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Lender Exposure and Effort in the Syndicated Loan Market

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Abstract

This paper tests for asymmetric information problems between the lead arranger and participants in a lending syndicate. One problem comes from adverse selection, whereby the lead has a private informational advantage over participants. A second problem comes from moral hazard, whereby the lead puts less effort in monitoring when it retains a smaller loan share. Applying an instrumental variables strategy using lending limits, borrower performance is improved by increasing the lead's share. The focus is on separating moral hazard from adverse selection and the results are consistently indicative of monitoring: First, the lead's share is more important for revocable credit lines than for fully funded term facilities. Second, a lead with greater liquidity risk reduces its share resulting in worse borrower performance, but its liquidity risk does not affect the quality of credits it chooses to syndicate in the first place. Third, covenants are paired with a higher lead share, and the sensitivity between share and borrower ex-post performance is greater on loans with more covenants.

JEL codes: D82, G21, G32
Keywords: Syndicated loans; Asymmetric information; Monitoring; Covenants

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1. INTRODUCTION

Financial innovations that have supported credit risk sharing markets have arguably helped make financial intermediaries better diversified and improved welfare. Reductions in committed capital and a greater flexibility in reallocating this limited capital are reflected in greater access to credit and lower financial transaction costs for borrowers (Rajan, 2005; IMF, 2006).

But credit risk sharing results in asymmetric information problems between informed lenders and outside investors. One asymmetric information problem comes from hidden information via adverse selection. An informed lender has an incentive to offload loans that it privately knows are poor quality but that it may have nonetheless decided to originate. Reasons the lender may have originated such loans include private benefits and other incentives coming from cross-selling opportunities with the borrower, for example. A second asymmetric information problem comes from hidden action via moral hazard in effort. A lender with a lower portion of a loan will have a weaker incentive to carry out due diligence and monitor the borrower over time. To curb these problems, economic theory shows that the lender should invest its capital into the loan. In the case of adverse selection, this provides a credible and positive signal by an informed party to outsiders (Leland and Pyle, 1977). Similarly in the case of moral hazard, this exposes the delegated monitor to losses if it fails to sufficiently monitor the borrower. The credibility the lender gains from retaining exposure to the borrower encourages other participants to provide funds, relying on the monitoring effort of the delegated agent (Diamond, 1984; Gorton and Pennacchi, 1995; Holmström and Tirole, 1997).

To assess whether and how an informed lender or a delegated monitor can mitigate problems associated with asymmetric information, this paper examines the syndicated loan market. Syndicated loans are loans in which a group of two or more lenders extend credit to a borrower, governed by one loan contract. Syndicated lending shares properties of both traditional relationship lending and market-based lending. Borrowers repeatedly access the market and often engage the same lenders. These "lead arrangers" – typically commercial or investment banks – are responsible for arranging the loan, taking a share, drafting an information memorandum, and inviting participant lenders. A priori, therefore, the lenders are not equally informed; and in practice, participant lenders also rely on the monitoring efforts of the lead arrangers after the loan is syndicated. The syndicated loan set-up, therefore, lends itself to problems of information asymmetry. An additional advantage is that considerable variation exists in the exposure that a lead arranger has to a borrower and this information can be observed by the researcher. Moreover, firms of varying credit quality and information opacity access this market (Dennis and Mullineaux, 2000; S&P, 2006; Sufi, 2007). And like other credit risk sharing markets, syndicated lending rapidly expanded before the financial crisis (e.g., loan issuance by U.S. borrowers reached close to $2 trillion in 2006 from $130 billion in 1987).

This study identifies evidence of asymmetric information problems in the syndicated loan market, by relating a borrower's longer run performance after syndication to the lead arranger's share of the loan. The hypothesis is that when the lead retains a greater share, problems of information asymmetry are moderated and should be reflected in improved ex-post performance by the borrower. I follow a two-pronged empirical approach by controlling for a range of observable characteristics at the time of syndication and by applying an instrumental variables research design similar to Ivashina (2009).[1] This approach is important because an unconditional correlation could be due to reverse causality, in that the lead arranger may hold more of a good quality loan, and it is publicly observed to be good quality at the time of syndication. At the same time, the correlation could go against identifying an asymmetric information effect if the lead holds more of a poor or opaque quality loan because it is forced to do so by participants concerned about shirking by the lead (as theoretically motivated by Greenbaum and Thakor, 1987, Holmström and Tirole, 1997, and empirically supported by Sufi, 2007, among others). Applying this approach, I find that the borrower's likelihood of subsequent default is reduced by the exposure of the lead arranger and the borrower's senior debt rating is more likely to be upgraded too.

A key aim of this study is to tease apart moral hazard from adverse selection. The collective evidence in this paper shows that moral hazard in monitoring is an empirically relevant problem. The existing literature largely stops on evidence of information asymmetry, and lumps together adverse selection and moral hazard problems as possible explanations.[2] To cite a few, Dennis and Mullineaux (2000), Jones, Lang, and Nigro (2005), and Sufi (2007) find that lead arrangers retain a larger share and the syndicate is more concentrated when borrowers are opaque or risky.

[1] Valid instruments should affect the lead's loan demand but should not be correlated with the degree of adverse selection or moral hazard in the syndicate. The instruments have a lending limit interpretation, in that lenders vary in their organization's internal risk limits on the degree of exposure they can have to individual borrowers. The instruments are constructed using information on the lender's previous syndicated loans, and in a robustness check, on its exposure in a separate market, that for mortgage securitizations and sales.

[2] This discussion is limited to corporate borrowers. More progress has been made in other markets (e.g., Keys, Mukherjee, Seru, and Vig (2010) for mortgages; Karlan and Zinman (2009) for consumer credit).

Ivashina (2009) finds that an instrumented increase in the lead's share lowers loan spreads. Dahiya, Puri, and Saunders (2003) find that a negative certification at the time of a secondary loan sale is borne out in ex-post poor borrower performance. Similarly, Berndt and Gupta (2009) track syndicated loans sold in the secondary market and find that they have lower risk-adjusted returns over the three year period following the sale. Loans securitized by collateralized loan obligations (CLOs) are also found to underperform similar unsecuritized loans (Bord and Santos (2011); in contrast, Benmelech, Dlugosz, and Ivashina (2012) find weaker evidence of underperformance, and only after 2005).[3]

What does monitoring mean in practice? Monitoring in this paper encompasses both information updating as the lead lender learns about the borrower over time, and active policing through, for example, the option to renegotiate contracts as information about the borrower is uncovered. Theoretical papers allow a malleable interpretation of monitoring. For example, in the view of Holmström and Tirole (1997), monitoring means the "inspection" of various aspects of the borrowing firm that include ongoing communication with management, determining the frequency of cash flow reviews, examining balance sheets and sales projections, and making sure that the borrower meets the covenants in its contract. Similarly, Fama (1985) discusses the periodic payment of "monitoring fees" by firms for lines of credit (even if funds are not drawn) simply to provide a signal about their outside debt. Being inside debt, the bank lender is party to private information such as the borrower's deposit history with the bank. But monitoring can also mean active intervention in the business of the firm (Gorton and Winton, 2003).

I, therefore, test for the lead's hidden action by taking advantage of variation in syndicated loans along three dimensions with hypothesized differences in the intensity of monitoring. The first dimension is the nature of the credit facility. More intensive monitoring is expected on facilities that are not fully funded when the loan is originated (credit lines) than on those that are (term loans). Credit lines have been characterized as monitored liquidity insurance, where the lender retains revocation rights that are invoked when the borrower's cash-flow risk increases (Fama, 1985; Sufi, 2009; Acharya, Almeida, Ippolito, and Perez, Forthcoming). The results in

[3] There remains, however, much scope for more analysis in this area. First, as discussed, the source of information asymmetry has not been identified in these studies (for example, Dahiya, Puri, and Saunders (2003) implicitly attribute their finding to a negative signal but it is equally consistent with reduced monitoring following the sale). Second, loan sales are not instrumented, so the interpretation is susceptible to reverse causality. Third, the sales data on syndicated loans do not indicate actual trades, only quotations (as discussed by Drucker and Puri, 2009). Therefore, it is difficult to assess if the poor performance was expected by the market and properly priced in at the time of the loan sale.

this paper are supportive of this monitoring view, in that increasing the lead's retained share on credit lines improves performance more than a similar increase on term loans.

The second dimension of syndicated loans that can be exploited is the liquidity and solvency risk of different lead lenders. These differences are expected to influence both the share the lead retains in its portfolio and the type of loans it syndicates in the first place. For example, a lead bank that has extended a lot of unused commitments is vulnerable to a liquidity shock if its borrowers decide to draw down these credit lines and other commitments. Therefore, it is hypothesized that lead banks at a greater risk of illiquidity retain smaller shares (Gorton and Pennacchi, 1995), resulting in the standard expected effect of worse borrower performance. This prediction is confirmed in the results of this paper. But in addition, a lead bank exposed to liquidity shocks might be more likely to sell or syndicate loans because it is forced to do so than because it privately knows that the loans are poor quality. In other words, if ex ante adverse selection were the salient problem, one expects that a lead bank with low liquidity risk will be more likely to offload bad credits than a bank with high liquidity risk. This paper does not find compelling support for this adverse selection alternative.

The third dimension along which syndicated loans vary is the extent of covenants included in the loan. Covenants are terms and conditions in the loan contract that are designed to mitigate agency problems at some future point in time. For example, Rauh and Sufi (2010) conclude that the "existence and enforcement of covenants are indicative of monitoring by creditors" (see also Rajan and Winton, 1995; Park, 2000; Chava and Roberts, 2008; Sufi, 2009). Covenants can serve as "tripwires" that increase the efficiency of a financial contract and the flexibility of renegotiating it. They can discipline the borrower whose aim is to avoid violating the covenant and transferring control rights to the lender (Dichev and Skinner, 2002). They can also enhance the lender's incentives to monitor in the first place, in order to accurately observe and demonstrate whether the covenant has been violated or not (Rajan and Winton, 1995). The results in this paper show that loan covenants go together with a greater lead share and that the sensitivity of a borrower's longer run performance to the lead's instrumented share is indeed higher when a loan has more covenant constraints.

Why is it important to separate moral hazard and adverse selection? Both could be important sources of asymmetric information but each problem has different mechanisms that could facilitate market efficiency. The syndication process itself does not affect the extent of the adverse selection problem – whether the lead has an informational advantage over other syndicate participants about the innate riskiness of the borrower (and the lead signals quality by retaining a larger share at the close of the loan). In contrast, moral hazard in effort is endogenous to the process of syndication, as all lenders are initially unfamiliar with the borrower. If adverse selection is a more prominent problem, then one implication is to release more information on borrowers via credit registries, for example. Indeed, the introduction of credit ratings for loans can be understood as a market mechanism that evolved to reduce an adverse selection problem. While if moral hazard is a more severe problem, then in addition to minimum "skin in the game" requirements, enhanced covenants, and dynamic contracting schemes are recommended.

The rest of this paper is organized as follow: Sections 2 and 3 discuss the data and method applied. The results are laid out in Sections 4 and 5. Section 6 offers some concluding thoughts.

2. DATA

Data on individual syndicated loan facilities for U.S. corporate borrowers were collected from Loan Pricing Corporation's (LPC) Dealscan database (December 2008 extract from Dealscan's online LoanConnector service). LPC gets the majority of this data from loan agreements and commitments in filings with the SEC as well as from loan originators and other contacts within the credit market. Lenders have an interest in maintaining their rankings in LPC's league tables and therefore voluntarily report their loans, which are then confirmed. As noted in a number of previous studies, syndicated loans in Dealscan cover a majority of the value of commercial loans in the U.S. The unit of observation in Dealscan is a facility or a tranche. To accommodate the borrower's funding needs and to cater to different investors, a loan is often split into facilities. Nonetheless, as Sufi (2007) and others argue, the syndicated loan contract is drafted at the loan deal level. Therefore, the main analysis in this paper evaluates syndicated loan deals, although disaggregated facility-level data are examined for several of the monitoring hypotheses. And aggregated borrower-level data are also examined in robustness checks.

Descriptive statistics on syndicated loans to U.S. borrowers are shown in Table 1. Summary statistics are presented for the sample of loans issued in the period from 1990 to 2006, which coincides with the main regression sample (6,204 loans).[4] The sample of syndicated loans in the analysis follows a data structure that can best be described as pooled cross sections over time. Methods for cross section analysis can be applied, though typically a time effect such as year dummies is controlled for (see the methodology in the next section).

[TABLE 1]

Dealscan data are used to construct variables commonly applied in the literature such as the loan contract's size, interest spread, previous number of loans to the borrower, and measures of reciprocity and repeat interactions between the lead and participants, as well as the main instruments (Section 3.3 describes the instruments). The key variable of interest is the share retained by the lead arranger. The average share held by the lead is about 28% of the loan, with considerable variation (18% standard deviation).[5]

The main dependent variable in the study is an indicator recording default by issuer, obtained from Moody's Default Risk Service Database (2008 extract).[6] Moody's recorded 1,218 issuer defaults of the total 17,686 U.S. issuers in the database (a 6.9% default rate). The timing of default is also recorded and this information is employed in this study to evaluate whether a borrower defaults following the loan origination date. The default analysis is also conducted fixing the window over which default is observed. Moody's issuer identifiers were cross-checked

[4] Because a number of variables such as previous relationships and lending limits are constructed using loan information over the previous three years, it makes sense to begin the sample in 1990. This allows information from the beginning of the Dealscan data set in 1987 to be captured. 2006 serves as a natural end to the sample – both because it precedes the 2007-2009 financial crisis and because it allows a sufficient window to observe borrower performance following syndication.

[5] The sample of loans is confined to the sample with available lead share information as well as borrower characteristics (Compustat). As discussed by Ivashina (2009), the lead's share is underreported in Dealscan (e.g., in 38% (36%) of her (my) sample conditional on the availability of the other variables). She shows, however, that no systematic bias exists in the characteristics of companies that enclose loan distributions and often the same borrower receives loans both with and without a reported lead share (roughly half of companies, which is also the case in my sample). There is evidence, however, of reporting bias by facility type. For example, the lead share is reported on 26%, 18%, and 7% of revolving line facilities, term loans A, and term loans B, respectively. The latter term loans (TLB) are allocated to institutional investors while TLA are typically allocated to banks. Therefore, following suggestions, TLB facilities are excluded from the consolidation of lead share information at the loan level, but not for the purpose of controlling for loan size (results are similar if TLBs are not excluded). Lead shares for institutional tranches are also examined in a separate test in Section 4.2.

[6] As noted in the Moody's documentation, these are not just bankruptcies but include strategic defaults on some securities like bonds (such as a distressed exchange or missed interest payments) but are not "technical defaults" due to covenant violations. Tests on the type of default are conducted in Section 4.2.

and hand-matched to Compustat. This led to 894 identifiable unique borrower defaults of the 1,218 U.S. issuers recording a default; 630 matched to syndicated borrowers in Dealscan.[7]

This paper focuses on a borrower's default because it is an unambiguous indicator of poor performance, as discussed by Dahiya, Puri, and Saunders (2003). Indeed, from a creditor's point of view, the key borrower condition that matters for its payoff is whether the borrower defaults. Ideally, this measure of performance would be on a particular loan, as applied in Bord and Santos' (2011) assessment of CLO riskiness. However, their measure was based confidential bank examination data. Nonetheless, borrower and loan-specific defaults are highly correlated. For example, roughly 75% of issuers defaulting on bonds also default on other debt including loans, based on Moody's. This paper also evaluates an alternative measure of performance, which is the rating change on a borrower's senior debt (following Benmelech, Dlugosz, and Ivashina, 2012). The Moody's default database was also used to calculate, as a control, measures of industry default probabilities based on outstanding bonds in a 2-digit industry transitioning into default status.

The remaining controls are borrower and lender characteristics (where borrower characteristics are measures commonly used in the literature such as profitability, size, and leverage).[8] A rich set of lender characteristics is one distinct advantage of this study over existing studies that have focused on borrower characteristics. As a result, this paper can test whether the lead's choice over loans to syndicate and its choice over share to keep are determined by its opportunity cost of holding loans (relating to, for example, its liquidity position). Lenders were consolidated to the parent company, and in the event of mergers, the acquiring company inherited the relationships of the target, following Sufi (2007) and others.[9] The lender matching exercise ultimately led to roughly 3,000 unique parent company lenders (whether lead arranger

[7] Note that due to research assistance constraints, it was not feasible to hand-match the full Moody's sample of non-defaulting issuers as well. Nonetheless, several pieces of evidence suggest that this was a reasonable strategy and that the coverage of defaults in Moody's is comparable to that in Dealscan. For example, the 630 matched defaulting loan borrowers correspond to a default rate of 8.9% in Dealscan, similar to the Moody's rate. In addition, direct evidence on the performance of syndicated loans from the Shared National Credit Review finds that criticized loans as a fraction of total commitments was 8.8% on average over the 1989-2009 period. Finally, any potential omission of defaulted borrowers in the matched loan sample should work against finding results supportive of the hypothesis.
[8] Dealscan data were matched to Compustat company identifiers and manually checked. I also benefited from the Dealscan-Compustat link data provided by Michael Roberts (Chava and Roberts, 2008).
[9] Briefly, lender information from Dealscan was used, together with other sources such as SNL Financial and regulatory filings (FR Y-9C), to identify lenders and mergers (Victoria Ivashina and Amir Sufi also kindly sent me their merger information, which was used as a supplement and cross-check). The merger information used in this study is available upon request.

or participant lender) over the full Dealscan sample. Considerably fewer served as lead arrangers (1,055 lenders). The top 100 lead arrangers represent most deals; in my sample they are on 93% of loans, similar to Sufi (2007) and others. Finally, data from balance sheet and income statements were included for the subset (a majority) of lead arrangers that can be matched to U.S. bank holding companies.

3. METHOD

This section describes the empirical method, which is to first test whether a borrower's outcome is improved by increasing the share of the syndicated loan held by its lead. Second and if so, is the information asymmetry an informational advantage that the lead has over other syndicate participants, or are all lenders initially equally uninformed about the borrower, so that the lead arranger has to exert effort to learn about the borrower (according to how the terms in the contract induce it to do so)?

3.1 The Benchmark Model

The benchmark specification – before attempting to distinguish the source of information asymmetry – estimated in this paper is the following:

$$Default_i = \alpha + \beta(Lead\ Arranger\ Share_i) + \gamma X_i + \sum_{s=1990}^{2006} Z_s + \varepsilon_i \qquad (1)$$

The model is first estimated employing the loan-deal data so that each observation is a different loan. The coefficient of interest is β, which is expected to be negative under the null of asymmetric information: the greater the lead's share on loan i to a particular borrower at time of syndication, the less likely that the borrower will subsequently default. In an alternative formulation, the dependent variable is the rating change on a borrower's senior debt, in which case increasing the lead's share is expected to increase the likelihood of a rating upgrade and, likewise, decrease the likelihood of a rating downgrade. The control variables (X) include loan (contract and syndicate) characteristics, borrower characteristics (including the borrower's industry characteristics), and syndication year dummies (Z). Lead bank characteristics are also included in a model for loans arranged by U.S. banks.

The empirical implementation must overcome several potential problems. First, the possibility of reverse causality exists if a borrower that performs well in the future was publicly anticipated to do so by all lenders. In this case, the lead arranger could have passively chosen to keep a larger share of a high quality loan, having no informational advantage over participant lenders when the loan was closed. Thus, there is no adverse selection problem. Moreover, it would be wrong to attribute an unconditionally estimated relation to hidden action by the lead, as there is no moral hazard problem either. A second result that also would not be particularly interesting would be if the estimated correlation went in the opposite direction. That is, the lead arranger holds a greater portion of low quality loans because it is forced to do so by participants concerned about shirking and these loans perform poorly. In this case, any possible asymmetric information effect would be washed over by such a correlation. This issue is a concern because it is precisely what other studies find; lead arrangers hold a larger share of the loans to riskier and more opaque borrowers (e.g., Sufi, 2007).[10]

The two endogeneity problems described should be collectively minimized by controlling for loan, borrower, and lender covariates. Arguably, however, there can be some known risk characteristics that are observable to participants but are not controlled for in the empirical specification because they are not observed by the researcher. The resulting endogeneity would be reflected in the coefficient on the lead arranger's share. To address this concern, the empirical strategy instruments the lead's share with variables that affect the lead's loan demand decision but are not correlated with the extent of asymmetric information in the syndicate in question. Or more generally, the instruments should be correlated with the causal variable of interest but uncorrelated with other determinants of the dependent variable, the borrower's outcome. The instruments, described in detail later in Section 3.3, have a lender-specific loan limit interpretation. That is, considerable cross-sectional heterogeneity is found in internal risk limits of different lenders. Some banking organizations are more tolerant of a concentrated exposure to a borrower than other organizations.

Equation (1) is, therefore, estimated using IV methods. The main method employed is linear IV (2SLS) and the results are compared to ordinary least squares. I employ linear IV for

[10] These findings are also consistent with the theory proposed by Greenbaum and Thakor (1987) that higher-quality assets will be securitized while lower quality assets that are sensitive to asymmetric information will be funded with deposits. Likewise, if the lead arranger were to hold little or none of a loan to a borrower requiring intensive monitoring, then participant lenders correctly expect such shirking by the lead arranger and would seek to reduce their holdings (Gorton and Pennacchi, 1995; Holmström and Tirole, 1997).

computational simplicity and also because it provides a consistent estimate of the average causal response, regardless of whether the dependent variable is binary or continuously distributed (see Angrist and Pischke, 2009; Wooldridge, 2002).[11] Finally, standard errors are heteroskedasticity robust, where the individual loan error terms are allowed to be correlated for all loans of the same borrower and also for different firms in a particular year (i.e., standard errors are two-way – borrower and year – cluster robust).

3.2 Hypothesis Development for Moral Hazard in Monitoring

A key aim of this study is to separate the source of information asymmetry in the syndicated loan market. Concrete evidence is sparse, even for other credit markets, because identifying the source of information asymmetry is not easy nor are the methods often generalizable. For example, one recent study runs a field experiment in a South African consumer credit setting to separate hidden information effects due to ex ante selection effects from hidden action effects due to moral hazard in effort induced by the loan contract terms (Karlan and Zinman, 2009). Randomizing loan offers to consumers along different offer and contract rates, the authors find strong evidence in support of moral hazard.

Analogously, several dimensions of syndicated loans are exploited in this paper to test for hypothesized differences in monitoring effort. The first hypothesis relates the degree of monitoring to the nature of the credit facility. Monitoring intensity is expected to be greater on facilities that are not fully funded at origination than on facilities that are fully funded. The reason is that contracted loan facilities whose funds are not entirely drawn at origination (such as credit lines) are subject to later revocations and access restrictions by the lender. In this way, credit lines are not perfectly pre-committed but are a form of monitored liquidity insurance that is contingent on the borrower maintaining healthy cash flows. For example, Sufi (2009), relying on repeated SEC filings by the borrower, shows that access is restricted by the lender following a negative shock to the borrower's profitability. Similarly, Acharya, Almeida, Ippolito, and Perez (Forthcoming) develop a model showing that the lender's option to revoke a credit line is an

[11] The results of probit IV models are qualitatively similar to the linear IV estimates discussed later in Section 4. Probit IV can be estimated in two alternative ways; the first is maximum likelihood estimation which is more efficient but has a computational drawback and sometimes does not converge. The alternative is the two-step estimator. For the latter, I follow the procedure described in Wooldridge (chapter 15, p.475) to derive marginal effects from the estimated parameters. Results are available on request.

optimal monitoring mechanism. That is, a fully committed (irrevocable) line may not be optimal because it can induce excessive illiquidity-seeking behavior by the borrower.

Drucker and Puri (2009) also show that loans sold in the secondary market are less likely to be credit lines, attributing this fact to the need for more monitoring of credit lines. A borrower has an incentive to draw down the credit line just as its performance deteriorates. But nonbank buyers such as pension funds are not as good as banks at collecting private information on how the borrower's financial position evolves over time.

The first hypothesis is, therefore, formalized for the syndicated loan market as follows:

H1: An increase in the lead's share on a credit line facility should result in better borrower performance than a similar increase in the lead's share on a term loan facility (because a higher share is expected to induce the lead to put more monitoring effort, which is hypothesized to be more valuable for credit lines). In contrast, an adverse selection problem should not result in a materially different effect between credit lines and term loans.

The second hypothesis relates monitoring and the incidence of adverse selection to the characteristics of the lead lender. Lenders differ in their own liquidity and insolvency risk. These differences are expected to influence at least two of the lead's choices. One choice is over what share of the loan to keep in its portfolio. Another choice is over what type of loans to sell and syndicate in the first place. Turning to the first choice, as described in the introduction, a bank that has already extended a lot of unused commitments is exposed to a liquidity shock if borrowers draw down these credit lines and other commitments all at the same time. Thus to alleviate its liquidity constraint, this bank is less likely to retain a large share of a new loan. The example is generalizable. Indeed, Gorton and Pennacchi (1995) describe how the loan sales market grew as banks' internal funding costs increased from previously low levels. One reason that banks' internal funding costs rose was because of the lifting of interest rate ceilings (elimination of Regulation Q). Two other reasons they discuss were the deregulation of interstate banking that led to an increase in competition for deposits, as well as the increase in bank capital requirements. As a result, selling a loan or syndicating it became a less expensive form of financing than deposit or equity financing (as long as the lender's monitoring incentive is preserved in Gorton and Pennacchi's model). Therefore, I refer to this second hypothesis as the lead arranger's opportunity cost hypothesis and formalize it as follows:

H2a: A lead bank with a high internal funding cost (proxied by its capital and liquidity risk) should retain a smaller loan share than a bank with a low internal funding cost. In the second stage, this smaller retained share should therefore result in borrower underperformance.

While this hypothesis has an easy monitoring interpretation, supportive results could be reconciled with an alternative adverse selection problem, although unlikely. For example, a correlation could exist between a bank's propensity to extend unused commitments and a particularly poor quality loan portfolio (privately known by the bank, albeit this is not evident theoretically or in practice). The second part of the hypothesis, therefore, isolates a channel through which an adverse selection problem should be captured. Specifically, a bank with a high internal funding cost is likely to sell or syndicate loans precisely because it is more likely to be hit by a liquidity shock, for example. As a result, it will be forced to sell good loans and not only bad loans. This loan mix means that the quality of its syndicated loans will reflect that of the average borrower. In contrast, a bank with low internal funding costs is more likely to syndicate bad loans due to an adverse selection problem because it has less of a need to offload good loans. A similar idea occurs in Parlour and Plantin (2008), where a pooling equilibrium (supporting a liquid loan market) is more likely to be sustained in the presence of adverse selection when liquidity and capital shocks are more frequent. Therefore, the second part of the hypothesis is formalized as follows:

H2b: If adverse selection is a salient problem, then loans syndicated by a bank with a high internal funding cost should perform better than loans syndicated by a bank with a low internal funding cost.

Finally, the last hypothesis focuses on the dimension of loan covenants. As discussed in the introduction, a common view in the literature is that covenants are indicative of monitoring because they can help align the incentives of the borrower and lender, reducing agency problems that could develop over time. There are a number of competing views on the function of covenants and these are well articulated in a review by Gorton and Winton (2003). However, these views are not mutually exclusive because different covenants can serve different complementary functions. In the traditional view (Smith and Warner, 1979), covenants protect debtholders by limiting risk-shifting behavior by the borrower (such as asset-substitution by shareholders) and by curbing managerial rent-seeking (such as shirking by the management and investing in private benefit ventures).

The modern view sees covenants in a more dynamic way. Covenants can serve as "tripwires" that increase the efficiency and flexibility of financial contracting and renegotiation. For example, tight covenants increase the incentive of the borrower to avoid violating the covenant, as a violation would shift control rights to the lender and provide the lender with an option to renegotiate the contract (Aghion and Bolton, 1992; Dichev and Skinner, 2002). Dichev and Skinner show that covenants are set tightly and discontinuities exist in covenant slack measures, which are consistent with managers making accounting choices to just avoid violating the covenant. The borrower's cost of deviating and violating the covenant is higher for loans and other private debt than it is for public debt. The reason is because private debt is concentrated, while public debt is held by many dispersed creditors, making the cost of renegotiating and restructuring the contract lower for private loans. In fact, Rauh and Sufi (2010) show that low credit quality borrowers are more likely to take out both secured bank debt with tight covenants and subordinated non-bank debt with loose covenants, reasoning that these firms cannot issue non-bank debt in the absence of a bank facility with tight covenants (see also Kahan and Tuckman (1993) and S&P (2006) for evidence of extensive and confidential disclosure requirements on private debt such as supplemental financial projections and quarterly compliance certificates).

The emphasis so far has been on the borrower's incentive. But theory also shows that covenants can increase the lender's incentive to monitor a loan in the first place (Rajan and Winton, 1995; Park, 2000). In this view, covenants provide the lender with an incentive to accurately gather information to observe whether a covenant has been violated or not. Without monitoring the borrower's condition based on information only available to the public at a cost, the bank would not be able to later take action to demonstrate that the covenant has been violated. The loan's effective maturity is, therefore, contingent on monitoring by the lender. And in practice, participant lenders rely on the monitoring efforts of the lead arrangers. Rajan and Winton discuss how courts do not support a lender's claim to enforce a covenant if previous inaction implicitly meant that the covenant had been waived. To summarize, theory and evidence shows that covenants are tripwires helping to reduce the misalignment of borrower and lender incentives. Therefore, the third hypothesis is empirically formalized for syndicated lending as follows:

H3:If covenants are a monitoring mechanism, then loans with more restrictive covenants should exhibit a greater sensitivity between a borrower's ex-post performance and the lead's share than loans with less restrictive or no covenants (H3a). And if covenants are a monitoring mechanism, more restrictive covenants should be agreed jointly with a higher lead share in the syndicated loan contract (H3b).

3.3 The Instrumental Variables Approach

The main set of instruments for the lead's share are measures of the lead arranger's internal lending limits. Considerable variation in limits on lending to distinct borrowers exists across banks, indicative of differences in risk tolerance across organizations. These differences are expected to influence the loan demand decisions of different banks. In this way, lending limits have a lender-specific interpretation and can also be time-varying.

Regulatory limits constrain how concentrated a bank's exposure can be to any one borrower. Regulatory lending limits are clearly defined in Section 32.3 of the Code of Federal Regulations (Title 12, Banks and Banking): "A national bank's total outstanding loans and extensions of credit to one borrower may not exceed 15 percent of the bank's capital and surplus, plus an additional 10 percent of the bank's capital and surplus, if the amount that exceeds the bank's 15 percent general limit is fully secured by readily marketable collateral." Legal lending limits for state-chartered banks are normally more relaxed and vary from state to state (e.g., more rural states have higher lending limits). Nonetheless, banks typically set more restrictive internal lending limits and these are often binding (Ivashina, 2009).

I gathered evidence from SEC EDGAR filings from 1/1/2010 through 12/31/2010 to shed more light on internal limits (search terms included "internal lending limit", "internal limit", "house lending limit", or "house limit", and resulted in 52 non-duplicate bank holding company observations). The upshot of this descriptive evidence was that internal lending limits vary considerably across financial institutions, but on average, the lending limit is half the regulatory one (consistent with Bromiley and Stansifer, 1994). For example, measured as a fraction of the legal limit, the internal limit varied between 7% and 100%, with a mean (median) of 50%, and a standard deviation of 25% (data available upon request).[12]

[12] Additional evidence on lending limits is provided in a news search. For example, following a merger with Union Planters (that increased total assets at Regions Financial Corporation to $80 billion from $48 billion), Regions'

As internal limits are not typically observed, I follow Ivashina (2009) in backing these out from the lead's previous syndicated loans. I use the 75th percentile dollar size of the lead's share on its loans in the previous three years in the Dealscan syndicated sample. Following Ivashina, the 75th percentile is merely meant to measure an upper threshold for the lender's risk tolerance and the instrument is also time-varying (robustness checks were carried out on other cutoffs, such as the 60th and 90th percentiles, and there do not appear to be discontinuities in the distribution of the dollar size of the lead's loans). I also construct a closely related instrument to help address a possible weak instrument issue, if for example, there is measurement error. The second instrument is the lending limit on loans where the lead arranger previously served as a participant lender, not as a lead arranger. As expected, these limits are smaller in magnitude but should also be positively correlated with the lead arranger's share on a loan because it is reasonable that internal lending limits govern the lender's share retained on its loans irrespective of whether the lender is the lead arranger or a participant. The results in the next section are robust to using only the lending-limit-as-lead instrument. Finally, note that the lending limit instruments are robust to controlling for other bank characteristics, including lender size and risk measures as shown in Section 5.2. Robustness checks are also conducted on different lending limits and lead exposure in the appendix.[13]

Lending limits also can be inferred from the lead's exposure in another market, that for mortgage securitizations and sales. Insofar as lending limits and credit risk exposure are determined by the internal organization of the lender, then its exposure to mortgage securitizations should be highly correlated with its retained share of a syndicated loan but not correlated with the error term of the borrower's performance. I construct this instrument for the

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borrowing limit doubled to $100 million and was seen as a critical part of a business strategy to attract larger borrowers (American Banker, 8/31/2004, "Regions to Offer Higher Business Loan Limit"). A similar story is reported for Emigrant Bancorp in New York that tripled its lending limits upon changing ownership (American Banker, 12/21/2004, "New Strategy for Emigrant").

[13] Ivashina (2009) also uses an instrument meant to capture the loan's contribution to the idiosyncratic credit risk of the lead's loan portfolio, which is made up of its previous loans to various industries. Reasoning that the lead wishes to hold a more diversified portfolio, the lead should have a reduced demand for loans that cause the default variance of its portfolio to increase, all else fixed. Using Moody's data and following the method in De Servigny and Renault (2003), I did not find this instrument to be significantly correlated with the lead's share, and the correlation was positive. To make sure this was not a methodological issue, I constructed industry default correlations using the data and found that they largely match those reported in De Servigny and Renault. I also constructed a simpler instrument, which is the share of loans originated by the lead in a borrower's 2-digit SIC industry, and found that this instrument is positively correlated with the lead's retained share too. These results, however, can be reconciled with a "local" advantage that a bank gains from focusing on a few sectors instead of diversifying into unfamiliar sectors (Winton, 1999).

subset of loans with a U.S. lead bank, as this information is reported in the regulatory filings of the bank holding company (Schedule HC-S). The limitation with this instrument is that it is only available for loans arranged by U.S. banks and has only been reported since 2001. Therefore, this instrument is tested in an extension of the main results.

4. INFORMATION ASYMMETRY AND SUBSEQUENT BORROWER PERFORMANCE

4.1 Benchmark Results

In the results shown in Table 2, I examine the relation between the lead's share and the likelihood of future default by the borrower, estimating equation (1). In addition to the variable of interest, common controls applied in the literature are in all regressions (see Section 2). The first column shows the results of ordinary least squares. While the coefficient on the lead's share is negative – in line with asymmetric information – the correlation is small and statistically insignificant. This is suggestive evidence that a possible asymmetric information effect (or a spurious link between observably good quality and a high lead share) may be offset by the lead being forced to keep a larger share of loans extended to weak borrowers.

[TABLE 2]

The results of the benchmark instrumental variables regression identifying the conditional effect are shown in the next two columns. Tests of the endogenous regressor reveal that the null of exogeneity can be rejected, and the lead share should therefore be treated as endogenous. The first stage results are in column (2) followed by the results of the IV strategy in column (3). As discussed earlier, the two instruments are lending limits measured over loans on which the lead previously served as a lead arranger and over loans on which it previously served as a participant lender, respectively. The IV-estimated coefficient on the lead arranger's share of the loan is negative, larger in magnitude, and statistically significant, supporting asymmetric information in the syndicate. The estimated coefficient equals -0.164 (0.089 standard error) and implies that a one standard deviation increase in the lead arranger's share yields a 3% fall in the probability of default.[14]

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[14] The results shown are conservative because loans in which the lead share was 100% are excluded. These are not bilateral loans, but are classified as syndicated loans that, in quite a few cases, include, for example, a credit line facility with 100% share and the loan may then be split for the other facilities. In other syndicated loans, the leads may have split the loan between themselves. The significance levels are stronger when these loans are not excluded from the analysis. For example, the result in Table 2(3) is significant at the 5% level when the regression is conducted on the sample without exclusions.

Various tests of the instruments confirm that they are valid instruments. The lending limit measures enter positively and are jointly significant in explaining the lead's retained share, consistent with their economic interpretation and Ivashina (2009). The variables also meet the conditions for suitable instruments: they should be neither weak instruments nor correlated with the error term. First, they are well correlated with the endogenous variable; the F-statistic for the joint significance of the coefficients on the two instruments is equal to 90.2, well above the value of ten, which has become a benchmark for whether weak instruments can cause a bias problem in the second stage estimates (see for example, Stock and Yogo, 2005). Second, the instruments are exogenous. Because there is more than one instrument, overidentifying restrictions can be tested. The p-values on the test statistics are about 0.85, consistent with the null that the instruments and the model are correctly specified.

The remaining variables in the first stage regression are correlated with the lead arranger's share in many ways previously documented in the syndicate structure literature (e.g., Dennis and Mullineaux, 2000; Sufi, 2007; Ivashina, 2009). Therefore, this discussion will be very brief. For example, the lead's share is decreasing in the loan's size and maturity. If the lead arranger previously served as a lead, then it holds a lower portion (controlling for the number of loans previously syndicated by the borrower, which also enters negatively).[15] Higher reputational measures are also associated with a lower share, and these range from the lead's market share, to repeat interactions and reciprocity between the lead arranger and participants, to the syndicate lead being a commercial bank.[16]

Returning to the second stage results, most controls enter with the expected sign. Borrowers that are ex ante riskier validate expectations at origination and experience more defaults (e.g., loans with higher interest rate spreads, low rated[17] and unrated borrowers, less profitable, and

[15] As Sufi (2007) points out, this finding is compatible with a moral hazard problem, where the information asymmetry is shared by all lenders, not an adverse selection problem. That is, as the lead monitors the loan and learns about the borrower, the information asymmetry is reduced and the lead can form a more diffuse syndicate. In contrast, the adverse selection problem lies in an informational advantage that the lead has over the participants and participants would, therefore, require the lead to retain more as this advantage becomes more precise with repeated lender-borrower interactions.

[16] In other results, loans with a guarantor or a sponsor, as well as loans with resale constraints are associated with a lower lead share but also a lower chance of default. For example, minimum resale constraints could help ensure that fewer lenders hold the loan in the presence of a secondary market. That said, evidence exists that lead arrangers retain their shares following origination (Ivashina and Sun, 2011).

[17] Fine ratings (19 dummies) are not shown in Table 2 in the interest of space, but the coefficient rankings are as expected. For example, borrowers rated BBB and below are significantly more likely to default than AAA-rated borrowers and in an increasing manner as the rating worsens.

leveraged companies). To control for industry performance, borrowers in industries that later experience higher default rates are also more likely to default. Two reputational factors especially help mitigate defaults: lead arrangers as commercial banks and when the interaction between the lead arranger and a participant lender is a reciprocal one. The latter finding supports Cai (2009). Recent stylized facts support the former. For example the Shared National Credit review found that a disproportionate share of problem syndicated loans are held by nonbanks (consistent with both the lower reputations of these institutions and their inferior in-house credit assessment and monitoring capacities as discussed in Dennis and Mullineaux, 2000, and S&P, 2006).

An alternative model is estimated in the last column of Table 2, where loans to the same borrower are aggregated so that the analysis is at the borrower level. This helps address the view that clustering the standard errors at the borrower level may not be enough when loans originated to the same borrower are correlated. Also, default is observed at the borrower level. The estimated effect on the lead share is economically larger (-0.560; standard error 0.166). This is likely because the effect of loan outliers is minimized when loans to a borrower are aggregated.

An alternative measure of performance is analyzed in Table A1. These are dummy variables indicating rating changes on the borrower's senior debt over a one-year horizon following origination (qualitatively similar results are found for a two-year horizon but are less precisely estimated). Specifically, fine letter ratings were converted into a numerical scale and borrowers are considered to be "downgraded" or "upgraded" when the numerical rating changes in the respective direction. The loan-level results are shown in the first two columns. The effects are in the hypothesized direction, where for example, a one standard deviation increase in the lead's share raises the likelihood of an upgrade by 3.7%. Note that these regressions also control for the average rating change in the borrower's 2-digit industry over the comparable horizon.

4.2 Robustness Checks

Additional robustness tests were run on different measures of exposure taken by the lead and different instruments. The first column of Table A2 examines the lead shares for institutional tranches in a test of whether an exogenously strong institutional demand may cause the lead to retain less of the institutional tranches, decreasing its monitoring intensity.[18] The results show that, all else fixed (including the lead's share on the bank tranche), a larger wedge between the bank and institutional tranche is significantly associated with a higher default probability. Column (2) shows that the IV results are similar when the lead share in percent is replaced with a different measure of exposure – log of the loan's dollar amount kept by the lead. Column (3) expresses the lead's exposure in the closest way to how regulatory (and internal) lending limits are determined in practice. That is, for the subset of loans arranged by a bank (and capital levels are therefore available from Call Reports), the lead's exposure to the borrower is scaled by the bank's capital, and likewise for the instruments. Results are similar and significance levels are stronger. Finally, confirming the exogenous cross-lead variation in lending limit instruments, the results in column (5) replace the limit instruments with lead fixed effects. The estimated effect (-0.108) is smaller but comparable to the effect estimated in the benchmark model in Table 2(3).[19]

Table A3 conducts the default analysis so that the horizon for observing default is defined. The results are shown for each of i) default within 3 years, ii) default before loan matures, and iii) default only applies to the last loan originated prior to default. The median time between loan origination and default is 3 years for all these measures, while it is 5 years for the main unrestricted regressions. Columns (4) and (5) apply firm fixed effects to better isolate the lead's effect. Assuming that a valid source of exogenous variation has been identified in the lending limits (as previously established), firm fixed effects can be used to understand the timing of default. That is, a borrower is more likely to default in a particular year when for exogenous reasons the lead could not take a larger stake, and as a result, did not exert sufficient effort in monitoring the borrower. The results are supportive of this prior.

Table A4 evaluates whether the instrumental variable approach is susceptible to the potential endogeneity of the all-in-spread variable. The results are robust to various checks such as excluding the all-in-spread from the regressions or instrumenting it with the market-level spread.[20] Table A5 evaluates the relation between lead share and different types of defaults:

[18] I thank an anonymous referee for this test and for other robustness-check suggestions.
[19] These results are stronger if lead bank characteristics are also controlled for (-0.147 significant at the 1% level). Note that the overidentifying restrictions test is not rejected.
[20] The issue here is whether a relation between the variable of interest and other explanatory variables poses a problem for the identification strategy. While this would be a problem in a OLS regression, the key advantage of IV is that the instrumented component of lead share is exogenous. So the instrument has no effect on outcomes other than through the first-stage channel. The first stage residual is also, by construction, uncorrelated with the included covariates.

bankruptcy, distressed exchange, and missed payment. Increasing the lead share on a loan has the greatest effect in preventing bankruptcies, which have been shown in previous research to be the worst outcome for creditors.

Finally, as predicted by the theory, asymmetric information problems (both adverse selection and moral hazard) should be more acute for opaque borrowers. The results in Table A6 collectively support this prior. Increasing the lead's share is, for example, more critical for borrowers with leveraged loans, lower profitability and Altman z-scores, higher equity volatility, and borrowers that are in relatively less familiar industries, or that are not investment grade.

5. TESTS OF MORAL HAZARD IN MONITORING

5.1 Testing the Monitoring Intensity of the Credit Facility

In this section, tests are carried out on the hypotheses outlined in Section 3.2 to help identify whether moral hazard in monitoring plays an important role in practice. Following Fama (1985) and others, the first hypothesis (H1) contends that one main aspect of monitoring is for the lender to maintain and manage credit line availability. Increasing the lead's share on a revocable credit facility should increase the lead's monitoring of the facility after it is first contracted (regardless of whether or not the borrower later draws down funds). As the lead discovers new information about the borrower – for example, whether the borrower has taken on too much liquidity risk – the lead has the option to revoke the facility or to reduce the available funds committed. Therefore, monitoring should be more valuable for credit lines than for term loans. To test this hypothesis, the analysis is evaluated at the facility-level instead of loan-level data used for the main results. Facilities are partitioned into two different samples, depending on whether the facility is a revolving credit line or a fully funded facility (term loan). Evaluating the sensitivity of performance to lead share within facility classes helps control for the possibility that there are other fundamental differences between borrowers in the two classes that may not be controlled for. For example, Sufi (2009) notes that firms with access to credit lines are generally more likely to have high cash flows and are less financially constrained.

The results are in columns (4) and (5) of Table 2 (default) and the last two columns of Table A1 (rating changes). As predicted, increasing the lead's share on a credit line produces significantly better borrower performance. In contrast, increasing the lead's share on a term facility is not associated with better performance. For example, the IV-estimated coefficient on the share in Table 2 is a statistically significant -0.216 in the case of credit lines and an insignificant -0.127 in the case of term loans. Similarly, Table A1 shows the results for rating upgrades and downgrades for credit lines (results for term facilities are weaker and are omitted in the interest of space). Increasing the lead's share on a credit line facility by one standard deviation is associated with a 5.7% increase in the likelihood of a rating upgrade (column (4)), higher than the effect found for the average loan (column (2)). Moral hazard in monitoring is a compelling explanation for these results. In contrast, if the lead possesses private information on the borrowing firm when the loan is closed, its share should be equally important for signaling this information – regardless of whether the loan is a term loan or a credit line.

One possible confounding issue is that there are more commercial banks than nonbanks on credit lines compared with term loans (based on Gatev and Strahan, 2009, as well as the sample in this study). Gatev and Strahan note that banks have a natural advantage in managing credit lines than do institutional investors because credit lines expose the lender to higher liquidity risk. Banks are less vulnerable to liquidity risk because of a natural synergy that comes from combining deposit-taking with lending. Therefore, the sample is further conditioned on those facilities with only banks as leads in a separate test not shown. The results continue to show that credit lines exhibit greater sensitivity to the lead bank's share, in line with Sufi (2009) and Acharya, Almeida, Ippolito, and Perez (Forthcoming) discussed earlier. Interestingly, the latter paper also documents how firms with the highest coincidence of their cash flows and investment opportunities are the most likely to use credit lines. And their credit lines are less likely to contain covenants precisely because such firms are unlikely to violate the terms. Covenant tests are taken up in Section 5.3.

5.2 Testing the Lead's Opportunity Cost Hypothesis

This section tests the second hypothesis – the opportunity cost hypothesis (H2) – that relates monitoring and the incidence of adverse selection to the lead's opportunity cost of holding the loan against offloading it. To test this hypothesis, lead bank conditions are included with a particular focus on measures of a bank's internal funding costs. How a lending syndicate can be shaped by the condition of the lead arranger also contributes more generally to the extant literature that has largely focused on borrower drivers and ignored lender conditions. The first part of the hypothesis concerns the choice made by the lead over what share of the loan to hold

(H2a). Leads with high internal funding costs optimally retain a lower share. Results of the first stage of the IV-regression are, therefore, the primary interest of this part of the hypothesis.

Empirically, I approximate the opportunity cost by the lead's capital constraint, by how likely the lead is to experience liquidity shocks (that is, if it holds a low share of liquid assets or if it has extended a lot of unused commitments that could be drawn down unexpectedly), and by its funding interest rates (deposit and wholesale) controlling for its loan rate. Lastly, a lead bank's size and profitability also control for measures of the lead's reputation. Bank measures are shown in Table 3 for the subset of loans arranged by a U.S. bank.

[TABLE 3]

The results of the first stage regression in column (1) of Table 3 are mostly as predicted by H2a. First, a capital-constrained bank keeps a lower share of the loan (consistent with the model in Gorton and Pennacchi (1995) and the findings of Dennis and Mullineaux (2000) and Jones, Lang, and Nigro (2005)). Second, a bank with a high unused commitments ratio also keeps less to alleviate its liquidity constraint. Although, banks with more liquid assets do not appear to retain more as would be predicted. This finding could be due to a reputational effect. Reputational reasons also show up in the result that large banks and more profitable banks retain smaller shares. Third, a bank with a high deposit rate (relative to its loan rate) also reduces its share held as predicted.[21]

Therefore, the collective evidence from the first stage regression supports hypothesis H2a, which predicts that increasing the internal funding cost of a lead bank causes it to decrease its share of a syndicated loan. Then in the second stage (column (2)), the instrumented decrease in the lead's share is associated with a higher probability of default. As discussed in Section 3.2, this finding has an intuitive monitoring explanation, in that a liquidity or capital constrained bank simply reduces its monitoring level (and hence the project's expected return) in response to its incentive-compatibility constraint. Participants and other investors are aware that the bank is monitoring less and, therefore, demand a higher return on their invested capital (as shown, for example, by Gorton and Pennacchi, 1995; Ivashina, 2009). Nonetheless, an adverse selection problem (however remote) cannot be perfectly ruled out if, for example, a bank vulnerable to a

[21] In a few specifications, a bank's wholesale interest rate has a significantly positive effect on the share held, counter to the expected negative effect. This can be reconciled with an offsetting reputational effect, in that a bank facing funding problems in the federal funds and repo markets also is forced by participant lenders to retain a larger share.

liquidity shock happens to be inclined to arrange syndicated loans that it privately knows are poor quality, leading it to retain a smaller share. It is not evident why this would consistently be the case but such a correlation could be picked up in the results described.

A clear-cut strategy is outlined in the second part of the hypothesis (H2b). An adverse selection problem should result in the underperformance of loans syndicated by a bank with a low internal funding cost compared to those syndicated by a bank with a high internal funding cost. A bank with a low funding cost (such as a well-capitalized bank with a small share of unused commitments and low deposit rates) can afford to hold good loans in its portfolio. As a result, the average quality of its syndicated loans should be later revealed to have been poor if the adverse selection problem is a significant one as predicted in the model by Parlour and Plantin (2008).

Therefore, the focus of this hypothesis is on the second stage results. The results in column (2) are not especially supportive of H2b. Only the coefficient on the unused commitments ratio (-0.055; standard error 0.060) is signed as predicted by an adverse selection problem. Interestingly, evidence of an adverse selection problem seems stronger when zooming in on credit lines in columns (3) and (4). For example, the coefficient estimate on unused commitments is -0.103 (standard error 0.059), meaning that a one standard deviation increase in a bank's unused commitments results in close to a 1% lower likelihood of default. This result makes sense because a bank's decision to offload loans will be especially sensitive to the liquidity risk inherent in the additional loan it syndicates. A bank that has a lot of outstanding credit lines and other commitments is predicted to syndicate out more good quality credit lines than good quality term loans that have inherently less liquidity risk. Moreover, such a lead should keep a lower share of a new credit line compared with a typical new loan as predicted by H2a (e.g., the coefficient on unused commitments in the first stage regression in column (3) equals -0.071 standard error 0.036 compared with -0.057 standard error 0.034 in column (1)). To summarize, there exists possible evidence of a limited adverse selection problem in the case of credit line facilities only. Results supportive of H2a add further weight, therefore, to a moral hazard in monitoring problem.

The final two columns of Table 3 show the results of a complementary IV estimation approach, where the lead arranger share is instrumented with the two lending limit instruments plus a new instrument, which is the lead bank's credit risk exposure in the mortgage securitization and sales market (only available from 2001). The effect of this instrument is consistent with its economic motivation (0.023; standard error 0.010). Banks that retain a greater credit exposure to mortgage loan securitizations also retain a greater share of syndicated loans.

5.3 Testing Covenants as a Monitoring Mechanism

This section tests the third and final hypothesis, which contends that covenants act as tripwires providing the lender with an option to intervene and renegotiate loan terms. Equally, the borrower has a strong incentive to avoid violating the covenant and losing control rights, especially when its debt is privately held and concentrated. Thus, the syndicated loan market is a good testing ground for the theory summarized in Section 3.2. If covenants facilitate monitoring, defined broadly, then a stronger relation should exist between a lead's share and outcomes for loans with more covenant constraints (H3a).

The results in Table 4 are in the predicted direction. Panel A shows results for a covenant split according to contemporaneous covenants, while Panel B shows results for a covenant split according to covenants on a borrower's previous loans to account for the dynamic function of covenants.

[TABLE 4]

The results show that the lead's share has a stronger effect on subsequent default for loans with a financial covenant compared to those without (e.g., the coefficient estimate in column (1) is -0.197 standard error 0.082 versus -0.091 standard error 0.155 in column (2) for loans lacking a financial covenant). A similar statistically significant relation is found for borrowers whose previous loans had financial covenants. Similar results also hold when running a comparison according to the number of covenants in columns (3) and (4) (calculated, along with slack measures, following Drucker and Puri, 2009). A third measure of covenant constraints can be approximated by how much slack a borrower has on a particular covenant. For example, net worth covenant slack is measured as the difference between the borrower's actual net worth and the minimum level defined in the covenant and normalized by the borrower's assets. Increasing the lead's share on a loan with a tight covenant should be associated with better performance than a similar increase on a loan with a loose covenant. The results in columns (5) and (6) of Panel B fit the prediction (where covenant slack is measured from previous loans). Panel A indicates, however, that the effect is larger (but insignificant) for loans with loose contemporaneous covenants, although having a concentrated lead exposure on such loans could help offset the direct negative effect that slack has on performance (column (6)).

These results are overall consistent with the literature's findings that covenants have significant effects in practice. Sufi (2009) shows that banks restrict credit line access following covenant violations. For example, a cash-flow based financial violation is associated with up to a 25% decrease in the availability of lines of credit. Sufi cites this as evidence that covenants facilitate monitoring.[22] Other studies also analyze the state-contingent transfer of control rights to creditors. For example, Chava and Roberts (2008) find that a borrower's investment is reduced following a covenant violation. They also find that violations on loans with a single lender lead to a much larger investment decline compared with violations on loans with more diffuse syndicates. This finding is consistent with the lead arranger having a greater incentive to reassess and restructure its lending position when it is particularly exposed to the borrower.

A stylized fact is that private debt contains relatively more and tighter covenants than public debt does (Kahan and Tuckman, 1993). Managers also make accounting choices to avoid violating these covenants (Dichev and Skinner, 2002). Moreover, covenant usage increases more on bank debt than on bonds as the borrower's credit quality worsens (Rauh and Sufi, 2010). Loans with more stringent covenants result in a higher recovery rate (upon default) for the lender, also consistent with covenants allaying value-reducing activities by shareholders (Zhang, 2010). But covenant usage by the lender also increases following a worse performance of its loan portfolio. Murfin (2012) rationalizes this finding by a lender updating its belief about its screening ability and, therefore, substituting stronger ex post monitoring through tighter covenants.

If loan covenants help induce the lead to monitor the borrower, or equally, if they increase the incentive of the borrower to avoid violating the terms, it is important to understand how loan covenants are set in the contract in the first place. First, loan covenants depend on the business cycle and are characterized by common trends, such as the proliferation of "covenant-lite" loans in the period before the 2007-2009 financial crisis. Lenders partly ceded renegotiation rights by agreeing to such loans. The evolution of covenants over time is traced out in Table 5. Coverage

[22] In a different application, there is evidence that restrictive covenants increase the ability of subordinated debtholders to discipline banks. For example, Ashcraft (2008) shows that subordinated debt was associated with lower financial distress and bank failures before Basel was introduced. But the Basel Accord did not allow subordinated debt to count as Tier 2 capital if it had covenants. Ashcraft finds that, after Basel, subordinated debt was no longer associated with better outcomes.

of covenants in Dealscan is limited before the mid-1990s (Chava and Roberts, 2008). In the decade from 1996 to 2006, covenant restrictions eased, in particular, toward the end of the sample. For example, the number of covenants in 2006 was on average one compared with 1.8 over the sample; the slack in the net worth covenant reached 0.13 compared with 0.09 over the sample. Similar trends are found for the other covenant slack measures such as for tangible net worth and interest coverage. Murfin (2012) also documents the significant loosening of covenants that took place from 2002 to 2006 and the tightening after 2006.

[TABLE 5]

The degree of covenant rigor is, however, endogenously chosen together with other loan terms, in particular, the lead's share. The null hypothesis (H3b) is that covenants should be paired with a higher share – whether to increase the delegated monitor's effort (Rajan and Winton, 1995) or to increase the borrower's cost of violation (Dichev and Skinner, 2002). In both cases, incentives are weakened by increasing other claimants on the borrower. But an alternative hypothesis runs counter to H3b, which is that covenants substitute for delegated monitoring. For example, Drucker and Puri (2009) discuss how covenants can serve as a "public monitoring device". They show that loans with greater covenant restrictions facilitate loan sales, hypothesizing that dispersed investors can use them to benchmark a borrower's performance.

To test H3b, Table 6 models the relation between covenant constraints and the lead arranger's share. These models control for the business cycle and the borrower's previous covenant characteristics. All the standard covariates included in Table 2 are also controlled for.[23] Columns (1), (3), and (5) show the results of ordinary least squares for the financial covenant indicator, the number of covenants, and the net worth covenant slack measure, respectively. Columns (2), (4), and (6) repeat the analysis with IV estimation (using the lending limit instruments) to isolate the exogenous impact of the lead's share on covenant design in the loan contract.

[TABLE 6]

The striking result is that the OLS relation between covenant intensity and lead exposure is a negative one but the IV-estimated relation is a positive one. That is, covenants appear to

[23] While not the focus of this paper, there is evidence that covenants are cyclical (at least in incidence and number) echoing results in Zhang (2010), and Murfin (2012), among others. There is also more covenant slack for less risky borrowers (e.g., as proxied by leverage and profitability) echoing results in Billett, King, and Mauer (2007), and Rauh and Sufi (2010), among others.

substitute for delegated monitoring but the true relation is one in which covenants go hand in hand with monitoring by the lead. The OLS effect is likely swamped by reverse causality – in that tighter covenants then allow the lead to retain a smaller share as participant lenders are persuaded to increase their exposure. The estimates imply that a one standard deviation increase in the lead arranger's share yields a 4.2% increase in the probability that the loan has a financial covenant (column (2)) compared with about a 0.1% decrease based on the least squares estimate (column (1)). Similarly, a one standard deviation increase in the lead's share is associated with a 0.20 increase in the number of covenants (while the OLS results suggest a 0.08 decrease when comparing the results in columns (3) and (4)).

A similar, though weaker, direction is also present when looking at the slack in the net worth covenant. For example, the OLS result suggests that increasing the lead's share by one standard deviation can increase slack by 0.0067 while IV finds a much weaker insignificant effect. The covenant slack focus in the analysis has so far been on the net worth covenant because Drucker and Puri (2009) point out that it is associated with technical default and is also easier to measure. Other slack measures are more difficult to measure unambiguously because it is harder to determine the relevant leverage or cash flow values. Nonetheless, Table 7 presents additional results for covenants that are relatively easy to calculate (the tangible net worth covenant, the debt to tangible net worth covenant, and the interest coverage covenant). The results also support H3b, in that tighter covenants are contracted together with a larger lead share.[24]

[TABLE 7]

Taken together, compelling evidence exists for the view that covenants and the lead's share are complements, which contrasts with Drucker and Puri (2009). They conclude that covenants substitute for delegated monitoring because loans that are sold have more restrictive covenants. However, in the absence of an instrument for loan sales in their study, it is somewhat inconclusive. It is possible also that loan sales in the secondary market and syndications in the primary market are significantly different even though they share common features (see

[24] To the extent that the results are based on only straightforward covenants, the problem may be even greater in practice because, for example, not all future effort by the delegated monitor can be contracted on. That said, even relatively crude covenants require monitoring and make it possible to learn about the borrower's state without much costly effort, as discussed in Rajan and Winton (1995).

Benmelech et al., 2012). This topic deserves further investigation. The implication of the results in this paper is that the lead's incentives cannot be separated from covenants.[25]

6. CONCLUSION

This study has uncovered evidence of asymmetric information in the syndicated loan market, in a manner consistent with the related theory. An important contribution of this study was showing that moral hazard in monitoring is a significant problem in practice (albeit without dismissing entirely the possibility of adverse selection).

While the adverse effects of credit sharing have taken center stage in this paper, this does not necessarily imply that credit risk sharing reduces welfare. Such markets provide a valuable form of insurance for lenders as they free up capital and enable credit expansion. The results in this paper show that banks retain a lower portion of loans when the cost of holding loans in portfolio is high. Moreover, firms whose loans are sold typically maintain lending relationships and have increased access to loans (Drucker and Puri, 2009). This finding helps explains why borrowers are willing to pay for the intermediary's asymmetric information problem in the form of higher loan interest rate spreads (Ivashina, 2009). In addition, the shift from relationship-based banking to arm's length finance is endogenous and has been facilitated by technical, regulatory, and institutional change (Rajan, 2005; Parlour and Plantin, 2008). While relationship lending offers more flexible liquidity, it comes at the cost of hold-up problems by informed lenders exploiting their monopoly advantage.

The tension between insurance and incentives has yet to be resolved. We have to wait until the dust settles from foreclosed houses to appreciate what direction financial intermediation takes. A paper by Cerasi and Rochet (2008) speaks to the optimal design of bank capital regulation in the presence of credit risk transfer activities. This diversification should allow banks to decrease their value-at-risk and with that their regulatory capital. But a decrease in regulatory capital fails to consider monitoring incentives. The optimal capital ratio should be increasing in the severity of the bank's moral hazard problem.

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[25] In practice, both Rajan and Winton's take and Drucker and Puri's take are compatible. Some covenants can be publicly monitored at little or no cost, while other covenants may require more effort by a delegated monitor to observe whether a violation has occurred. For example, Diamond (1984) conjectures that contingent covenants are costly to monitor, such as determining that the borrower's working capital not fall below some level unless necessary for expansion of inventory.

REFERENCES

Acharya, V., H. Almeida, F. Ippolito, and A. Perez, Forthcoming, Credit Lines as Monitored Liquidity Insurance: Theory and Evidence, *Journal of Financial Economics*.

Aghion, P., and P. Bolton, 1992, An Incomplete Contracts Approach to Financial Contracting, *Review of Economic Studies*, 59: 473-494.

Altman, E., 1968, Financial Ratios, Discriminant Analysis, and the Prediction of Corporate Bankruptcy, *Journal of Finance*, 23: 589-609.

Amihud, Y., 2002, Illiquidity and Stock Returns: Cross-Section and Time-Series Effects, *Journal of Financial Markets*, 5: 31-56.

Angrist, J.D., and J.-S. Pischke, 2009, *Mostly Harmless Econometrics: An Empiricist's Companion* (Princeton and Oxford: Princeton University Press).

Ashcraft, A., 2008, Does the Market Discipline Banks? New Evidence from Regulatory Capital Mix, *Journal of Financial Intermediation*, 17: 543-561.

Benmelech, E., J. Dlugosz, and V. Ivashina, 2012, Securitization Without Adverse Selection: The Case of CLOs, *Journal of Financial Economics*, 106: 91-113.

Berndt, A., and A. Gupta, 2009, Moral Hazard and Adverse Selection in the Originate-to-Distribute Model of Bank Credit, *Journal of Monetary Economics*, 56: 725-743.

Billett, M., T.-H. King, and D. Mauer, 2007, Growth Opportunities and the Choice of Leverage, Debt Maturity, and Covenants, *Journal of Finance*, 62: 697-730.

Bord, V., and J. Santos, 2011, Did the Rise of CLOs Lead to Riskier Lending? Working Paper, Federal Reserve Bank of New York.

Bromiley, P., and W. Stansifer, 1994, Loan-Size Limits: A Simple Model, *Journal of Commercial Lending*, 17-28.

Cai, J., 2009, Competition or Collaboration? The Reciprocity Effect in Loan Syndication, Working Paper, Federal Reserve Bank of Cleveland.

Cerasi, V., and J.-C. Rochet, 2008, Solvency Regulation and Credit Risk Transfer, Working Paper, Paolo Baffi Centre.

Chava, S., and M. Roberts, 2008, How Does Financing Impact Investment? The Role of Debt Covenants, *Journal of Finance*, 63: 2085-2121.

Dahiya, S., M. Puri, and A. Saunders, 2003, Bank Borrowers and Loan Sales: New Evidence on the Uniqueness of Bank Loans, *Journal of Business*, 76: 563-582.

De Servigny, A., and O. Renault, 2003, Correlation Evidence, *Risk*, 16: 90-94.

Dennis, S., and D. Mullineaux, 2000, Syndicated Loans, *Journal of Financial Intermediation*, 9: 404-426.

Diamond, D., 1984, Financial Intermediation and Delegated Monitoring, *Review of Economic Studies*, 51: 393-414.

Dichev, I., and D. Skinner, 2002, Large-Sample Evidence on the Debt Covenant Hypothesis, *Journal of Accounting Research*, 40: 1091-1123.

Drucker, S., and M. Puri, 2009, On Loan Sales, Loan Contracting, and Lending Relationships, *Review of Financial Studies*, 22: 2835-2872.

Fama, E., 1985, What's Different About Banks? *Journal of Monetary Economics*, 15: 29-39.

Gatev, E., and P. Strahan, 2009, Liquidity Risk and Syndicate Structure, *Journal of Financial Economics*, 93: 490-504.

Gorton, G., and G. Pennacchi, 1995, Banks and Loan Sales: Marketing Nonmarketable Assets, *Journal of Monetary Economics*, 35: 389-411.

Gorton, G., and A. Winton, 2003, Financial Intermediation, in: G. Constantinides, M. Harris, and R. Stulz, eds., *Handbook of the Economics of Finance: Corporate Finance* (Amsterdam: North Holland), pp. 431-552.

Greenbaum, S., and A. Thakor, 1987, Bank Funding Modes: Securitization versus Deposits, *Journal of Banking and Finance*, 11: 379-401.

Holmström, B., and J. Tirole, 1997, Financial Intermediation, Loanable Funds, and the Real Sector, *Quarterly Journal of Economics*, 112: 663-691.

International Monetary Fund, 2006, *Global Financial Stability Report*, April.

Ivashina, V., 2009, Asymmetric Information Effects on Loan Spreads, *Journal of Financial Economics*, 92: 300-319.

Ivashina, V., and Z. Sun, 2011, Institutional Demand Pressure and the Cost of Corporate Loans, *Journal of Financial Economics*, 99: 500-522.

Jones, J., W. Lang, and P. Nigro, 2005, Agent Bank Behavior in Bank Loan Syndications, *Journal of Financial Research*, 28: 385-402.

Kahan, M., and B. Tuckman, 1993, Private vs. Public Lending: Evidence from Covenants, Working Paper, Anderson Graduate School of Management, UCLA.

Karlan, D., and J. Zinman, 2009, Observing Unobservables: Identifying Information Asymmetries with a Consumer Credit Field Experiment, *Econometrica*, 77: 1993-2008.

Keys, B., T. Mukherjee, A. Seru, and V. Vig, 2010, Did Securitization Lead to Lax Screening? Evidence from Subprime Loans, *Quarterly Journal of Economics*, 125: 307-362.

Leland, H., and D. Pyle, 1977, Informational Asymmetries, Financial Structure, and Financial Intermediation, *Journal of Finance*, 32: 371-387.

Murfin, J., 2012, The Supply-Side Determinants of Loan Contract Strictness, *Journal of Finance*, 67: 1565-1601.

Park, C., 2000, Monitoring and the Structure of Debt Contracts, *Journal of Finance*, 55: 2157-2195.

Parlour, C., and G. Plantin, 2008, Loan Sales and Relationship Banking, *Journal of Finance*, 63: 1291-1314.

Rajan, R., 2005, Has Financial Development Made the World Riskier? in: *The Greenspan Era: Lessons for the Future*, a Symposium Sponsored by the Federal Reserve Bank of Kansas City, August 25-27.

Rajan, R., and A. Winton, 1995, Covenants and Collateral as Incentives to Monitor, *Journal of Finance*, 50: 1113-1146.

Rauh, J., and A. Sufi, 2010, Capital Structure and Debt Structure, *Review of Financial Studies*, 23: 4242-4280.

S&P, 2006, *A Guide to the Loan Market* (New York: The McGraw-Hill Companies, Inc.).

Smith, C., and J. Warner, J., 1979, On Financial Contracting: An Analysis of Bond Covenants, *Journal of Financial Economics*, 7: 117-161.

Stock, J., and M. Yogo, 2005, Testing for Weak Instruments in Linear IV Regression, in: D. Andrews and J. Stock, eds., *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg* (Cambridge: Cambridge University Press), pp. 80-108.

Sufi, A., 2007, Information Asymmetry and Financing Arrangements: Evidence from Syndicated Loans, *Journal of Finance*, 62: 629-668.

Sufi, A., 2009, Bank Lines of Credit in Corporate Finance: An Empirical Analysis, *Review of Financial Studies*, 22: 1057-1088.

Winton, A., 1999, Don't Put All Your Eggs in One Basket? Diversification and Specialization in Lending, Working Paper, University of Minnesota.

Wooldridge, J.M., 2002, *Econometric Analysis of Cross Section and Panel Data* (Cambridge and London: MIT Press).

Zhang, Z., 2010, Recovery Rates and Macroeconomic Conditions: The Role of Loan Covenants, Working Paper, Boston College.

Table 1. Summary Statistics of Main Regression Variables
Syndicated loan deals to U.S. borrowers, 1990 - 2006, Sample observations = 6,204 loan deals

	Mean	Standard Deviation	10th Percentile	Median	90th Percentile
Dependent variables					
Borrower default	0.070	0.255	0.000	0.000	0.000
Borrower 1-year downgrade	0.134	0.341	0.000	0.000	1.000
Borrower 1-year upgrade	0.097	0.296	0.000	0.000	0.000
Instruments					
Lead lending limit, as lead (US$ million)	62.498	48.162	28.400	47.490	123.750
Lead lending limit, as participant (US$ million)	47.252	28.034	22.500	40.000	94.990
Lead exposure to mortgage securitization	0.139	0.240	0.008	0.057	0.450
Contract characteristics					
Lead share	0.276	0.181	0.086	0.227	0.534
Lead exposure (Amount to lead bank's capital)	0.006	0.053	0.001	0.002	0.010
Number of lead arrangers	1.159	0.380	1.000	1.000	2.000
Total number of lenders	10.534	9.255	2.000	8.000	22.000
All-in-spread drawn (%)	1.362	1.023	0.300	1.125	2.750
Loan amount (US$ million)	481.875	1096.279	45.000	200.000	1050.000
Maturity (months)	42.820	21.693	12.000	38.000	64.500
Secured	0.423	0.494	0.000	0.000	1.000
Number of tranches	1.435	0.738	1.000	1.000	2.000
Financial covenant	0.690	0.462	0.000	1.000	1.000
Number of covenants	2.726	2.380	0.000	3.000	6.000
Covenant slack net worth	0.106	0.141	-0.003	0.098	0.264
Borrower characteristics					
Rated	0.531	0.499	0.000	1.000	1.000
Profitability (ROA)	0.128	0.081	0.043	0.124	0.225
Leverage	0.336	0.213	0.068	0.318	0.612
Size (log(assets))	7.056	1.750	4.983	6.825	9.531
Industry default probability	0.011	0.020	0.000	0.004	0.027
Previous loans	4.048	4.705	0.000	3.000	10.000
Syndicate group characteristics					
Previous lead	0.676	0.468	0.000	1.000	1.000
Lead fraction banks	0.926	0.249	1.000	1.000	1.000
Lead country US	0.929	0.257	1.000	1.000	1.000
Lead market share	0.100	0.117	0.002	0.055	0.272
Repeat interactions lead to participant	1.721	4.884	0.121	1.008	4.039
Reciprocal	0.966	0.182	1.000	1.000	1.000
Lead bank characteristics					
Size (log(assets))	19.240	1.165	17.705	19.364	20.816
Income	0.010	0.004	0.006	0.011	0.014
Capital	0.074	0.013	0.059	0.074	0.090
Liquidity	0.177	0.073	0.106	0.158	0.274
Unused commitments	0.404	0.093	0.308	0.394	0.506
Loan interest rate	0.075	0.017	0.054	0.075	0.100
Deposit interest rate	0.037	0.014	0.016	0.039	0.057
Wholesale interest rate	0.043	0.019	0.017	0.045	0.061

This table presents summary statistics of the main regression variables for syndicated loans (deals) to U.S. borrowers between 1990 and 2006. *Borrower default* is an indicator of a borrower's default on securities, mostly bonds, recorded by Moody's Default Risk Service Database, 2008 download. *Borrower downgrade (upgrade)* indicate whether a borrower was downgraded (upgraded) over a 1-year horizon, based on S&P senior debt fine ratings. *Lead lending limit, as lead* is the 75th percentile of the dollar size of the lead's share on its syndicated loans over the preceding three years where it served as lead. *Lead lending limit, as participant* reflects its limit based on previous loans where it served as a participant only. *Lead exposure to mortgage securitization* reflects the maximum credit exposure from recourse and other credit enhancements as a share of 1-4 family residential loans securitized or sold averaged over previous 3 years taken from Y-9C bank regulatory filings. *Lead share* is the fraction of the loan retained by the lead arranger at origination. In the case of more than one lead arranger, the sum of the share is taken. *Lead exposure* measures the lead's dollar amount relative to the lead bank's capital. *Number of lead arrangers* is the number of lead arrangers on a loan, while *total number of lenders* also includes the number of other lenders in a lead or participant role. *All-in-spread drawn* is the interest margin paid over LIBOR. *Loan amount* is the total size of the loan (deal) amount in US$ millions. *Maturity* is the loan's tenor measured in months. *Secured* is a dummy equal to one if the loan is secured and zero otherwise. *Number of tranches* is the number of tranches (facilities) that make up a loan. *Financial covenant* is a dummy equal to one if the loan has financial covenants and zero otherwise. *Number of covenants* is the sum of the number of financial covenants and sweep covenants plus one if the loan has a dividend restriction, following Puri and Drucker (2009). *Covenant slack net worth* is defined as net worth - covenant minimum level divided by book assets, where accounting variables are from Compustat. *Rated* is a dummy equal to one if the borrower's senior debt was rated by S&P or Moody's at the close of the loan and zero otherwise. *Profitability* is EBITDA to total assets. *Leverage* is ratio of book value of debt to total assets. *Size* is the natural log of borrower's total assets. *Industry default probability* is the 2-digit industry default probability measured over the previous 3 years using data on bonds transitioning to default from Moody's DRS following De Servigny and Renault (2003). *Previous loans* is the number of a borrower's previous syndicated loans. *Previous lead* is a dummy equal to one if the lead arranger(s) was a lead on a previous loan to the borrower. Lenders are aggregated to their parent company and inherit the characteristics of the parent as in Sufi (2007). In the event of mergers between lenders, the acquiring firm inherits the relationships of the target firm at the merger completion date. *Lead fraction banks* is the fraction of the lead arrangers that are "banks" following Gatev and Strahan (2009). *Lead country US* is a dummy equal to one if the lead arranger is a US lender. *Lead market share* is the syndicated market share of the lead arranger measured over the previous 3 years. *Repeat interactions lead to participant* is the number of links between the lead arranger and other members of the syndicate over the previous 3 years, scaled by the number of previous loans arranged by the lead. *Reciprocal* is a dummy equal to one if the lead arranger was a participant in a syndicate led by one of the participants. Lead bank characteristics, including *size* measured by the natural log of lead bank's assets at end of year, are for the subset of lenders that belong to U.S. bank holding companies (Y-9C). *Income* is net income before extraordinary items to total assets. *Capital* is the lead bank's book capital ratio. *Liquidity* is the lead bank's liquid assets to total assets, where liquid assets are cash, securities and net federal funds sold & repos. *Unused commitments* are measured as a share of total unused commitments and gross loans. *Loan (deposit) interest rate* are implicit rates measured by the interest on loans (deposits) divided by the quarterly-average balances of loans (deposits). *Wholesale interest rate* is the expense on federal funds purchased and repos sold to the quarterly averages of these balances.

Table 2. Lead Arranger Syndicate Exposure and Subsequent Borrower Default

	(1) OLS Loan deals	(2) 2SLS 1st Stage Loan deals	(3) 2nd Stage Loan deals	(4) 2nd Stage Credit lines	(5) 2nd Stage Term loans	(6) 2nd Stage Borrower-Level
Instruments						
Lead lending limit, as lead		0.0005**				
		(0.0002)				
Lead lending limit, as participant		0.0008***				
		(0.0003)				
Contract characteristics						
Lead share	-0.020		-0.164*	-0.216**	-0.127	-0.560***
	(0.025)		(0.089)	(0.106)	(0.142)	(0.166)
All-in-spread drawn	0.007	0.016***	0.009	0.012*	0.004	0.016
	(0.007)	(0.003)	(0.007)	(0.007)	(0.009)	(0.011)
Log (loan amount)	-0.001	-0.079***	-0.012**	-0.007	-0.014	-0.051***
	(0.006)	(0.004)	(0.006)	(0.006)	(0.011)	(0.014)
Log (maturity)	-0.003	-0.010	-0.005	-0.007	0.000	-0.014
	(0.007)	(0.008)	(0.007)	(0.006)	(0.013)	(0.011)
Secured	0.002	-0.008	0.000	-0.001	0.034	-0.004
	(0.011)	(0.007)	(0.011)	(0.013)	(0.029)	(0.015)
Financial covenant	0.000	-0.004	0.000	-0.001	0.020	-0.026
	(0.008)	(0.009)	(0.009)	(0.009)	(0.018)	(0.016)
Number of tranches	-0.001	0.014***	0.001			-0.006*
	(0.006)	(0.004)	(0.006)			(0.003)
Borrower characteristics						
Rated	-0.062***	0.070***	-0.050**	-0.057***	-0.127	-0.022
	(0.023)	(0.016)	(0.024)	(0.022)	(0.103)	(0.037)
Profitability (ROA)	-0.119**	-0.035	-0.125**	-0.122**	-0.269***	-0.192**
	(0.051)	(0.025)	(0.051)	(0.054)	(0.076)	(0.082)
Leverage	0.114***	-0.007	0.114***	0.095***	0.072	0.174***
	(0.024)	(0.012)	(0.024)	(0.024)	(0.050)	(0.034)
Size (log(assets))	0.010**	-0.010***	0.009**	0.005	0.032***	0.013*
	(0.005)	(0.004)	(0.005)	(0.006)	(0.010)	(0.007)
Industry default probability	0.217	0.151	0.238	0.089	0.098	0.223
	(0.255)	(0.128)	(0.255)	(0.246)	(0.521)	(0.371)
Industry default probability, lead 3	0.885***	0.040	0.895**	0.969***	-0.041	0.703
years	(0.299)	(0.149)	(0.296)	(0.359)	(0.730)	(0.466)
Log (1+ previous loans)	0.001	-0.005	0.000	-0.005	0.011	-0.005
	(0.009)	(0.003)	(0.009)	(0.008)	(0.022)	(0.011)
Syndicate characteristics						
Previous lead	-0.005	-0.011*	-0.006	-0.002	-0.044*	-0.023
	(0.008)	(0.006)	(0.008)	(0.008)	(0.026)	(0.015)
Lead fraction banks	-0.037*	-0.024**	-0.042*	-0.041**	0.010	-0.071**
	(0.022)	(0.011)	(0.022)	(0.020)	(0.027)	(0.028)
Lead country US	-0.031*	0.034***	-0.028	-0.031*	-0.033	0.023
	(0.019)	(0.010)	(0.019)	(0.017)	(0.028)	(0.025)
Lead market share	0.026	-0.158***	0.027	0.023	0.155	-0.030
	(0.027)	(0.038)	(0.027)	(0.030)	(0.102)	(0.054)
Repeat interactions lead to participant	-0.001	-0.002	-0.001	-0.001	-0.013	-0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.012)	(0.002)
Reciprocal	-0.048**	-0.119***	-0.064***	-0.085***	0.040	-0.063*
	(0.019)	(0.014)	(0.022)	(0.024)	(0.033)	(0.035)
Loan purpose dummies; Fine rating	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes
dummies; Year and Industry dummies	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes
Observations	6204	6204	6204	6855	1614	2784
R^2	0.13	0.50	0.12	0.12	0.17	0.10

This table reports results of five sets of regressions: The dependent variable is an indicator for whether the borrower defaults in any year following the loan syndication on loans to U.S. borrowers originated between 1990 and 2006. The explanatory variable of interest is the lead arranger's retained loan share at syndication. See Table 1 for variable definitions. The first regression in column (1) is OLS, while the second regression in columns (2) and (3) is 2SLS, where the two instruments used in the first stage (column (2)) are proxies for the lead arranger's internal lending limit; these are backed out from previous syndicated loans of the lead, both when it served as a lead arranger and when it served as a participant. The results of the second stage are in column (3). The next two regressions in columns (4) and (5) are the second stage results for credit lines and term facilities, respectively (credit lines are facilities whose type is "Revolver/Line < 1 Yr.", "Revolver/Line >= 1 Yr.", "364-Day Facility", or "Revolver/Term Loan"). The latter two regressions are at the facility-level (and the loan amount for these is the facility amount) while the first two regressions are at the loan deal-level. In addition to the characteristics of the loan contract, the borrower, and the syndicate, all regressions include loan purpose dummies (corporate, acquisition, refinancing, and backup line), fine rating dummies (19 dummies indicating the borrower's senior debt rating at the close of the loan from AA+ to CC and below), year, and industry dummies. The final column (6) reports the regression conducted at the borrower-level. Loans issued to a particular borrower are aggregated by computing the average loan characteristics, weighted by loan sizes. On average, 2.3 loans are issued to each borrower (in this regression, the "number of tranches" is the number of loans). Standard errors are robust to heteroskedasticity, clustered at the borrowing firm level and year, and are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 3. The Opportunity Cost of Retaining Loans: Lead Bank Characteristics and Subsequent Borrower Default

	(1) 2SLS 1st Stage Loan deals	(2) 2nd Stage Loan deals	(3) 2SLS 1st Stage Credit lines	(4) 2nd Stage Credit lines	(5) 2SLS 1st Stage Credit lines	(6) 2nd Stage Credit lines
Instruments						
Lead lending limit, as lead	0.0008***		0.0008***		0.0003	
	(0.0002)		(0.0002)		(0.0002)	
Lead lending limit, as participant	0.0008***		0.0006***		0.0011***	
	(0.0003)		(0.0003)		(0.0002)	
Lead exposure to mortgage securitization					0.023**	
					(0.010)	
Contract characteristics						
Lead share		-0.194**		-0.226**		-0.122†
		(0.088)		(0.109)		(0.080)
Lead bank characteristics						
Size (log(assets))	-0.018***	0.001	-0.016***	0.004	-0.022***	-0.007*
	(0.003)	(0.005)	(0.003)	(0.005)	(0.007)	(0.004)
Income (Profitability)	-0.652	0.009	-0.088	-0.051	-0.116	-0.420
	(0.833)	(0.694)	(0.844)	(0.657)	(1.080)	(0.712)
Capital	0.614*	-0.233	0.505	-0.212	-0.352	-0.102
	(0.377)	(0.445)	(0.408)	(0.413)	(0.632)	(0.303)
Liquidity	-0.137***	-0.058	-0.090***	-0.043	0.036	-0.035
	(0.038)	(0.071)	(0.031)	(0.067)	(0.074)	(0.064)
Ununsed commitments	-0.057*	-0.055	-0.071**	-0.103*	-0.163***	0.004
	(0.034)	(0.060)	(0.036)	(0.059)	(0.059)	(0.110)
Loan interest rate	0.428*	-0.045	0.336	-0.295	3.137***	2.187***
	(0.260)	(0.438)	(0.283)	(0.657)	(0.873)	(0.510)
Deposit interest rate	-1.414**	0.054	-1.194**	0.284	-1.522*	-0.796
	(0.260)	(0.594)	(0.569)	(0.658)	(0.821)	(1.714)
Wholesale interest rate	0.363	0.629**	0.437*	0.695*	1.993**	1.342***
	(0.248)	(0.270)	(0.259)	(0.378)	(0.886)	(0.402)
Other contract characteristics; borrower	Yes	Yes	Yes	Yes	Yes	Yes
characteristics; syndicate characteristics	Yes	Yes	Yes	Yes	Yes	Yes
in benchmark model also included	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose dummies; Fine rating	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes
dummies; Year and Industry dummies	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes
Observations	5189	5189	5764	5764	2102	2102
R^2	0.54	0.12	0.54	0.12	0.51	0.11

This table reports results of three sets of regressions: The dependent variable is an indicator for whether the borrower defaults in any year following the loan syndication on loans to U.S. borrowers originated between 1990 and 2006. The explanatory variable of interest is the lead arranger's retained loan share at syndication. See Table 1 for variable definitions. All regressions also include the covariates in the baseline regression, Table 2 column (3), not shown in the interest of space but available upon request. The first regression in columns (1) and (2) uses the same instruments as in Table 2 (lending limits), but the regressions also include characteristics of the lead bank including reputational measures (such as size) and opportunity cost measures (such as the bank's capital to asset ratio and unused commitments). The second regression in columns (3) and (4) repeats the analysis for credit line facilities to assess whether the lead bank's characteristics have different effects on credit lines. The third specification in columns (5) and (6) adds a third instrument, which is the lead bank's credit exposure to residential mortgage securitizations. This variable is, however, only available in the Call Reports from 2001. In addition to the characteristics of the loan contract, the borrower, the syndicate, and the lead bank, all regressions include loan purpose dummies (corporate, acquisition, refinancing, and backup line), fine rating dummies (19 dummies indicating the borrower's senior debt rating at the close of the loan from AA+ to CC and below), year, and industry dummies. Standard errors are robust to heteroskedasticity, clustered at the borrowing firm level and year, and are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. †Note that the coefficient estimate on the lead share in column (6) is significant at the 15% level; a similar regression at the loan deal-level produces an estimate of -0.115 significant at the 10% level.

Table 4. Tests of Moral Hazard: Loan Covenants and Subsequent Borrower Default

Panel A.

	(1)	(2)	(3)	(4)	(5)	(6)
	Financial covenant		Number of covenants		Covenant slack net worth	
	Yes	No	High	Low	Tight	Loose
Lead share	-0.197**	-0.091	-0.252*	-0.161*	-0.199	-0.362
	(0.082)	(0.155)	(0.138)	(0.093)	(0.171)	(0.257)
Covenant slack net worth					0.007	0.218**
					(0.077)	(0.107)
All covariates in benchmark model	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4283	1921	2208	3996	543	579
R^2	0.13	0.14	0.14	0.12	0.22	0.16

Panel B.

	(1)	(2)	(3)	(4)	(5)	(6)
	Previous financial covenant		Previous number of covenants		Previous covenant slack net worth	
	Yes	No	High	Low	Tight	Loose
Lead share	-0.189**	-0.262	-0.351***	-0.129	-0.424**	0.079
	(0.085)	(0.199)	(0.129)	(0.109)	(0.219)	(0.167)
Previous covenant slack net worth					-0.040	0.044
					(0.087)	(0.083)
All covariates in benchmark model	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3128	2000	860	4268	487	594
R^2	0.17	0.14	0.25	0.14	0.28	0.31

This table reports results of regressions (the second stage of 2SLS) that test whether loan covenants or loans with more restrictive covenants enhance the lead arranger's monitoring efforts, as inferred by the relationship between subsequent borrower default and the lead arranger's retained share on loans with and without covenants. Panel A measures covenants on the current syndicated loan, while Panel B measures covenants on the borrower's previous syndicated loans. Columns (1) and (2) present results distinguishing between loans with financial covenants and not. Columns (3) and (4) present results distinguishing between loans with a "high" number of covenants (above median number, which is 3 covenants) and loans with a "low" number of covenants. Columns (5) and (6) present results distinguishing between loans that have considerable slack on the net worth covenant and those loans without much slack. The latter are denoted as "tight" and the former are denoted "loose" (based on figures for median slack; see Table 1 for summary statistics). All regressions include the covariates in the baseline regression, Table 2 column (3). Also included in the regressions shown in columns (3), (4), (5) and (6) are the number of covenants and the number of previous covenants. These measures are not statistically significant. Standard errors are robust to heteroskedasticity, clustered at the borrowing firm level and year, and are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 5. The Evolution of Covenants on Syndicated Loans

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
Financial covenant	0.450	0.427	0.482	0.444	0.403	0.451	0.474	0.477	0.491	0.403	0.318
Number of covenants	2.300	2.213	2.549	2.322	1.710	1.704	1.784	1.826	1.524	1.359	1.039
Covenant slack net worth	0.087	0.086	0.065	0.079	0.089	0.067	0.073	0.115	0.112	0.146	0.128
Covenant slack tangible net worth	0.104	0.073	0.041	0.057	0.062	0.046	0.036	0.052	0.071	0.129	0.093
Covenant slack debt to tangible net worth	2.517	1.098	1.850	1.653	1.569	1.570	1.402	0.512	2.122	1.896	1.055
Covenant slack interest coverage	4.720	4.432	3.639	4.015	2.959	3.708	5.260	5.294	6.825	6.730	8.161

This table reports how loan covenants on syndicated loans changed over time. "Financial covenant" is an indicator for whether the loan has at least one financial covenant. The number of covenants are measured following the approach in Drucker and Puri (2009). Specifically, this is the sum of the total number of financial covenants and sweep covenants (asset, equity, debt) plus one if the loan has a dividend restriction. "Covenant slack net worth" measures the extent of slack on loans with a corresponding net worth financial covenant. It is equal to the borrower's net worth less the minimum level specified in the covenant, and normalized by the borrower's book assets. "Covenant slack tangible net worth" equals the borrower's tangible net worth less the minimum level specified in the covenant, and normalized by the borrower's book assets. "Covenant slack debt to tangible net worth" equals the minimum level specified in the covenant less the borrower's short and long-term debt ratio to tangible net worth. "Covenant slack interest coverage" equals the borrower's EBITDA ratio to interest expense less the minimum level specified in the covenant. The figures shown are equally-weighted averages of loans syndicated in a given year. The figures corresponding to financial covenant represent the fraction of loans that have financial covenants.

Table 6. The Relationship Between Loan Covenants and Lead Exposure

	(1)	(2)	(3)	(4)	(5)	(6)
	Financial covenant		Number of covenants		Covenant slack net worth	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Variables of interest						
Lead share	-0.004	0.231*	-0.437**	1.123*	0.037	0.010
	(0.030)	(0.125)	(0.189)	(0.654)	(0.034)	(0.101)
Cyclicality GDP growth	-3.067***	-2.928***	-16.803***	-15.876***	-0.047	-0.094
	(0.715)	(0.722)	(3.781)	(3.807)	(0.731)	(0.735)
Previous covenant characteristics						
Previous financial covenant	0.108***	0.105***	-0.130	-0.147*	0.007	0.008
	(0.018)	(0.018)	(0.079)	(0.079)	(0.013)	(0.012)
Previous number of covenants	0.004	0.005*	0.285***	0.293***	-0.004	-0.004
	(0.003)	(0.003)	(0.021)	(0.021)	(0.003)	(0.003)
Other contract characteristics						
All-in-spread drawn	-0.001	-0.005	0.230***	0.205***	-0.004	-0.004
	(0.007)	(0.007)	(0.043)	(0.044)	(0.008)	(0.008)
Log (loan amount)	0.020***	0.037***	0.101***	0.214***	-0.005	-0.008
	(0.008)	(0.011)	(0.039)	(0.060)	(0.009)	(0.013)
Log (maturity)	0.018**	0.020**	0.372***	0.382***	0.004	0.004
	(0.009)	(0.009)	(0.044)	(0.044)	(0.009)	(0.008)
Secured	-0.046***	-0.045***	0.430***	0.442***	0.000	-0.001
	(0.011)	(0.011)	(0.069)	(0.070)	(0.011)	(0.011)
Number of tranches	0.018***	0.014**	0.406***	0.382***	-0.001	0.000
	(0.006)	(0.006)	(0.045)	(0.045)	(0.007)	(0.007)
Borrower characteristics						
Rated	-0.057	-0.072	-1.023***	-1.122***	0.046*	0.048*
	(0.075)	(0.072)	(0.356)	(0.351)	(0.027)	(0.027)
Profitability (ROA)	0.083	0.090	0.351	0.398	0.487***	0.487***
	(0.065)	(0.064)	(0.342)	(0.340)	(0.085)	(0.082)
Leverage	-0.074***	-0.074***	-0.095	-0.097	-0.237***	-0.236***
	(0.023)	(0.023)	(0.140)	(0.142)	(0.035)	(0.034)
Size (log(assets))	-0.031***	-0.030***	-0.268***	-0.258***	0.030***	0.030***
	(0.007)	(0.007)	(0.031)	(0.031)	(0.010)	(0.010)
Industry default probability	0.322*	0.321*	0.200	0.197	0.068	0.075
	(0.178)	(0.176)	(1.291)	(1.291)	(0.163)	(0.159)
Log (1+ previous loans)	-0.019*	-0.019*	0.069	0.067	-0.034***	-0.034***
	(0.010)	(0.010)	(0.052)	(0.052)	(0.012)	(0.012)
Syndicate characteristics						
Previous lead	-0.015	-0.012	0.004	0.021	-0.001	-0.001
	(0.011)	(0.011)	(0.063)	(0.063)	(0.011)	(0.011)
Lead fraction banks	-0.012	-0.002	0.359***	0.422***	0.012	0.012
	(0.015)	(0.016)	(0.113)	(0.116)	(0.019)	(0.018)
Lead country US	0.016	0.011	0.008	-0.022	-0.033	-0.032
	(0.017)	(0.017)	(0.103)	(0.104)	(0.020)	(0.020)
Lead market share	0.101**	0.094**	-0.521**	-0.568***	0.090**	0.092**
	(0.044)	(0.044)	(0.211)	(0.213)	(0.046)	(0.045)
Repeat interactions lead to participant	-0.002**	-0.001	-0.006**	-0.003	-0.001**	-0.001*
	(0.001)	(0.001)	(0.003)	(0.004)	(0.000)	(0.000)
Reciprocal	-0.007	0.024	0.175	0.378**	-0.040	-0.043
	(0.023)	(0.027)	(0.148)	(0.173)	(0.029)	(0.031)
Loan purpose dummies; Fine rating	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes
dummies; Year and Industry dummies	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes
Observations	5589	5589	5589	5589	1024	1024
R^2	0.57	0.56	0.56	0.55	0.32	0.32

This table reports results of three sets of regressions to test whether loan covenants are set to increase the lead's incentives to monitor (the "tripwire" view of Rajan and Winton (1995)) or instead substitute for delegated monitoring by the lead. The dependent variable in columns (1) and (2) is an indicator for whether the loan has a financial covenant; the dependent variable in columns (3) and (4) is the number of loan covenants; the dependent variable in columns (5) and (6) measures the slack on the borrower's net worth covenant for those loans with a net worth covenant. The explanatory variable of interest is the lead arranger's retained loan share at syndication. See Table 1 for variable definitions. The first regression of each set (columns (1), (3) and (5)) is OLS, while the second regression (columns (2), (4), and (6)) is the second stage of 2SLS, using the lending-limits to instrument the lead arranger's retained share. In addition to the characteristics of the loan contract, the borrower, the syndicate, previous loan covenants, and a measure of cyclicality, all regressions include loan purpose dummies (corporate, acquisition, refinancing, and backup line), fine rating dummies (19 dummies indicating the borrower's senior debt rating at the close of the loan from AA+ to CC and below), year, and industry dummies. Standard errors are robust to heteroskedasticity, clustered at the borrowing firm level, and are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 7. The Relationship Between Additional Loan Covenant Slack Measures and Lead Exposure

	(1)	(2)	(3)	(4)	(5)	(6)
	Tangible net worth		Debt to tangible net worth		Interest coverage	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Variables of interest						
Lead share	0.060	-0.459	-0.583	-14.821*	-1.427	-18.700***
	(0.054)	(0.358)	(1.558)	(9.232)	(1.790)	(4.780)
All covariates in Table 6 included	Yes	Yes	Yes	Yes	Yes	Yes
Observations	559	559	196	196	1600	1600
R^2	0.38	0.24	0.47	0.21	0.50	0.47

This table reports results of three additional sets of regressions to test whether loan covenants are set to increase the lead's incentives to monitor (the "tripwire" view of Rajan and Winton (1995)) or instead substitute for delegated monitoring by the lead. The dependent variable in columns (1) and (2) measures the slack on the borrower's tangible net worth covenant for those loans with a tangible net worth covenant. The dependent variable in columns (3) and (4) measures the slack on the borrower's debt to tangible net worth covenant for loans with a debt to tangible net worth covenant. And the dependent variable in columns (5) and (6) measures the slack on the borrower's interest coverage covenant for loans with an interest coverage covenant. The first regression of each set (columns (1), (3) and (5)) is OLS, while the second regression (columns (2), (4), and (6)) is the second stage of 2SLS, using the lending-limits to instrument the lead arranger's retained share. All regressions include the covariates in the regressions included in Table 6. Standard errors are robust to heteroskedasticity, clustered at the borrowing firm level, and are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A1. Lead Arranger Syndicate Exposure and Subsequent Borrower Rating Change

	(1) 1-year Downgrade Loan deals	(2) 1-year Upgrade Loan deals	(3) 1-year Downgrade Credit lines	(4) 1-year Upgrade Credit lines
Contract characteristics				
Lead share	-0.112	0.207	-0.143	0.315*
	(0.193)	(0.163)	(0.230)	(0.184)
All-in-spread drawn	0.011	0.012	0.009	0.013
	(0.012)	(0.010)	(0.012)	(0.010)
Log (loan amount)	-0.005	0.011	-0.002	0.012
	(0.015)	(0.012)	(0.012)	(0.010)
Log (maturity)	-0.025**	0.010	-0.017**	0.011*
	(0.011)	(0.008)	(0.009)	(0.006)
Secured	-0.028*	0.012	-0.027	0.013
	(0.017)	(0.017)	(0.018)	(0.018)
Financial covenant	0.007	0.007	-0.007	0.010
	(0.017)	(0.015)	(0.019)	(0.015)
Number of tranches	-0.003	-0.011		
	(0.008)	(0.007)		
Borrower characteristics				
Profitability (ROA)	-0.509***	0.620***	-0.510***	0.618***
	(0.101)	(0.082)	(0.117)	(0.091)
Leverage	0.092**	-0.087***	0.055	-0.085***
	(0.037)	(0.029)	(0.039)	(0.030)
Size (log(assets))	0.007	0.034***	0.002	0.035***
	(0.009)	(0.007)	(0.008)	(0.008)
Industry default probability	0.097	-0.403	0.063	-0.395
	(0.249)	(0.284)	(0.281)	(0.294)
Industry rating downgrades, lead 1 year	0.995***		1.003***	
	(0.086)		(0.093)	
Industry rating upgrades, lead 1 year		1.018***		1.013***
		(0.089)		(0.099)
Log (1+ previous loans)	-0.008	-0.008	-0.008	-0.005
	(0.012)	(0.009)	(0.013)	(0.009)
Syndicate characteristics				
Previous lead	-0.018	0.017	-0.011	0.019
	(0.015)	(0.013)	(0.016)	(0.014)
Lead fraction banks	-0.008	-0.015	0.008	-0.002
	(0.027)	(0.027)	(0.028)	(0.025)
Lead country US	-0.005	-0.051**	-0.001	-0.046**
	(0.022)	(0.023)	(0.025)	(0.023)
Lead market share	0.003	-0.029	0.014	-0.031
	(0.060)	(0.043)	(0.063)	(0.045)
Repeat interactions lead to participant	-0.002	0.002	-0.002	0.003
	(0.002)	(0.002)	(0.002)	(0.003)
Reciprocal	0.016	0.032	-0.030	0.082
	(0.056)	(0.050)	(0.070)	(0.063)
Loan purpose dummies; Fine rating	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes
dummies; Year and Industry dummies	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes
Observations	3496	3496	3963	3963
R^2	0.11	0.14	0.11	0.14

This table reports results of four sets of regressions: The dependent variable indicates whether a borrower was downgraded or upgraded over a 1-year horizon after loan origination on loans to U.S. borrowers originated between 1990 and 2006. The ratings data are based on senior debt fine ratings from S&P (Compustat) and the loans are therefore limited to senior loans (exclude 2nd-lien facilities). The explanatory variable of interest is the lead arranger's retained loan share at syndication. See Table 1 for variable definitions. The regressions in columns (1) and (2) are at the loan deal-level while the regressions in columns (3) and (4) are for credit line facilities (the loan amount in these is the facility amount). The results presented are the second stage of the 2SLS where the two instruments used in the first stage are proxies for the lead arranger's internal lending limit; these are backed out from previous syndicated loans of the lead, both when it served as a lead arranger and when it served as a participant. In addition to the characteristics of the loan contract, the borrower, and the syndicate, all regressions include loan purpose dummies (corporate, acquisition, refinancing, and backup line), fine rating dummies (19 dummies indicating the borrower's senior debt rating at the close of the loan from AA+ to CC and below), year, and industry dummies. Standard errors are robust to heteroskedasticity, clustered at the borrowing firm level, and are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A2. Robustness Check on Lender Exposure and Lending Limits

	(1) Exposure is lead share	(2) Alternative exposure (log of lead dollar amount)	(3) Alternative exposure (lead bank dollar amount normalized by lead bank capital)	(4) Alternative instruments: Lead fixed effects (exposure is lead share)
Contract characteristics				
Lead exposure	-0.159*	-0.037*	-0.063***	-0.108*
	(0.087)	(0.021)	(0.021)	(0.061)
Difference in lead share between bank tranche and institutional tranche	0.066*			
	(0.038)			
All-in-spread drawn	0.009	0.008	0.002	0.008
	(0.007)	(0.007)	(0.008)	(0.007)
Log (loan amount)	-0.012*	0.025	0.005	-0.008
	(0.006)	(0.017)	(0.007)	(0.007)
Log (maturity)	-0.004	-0.003	-0.008	-0.004
	(0.007)	(0.007)	(0.007)	(0.007)
Secured	0.000	0.000	-0.001	0.001
	(0.011)	(0.012)	(0.013)	(0.011)
Financial covenant	0.000	-0.001	-0.002	0.000
	(0.009)	(0.009)	(0.008)	(0.009)
Number of tranches	0.002	-0.014	0.002	0.001
	(0.006)	(0.010)	(0.007)	(0.006)
Borrower characteristics				
Rated	-0.052**	-0.045*	-0.064**	-0.055**
	(0.025)	(0.027)	(0.026)	(0.023)
Profitability (ROA)	-0.124**	-0.120**	-0.078	-0.122**
	(0.051)	(0.051)	(0.052)	(0.052)
Leverage	0.114***	0.111***	0.100***	0.114***
	(0.024)	(0.025)	(0.027)	(0.024)
Size (log(assets))	0.009**	0.008*	0.010*	0.009**
	(0.005)	(0.005)	(0.006)	(0.005)
Industry default probability	0.232	0.162	0.159	0.230
	(0.255)	(0.247)	(0.224)	(0.257)
Industry default probability, lead 3 years	0.893***	0.965***	0.979***	0.891***
	(0.297)	(0.295)	(0.297)	(0.298)
Log (1+ previous loans)	0.000	0.001	-0.004	0.000
	(0.009)	(0.009)	(0.008)	(0.009)
Syndicate characteristics				
Previous lead	-0.006	-0.005	-0.003	-0.006
	(0.008)	(0.008)	(0.009)	(0.008)
Lead fraction banks	-0.042*	-0.035	-0.050	-0.040*
	(0.022)	(0.023)	(0.032)	(0.023)
Lead country US	-0.028	-0.029	-0.031	-0.029
	(0.019)	(0.019)	(0.067)	(0.019)
Lead market share	0.028	0.027	0.045	0.027
	(0.027)	(0.028)	(0.031)	(0.027)
Repeat interactions lead to participant	-0.001	-0.001	-0.008**	-0.001
	(0.001)	(0.001)	(0.003)	(0.001)
Reciprocal	-0.063***	-0.051**	-0.024	-0.058***
	(0.022)	(0.021)	(0.023)	(0.020)
Loan purpose dummies; Fine rating	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes
dummies; Year and Industry dummies	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes
Observations	6204	6141	5190	6204
R^2	0.12	0.11	0.13	0.13

This table examines alternative measures of a lead arranger's exposure to a loan and alternative proxies for its lending limit in robustness checks of the baseline 2SLS regression in Table 2(3). Column (1) includes a proxy for institutional demand on a particular loan-deal, defined as the difference in the lead share between the bank tranche and institutional tranche (Term Loan B). Column (2) defines exposure by the log of the dollar size of the lead's loan share. Column (3) defines exposure by the lead's dollar loan amount relative to its capital. This measure is closer to how regulatory (and internal) lending limits are set in practice, but data on capital are only available for the subset of lead arrangers that are banks. Column (4) explores alternative proxies for a lead's lending limit. Instead of backing out lending limit measures from previous syndicated loans of the lead, lead fixed effects are directly used as instruments (based on the 1,055 lead arrangers). Finally, In addition to the characteristics of the loan contract, the borrower, and the syndicate, all regressions include loan purpose dummies (corporate, acquisition, refinancing, and backup line), fine rating dummies (19 dummies indicating the borrower's senior debt rating at the close of the loan from AA+ to CC and below), year, and industry dummies. Standard errors are robust to heteroskedasticity, clustered at the borrowing firm level and year, and are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A3. Robustness Check on Timing of Subsequent Default

	(1) Default within 3 year horizon	(2) Default within loan maturity horizon	(3) Default within loan maturity horizon	(4) Default within loan maturity horizon	(5) Only last loan is default	(6) Default within loan maturity horizon
			Excluding previous loans of defaulting borrower	With borrower firm fixed effects (2779 borrowers)	With borrower firm fixed effects (2779 borrowers)	Borrower-Level Analysis
Contract characteristics						
Lead share	-0.067	-0.072	-0.095*	-0.081**	-0.092*	-0.330**
	(0.047)	(0.046)	(0.051)	(0.041)	(0.057)	(0.134)
All-in-spread drawn	0.011**	0.009*	0.010*	0.010*	0.005	0.020**
	(0.005)	(0.005)	(0.006)	(0.005)	(0.007)	(0.009)
Log (loan amount)	-0.004	-0.005	-0.007*	-0.004	-0.011	-0.030**
	(0.005)	(0.004)	(0.004)	(0.004)	(0.007)	(0.012)
Log (maturity)	-0.007*	0.016***	0.014***	0.013***	0.005	0.010
	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.009)
Secured	-0.005	0.005	0.004	0.005	0.003	-0.016
	(0.007)	(0.006)	(0.006)	(0.004)	(0.008)	(0.011)
Financial covenant	0.000	-0.003	-0.003	-0.007	-0.008	0.000
	(0.004)	(0.004)	(0.004)	(0.005)	(0.007)	(0.012)
Number of tranches	-0.002	0.002	0.001	0.003	0.001	-0.016***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.003)
Borrower characteristics						
Rated	-0.009	-0.015	-0.015	0.010	0.039**	0.016
	(0.013)	(0.015)	(0.016)	(0.018)	(0.016)	(0.027)
Profitability (ROA)	-0.134***	-0.147***	-0.149***	-0.110**	-0.155***	-0.246***
	(0.038)	(0.036)	(0.036)	(0.046)	(0.060)	(0.067)
Leverage	0.051***	0.069***	0.076***	0.033	0.058*	0.120***
	(0.012)	(0.015)	(0.016)	(0.031)	(0.035)	(0.029)
Size (log(assets))	0.002	0.005*	0.006*	-0.002	0.003	0.010
	(0.004)	(0.003)	(0.003)	(0.007)	(0.009)	(0.006)
Industry default probability	-0.074	-0.169***	-0.153**	0.238*	0.211	-0.229
	(0.051)	(0.062)	(0.071)	(0.134)	(0.177)	(0.242)
Industry default probability, lead 3 years	0.405*	0.541***	0.685***	0.305	0.872***	1.089**
	(0.230)	(0.199)	(0.198)	(0.219)	(0.287)	(0.479)
Log (1+ previous loans)	-0.003	-0.003	-0.002	0.000	0.021***	0.028***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.008)	(0.010)
Syndicate characteristics						
Previous lead	-0.001	0.000	-0.002	0.000	0.003	-0.018
	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)	(0.012)
Lead fraction banks	-0.017*	-0.023**	-0.026**	0.007	-0.006	-0.056**
	(0.009)	(0.010)	(0.013)	(0.012)	(0.016)	(0.025)
Lead country US	-0.006	-0.015	-0.015	-0.005	-0.019	-0.001
	(0.007)	(0.013)	(0.014)	(0.012)	(0.013)	(0.021)
Lead market share	0.010	0.012	0.015	-0.019	0.012	-0.036
	(0.015)	(0.014)	(0.014)	(0.014)	(0.026)	(0.044)
Repeat interactions lead to participant	0.000	0.000	0.000	0.000	0.000	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Reciprocal	-0.016	-0.013	-0.020	0.049*	0.003	-0.038
	(0.015)	(0.013)	(0.015)	(0.025)	(0.029)	(0.029)
Loan purpose dummies; Fine rating	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes
dummies; Year and Industry dummies	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes
Observations	6204	6204	5955	6204	6204	2686
R^2	0.08	0.10	0.11	0.84	0.77	0.14

This table examines the timing of default. In contrast to the main regressions where the dependent variable is an indicator for whether the borrower defaults in any year following the loan syndication, in these regressions, the horizon for observing default is defined. The median time between loan origination and default is 3 years for these measures, while it is 5 years in the unrestricted subsequent default results. In column (1), default is restricted to occur within 3 years of syndication, so that loans issued to the borrower more than 3 years prior to default are considered not to have defaulted. In columns (2)-(4), default is restricted to occur by the time of loan maturity. Loans maturing before default occurs are considered not to have defaulted in column (2), while these loans are excluded from the regression in column (3). The regression in column (4) is the same as column (2) but also includes borrower firm fixed effects. In column (5), default status only applies to the final loan taken out by the borrower before it defaults. Column (6) repeats the analysis in column (2) but at the borrower-level. Note that the analysis shown is conservative because in the case that Moody's records more than one default event for a borrower, only the final recorded default is used. The results are stronger if the analysis is repeated allowing loans to be in default status when they are in a similar horizon preceding the initial default. For example, the estimated effect on lead share is -0.091 in column (1) and -0.104 in column (2), significant at the 10% and 5% level, respectively. In addition to the characteristics of the loan contract, the borrower, and the syndicate, all regressions include loan purpose dummies (corporate, acquisition, refinancing, and backup line), fine rating dummies (19 dummies indicating the borrower's senior debt rating at the close of the loan from AA+ to CC and below), year, and industry dummies. Standard errors are robust to heteroskedasticity, clustered at the borrowing firm level and year, and are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A4. Robustness Check: Instrumenting the Loan Spread

	(1) 2SLS	(2) 2SLS 1st Stage	(3) 2SLS 1st Stage	(4) 2nd Stage	(5) 2nd Stage
	Excluding spread	Dependent: Lead share	Dependent: All-in-spread drawn	Instrument is the market-level spread (quarterly)	Instrument is the industry-level spread (quarterly)
Instruments					
Lead lending limit, as lead		0.0006**	0.0003		
		(0.0003)	(0.0004)		
Lead lending limit, as participant		0.0008***	0.0001		
		(0.0003)	(0.0005)		
Market-level spread (quarterly)		0.011	0.395***		
		(0.014)	(0.088)		
Contract characteristics					
Lead share	-0.161*			-0.167*	-0.162*
	(0.089)			(0.086)	(0.094)
All-in-spread drawn				0.017	0.001
				(0.084)	(0.102)
Log (loan amount)	-0.014**	-0.081***	-0.153***	-0.011	-0.013
	(0.007)	(0.004)	(0.020)	(0.014)	(0.015)
Log (maturity)	-0.006	-0.012	-0.080***	-0.004	-0.006
	(0.007)	(0.008)	(0.023)	(0.012)	(0.013)
Secured	0.005	0.001	0.551***	-0.004	0.004
	(0.010)	(0.007)	(0.042)	(0.046)	(0.057)
Financial covenant	-0.001	-0.005	-0.030	0.000	-0.001
	(0.009)	(0.009)	(0.032)	(0.009)	(0.010)
Number of tranches	0.003	0.017***	0.179***	0.000	0.003
	(0.006)	(0.004)	(0.018)	(0.015)	(0.018)
Borrower characteristics					
Rated	-0.052**	0.067***	-0.189	-0.049*	-0.052*
	(0.024)	(0.014)	(0.280)	(0.028)	(0.030)
Profitability (ROA)	-0.139***	-0.061**	-1.552***	-0.113	-0.137
	(0.052)	(0.026)	(0.226)	(0.136)	(0.145)
Leverage	0.120***	0.004	0.654***	0.109*	0.119*
	(0.023)	(0.013)	(0.085)	(0.062)	(0.069)
Size (log(assets))	0.008*	-0.012***	-0.098***	0.010	0.008
	(0.004)	(0.004)	(0.015)	(0.010)	(0.011)
Industry default probability	0.242	0.158	0.447	0.235	0.241
	(0.255)	(0.132)	(0.577)	(0.259)	(0.251)
Industry default probability, lead 3 years	0.904***	0.055	0.924	0.889***	0.906***
	(0.296)	(0.154)	(0.834)	(0.293)	(0.332)
Log (1+ previous loans)	0.000	-0.004	0.033*	0.000	0.000
	(0.009)	(0.003)	(0.018)	(0.010)	(0.010)
Syndicate characteristics					
Previous lead	-0.006	-0.011*	0.004	-0.006	-0.006
	(0.008)	(0.006)	(0.018)	(0.008)	(0.009)
Lead fraction banks	-0.045**	-0.030**	-0.376***	-0.039	-0.045
	(0.022)	(0.011)	(0.051)	(0.035)	(0.045)
Lead country US	-0.027	0.035***	0.041	-0.028	-0.028
	(0.019)	(0.010)	(0.038)	(0.019)	(0.020)
Lead market share	0.029	-0.157***	0.079	0.026	0.028
	(0.027)	(0.039)	(0.100)	(0.029)	(0.032)
Repeat interactions lead to participant	-0.001	-0.002	0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Reciprocal	-0.066***	-0.122***	-0.200***	-0.063**	-0.065**
	(0.022)	(0.014)	(0.052)	(0.025)	(0.030)
Loan purpose dummies; Fine rating	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes
dummies; Year and Industry dummies	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes
Observations	6204	6204	6204	6204	6200
R^2	0.12	0.50	0.59	0.12	0.12

This table reports results of three sets of regressions examining the potential endogeneity of the all-in-spread variable. The first regression in column (1) repeats the baseline 2SLS regression in Table 2(3) but excludes the spread in order to check whether the main result is affected. The second regression in columns (2)-(4) shows the first stage and the second stage of 2SLS, where in addition to treating the lead share as endogenous, the all-in-spread variable is treated as endogenous as well. The instrument for the spread is the market-level loan spread on all other syndicated loans originated during the same quarter (excluding the loan in question). The results of the second stage are in column (4). Similarly, column (5) presents the results of the second stage, but where the instrument for the all-in-spread variable is allowed to vary by industry of the borrower in addition to the quarter of loan syndication. In addition to the characteristics of the loan contract, the borrower, and the syndicate, all regressions include loan purpose dummies (corporate, acquisition, refinancing, and backup line), fine rating dummies (19 dummies indicating the borrower's senior debt rating at the close of the loan from AA+ to CC and below), year, and industry dummies. Standard errors are robust to heteroskedasticity, clustered at the borrowing firm level and year, and are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A5. Robustness Check: Type of Default

	(1) Bankruptcy	(2) Bankruptcy	(3) Distressed Exchange	(4) Distressed Exchange	(5) Missed Payment	(6) Missed Payment
		Excluding other defaults		Excluding other defaults		Excluding other defaults
Contract characteristics						
Lead share	-0.107*	-0.122*	-0.043	-0.060*	-0.014	-0.031
	(0.064)	(0.065)	(0.027)	(0.031)	(0.058)	(0.058)
All-in-spread drawn	0.010	0.009	0.000	0.000	0.000	0.000
	(0.006)	(0.007)	(0.003)	(0.003)	(0.004)	(0.004)
Log (loan amount)	-0.002	-0.004	-0.004	-0.006*	-0.006	-0.007
	(0.006)	(0.006)	(0.003)	(0.003)	(0.005)	(0.005)
Log (maturity)	-0.001	0.000	-0.002	-0.002	-0.002	-0.003
	(0.005)	(0.006)	(0.002)	(0.002)	(0.004)	(0.004)
Secured	0.012*	0.011	-0.002	-0.002	-0.010	-0.010
	(0.007)	(0.008)	(0.003)	(0.004)	(0.008)	(0.008)
Financial covenant	-0.001	-0.002	0.000	0.000	0.000	0.000
	(0.009)	(0.009)	(0.003)	(0.003)	(0.004)	(0.004)
Number of tranches	0.001	0.001	0.000	0.000	0.001	0.001
	(0.004)	(0.005)	(0.002)	(0.002)	(0.005)	(0.005)
Borrower characteristics						
Rated	-0.040**	-0.040**	-0.001	0.000	-0.009	-0.010
	(0.018)	(0.019)	(0.004)	(0.005)	(0.011)	(0.012)
Profitability (ROA)	-0.067	-0.081	0.006	0.001	-0.064**	-0.073**
	(0.048)	(0.052)	(0.017)	(0.018)	(0.030)	(0.031)
Leverage	0.035*	0.047**	0.018**	0.022**	0.061***	0.069***
	(0.021)	(0.022)	(0.008)	(0.009)	(0.016)	(0.017)
Size (log(assets))	0.007*	0.007	0.001	0.001	0.001	0.002
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
Industry default probability	0.018	0.020	0.049	0.064	0.171	0.186
	(0.121)	(0.129)	(0.089)	(0.100)	(0.191)	(0.206)
Industry default probability, lead 3 years	0.441*	0.464*	0.100	0.117	0.355*	0.469**
	(0.238)	(0.258)	(0.105)	(0.130)	(0.205)	(0.224)
Log (1+ previous loans)	0.010	0.010	-0.002	-0.002	-0.008	-0.007
	(0.007)	(0.007)	(0.003)	(0.003)	(0.005)	(0.006)
Syndicate characteristics						
Previous lead	-0.014**	-0.014**	-0.001	-0.001	0.008	0.008
	(0.007)	(0.007)	(0.002)	(0.002)	(0.005)	(0.005)
Lead fraction banks	-0.034*	-0.037*	-0.004	-0.005	-0.004	-0.009
	(0.018)	(0.019)	(0.003)	(0.004)	(0.009)	(0.011)
Lead country US	-0.019	-0.022	0.005**	0.005**	-0.013	-0.014
	(0.015)	(0.016)	(0.002)	(0.002)	(0.012)	(0.013)
Lead market share	-0.009	-0.003	0.019	0.020	0.017	0.018
	(0.022)	(0.021)	(0.016)	(0.016)	(0.023)	(0.022)
Repeat interactions lead to participant	-0.001	-0.001	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Reciprocal	-0.036*	-0.043**	-0.006	-0.009	-0.022	-0.028
	(0.019)	(0.020)	(0.005)	(0.006)	(0.020)	(0.022)
Loan purpose dummies; Fine rating	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes
dummies; Year and Industry dummies	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes
Observations	6204	5995	6204	5803	6204	5950
R^2	0.07	0.09	0.05	0.07	0.06	0.08

This table reports results of regressions examining the type of default. The three main categories for default in the Moody's DRS database can be grouped into bankruptcy, distressed exchange, and missed payment. Note that "bankruptcy" includes in addition to chapter 11, chapter 7, conservatorship, receivership, and seized by regulators. "Distressed exchange" refers to an out-of-court negotiated restructuring where debt holders are offered a new security that results in a reduced financial obligation such as a debt with a lower par value. And "missed payment" includes missed interest payments, missed principal payments, payment suspensions or moratoria, cross default, and dividend omissions. In addition to the characteristics of the loan contract, the borrower, and the syndicate, all regressions include loan purpose dummies (corporate, acquisition, refinancing, and backup line), fine rating dummies (19 dummies indicating the borrower's senior debt rating at the close of the loan from AA+ to CC and below), year and industry dummies. Standard errors are robust to heteroskedasticity, clustered at the borrowing firm level and year, and are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A6. Robustness Check: Opacity, Lead Exposure, and Subsequent Borrower Default

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Leveraged loan		Firms in same industry		Profitability		Altman z-score	
	Yes	No	Low	High	Low	High	Low	High
Lead share	-0.429**	-0.006	-0.302**	-0.089	-0.342**	0.013	-0.218	-0.037
	(0.172)	(0.087)	(0.150)	(0.107)	(0.171)	(0.105)	(0.194)	(0.087)
All covariates in benchmark model	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2967	3237	3112	3092	3068	3136	2489	2485
R^2	0.12	0.07	0.13	0.14	0.14	0.10	0.16	0.12

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Subinvestment grade		Equity volatility		Equity bid-ask spread		Equity Amihud illiquidity	
	Yes	No	High	Low	High	Low	High	Low
Lead share	-0.364**	-0.032	-0.267	-0.030	-0.089	-0.087	-0.243	0.058
	(0.145)	(0.085)	(0.184)	(0.088)	(0.094)	(0.192)	(0.226)	(0.098)
All covariates in benchmark model	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4243	1961	2477	2478	2515	2440	2505	2450
R^2	0.10	0.11	0.16	0.09	0.12	0.16	0.16	0.11

This table evaluates whether the lead arranger retaining a greater portion of the loan is more critical for opaque or poorly performing borrowers. Alternative measures of opacity include: borrowers with leveraged loans (these are loans priced at 125 basis points or more above LIBOR), borrowers that are in relatively less familiar industries (proxied for by the fraction of public firms that are in the borrower's 2-digit SIC industry in the year of loan origination based on Compustat data), borrowers with below median profitability, borrowers with below median Altman z-score, borrowers that are either subinvestment grade (below BBB- rating) or not rated, borrowers with higher equity volatility, borrowers with a higher bid-ask spread on their equity, and borrowers with more illiquid equity. "Low" refers to below the median, while "High" refers to above the median of the variable of interest. All regressions include the covariates in the baseline 2SLS regression, Table 2 column (3). In addition, the regressions in columns (3) and (4) include the measure of firms in same industry, regressions in column (7) and (8) include the Altman z-score, and regressions in columns (11) - (16) include equity volatility, equity bid-ask spread, and equity Amihud illiquidity measures. Standard errors are robust to heteroskedasticity, clustered at the borrowing firm level and year, and are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.