirically, we measure changes in borrower conditions 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. Prediction VI is that monitoring will become more (less) frequent as financial health deteriorates (improves).

Figure 5 shows the monitoring frequency CDFs of upgrade loans (the marked line) and downgrades loans (the unmarked line). Here, the sample is restricted to loans that were originated at least two years before our observation date. Furthermore, for the purposes of this figure we include only loans with an internal rating change in the previous year. Consistent with prediction VI, recently downgraded loans are monitored significantly more frequently than loans that have been recently upgraded.[16] For example, recently downgraded loans are approximately 50% more likely to be monitored on at least a monthly frequency.

## 5 Regression Analysis

We employ a series of regression specifications with the natural log of the annual monitoring frequency, as defined in Section 3, as the dependent variable. Our primary explanatory variables of interest empirically capture our empirical predictions regarding the bank's incentive to monitor, the expected information production of frequent monitoring, and the value of information gathered from monitoring.

[16] The group of loans that have not been upgraded or downgraded falls between the marked and unmarked lines.

We therefore estimate the following regression:

$$\begin{aligned} Monitoring\ Frequency_{ijt} = c_t + \alpha_1 Lead\ Share_{ijt} + \alpha_2 Market\ Share_{jt} + \\ \alpha_3 High\ Volatility\ Collateral_{ijt} + \alpha_4 Low\ Volatility\ Collateral_{ijt} + \\ \alpha_5 Log(Maturity)_{ijt} + \alpha_6 Number\ of\ Covenants_{ijt} + \beta X_{ijt} + \epsilon_{ijt} \quad (1) \end{aligned}$$

where $Monitoring\ Frequency_{ijt}$ is the natural logarithm of the number of times loan $i$ is evaluated by lead bank $j$ within a given year $t$.

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, we include a variety of fixed effects to control for other potentially unobservable factors. To control for the 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 alleviates concerns that our findings are attributable to differences in monitoring practices that are common to certain industries or banks.

Perhaps most importantly, we use loan rating fixed effects to control for loan quality. We have lead lender and examiner ratings under the 5-grade scale described above for all 2,210 loans in our sample. 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)). That is why in some of our specifications we also include indicators for the rating grades of each lead bank's internal rating scale, alleviating concerns that could arise from the concordance mapping process. In this set of tests we restrict the sample to the 24 largest lead arrangers by total dollar amount of outstanding loans in the SNC database during our sample period that have not modified their rating scale during the sample period of 2007-2015 SNC exams.

## 5.1 Lead Bank Incentives

We begin by investigating two mechanisms through which lead arrangers may have incentives to monitor, despite the moral hazard problem present in syndicated lending. First, we expect a positive relation between the lead banks loan share and monitoring frequency.

Column (1) of Table IV presents single variable regression results, which indicate a positive and highly significant relation between lead share and monitoring frequency. Columns (6) through (9) show that the statistical significance of this positive association is robust to controlling for loan terms, time trends as well as lender, borrower, and industry characteristics. In terms of economic significance, multiplying the lead share coefficient, which is approximately 0.59 when controlling for banks' own ratings in column (10), by the standard deviation of lead share of 0.18 (see Table I), suggests that a one standard deviation increase in lead share is associated with a 0.10 increase in the dependent variable, which amounts to an approximately 10% increase in monitoring frequency. In sum, consistent with prediction I, the results suggest that retaining a larger loan share increases monitoring incentives.

This positive association between the stake of the lead arranger and monitoring frequency 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.

The second mechanism that could mitigate the moral hazard problem between the lead and other syndicate members is the lead bank's reputation. Prediction II states that reputable banks monitor more often to protect their reputation. Column (2) of Table IV shows that as predicted lender reputation is positively related to monitoring frequency, although the effect is statistically insignificant. Columns (6), (7), and (8) show that after controlling for other loan characteristics, year and industry fixed effects, as well lead-bank and examiner ratings, the point estimate becomes marginally statistically significant. This evidence is consistent with prediction II that lender reputation playing a role in mitigating the within syndicate moral hazard problem.

However, lender reputation is relatively stable over time. In columns (9) and (10) we exclude this variable as we have lead-bank fixed effects in the specifications – variation across banks is absorbed by the bank fixed effects. Hence, one potential concern with interpreting our reputation results is that we cannot rule out that it proxies for bank characteristics other than reputation.

With this caveat in mind, we investigate whether a large lead share and lender reputation are simultaneously used to mitigate moral hazard within the syndicate or whether they are used for different types of loans. In particular, we predict that reputation is a preferable commitment mechanism because it allows lead arranger to diversify. Further, we argue that reputation is more likely to be effective at mitigating moral hazard when monitoring effort is more verifiable ex-post. To test this prediction we partition the sample on the borrower's public status because public filings and disclosures allow non-lead syndicate members to more easily verify monitoring behavior.

In Table V we partition the sample on public status and estimate our main specification. In columns (1) and (3) we include our main variables of interest and control variables, while in columns (2) and (4) we also add year, year-quarter, and industry fixed effects as well as examiner and examiner-scale lead bank ratings. We do not include bank fixed effects so that we are able to compare the effect of lender reputation across the two subsamples.

For public borrowers we find no significant relation between the lead arranger's loan share and monitoring frequency, but a significantly positive relation between the lead's reputation and monitoring frequency. For private firms, we find the opposite. These findings are consistent with reputation being a more effective method of mitigating the intra-syndicate moral hazard problem for public borrowers than for private borrowers. For private borrowers, the lead arranger is more likely to mitigate this problem by retaining a larger stake in the loan.

Overall, the results in this section confirm the intuition that lead banks' incentives to monitor syndicated loans are greater when they retain a larger stake in the loan or when they have reputation at stake.

## 5.2 Expected Information Production

We now turn to the relationship of monitoring frequency and the likelihood of monitoring producing new information. We empirically measure the likelihood of information production in two ways: the volatility of the value of underlying collateral and whether the firm is public or private.

Prediction III states that monitoring will be increasing in the volatility of collateral value. If the value of an asset changes frequently, then without monitoring its value will quickly become uncertain, which increases the information production of monitoring. Column (3) of Table IV shows that banks monitor loans with low volatility collateral significantly less than loans with high volatility collateral. The results is robust to including controls and loan characteristics fixed effects (Columns 6 through 9). Table V further shows that the estimated effect of collateral volatility on monitoring is similar for public and private borrowers. Hence, consistent with prediction III, monitoring is increasing in the volatility of collateral value.

In addition to providing some of the first evidence on the relation between information production and monitoring frequency, this finding also sheds new light on the common assumption that collateral substitutes for monitoring (see Holmstrom and Tirole (1997)). Intuitively, our findings suggest that this assumption is most appropriate when the collateral value is stable.

As a second test of the relation between expected information production and monitoring frequency we investigate the association between public status and monitoring frequency. Prediction IV is that banks will monitor private, informationally opaque borrowers more frequently. Sufi (2007) argues that monitoring is likely to be more important for private firms because there is less available information for these firms. The negative coefficient on the indicator for public firms in Table IV columns 7 though 10, qualitatively supports prediction IV, although the effect is not statistically significant with the inclusion of lender fixed effects.

One explanation for why we find a more robust association between collateral volatility and monitoring frequency than between public status and monitoring frequency is that the latter may require intensive, but not necessarily frequent monitoring. This case is likely if private firms are difficult to value, but do not necessarily have volatile values that necessitate continuous monitoring.

Overall, this evidence suggests that monitoring is more frequent when it is likely to produce new information. The evidence is strongest when we measure the value of new information using collateral volatility, which links directly to monitoring frequency as opposed to other dimensions of monitoring intensity.

### 5.3 The Value of Information

Bank monitoring is likely to be increasing not only in the probability of producing new information, but also in the value of that information. Theory suggests that bank monitoring will become more frequent as the information produced from monitoring becomes more valuable. This idea underlies the arguments in Barclay and Smith (1995), Rajan and Winton (1995) and Park (2000) that shortening a loan's maturity makes monitoring more useful. Shorter maturity loans provide more opportunity to use information because they involve more frequent renegotiation.

Prediction VI states that shorter maturity loans should be monitored more frequently. The negative association between maturity and monitoring frequency in Column (4) of Table IV empirically supports this prediction. Columns (6) through (9) show that this result is robust to the inclusion of examiner and banks' own internal ratings, industry, time, and lead bank fixed effects as well as our standard set of control variables.

A second measure of information value is number of covenants. However in this case the literature is ambiguous about the expected sign. Rajan and Winton (1995) argue that loan covenants increase the value of information because they make it more likely that the information can be immediately useful, either in triggering default or during subsequent renegotiations. However, since covenant violations reallocate control rights to lenders, lenders may be less willing to monitor and step in only after an adverse shock. Hence, it is not clear whether covenants are complements or substitutes to active monitoring. The negative association between the number of covenants and monitoring frequency in Column (5) of Table IV suggests that, on average, covenants are substitutes for active monitoring. This result is robust to the inclusion of all fixed effects (Columns 7 through 10).

### 5.3.1 Borrower Financial Condition

A particularly important example of a time when a lender's value of information increases is when a borrower's financial health deteriorates. Prediction VI states that as borrower financial health deteriorates lenders will increase monitoring frequency.

To test whether a change in financial condition affects monitoring frequency we regress monitoring frequency on separate indicators for lender rating upgrades and downgrades during the previous year.[17] This test requires that we restrict the sample to loans that have been in our sample for at least two years prior to our observation year, reducing our sample size to 682 observations and weighting our sample toward longer maturity loans.[18] Overall, the test sample here consists of 106 loans that have been upgraded, 220 loans that have been downgraded, and 356 loans with no change in the internal rating.

Consistent with prediction VI, Columns (1) and (2) of Table VI show that banks monitor firms significantly less (more) frequently following ratings upgrades (downgrades). Columns (3) and (4) show that these results are robust to including all variables in our full specification.

[17] The advantage of this method is that we measure whether borrower credit quality has changed across all banks for which we have collected rating scales information. However, we cannot measure how much credit quality has changed as the internal ratings scales of different banks are not comparable. This may lead to some underestimation of the association between credit quality changes and monitoring frequency.

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

These findings represent the first evidence that banks dynamically adjust their monitoring frequency over the life of the loan. Moreover, the result suggests that banks allocate monitoring efforts based on the expected benefits to doing so – as financial health deteriorates information becomes more valuable because covenants tighten and the volatility of loan value increases.

# 6 Additional Analyses: Collateral and Covenants

In this section, we conduct additional tests to more precisely investigate how different types of collateral and covenants relate to monitoring frequency.

## 6.1 Collateral Types

The results presented in section 5.2 suggest that monitoring is increasing in the volatility of collateral value. We now decomposes our collateral measures into 6 groups: accounts receivable, inventories, securities, fixed assets (such as property, plant, and equipment), real estate, and other types of assets (these are mostly a mixture of PPE and real estate and sometimes receivables and inventory). For lenders, the perhaps most opaque type of collateral is receivables. Receivables can fluctuate substantially. Moreover, developments in receivables may also be informative about firm performance. In contrast, it is unlikely that frequent reevaluation of fixed assets or real estate will yield new information.

Table VII presents the regression results for the collateral groups. For comparison, columns 1 and 2 restate the results for high and low volatility collateral indicators from table IV, columns 3 and 9. Next, we use indicators for the 6 collateral groups described above. Note that these collateral groups are not mutually exclusive because most loans are secured by multiple types of collateral. The results in columns (3) and (4) suggest that the positive association between volatile collateral and monitoring frequency is largely driven by loans secured by accounts receivable, although loans secured by inventories are also contributing to the association – the coefficient estimate on the *Inventory* indicator is positive and large in column (4) (although not statistically significant). Securities are not significantly associated with monitoring, possibly because there are very few loans secured by securities. In addition, loans secured by fixed assets and real estate seem to drive the negative association between low volatility collateral and monitoring frequency, although neither effect is statistically significant on its own.

In sum, the results for the collateral subgroups are consistent with monitoring frequency increasing with the likelihood producing new information. The most opaque type of collateral, receivables, has the strongest association with monitoring frequency.

## 6.2 Covenant Types

The evidence presented in section 5.3 suggests that monitoring frequency is negatively related to the number of covenant types. However, it is possible that certain types of covenants are more relevant to the monitoring decision than others. For instance, a covenant on cash-flow may allocate control rights to lenders before the financial conditions of a firms has deteriorated severely. Hence, banks may be less inclined to monitor if they are confident that they can intervene on the onset of a firm's financial difficulties.

We decompose the number of covenants into its components to gain more insight into the results in section 5.3. Table VIII reports the regression results for covenants types. For comparison, columns 1 and 2 restate the results for number of covenants from table IV, columns 3 and 9. Our findings indicate that four of the six covenant types are negatively associated with monitoring frequency. However, the only statistically significant relation is between cash flow covenants and monitoring frequency. This finding is consistent with lenders monitoring less when they know they will receive control rights if firm fundamentals deteriorate significantly.

In sum, covenants appear to substitute for active monitoring for the average bank loan in our sample. This result is driven by covenants that are directly linked to firms' ability to meet their obligations to the lenders.

# 7 Addressing Potential Selection

As mentioned in Section 2, we restrict our analysis to loans of U.S.-based borrowers for which we can identify the number of monitoring events throughout the year. Our final sample consists of a total of 2,210 loan-years with sufficient data. It is natural to investigate whether our results are affected by selection concerns. This will provide insight into the extent to which we can generalize our findings from the SNC exam sample to the entire population of loans.

To this end, we employ a Heckman selection model where we first model the probability that a given loan is included in our test sample. 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 test sample. [19] This identification strategy is similar to Sampat and Williams (2015) who use patent examiner fixed effects as an instrument for a patent being granted. Our second stage replicates the analysis from Section 5.1, using the inverse Mills-ratio from the first stage to control for unobservables that may result in a given loan ending up in our sample. Formally, our second stage can be

[19] 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.

written as:

$$\begin{aligned}Monitoring\ Fr_{ijt} =&\alpha_0 + \alpha_1 Lead\ Share_{ijt} + \alpha_2 Market\ Share_{jt} + \\ &\alpha_3 High\ Volatility\ Collateral_{ijt} + \alpha_4 Low\ Volatility\ Collateral_{ijt} + \\ &\alpha_5 Log(Maturity)_{ijt} + \alpha_6 Number\ of\ Covenants_{ijt} + \\ &\delta\phi_{ijt} + \gamma X_{ijt} + \epsilon_{ijt}, \end{aligned} \tag{2}$$

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

Table IX reports the second-stage results of our Heckman specification. This table replicates the first nine columns of Table IV. We find that the results in Table IX for our main variables of interest are very similar and generally statistically indistinguishable from those in Table IV. The inverse Mills-ratio in the estimated second-stage equation is largely statistically insignificant, especially after the inclusion of lead bank fixed effects. 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 exam loans with information on monitoring frequency do not appear to differ materially from the loans in the full SNC exam sample and is likely based on idiosyncratic factors.

# 8 Concluding Remarks

Both Diamond (1984) and Fama (1985) argue that a central of banks is to monitor borrowers. Subsequently, many theories have discussed the benefits to bank monitoring and the determinants of a bank's monitoring incentives. However, recently the rise of syndicated lending calls into question how much banks actually monitor. In this paper, we provide direct empirical evidence on monitoring frequency in a large sample of US syndicated loans.

The first contribution of this paper is to show that banks monitor syndicated loans frequently and that there is substantial variation in monitoring frequency. Monitoring activities range from daily monitoring of collateral to annual or quarterly monitoring of financial statements and plant and client visits. For example, approximately 50% of loans are monitored at least on a monthly basis, 5% are monitored every day, and 29% are monitored only once per year.

Our second contribution is to provide new evidence on what gives banks the incentive to monitor. Our results suggest that both retaining a large loan share and lenders' reputational considerations significantly increase monitoring frequency, but it does so differently for public and private firms. For public borrowers, for which it is presumably easier for non-lead syndicate members to verify monitoring effort ex-post, we find that lender reputation is positively related to monitoring frequency, all else equal, but the lead's loan stake is not. For private borrowers, we find the lead's share is positively related to monitoring frequency but fail to find an association between the lead's reputation and monitoring frequency. This is consistent with lead arrangers preferring to commit to monitoring through reputation, but that this is possible to the extent that monitoring effort is verifiable.

We also provide evidence that monitoring is more frequent when it is more likely to produce new information and when that information is likely to be valuable to the lender. For example, banks monitor more frequently for loans with risky collateral and short maturities more frequently and when borrowers' financial health is deteriorating. This latter result suggests that banks dynamically adjust their monitoring frequency over the course of a lending agreement.

Overall, our study empirically demonstrates that banks respond to direct economic incentives. Taken together, this evidence highlights the importance of ensuring that banks continue to be properly incentivized to monitor syndicated loans.

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# Appendix A - Variable Definitions

*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.

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

*Mkt. Share* is defined as the number of interactions (syndications) between the lead bank and other bank and non-bank institutions in a given year divided by the total number of interactions in the SNC database in the same year.

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

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

*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.

*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.

*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.

*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.

*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.

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

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

*Year Fixed Effects*: these are indicators for the year of each loan observation.

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

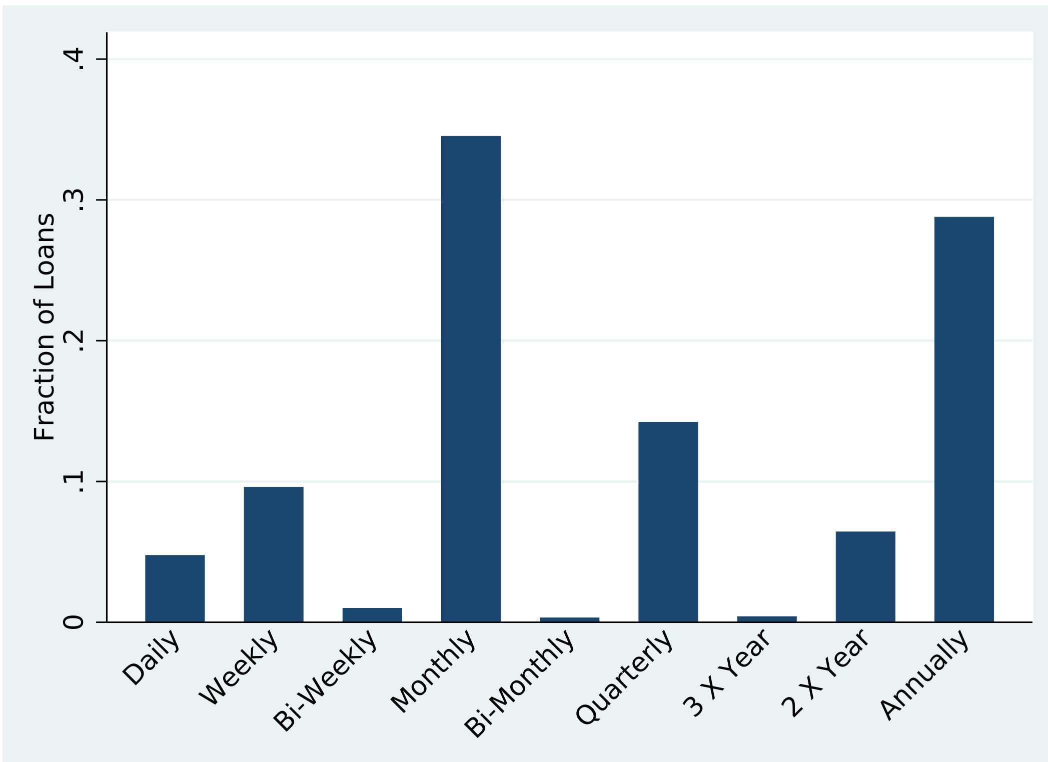
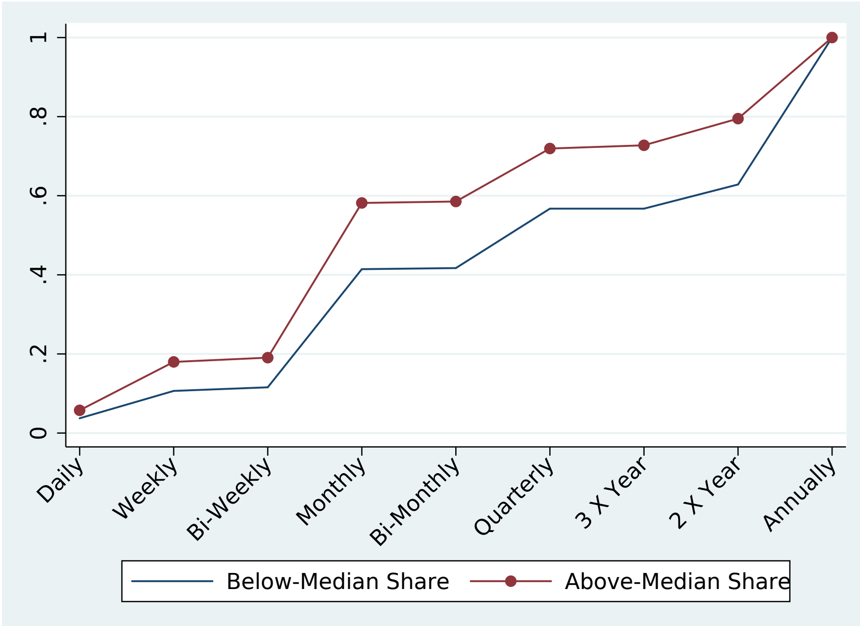
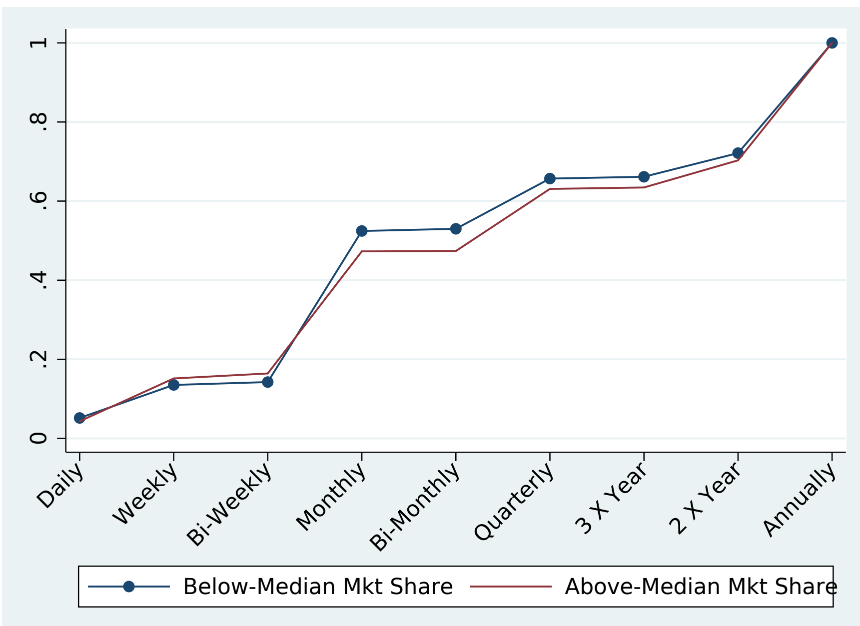



**Figure 1: Distribution of Monitoring Frequency.** This figure plots the distribution of monitoring frequency for our main test sample (2,210 loans).

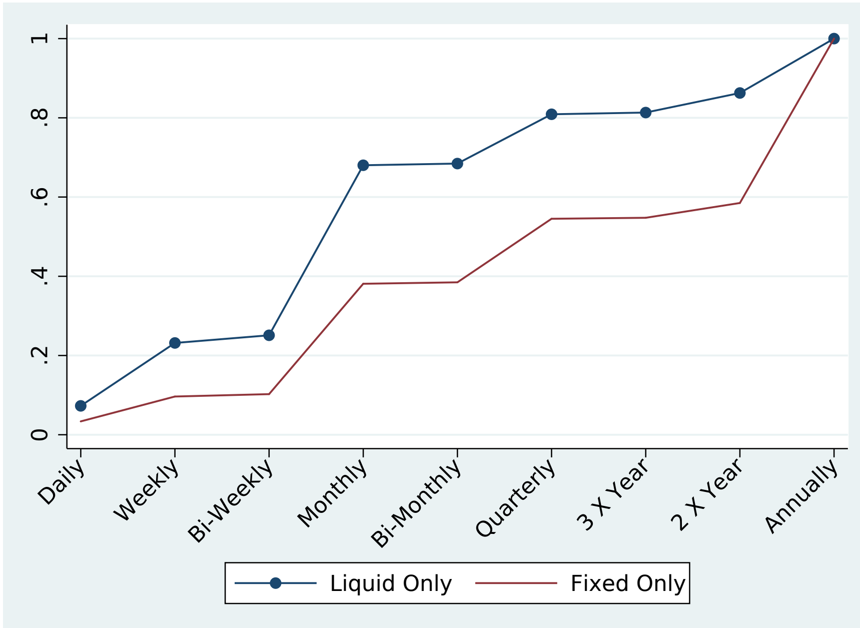



(a) *Monitoring Frequency and Lead Share*

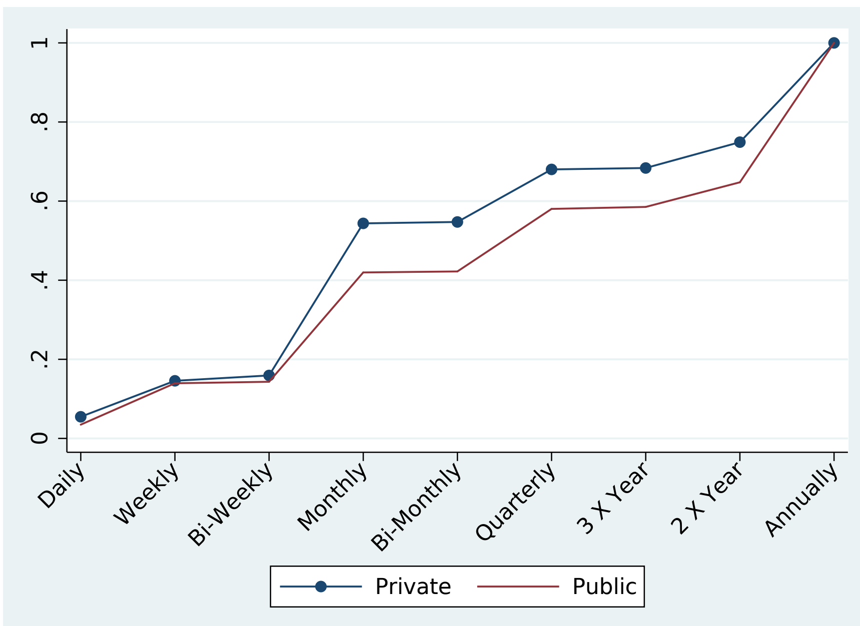



(b) *Monitoring Frequency and Lead Market Share*

**Figure 2: Monitoring Frequency and Lead Bank Variables** This figure 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.

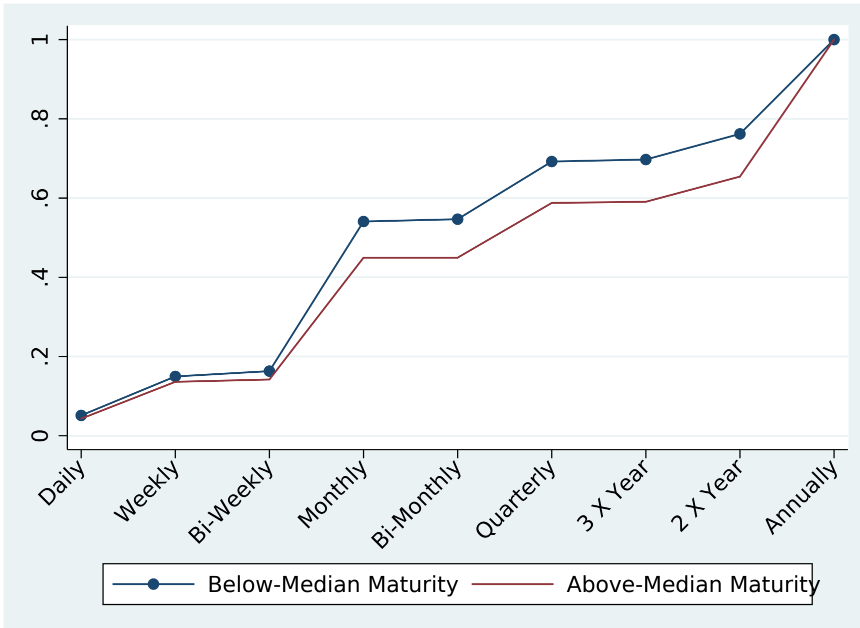



(a) *Monitoring Frequency and Collateral Type*

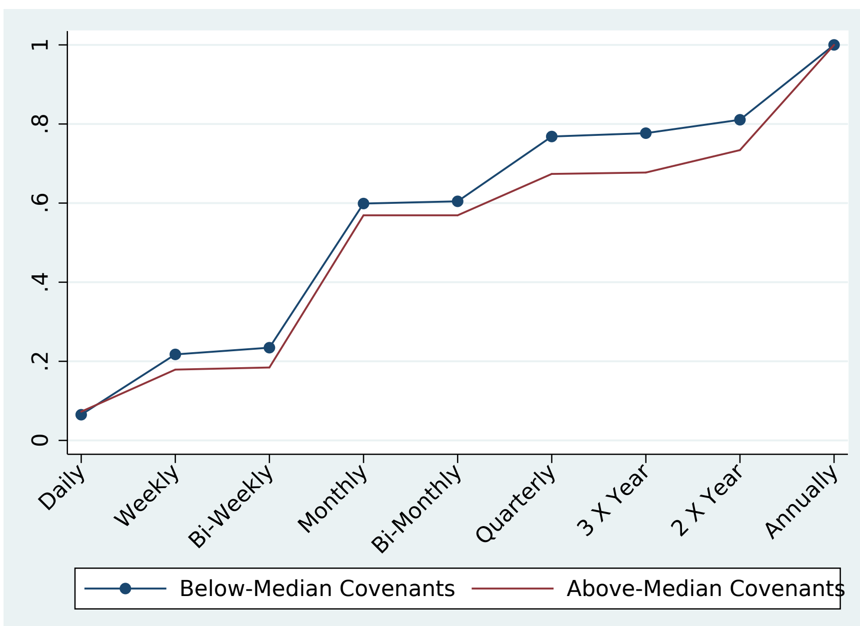



(b) *Monitoring Frequency and Information Opacity*

**Figure 3: Monitoring Frequency and Information.** This figure plots the cumulative density function (CDF) of monitoring frequency partitioned by whether the loans are secured by collateral with highl value volatility (liquid assets) or collateral with low value volatility (fixed assets). 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 Maturity*




(b) *Monitoring Frequency and Covenants*

**Figure 4: Monitoring Frequency and (Effective) Maturity.** This figure plots the cumulative density function (CDF) of monitoring frequency partitioned by whether the loans are secured by collateral with highl value volatility (liquid assets) or collateral with low value volatility (fixed assets). 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.

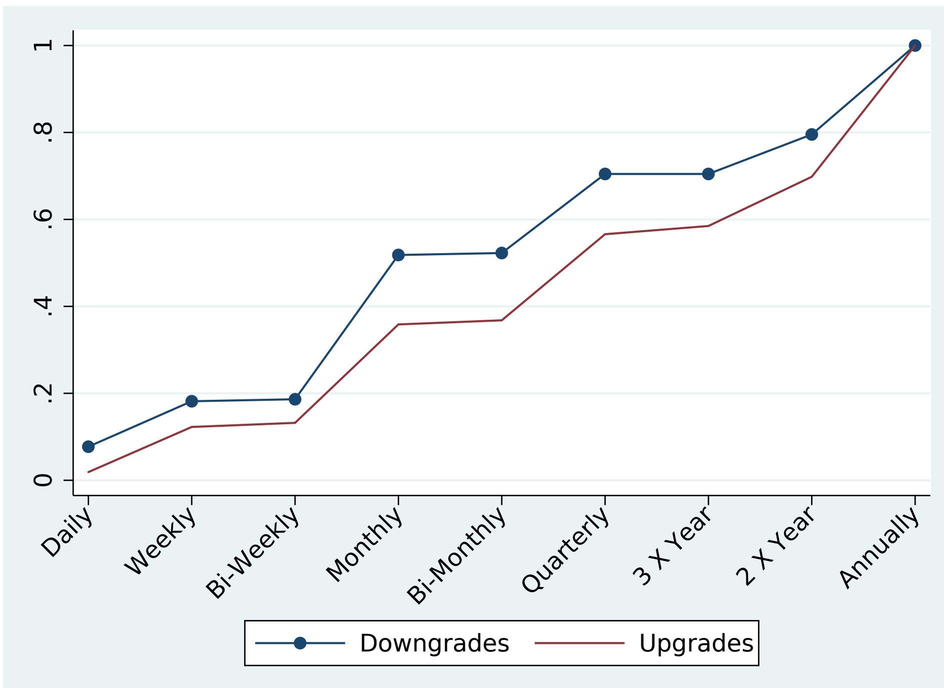



**Figure 5: Monitoring Frequency and Internal Ratings Changes.** This figure plots the cumulative density function (CDF) of monitoring frequency partitioned by whether the loans are upgraded or downgraded. The x-axis plots monitoring frequency, thus a point on the figure corresponds to the percentage of loans that are monitored at least as frequently as the interval listed on the x-axis.

**Table I: Summary Statistics: Test Sample.** This table provides summary statistics for the key variables employed in our analysis. *Loan Amount* is the total dollar amount of each credit facility, *Loan Maturity* is the loan maturity of a given credit facility in days, *Lead Share* is the fraction of the total loan amount retained by the lead lender, and *Mkt. Share* is defined as the number of interactions (syndications) between the lead bank and other bank and non-bank institutions in a given year divided by the total number of interactions in the SNC database in the same year. *Public* is equal to one whenever the borrower is a publicly traded company and zero otherwise, the *Lender Herfindahl* is defined as the Herfindahl index of the non-lead lenders in the loan syndicate, *Fraction Used* is the dollar amount used by the borrower divided by the total dollar amount of a loan commitment, and *Term Loan* takes the value of one if the loan facility is a term loan and zero otherwise. *Unsecured* takes the value of one if a loan is unsecured and zero otherwise, *Only Fixed Assets* take the value of one whenever the loan is secured by only PP&E or real estate, while *Only Liquid Assets* indicates a loan secured only by Accounts Receivable, Inventory, or Securities. Finally, *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, Cash, Current Ratio, Interest Coverage, Debt to Capitalization, Distributions.

| | *Mean* | *Median* | *St. Dev* | *N* |
|---|---|---|---|---|
| *Loan Amount* | 309 | 125 | 542 | 2,210 |
| *Loan Maturity* | 1,895 | 1,826 | 789 | 2,210 |
| *Lead Share* | 0.241 | 0.222 | 0.184 | 2,210 |
| *Mkt. Share* | 0.105 | 0.011 | 0.155 | 2,210 |
| *Public* | 0.363 | 0.000 | 0.481 | 2,210 |
| *Lender Herfindahl* | 0.127 | 0.108 | 0.115 | 2,210 |
| *Fraction Used* | 0.616 | 0.690 | 0.373 | 2,210 |
| *Term Loan* | 0.242 | 0.000 | 0.428 | 2,210 |
| *Unsecured* | 0.026 | 0.000 | 0.159 | 2,210 |
| *Low Volatility Collateral* | 0.401 | 0.000 | 0.490 | 2,210 |
| *High Volatility Collateral* | 0.211 | 0.000 | 0.408 | 2,210 |
| *Number of Covenants* | 1.822 | 2.000 | 1.224 | 2,210 |

**Table II: Summary Statistics: Comparison.** Columns 1 and 2 provide descriptive statistics for our test sample (N = 2,210). Columns 3 and 4 provide similar statistics for the entire exam sample for which we have covenant and collateral information (N = 18,798), while Columns 5 and 6 describe the entire SNC database from the May 2007 collection to the May 2015 collection (N = 79,402).

| | Test Sample | | Exam Sample | | Full Sample | |
|---|---|---|---|---|---|---|
| | *Mean* | *Median* | *Mean* | *Median* | *Mean* | *Median* |
| *Loan Amount* | 309 | 125 | 320 | 125 | 328 | 127 |
| *Loan Maturity* | 1,895 | 1,826 | 1,988 | 1,827 | 2,055 | 1,826 |
| *Lead Share* | 0.241 | 0.222 | 0.193 | 0.160 | 0.228 | 0.200 |
| *Mkt. Share* | 0.105 | 0.011 | 0.108 | 0.018 | 0.146 | 0.048 |
| *Public* | 0.363 | 0.000 | 0.378 | 0.000 | 0.393 | 0.000 |
| *Lender Herfindahl* | 0.127 | 0.108 | 0.120 | 0.100 | 0.124 | 0.106 |
| *Fraction Used* | 0.616 | 0.690 | 0.657 | 0.894 | 0.550 | 0.603 |
| *Term Loan* | 0.242 | 0.000 | 0.344 | 0.000 | 0.270 | 0.000 |
| *Unsecured* | 0.026 | 0.000 | 0.067 | 0.000 | | |
| *Low Volatility Collateral* | 0.401 | 0.000 | 0.605 | 1.000 | | |
| *High Volatility Collateral* | 0.211 | 0.000 | 0.128 | 0.000 | | |
| *Number of Covenants* | 1.822 | 2.000 | 1.735 | 2.000 | | |

**Table III: Monitoring Matix.** This table presents bank monitoring frequencies (see column entries) conditional on a loan being monitored at the maximum frequencies inducated 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 IV: Main Results: Determinants of Monitoring Frequency** OLS regression estimates are reported for the relation between the log of monitoring frequency (dependent variable) and key loan, lender, and borrower characteristics. 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) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| *Lead Share* | 1.221*** | | | | | 0.892*** | 0.794*** | 0.773*** | 0.418** | 0.591** |
| | (0.160) | | | | | (0.167) | (0.183) | (0.183) | (0.186) | (0.250) |
| *Mkt. Share* | | 0.310 | | | | 0.484*** | 0.569*** | 0.549*** | | |
| | | (0.192) | | | | (0.186) | (0.188) | (0.190) | | |
| *High Volatility Collateral* | | | 0.493*** | | | 0.330*** | 0.427*** | 0.437*** | 0.450*** | 0.607*** |
| | | | (0.072) | | | (0.073) | (0.083) | (0.083) | (0.083) | (0.104) |
| *Low Volatility Collateral* | | | −0.402*** | | | −0.264*** | −0.208*** | −0.223*** | −0.153** | −0.197** |
| | | | (0.058) | | | (0.059) | (0.063) | (0.062) | (0.063) | (0.079) |
| *Log(Maturity)* | | | | −0.330*** | | −0.350*** | −0.326*** | −0.313*** | −0.299*** | −0.379*** |
| | | | | (0.063) | | (0.084) | (0.085) | (0.086) | (0.087) | (0.108) |
| *Number of Covenants* | | | | | −0.143*** | −0.128*** | −0.124*** | −0.121*** | −0.111*** | −0.084*** |
| | | | | | (0.023) | (0.024) | (0.024) | (0.023) | (0.024) | (0.029) |
| *Lender Herfindahl* | | | | | | | 0.362 | 0.370 | 0.397* | 0.611** |
| | | | | | | | (0.299) | (0.302) | (0.241) | (0.264) |
| *Public* | | | | | | | −0.144** | −0.137** | −0.075 | −0.050 |
| | | | | | | | (0.063) | (0.063) | (0.063) | (0.076) |
| *Log(Committed)* | | | | | | | 0.003 | 0.008 | 0.027 | 0.055* |
| | | | | | | | (0.024) | (0.024) | (0.025) | (0.031) |
| *Fraction Used* | | | | | | | 0.121 | 0.084 | 0.002 | −0.104 |
| | | | | | | | (0.094) | (0.093) | (0.088) | (0.104) |
| *Term Loan* | | | | | | | −0.121 | −0.127 | −0.071 | −0.050 |
| | | | | | | | (0.082) | (0.080) | (0.077) | (0.092) |
| *Unsecured* | | | | | | | −0.542*** | −0.509*** | −0.540*** | −0.711*** |
| | | | | | | | (0.186) | (0.187) | (0.184) | (0.242) |
| Adjusted R-Squared | 0.028 | 0.001 | 0.056 | 0.012 | 0.017 | 0.167 | 0.173 | 0.177 | 0.269 | 0.288 |
| Observations | 2,210 | 2,210 | 2,210 | 2,210 | 2,210 | 2,210 | 2,210 | 2,210 | 2,210 | 1,713 |
| Year Fixed Effects | NO | NO | NO | NO | NO | NO | YES | YES | YES | YES |
| Origination Year-Quarter Fixed Effects | NO | NO | NO | NO | NO | NO | YES | YES | YES | YES |
| Industry Fixed Effects | NO | NO | NO | NO | NO | NO | YES | YES | YES | YES |
| Examiner Ratings | NO | NO | NO | NO | NO | NO | NO | YES | YES | YES |
| Examiner-Scale Lead Bank Ratings | NO | NO | NO | NO | NO | NO | NO | YES | YES | NO |
| Lead Bank Fixed Effects | NO | NO | NO | NO | NO | NO | NO | NO | YES | YES |
| Lead Bank Internal Ratings | NO | NO | NO | NO | NO | NO | NO | NO | NO | YES |

**Table V: Bank Monitoring and Public Status.** This table reports OLS regression estimates for the relation between $Log(Monitoring\ Frequency)$ and key variables as described in Appendix C partitioned on public status. All variables are defined in Appendix A. P-values are presented in parentheses and statistical significance is denoted as follows: $*p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$..

| | $Log(Monitoring\ Frequency)$ | | | |
|---|---|---|---|---|
| | Public Company | | Private Company | |
| | (1) | (2) | (3) | (4) |
| $Lead\ Share$ | 0.316 | $-0.023$ | $1.061^{***}$ | $1.068^{***}$ |
| | (0.314) | (0.318) | (0.225) | (0.231) |
| $Mkt.\ Share$ | $0.700^{***}$ | $0.637^{**}$ | 0.233 | 0.374 |
| | (0.269) | (0.280) | (0.267) | (0.268) |
| $High\ Volatility\ Collateral$ | $0.697^{***}$ | $0.608^{***}$ | $0.421^{***}$ | $0.289^{***}$ |
| | (0.131) | (0.130) | (0.104) | (0.107) |
| $Low\ Volatility\ Collateral$ | $-0.433^{***}$ | $-0.339^{***}$ | $-0.254^{***}$ | $-0.190^{**}$ |
| | (0.093) | (0.107) | (0.077) | (0.084) |
| $Log(Maturity)$ | $-0.356^{***}$ | $-0.452^{***}$ | $-0.146^{*}$ | $-0.282^{**}$ |
| | (0.117) | (0.160) | (0.078) | (0.110) |
| $Number\ of\ Covenants$ | $-0.129^{***}$ | $-0.131^{***}$ | $-0.101^{***}$ | $-0.109^{***}$ |
| | (0.038) | (0.039) | (0.028) | (0.031) |
| Adjusted R-Squared | 0.161 | 0.259 | 0.074 | 0.175 |
| Observations | 803 | 803 | 1,407 | 1,407 |
| Controls | YES | YES | YES | YES |
| Year Fixed Effects | NO | YES | NO | YES |
| Orig. Year-Quarter Fixed Effects | NO | YES | NO | YES |
| Examiner Ratings | NO | YES | NO | YES |
| Examiner-Scale Lead Ratings | NO | YES | NO | YES |
| Industry Fixed Effects | NO | YES | NO | YES |

**Table VI: Bank Monitoring and Bank Internal Ratings Upgrades and Downgrades.** This table reports OLS regression estimates for the relation between the log of monitoring frequency (dependent variable) and bank internal ratings downgrades and upgrades as well as key loan, lender, and borrower characteristics. 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) | (4) |
| *Upgrade* | $-0.283^{**}$ | | $-0.291^{*}$ | |
| | (0.129) | | (0.159) | |
| *Downgrade* | | $0.311^{***}$ | | $0.235^{*}$ |
| | | (0.115) | | (0.125) |
| Adjusted R-Squared | 0.004 | 0.010 | 0.276 | 0.276 |
| Observations | 682 | 682 | 682 | 682 |
| Controls | NO | NO | YES | YES |
| Year Fixed Effects | NO | NO | YES | YES |
| Orig. Year-Quarter Fixed Effects | NO | NO | YES | YES |
| Industry Fixed Effects | NO | NO | YES | YES |
| Examiner Ratings | NO | NO | YES | YES |
| Examiner-Scale Lead Ratings | NO | NO | YES | YES |
| Lead Bank Fixed Effects | NO | NO | YES | YES |

**Table VII: Bank Monitoring and Collateral.** This table reports OLS regression estimates for the relation between *Log(Monitoring Frequency)* and indicator variables for collateral type. The indicator variables *Receivables*, *Inventory*, and *Securities* take the value of one whenever loans are secured by accounts receivable, inventory, and securities, respectively. All other 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) | (4) |
| *High Volatility Collateral Only* | 0.493*** | 0.450*** | | |
| | (0.072) | (0.083) | | |
| *Low Volatility Collateral Only* | −0.402*** | −0.153** | | |
| | (0.058) | (0.063) | | |
| *Receivables* | | | 0.528*** | 0.502*** |
| | | | (0.093) | (0.107) |
| *Inventory* | | | 0.001 | 0.137 |
| | | | (0.101) | (0.117) |
| *Securities* | | | −0.295 | −0.095 |
| | | | (0.216) | (0.301) |
| *Fixed Assets* | | | −0.238*** | −0.163 |
| | | | (0.092) | (0.109) |
| *Real Estate* | | | 0.005 | −0.140 |
| | | | (0.092) | (0.117) |
| *Other* | | | −0.100 | −0.086 |
| | | | (0.067) | (0.080) |
| Adjusted R-Squared | 0.056 | 0.272 | 0.274 | 0.331 |
| Observations | 2,210 | 2,210 | 2,210 | 1,713 |
| Controls | NO | YES | YES | YES |
| Year Fixed Effects | NO | YES | YES | YES |
| Origination Year-Quarter Fixed Effects | NO | YES | YES | YES |
| Industry Fixed Effects | NO | YES | YES | YES |
| Examiner Ratings | NO | YES | YES | YES |
| Examiner-Scale Lead Bank Ratings | NO | YES | YES | YES |
| Lead Bank Fixed Effects | NO | YES | YES | YES |
| Lead Bank Internal Ratings | NO | NO | NO | YES |

**Table VIII: Bank Monitoring and Covenants.** This table reports OLS regression estimates for the relation between $Log(Monitoring\ Frequency)$ and indicators for different covenants types. All variables are described in Appendix A. P-values are presented in parentheses and statistical significance is denoted as follows: $^{*}p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

| | $Log(Monitoring\ Frequency)$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $Number\ of\ Covenants$ | $-0.143^{***}$ | $-0.111^{***}$ | | |
| | (0.023) | (0.024) | | |
| $Balance\ Sheet\ Covenant$ | | | $-0.004$ | $-0.032$ |
| | | | (0.068) | (0.083) |
| $Cash\ Flow\ Covenant$ | | | $-0.314^{***}$ | $-0.224^{***}$ |
| | | | (0.066) | (0.077) |
| $CAPEX\ Covenant$ | | | 0.008 | 0.041 |
| | | | (0.066) | (0.077) |
| $Distributions\ Covenant$ | | | 0.032 | 0.002 |
| | | | (0.072) | (0.086) |
| $Market\ Cap.\ Covenant$ | | | $-0.352$ | $-0.232$ |
| | | | (0.335) | (0.302) |
| $Loan-to-Value\ Covenant$ | | | $-0.264$ | $-0.282$ |
| | | | (0.191) | (0.240) |
| Adjusted R-Squared | 0.017 | 0.272 | 0.273 | 0.329 |
| Observations | 2,210 | 2,210 | 2,210 | 1,713 |
| Controls | NO | YES | YES | YES |
| Year Fixed Effects | NO | YES | YES | YES |
| Origination Year-Quarter Fixed Effects | NO | YES | YES | YES |
| Industry Fixed Effects | NO | YES | YES | YES |
| Examiner Ratings | NO | YES | YES | YES |
| Examiner-Scale Lead Bank Ratings | NO | YES | YES | YES |
| Lead Bank Fixed Effects | NO | YES | YES | YES |
| Lead Bank Internal Ratings | NO | NO | NO | YES |

**Table IX: 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) | (4) | (5) | (6) | (7) | (8) | (9) |
| *Lead Share* | 1.263*** | | | | | 1.192*** | 0.921*** | 0.853*** | 0.466** |
| | (0.163) | | | | | (0.165) | (0.185) | (0.184) | (0.192) |
| *Mkt. Share* | | 0.319* | | | | 0.333* | 0.544*** | | |
| | | (0.184) | | | | (0.182) | (0.186) | | |
| *High Volatility Collateral* | | | 0.515*** | | | 0.463*** | 0.528*** | 0.546*** | 0.493*** |
| | | | (0.076) | | | (0.075) | (0.090) | (0.090) | (0.089) |
| *Low Volatility Collateral* | | | −0.447*** | | | −0.449*** | −0.259*** | −0.276*** | −0.171*** |
| | | | (0.079) | | | (0.078) | (0.066) | (0.066) | (0.064) |
| *Log(Maturity)* | | | | −0.328*** | | −0.242*** | −0.378*** | −0.364*** | −0.319*** |
| | | | | (0.064) | | (0.061) | (0.082) | (0.083) | (0.080) |
| *Number of Covenants* | | | | | −0.147*** | −0.107*** | −0.114*** | −0.114*** | −0.107*** |
| | | | | | (0.023) | (0.023) | (0.023) | (0.023) | (0.023) |
| *Lender Herfindahl* | | | | | | | 0.468* | 0.425* | 0.441* |
| | | | | | | | (0.254) | (0.254) | (0.243) |
| *Public* | | | | | | | −0.137** | −0.120* | −0.071 |
| | | | | | | | (0.062) | (0.062) | (0.061) |
| *Log(Committed)* | | | | | | | 0.017 | 0.032 | 0.034 |
| | | | | | | | (0.026) | (0.026) | (0.026) |
| *Fraction Used* | | | | | | | 0.130 | 0.086 | 0.007 |
| | | | | | | | (0.087) | (0.088) | (0.083) |
| *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) |
| $\lambda$ | 0.053 | −0.085 | 0.111 | −0.013 | −0.115 | 0.188 | 0.283** | 0.289** | 0.117 |
| | (0.133) | (0.129) | (0.130) | (0.131) | (0.130) | (0.132) | (0.129) | (0.130) | (0.130) |
| Observations, second-stage | 2,210 | 2,210 | 2,210 | 2,210 | 2,210 | 2,210 | 2,210 | 2,210 | 2,210 |
| Observations, selection equation | 18,798 | 18,798 | 18,798 | 18,798 | 18,798 | 18,798 | 18,798 | 18,786 | 18,786 |
| Year Fixed Effects | NO | NO | NO | NO | NO | NO | YES | YES | YES |
| Origination Year-Quarter Fixed Effects | NO | NO | NO | NO | NO | NO | YES | YES | YES |
| Industry Fixed Effects | NO | NO | NO | NO | NO | NO | YES | YES | YES |
| Examiner Ratings | NO | NO | NO | NO | NO | NO | NO | YES | YES |
| Examiner-Scale Lead Bank Ratings | NO | NO | NO | NO | NO | NO | NO | YES | YES |
| Lead Bank Fixed Effects | NO | NO | NO | NO | NO | NO | NO | NO | YES |