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Information Asymmetry and the Structure of Loan Syndicates

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Abstract

This study explores the impact of information asymmetry between lenders and borrowers on loan syndicate structure. Using a sample of 17,839 loans raised by 8,701 US firms between January 1986 and August 2007, we confirm existing evidence that lead arrangers form concentrated syndicates when borrowers require intense monitoring and due diligence. We provide new evidence regarding the roles of borrower reputation, lead arranger reputation and the bank-borrower relationship. First, lead arranger reputation can reduce information asymmetry but only for the most reputable lead arrangers. Second, borrower reputation, measured by the borrower's past access of the loan market, reduces the problem of information asymmetry, with higher reductions for more recent and more regular borrowers. Third, our results regarding the past relationship between the borrower and the lead arranger support the moral hazard aspect of information asymmetry for all borrowers. We also find evidence for the adverse selection aspect of information asymmetry but only for opaque borrowers. The effect can, however, be overcome by the most reputable lead arrangers, as their behavior is strongly influenced by a fear of loss of reputation.

Keywords: syndicated loans, syndicate structure, information asymmetry, reputation.

JEL codes: D82, G21.

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1. Introduction

This paper studies the effects of information asymmetry in the syndicated loan market. Due to the specialization of banks in the syndicate, information asymmetry manifests itself not only between bank and borrower – as it does in bilateral bank lending – but also among different members of the lending syndicate. Here, participating banks that simply lend but are otherwise passive have an information disadvantage over lead arrangers who arrange the loan and actively screen and monitor borrowers. This differentiation in the banks' role adds complexity. When deciding whether to join the syndicate and how much to lend, participating banks consider not only the borrower but also the lead arranger, his reputation and his prior relationship with the borrower. Furthermore, syndicated lending combines characteristics of public financing with those of traditional bank lending (Boot, 2000). Diamond (1991) argues that borrowers upgrade themselves from bank loans to public debt by developing a stable credit reputation. Thus, syndicate structures are not only affected by information asymmetries between the different parties but also by the borrower's reputation. Detailed information on syndicated loans is publicly available, which makes the syndicated loan market more transparent and allows us to study the intricacies of the syndicated loan market in depth. Because syndicated loans have become a major source of external finance for a variety of firms (Trust and Corporation, 2008), it is important to understand whether and how the relationship between borrower, lead arranger and participating banks shapes the loan contract.

We use a sample of 17,839 syndicated loans[1] raised by 8,701 US firms between January 1986 and August 2007 that involve 1,080 different lead arrangers. Our findings are three-fold. First, we confirm the non-opportunistic behavior of lead arrangers documented in the literature (Simons, 1993; Jones et al., 2005; Lee and Mullineaux, 2004; Panyagometh and Roberts, 2010; Pichler and Wilhelm, 2001; Sufi, 2007; Ross, 2010). In particular, we verify that lead arrangers syndicate out a smaller portion of the loan if the borrower is opaque but that more reputable lead arrangers are able to syndicate out a larger portion of the loan. However, our findings also indicate that this latter effect is limited to the most reputable lead arrangers, who are able to use their reputation as a credible commitment device with participating banks and thereby reduce the moral hazard problem resulting from asymmetric information between themselves and the participating banks. This is consistent with the findings of Ross (2010), who shows that the most reputable banks, e.g., those with the highest market shares, are known for their superior screening and monitoring abilities. Second, while we confirm that borrower reputation generally mitigates the problem of information asymmetry, we discover that this mitigation is stronger both statistically and economically for borrowers whose reputation was established relatively recently or more persistently, e.g., via frequent

[1] We use the terms 'loan' and 'deal' interchangeably throughout the paper. Of our 17,839 loans, 27% consist of more than one tranche. In these cases, the multiple tranches jointly constitute the overall deal. We conduct our analyses on the deal level but provide tranche-level analyses as robustness checks.

and repeated borrowing over time. Third, the results from past relationships between borrowers and lead arrangers confirm the moral hazard aspect of information asymmetry for all borrowers. This moral hazard problem is strongest for recent bank-borrower relationships. For opaque borrowers, however, we discover new evidence not yet documented in the literature. In particular, we find evidence for the adverse selection aspect of information asymmetry, which is stronger for relatively recent relationships between borrowers and lead arrangers. This adverse selection aspect is driven by low-reputation lead arrangers, indicating that these lead arrangers – in contrast to high-reputation lead arrangers – do not fear the loss of reputation and are thus susceptible to adverse selection. This contrast between low- and high-reputation lead arrangers provides clear evidence for the important effects that reputation has on arranger behavior.

The rest of the paper is organized as follows. Section 2 introduces the syndicated loan market, and section 3 focuses on the role and effects of information asymmetry in syndicated lending. Section 4 elaborates on data and methodology, and section 5 presents the results of our study. Section 6 provides robustness checks, and section 7 summarizes our findings and concludes the paper.

2. Syndicated Lending

A sophisticated banking system plays a pivotal role in the economic development of a country. It spurs technological innovation by funding entrepreneurs with the best chances of successfully implementing innovative products and production processes (Levine, 1997). The banking system performs intermediation by accepting deposits from savers and channeling them to the borrowers for productive uses through lending activity (Dermirguc-Kunt and Levine, 1996; Ang, 2008). If a borrower requires a large loan or several different tranches, these are commonly provided by a group of lenders known as a syndicate. A syndicated loan agreement simplifies the borrowing process, as the borrower uses one agreement to cover the whole group of banks and different types of tranches rather than entering into a series of separate bilateral loans, each with different terms and conditions. In a syndicated loan, there is typically one lender, known as the lead arranger, who arranges the terms and conditions of the loan in the form of an information memorandum. The lead arranger then invites other banks to participate in the loan. These participating banks are rather passive in that they fund part of the loan but rely on the lead arranger for the screening and monitoring of the borrower.

Syndication allows lenders to diversify their loan portfolios and share different risks. There are three different types of syndication: underwritten, best efforts and club deals syndication. In underwritten deals, arrangers guarantee the entire commitment and then syndicate the loan. Consequently, they exhibit more credit risk because if the arrangers cannot fully subscribe the loan, they are forced to absorb the difference and sell the loan at a discount if the credit conditions deteriorate. Best efforts syndication entails less credit risk because arrangers commit to underwrite less than the full amount of the loan,

leaving the credit to the vicissitude of the market. Loan syndication, with regards to both the loan's primary distribution and secondary loan trading aspects, is one of the various tools that financial institutions can use to take on or shed credit risk (BIS, 2003). Finally, club deals are usually small deals for which the borrower selects the syndicate members; hence, these types of deals typically evoke no relationship. These smaller syndicates result in lower restructuring and monitoring costs and are thus preferred by lead arrangers when default is more likely. From this perspective, greater use of club deals may be an indication of both growing bank risk aversion and higher credit risk (Chui et al., 2010).

Gadanecz (2004) divides the development of the syndicated loan market into three phases. During the first phase, from 1971 to 1982, syndicated lending developed with governments as the main borrowers. This phase ended with Mexico's sovereign default in 1982 and the payment difficulties faced by many emerging market borrowers in the 1980s. Mexican debt was restructured into Brady bonds in 1989, which catalyzed a shift in patterns for emerging market borrowers toward bond financing and, in turn, resulted in a contraction in syndicated lending business. During the third phase, which began in the early 1990s, the market for syndicated loans experienced a revival and syndicated lending became a major source of external finance for a variety of firms (Trust & Corporation, 2008). Due to the onset of the current 2007 financial crisis, the syndicated loan market can be said to have entered its fourth phase, during which global syndicated lending fell by 41% in 2008 (Dealogic Loan Analytics, 2008; Ivashina and Scharfstein, 2010).

3. Information Asymmetry in Syndicated Lending

In a typical bilateral lending relationship between borrower and lender, asymmetric information manifests itself in the form of adverse selection and moral hazard. An adverse selection problem arises when one of the parties possesses private information *before* the loan contract has been signed. Here, the lender is not fully aware of the affairs of the borrower and selects a 'bad' borrower because of a lack of information. A moral hazard problem arises due to the existence of asymmetric information *after* the signing of the loan contract. The borrower begins shirking after the signature of a binding loan contract because it is not in the lender's control to determine borrower behavior. Banks can obtain private information by ex-ante screening or ex-post monitoring of the borrower. Additionally, repeated interactions between the borrower and the lender help to generate private information and, hence, decrease information asymmetry. A prolonged relationship is beneficial from the perspective of both parties. Borrowers gain due to the reduction in borrowing costs, the increase in the availability of credit and the easier access to future loan contracts. Similarly, banks benefit from the reduction in the counterparty risk and smooth future cash inflows (Diamond, 1991; Petersen and Rajan, 2004; Berger and Udell, 1994; Boot and Thakor, 1994; Ongena and Smith, 2001).

Contrary to the bilateral lending characterized by the bank-borrower relationship, there are three important relationships in syndicated lending: between borrowers and lead arrangers, between borrowers and participants and between lead arrangers and participants. To better grasp the information asymmetry in the syndication setting, we consider the three principal phases of a syndication transaction. The first is the pre-mandate phase, during which the details of the proposed transaction are discussed and finalized between the arrangers and the borrower. Because borrowers have an information advantage over lead arrangers, there is a potential adverse selection problem. This is more severe when the borrower is opaque, e.g., when very little public information is available about the borrower. Lead arrangers can reduce adverse selection through screening. A prior lending relationship between lead arrangers and borrowers can also reduce the severity of the adverse selection problem. The second phase is the post-mandate phase, during which the syndication itself takes place and facility agreements are negotiated. At this point, an information memorandum is drawn up, and information is ready for dispatch to potential participants. Until this time, participants have no information about the loan, and they depend on the arranger for due diligence. The information superiority of lead arrangers over participants can lead to an adverse selection problem. Because participants are ignorant about the dynamics of the loan and the affairs of the borrowers, the lead arrangers can shift bad loans toward participants. This problem is potentially more severe when lead arrangers fund only a small part of the loan and less severe for reputable arrangers. The third and final phase in the syndication process is the post-signing phase, which lasts for the life of the facility itself. After the disbursement of the loan to the borrower, lead arrangers generally assume the monitoring and administering responsibilities and bear all costs associated with the monitoring and administering. During this third phase, the information advantage of the borrower over all lenders leads to a moral hazard problem (Miller and Chew, 2008; Yener and Gadanecz, 2006; Rhodes and Dawson, 2004). This moral hazard problem is more severe when the borrower is opaque or when the lead arranger has no prior relationship with the borrower. There is, furthermore, a moral hazard problem between the lead arranger and the participant if the arranger does not fulfill the monitoring task as promised. This problem is potentially more severe when lead arrangers fund only a small part of the loan and less severe for reputable arrangers. Because lead arrangers are repeat players in the syndication loan market, shirking them would lead to a loss of reputation and future quasi rents (Pichler and Wilhelm, 2001).

Various studies have investigated the asymmetric information problems between lead arrangers and participants by analyzing the loan's syndicate structure. These studies differ, however, with respect to the factors that their authors believe affect the syndicate structure. One strand of literature confirms that informed lead arrangers do not exploit the opacity of the borrowers or take advantage of participants. Rather, lead arrangers retain a higher share of the loan and form more concentrated syndicates (Simons,

1993; Jones et al., 2005; Lee and Mullineaux, 2004). Lead arranger reputation has also been suggested to be consequential in the concentration of the syndicate. Sufi (2007) and Lee and Mullineaux (2004) have empirically shown that syndicates grow larger and more diffuse when arrangers are more reputable. In contrast, Dennis and Mullineaux (2000) discuss opportunistic behavior by lead arrangers and find that lead arrangers are more likely to syndicate out loans when the lead arranger has a strong reputation, the loan is large and the borrowing firm is public. They argue that, conditional on a loan being syndicated, a larger percentage of the loan is syndicated when there is public information available about the borrowing firm and the lead arranger has a strong reputation. In addition to these information asymmetry studies, Esty and Megginson, (2003), Esty (2004) and Qian and Strahan (2007) evaluate the impact of creditor's rights on syndicated loans and find that syndicates are more concentrated when creditor rights are stronger. Finally, Gatev and Strahan (2009) discuss the liquidity risk in the syndicated loan market. The authors decompose syndicated loan risk into credit, market and liquidity risk and test how these shape syndicate structure. They conclude that commercial banks dominate relative to non-banks in loan syndicates that expose lenders to liquidity risk and that this dominance is more pronounced when borrowers have high levels of credit or market risk.

Vu and Skully (2008) explore the risk-selling versus informational roles of a lead bank's decision to syndicate a loan. They conclude that syndications force lead banks to convey ex-ante private information to potential syndicate members, who accept lower loan yields as a result. However, the lead banks try to recover their information-selling costs by charging higher commitment fees. Ivashina (2009), Focarelli (2008) and Thomas and Wang (2004) discuss loan pricing in the syndicated loan market. Ivashina (2009) confirms the risk-selling argument of Vu and Skully (2008) and concludes that the observed relationship between syndicate structure and the loan spread is influenced not only by information asymmetry but also by diversification consideration. Focarelli (2008) notes that loans in which arrangers' retain a higher proportion are judged as less risky; hence, these loans carry lower interest rates. Ferreira and Matos (2012) elaborate that banks charge higher interest rate spreads and face less credit risk after origination when they have some role in the governance of the firm.

Our primary objective in this study is to gain additional insights on the effects of information asymmetry on the structure of the loan syndicate. First, we extend the scope of the analysis to include the population of lead arrangers. Whereas Sufi (2007), for example, focuses on a limited set of the top 100 most active and most reputable lead arrangers, our study includes all 1,080 lead arrangers listed in the LPC Dealscan database. By analyzing not only top lead arrangers but also those with small market shares, we are able to verify whether the benefits of reputation are universal or restricted only to the top lead arrangers. Our second contribution lies in the fact that we analyze information asymmetry in more depth. In contrast to Sufi’s approach to measuring the borrower reputation and the lead arranger-borrower

relationship throughout the history of the syndicated loan market, which is 15 years in his study, we hypothesize that 15 years is too long a period to measure reputation and relationship effectively. Therefore, we investigate several proxies of the borrower reputation, the lead arranger reputation and the relationship between lead arrangers and borrowers by considering how recently the reputation was acquired and the length of the relationship between the lead arrangers and the borrower.

4. Data and Methodology

4.1. The Sample

We obtain our sample of syndicated loans from LPC's Dealscan database, which provides information on more than 150,000 syndicated and bilateral loans dating back to 1986. Though lenders do self-report in this database, accuracy is maintained through teams of researchers based in New York, London, Hong Kong and Tokyo, who are in touch with loan syndication desks on a day-to-day basis. Additionally, they monitor newswires, market journals and the Internet, and this information is verified with one or more of the mandated banks (Rhodes and Dawson, 2004). The database provides detailed information on the syndicate structure, including the number of lead arrangers, the total number of lenders and the percentage share held by syndicate members for any particular deal. The database also reports loan-related variables, including the maturity of the loan, the deal and tranche size, the signing and maturity dates and the purpose of the loan. The borrower-related variables include the borrower's name, country of origin, sales, ticker and industry.

Our sample consists of 17,839 loan deals advanced to 8,701 US firms between January 1986 and August 2007.[2] Although Dealscan reports loans on the tranche level, we conduct our analysis on the deal level. Here, we follow Sufi (2007), who argues that the actual syndicated loan contract is drafted at the deal level and that covenants and all lenders are listed together on this contract, even if a specific lender loans only on one tranche. Moreover, multiple tranches of the same deal cannot be treated as independent observations because such an analysis would produce standard errors that are improperly small. To avoid sample bias, we take all loans signed during the above-mentioned period and do not restrict our sample to a particular number of lead arrangers or participants. We include deals for which the sales volume of the borrowers, the maturity of the loan and the deal amount are available. Furthermore, we include all the loans for which the percentage share of syndicate members is available. This demarcation allows us to explicitly measure the syndicate structure by, for example, defining the lending share of the lead arrangers or the concentration of the syndicate based on the lead arrangers lending shares. Our sample is therefore

[2] We end our sample period in August 2007 to exclude the 2007/08 financial crisis. Ivashina and Scharfstein (2010) show that the crisis had started by the end of the year 2007 and that loan volumes dropped. Thus, credit rationing during the crisis will only allow the best borrowers to raise syndicated loans, and the nature and impact of information asymmetry may be very different for this specific sub-sample of borrowers.

larger than those used in comparable studies and provides a stronger foundation for our conclusions. In their syndicate structure analyses, Sufi (2007) uses 4,414 loans to US borrowers, and Dennis and Mullineaux (2000) rely on a sample of 3,410 loans.

We include bilateral loans in our sample for which the information asymmetry dynamics are arguably of a different nature. As there are no participants in the syndicate, only the asymmetric information problem between borrower and lead arranger exists. Rather than considering this to be a loan type distinctly different from syndicated loans, we consider this as a corner solution to the asymmetric information problem. As asymmetric information problems increase, lead arrangers must hold a higher and higher lending share to attract participating banks. Ultimately, however, asymmetric information problems may become so severe that no other bank is willing to participate and the lead arranger has to fund the loan on its own. In this case, there is not much difference between a lead arranger with a 99% lending share for any particular loan and a lead arranger with a 100% lending share. Consistent with these arguments, Sufi (2007) empirically shows that borrowers with little or no credit reputation obtain syndicated loans that are similar to bilateral loans, while more reputable borrowers obtain syndicated loans that have more dispersed syndicates and are thus comparable to public debt. As we do not exclude borrowers with little or no credit reputation from our sample, we consider it appropriate to include bilateral loans. We will, however, exclude bilateral loans in a robustness check. It may be noted that our sample contains 5,328 loans with one lead arranger and no participants, 352 loans with multiple lead arrangers but no participants, 9,126 loans with one lead arranger and one or more participants and 3,033 loans with multiple lead arrangers and one or more participants. In the first two groups, the lead arranger's lending share is by definition 100%. In the latter two groups, lending shares range from 17.15% to 99.99%. Specifically, there are 176 syndicates with lending shares of 95-99% and another 41 syndicates with lending shares of 90-94%. The existence of loans with high lending shares confirms our view that bilateral loans are a corner solution.

4.2. Measuring the Syndicate Structure

In the Dealscan database, the two fields available from which it is possible to identify the lead arrangers are "Lead Arranger" and "All Lenders". We classify lenders listed in the "Lead Arranger" field as lead arrangers and all *other* lenders listed in the "All Lenders" field as participants. If the "Lead Arranger" field is missing, any lender listed as having a role of "Lead" in the "All Lenders" field is considered to be a lead arranger. While Sufi (2007) restricts his analysis to the top 100 lead arrangers, we consider all lead arrangers. Accordingly, we are not limited to the most active and most reputable lead arrangers; rather, we can investigate a wider range of lead arrangers, including those with a moderate to low market share, e.g., reputation. Furthermore, we aggregate all syndicate members to their parent company and assume

that the information about the borrowers and the participants is shared between subsidiaries and parent companies. Moreover, we assume an exchange of information when there is a merger or an acquisition because acquiring banks inherit both previous lead arranger-participant relationships and previous borrowing firm relationships of the acquired bank. Consistent with Sufi (2007), we use the average percentage share held by all lead arrangers as a proxy for syndicate structure. Dennis and Mullineaux (2000) use a similar proxy but focus on the percentage share held by the participants.

4.3. Determinants of the Syndicate Structure

4.3.1. Borrower Opaqueness

The opaqueness of the borrower determines the degree of information asymmetry between the borrower and the lender before screening, monitoring, prior relationships or other information asymmetry-reducing actions take effect. The banking literature often uses accounting ratios, such as market value of assets to the book value of assets or the ratio of gross total assets to gross physical assets of the borrower, as a measure of opacity (Strahan, 1999; Piatti and Dell'Ariccia, 2004). In contrast, we follow Dennis and Mullineaux (2000) and Sufi (2007) to determine opacity and employ dummy variables for different types of opacity. Dennis and Mullineaux (2000) argue that information is more likely to be transparent when the borrower has a credit rating, is a listed firm or is large (as reflected in annual sales). Based on the information about the borrower's rating and ticker given in the Dealscan database, we classify borrowers into three categories based on their opacity. The first type of borrower is a private firm without S&P senior debt rating or ticker. As very little public information is available for such borrowers, we categorize these borrowers as "highly opaque", indicating borrowers who are the least transparent, e.g., they have the greatest information asymmetry. The second type of borrower is only "semi-opaque", as it has either an S&P senior debt rating or a ticker but not both. These borrowers are more transparent compared to the private borrowers due to the availability of a rating or of traded securities and the associated disclosure requirements. The third type of borrower is the least opaque and is categorized as "transparent". This type of borrower has both an S&P senior debt rating and a ticker and, as such, discloses a great amount of information to the market.

4.3.2. Borrower Reputation in the Syndicated Loan Market

While a borrower may be opaque, if the borrower accessed the loan market in the past, he is already known among banks and information asymmetry may therefore be reduced. Thus the borrower is considered to be reputable. According to Sufi (2007), a reputable borrower is one who accessed the syndicated loan market prior to the loan in question. Thus, Sufi implicitly assumes that a borrower can build reputation by borrowing once and that this reputation remains unchanged over time. In contrast, we

postulate that borrower reputation changes over time. The more recently a borrower entered the market, the higher the borrower's reputation, i.e., the lower its information asymmetry. We therefore differentiate between the number of prior loans a borrower raised during the previous five years, three years and one year. Sufi (2007) finds that reputable but opaque borrowers have less concentrated syndicates, indicating that borrower reputation can overcome information asymmetry problems. With our more detailed proxies, we are the first to indicate how stable this reputation effect is over time. We measure these three proxies as the natural log of 1 plus the number of prior loans during the five years ($PB_{\#,5}$), three years ($PB_{\#,3}$) or one year ($PB_{\#,3}$) prior to the signing of the current loan. Additionally, we define dummy variables for different time periods prior to loan signing ($PB_{D,t}$) and code them as 1 if the borrower has raised at least one prior loan during the respective period and 0 otherwise. With respect to time periods, we consider the prior one year ($PB_{D,1}$), three years ($PB_{D,3}$) and five years ($PB_{D,5}$). We also split the total five-year period prior to loan signing into three non-overlapping sub-periods consisting of year one for the first sub-period ($PB_{D,1}$), years two and three for second sub-period ($PB_{D,2+3\ only}$) and years four and five for third sub-period ($PB_{D,4+5\ only}$). Our main proxy is $PB_{\#,5}$ and we will use the other proxies for in-depth analyses.

4.3.3 Arranger Reputation

To measure lead arranger reputation, we follow Sufi (2007) and use the market share of the lead arranger based on his actual lending share in the loans arranged in the year prior to the loan in question. Lead arranger reputation is valuable and can thus be used as a commitment device for participants. Reputable lead arrangers can lower their lending share when participants believe that the fear of reputation loss will keep the lead arrangers committed to monitoring. While Sufi (2007) only considers the top 100 lead arrangers in terms of market share, we provide a broader and more detailed analysis as we consider all 1,080 different lead arrangers listed in the Dealscan database for our sample of 17,839 loans. In addition to measuring their exact market share, we also distinguish high- from low-reputation lead arrangers. First, we divide all lead arrangers into the bottom, middle and top 33% groups based on the lead arranger's prior year market share. These categories are of equal size, with 360 lead arrangers in each. The 360 lead arrangers in the top percentile group are considered to be of high reputation. As such, the allocation of a specific lead arranger to one of the three categories can change from year to year. While the categories consist of the same number of lead arrangers, the number of loans associated with a top-reputation lead arranger is higher than the number of loans associated with a mid- or low-reputation lead arranger because our proxy is based on market shares and, thus, indirectly on loan numbers. We also consider the top 100 and top 20 most reputable lead arrangers as an even more restrictive selection. By focusing on the top 100 lead arrangers, we can compare our results more directly to Sufi's (2007), while the top 20 lead arrangers are truly those with the highest reputation, as evidenced in Table A-II of the appendix.

4.3.4 Borrower-Lead Arranger Relationship

When measuring the borrower-lead arranger relationship, Sufi (2007) uses a dummy variable equal to 1 if the current lead arranger has also served previously as lead arranger for the borrower. As Sufi (2007) explains, this proxy allows the distinction between the adverse selection aspect and the moral hazard aspect of information asymmetry between lead arranger and participants. On the one hand, if lead arrangers have private information from prior interactions with the borrower, they may be tempted to syndicate out more of the loan if the private information is negative. To prevent this adverse selection problem, participants require a higher lending share from these lead arrangers. On the other hand, if lead arrangers have private information from prior interactions with the borrower, then lead arrangers have already made an effort to acquire information and there is less need to commit to monitoring. Thus, the moral hazard problem between lead arrangers and participants is reduced, and the lead arranger can hold a smaller share in the loan.

Similar to our approach to borrower reputation, we revise this proxy by taking the time horizon of the relationship into account. Our main proxy for the relationship between the borrower and the lead arranger ($FL_{D,5}$) is based on the five-year time horizon prior to loan signing, and it is coded as 1 if the current lead arranger has been the lead arranger for the borrower during the past five years and 0 otherwise. Similarly, we consider the three-year time horizon ($FL_{D,3}$) and the one-year time horizon ($FL_{D,1}$). We also split the total five-year period prior to loan signing into three non-overlapping sub-periods consisting of year one for the first sub-period ($FL_{D,1}$), years two and three for the second sub-period ($FL_{D,2+3\ only}$) and years four and five for the third sub-period ($FL_{D,4+5\ only}$). Our main proxy is $FL_{D,5}$ and we will use the other proxies for in-depth analyses.

4.3.5. Other Determinants of the Syndicate Structure

We use a number of additional control variables that have been shown to determine syndicate structure. We use the sales of the borrower (borrower size) and deal size of the loan (loan size) as proxies for the size of the firm and the loan, respectively. Consistent with Sufi (2007), we also divide the deal size of the loan into three size groups based on the bottom, mid and top 33% of the distribution and define dummies for medium-sized (mid) and large loans (large) to capture the effects of loan size. Because longer-term loans have different dynamics compared to shorter ones, we include loan maturity as a control. From the lender's perspective, term loans entail less liquidity problems because they are drawn down immediately at the beginning of the loan; thus, we include term loan dummies in our analysis. To capture the impact of multiple-tranche deals, we use dummies for loans that belong to multiple-tranche deals. We also include

dummies for the year of loan signing and the industry of the borrower to capture their effects in our regressions. The exact definitions of the variables are listed in Table A-I of the appendix.

4.4. Methodology

We use regression analysis to investigate the relationship between syndicate structure and its potential determinants. We follow Esty and Megginson (2003), Lee and Mullineaux (2004) and Ferreira and Matos (2012) and estimate a tobit model as our dependent variable, the lending share percentage of the lead arrangers, is censored at both ends at 0% and 100%.[3] Greene (2008) argues that it is not appropriate to use a tobit regression if the data are always censored. However, it is appropriate to use a tobit model for a sample of observations (which may or may not be censored) that is randomly drawn from the population. For all regressions, we report standard errors that are heteroskedasticity robust and clustered at the borrower level.

5. Results

5.1. Descriptive Statistics

Table I provides an overview of the borrower, the loan and the syndicate structure characteristics of our sample. To better understand the dynamics of the syndicate structure and the loan characteristics in terms of information asymmetry, we classify firms into three categories based on their opaqueness. In our sample, 28% of all loans are incurred by highly opaque borrowers, 42% are incurred by semi-opaque borrowers and 30% are incurred by transparent borrowers.[4] Panel A of Table I reports the loan and borrower characteristics. Transparent borrowers tend to be large firms with on average of $4,680 million in sales. On average, transparent borrowers are approximately seven times larger than the semi-opaque borrowers and nine times larger than the highly opaque borrowers. Not surprisingly, transparent borrowers receive, on average, larger loans ($621 million) than semi-opaque ($130 million) and highly opaque ($101 million) borrowers and have borrowed more frequently in the past. As such, highly opaque borrowers suffer doubly from asymmetric information. Being opaque, they have no traded securities, no requirement to publish annual reports or other financial information and no benefit from certification by

[3] We also estimate OLS regression model and find very similar results except the interaction of lead arranger reputation with the opaque borrowers that we find it statistically insignificant. As this interaction term is significant in our non-linear tobit model, which itself is an indication of a non-linear relationship between lead arranger reputation and the share held by the lead arrangers in case of informationally opaque borrowers.

[4] Our categories of "highly opaque" and "semi-opaque" firms generally correspond to Sufi's (2007) private and unrated firms, respectively. The sample proportions are slightly different from Sufi (2007), whose sample includes relatively more transparent firms – a difference most likely driven by the fact that he focuses only on the top 100 lead arrangers. This seems plausible because lead arrangers with a high market share can, to some extent, select their borrowers and, thus, lend to the best, most transparent firms; as Gatti et al. (2012) show, firms also benefit by borrowing from prestigious lead arrangers. The higher average market share of lead arrangers who lend to transparent borrowers documented in Table I also supports this interpretation.

credit rating agencies. In addition, they have almost no history in the loan market and no bank with private information about them. Finally, term loans are more common among highly opaque borrowers, thereby giving liquidity relief to syndicate members. The remaining loan and firm characteristics do not differ substantially across the three firm types. Most of the borrowers belong to the manufacturing industry and raise funds for general corporate purposes and debt repayment.

[Insert Table I about here]

Panel B of Table I describes the syndicate structure for our three types of borrowers. On average, there are nine lenders in a loan syndicate for a transparent borrower compared to only three for a highly or semi-opaque borrower. While this difference is substantial, the average number of lead arrangers is close to one and similar for all types of borrowers. Thus, syndicates differ mainly in the number of participants. Furthermore, the fact that the median number of lenders equals one for highly and semi-opaque borrowers indicates that the bilateral loans included in our sample are most dominant in these two borrower groups. This substantial difference in the syndicate size provides strong initial support for our hypothesis that lead arrangers form concentrated syndicates when the borrower is opaque and that they syndicate out more when the borrower is transparent. A similar conclusion can be drawn from the average lending share of the lead arranger, which is substantially higher for highly opaque (69.35%) and semi-opaque (65.71%) borrowers than for transparent ones (27.67%). The average market share of the lead arrangers in the year prior to loan signing is 0.54% for private borrowers, 0.67% for unrated borrowers and 1.18% for transparent borrowers.[5] Thus, transparent borrowers seem able to attract more prestigious lead arrangers. This conclusion is also supported by the relatively high number of loans to transparent borrowers arranged by high-reputation lead arrangers. When we split the lead arrangers into three categories, that is, top-, mid- and low-reputation lead arrangers, we find that top-reputation lead arrangers arrange 71% of all loans to transparent borrowers but only 53% of all loans to very- and semi-opaque borrowers. While Ross (2010) shows that the most reputable banks, e.g., those with the highest market shares, are known for their superior screening and monitoring abilities, our sample seems to suggests that the most reputable lead arrangers do not predominantly use their superior abilities for the most difficult, e.g. opaque, borrowers. Furthermore, top-reputation lead arrangers arrange more loans but fund less of each loan compared to less reputable lead arrangers. This holds across all borrower types. However, lead arrangers' lending shares

[5] These figures represent the average market share across all lead arrangers in the syndicate. As Table A-II in the appendix shows, the syndicated loan market is highly concentrated with the top 20 lead arrangers accounting for 72% of the total volume of syndicated loans. Nevertheless, our sample includes 1,080 lead arrangers active in the syndicated loan market. Thus, for the average syndicated loan, the lead arranger reputation is rather low. The most reputable lead arrangers only affect the tail of distribution. At the 90, 95 and 99 percentile, the average market share across all lead arrangers in the syndicate is 2.4%, 4.0% and 9.1%, respectively.

are generally lower for loans to transparent than for loans to opaque borrowers. This could be driven by the reduced information asymmetry problem of transparent borrowers and by loan size, as transparent borrowers are larger firms with larger loans. When splitting borrowers into three size categories, we find that, for each borrower type, the lead arranger's lending share drops as borrower size increases. To ensure that our regression results are not driven by borrower size or loan size, we include both proxies in our regressions and – following Sufi (2007) – divide the loans into small, medium and large loans based on their deal size.

5.2. Main Effects of Information Asymmetry

Table II presents our basic regressions regarding the effects of information asymmetry on syndicate structure. The design of this table is closely related to Sufi (2007), but we use our modified proxies for previous borrower, lead arranger reputation and former lead. Our dependent variable is the average percentage share held by the lead arranger. In regression 1, the positive and significant coefficients for highly and semi-opaque borrowers confirm our main hypothesis that the more the borrower needs monitoring and due diligence, the more concentrated the syndicate is. By holding a higher lending share, lead arrangers signal their monitoring commitment to participants. In contrast, as the information asymmetry vis-à-vis the borrower decreases, lead arrangers make less of an effort to monitor the borrower, and consequently, the signal to participants can be weaker. In other words, the lead arranger can fund less of the loan. Furthermore, comparing both types of opaque firms shows that lead arrangers form more concentrated syndicates for highly opaque borrowers compared to semi-opaque borrowers. The coefficient for semi-opaque borrowers is smaller in absolute size than those for highly opaque borrowers, thus indicating that the former are more transparent. For the remainder of our analysis and consistent with Sufi (2007), we combine both types of borrowers as both show similar results in Table II, and we consider them to be opaque. Regression 2 of Table II confirms the findings of regression 1 and shows that when the borrower is opaque, lead arrangers retain a higher percentage share of the loan and syndicates are more concentrated.

Consistent with the literature, the negative and significant coefficient for our previous borrower proxy in regression 3 confirms that the reputation of the borrower reduces the problems of information asymmetry in the syndicated loan market. When we add an interaction term of opaqueness and borrower reputation in regression 4, this interaction term is statistically significant, but the direct effect of borrower reputation disappears. Thus, while lead arrangers have to signal their commitment to monitoring for opaque borrowers by holding larger lending shares, they need to make less of a commitment via lower lending shares for reputable opaque borrowers. Accordingly, borrower reputation reduces the information asymmetry problem only for opaque but not for transparent borrowers.

With respect to borrower reputation, lead arranger reputation can also reduce the problem of information asymmetry. The coefficient of lead arranger reputation is negative and significant in regression 5, thus indicating that more reputable lead arrangers can reduce their lending shares. However, the interaction term of opaqueness and lead arranger reputation in regression 6 shows that the reduction in lending share is stronger for opaque borrowers. This, in turn, indicates that lead arranger reputation is more valuable for these borrowers. Overall, we conclude that lead arrangers can use their reputation to signal their reduced moral hazard problem to the participating banks. As reputable lead arrangers fear a loss of reputation and drop in future business, they face less of a moral hazard problem and, therefore, have less need to signal their monitoring commitment with their lending share.

The past relationship between the lead arranger and the borrower allows us to distinguish between the adverse selection and moral hazard aspect of information asymmetry. If private information from prior interactions with the borrower leads to an adverse selection problem, then participants require a higher lending share from these lead arrangers, and we should find a positive coefficient for our former lead proxy. In contrast, due to private information from prior interactions with the borrower, the moral hazard problem between lead arrangers and participants is reduced, the lead arranger can hold a smaller share in the loan, and we should find a negative coefficient for our former lead proxy. Regressions 7 and 8 of Table II show the results. In support of the moral hazard aspect of information asymmetry, we find that lead arrangers hold less when they have a previous relationship with the borrower. This indicates that the lead arrangers have exerted efforts to monitor the borrower from prior multiple interactions, which provides comfort to the participants, who do not require that the lead arrangers hold more. However, as observed in regression 8, the interaction term of opaque borrowers with the former lead proxy supports the adverse selection aspect of information asymmetry and shows that participants require the former lead arrangers to commit to monitoring by holding more when the borrowers are opaque. In particular, our evidence for the existence of both moral hazard and adverse selection stands in contrast to Sufi (2007), who only finds evidence for moral hazard. In contrast to Sufi (2007), our sample includes not only the 100 most reputable lead arrangers but all 1,080 lead arrangers, including many low-reputation lead arrangers. This sample difference can very well be the driver for the differences in results if low-reputation lead arrangers are particularly susceptible to adverse selection because they have little reputation to lose. We will investigate this issue in more detail in section 5 with a specific focus on the role of different levels of lead arranger reputation.

The coefficients of our control variables are generally consistent with the literature and are stable across regressions 1 to 8. From Table I, we note that borrower size, deal size and maturity are higher for transparent firms. As Table II shows, these three control variables have a significant impact on the syndicate structure by themselves, as the percentage held by lead arrangers decreases with the size of the

firm, the size of the loan and the maturity of the loan. Nevertheless, our proxies for borrower transparency are still significant. In particular, our results for term loans are consistent with Gatev and Strahan (2009). Term loans create a less significant liquidity problem for lenders because they are disbursed at the beginning of the loan term and lenders face no uncertainty regarding their liquidity position. Due to this lower liquidity risk in the term loans, the lead arrangers are willing to hold more.

[Insert Table II about here]

5.3. Borrower Reputation

In Table III, we investigate the impact of borrower reputation on the information asymmetry and, hence, the loan retention by lead arrangers in more depth. We employ not only our main proxy based on the number of prior loans within the past five years ($PB_{\#,5}$) but also our additional proxies for the past three years ($PB_{\#,3}$) and one year ($PB_{\#,1}$). For ease of comparison, regression 3 replicates regression 8 of Table II. Our results show that the reputation of the *opaque* borrower reduces the problem of information asymmetry but that these effects are stronger for reputation build-up over the longer periods of three and five years. Reputation that is built up in just the prior year is inconsequential. Therefore, the results documented in Table III appear to be driven by borrowers who repeatedly access the syndicated loan market and are thereby exposing themselves to constant screening and monitoring by lead arrangers. As Table A-II of the appendix shows, the number of prior loans increases with the time horizon. For borrowers with prior loans, the average number of prior loans rises from 1.55 for the prior one year to 2.05 for the prior three years and to 2.44 for the prior five years. While it is not surprising that reputation is only valuable if built up over time, the documented effects reflect both the time horizon and the number of prior loans. To focus on the time horizon aspect of reputation independent of the number of loans, we consider alternative reputation proxies that measure the access to the syndicated loan market as dummies. We first consider dummies that reflect whether a borrower had at least one loan in the past one year ($PB_{D,1}$), three years ($PB_{D,3}$) or five years ($PB_{D,5}$). Regressions 1 to 3 in Table IV show that all three borrower reputation measures have an economically similar effect. However, the three proxies are not mutually exclusive because, for example, the number of loans in the prior year of loan signing is included in all three proxies. Therefore, in regression 4, we distinguish between borrowers who have at least one loan in the year before loan signing ($PB_{D,1}$), borrowers who have at least one loan in the 2^{nd} or 3^{rd} year before loan signing but no loans in the year immediately prior to loan signing ($PB_{D,2+3\ only}$) and borrowers who have at least one loan in the 4^{th} or 5^{th} year before loan signing but no loans in the first 3 years prior to loan signing ($PB_{D,4+5\ only}$). Regression 4 reveals that only $PB_{D,1}$ has the strongest negative and significant coefficient. In combination, Table IV reveals that reputation effects are relatively short lived, i.e., limited

to the year prior to loan signing, while Table III shows that the reputation effect is only more persistent for those few borrowers who repeatedly enter the syndicated loan market over time. Overall, we conclude that reputation of the *opaque* borrower reduces the problems of information asymmetry. However, borrower reputation is not permanent; rather, it is temporal and diminishes over time. This seems plausible, considering rapid changes in the industry and the financial health of the borrower, on the one hand, and changes in the economic conditions, on the other hand. Borrowers can build up a valuable reputation by either borrowing repeatedly over time and, thus, being exposed to continuous monitoring or, if borrowing only infrequently, being exposed to recent monitoring that reveals the most current information about the borrower.

[Insert Tables III and IV about here]

5.4. Lead Arranger Reputation

Next, we analyze lead arranger reputation in more detail. In particular, we consider highly reputable lead arrangers and create three dummy variables that indicate whether a lead arranger belongs to a high-reputation group. First, we consider the top 33% of lead arrangers based on their market share in the syndicated loan market in the year prior to loan signing ($LR_{high,D}$). Second and consistent with Sufi (2007), we consider only the 100 most reputable lead arrangers ($LR_{100,D}$). Third, given the highly concentrated nature of the syndicated loan market shown in Table A-II of the appendix, we also consider the 20 most reputable lead arrangers ($LR_{20,D}$). Only the most reputable lead arrangers – either the top 20, top 100 or top 33% – can claim substantial market shares, and it is therefore possible that they are driving the results documented in Table II for lead arranger reputation and the arranger-borrower relationship.

Table V shows the results when we include a proxy and interaction terms for the most-reputable lead arrangers. For each comparison, regression 1 replicates our benchmark results, e.g., regression 8 of Table II. Interestingly, we find that only the most reputable lead arrangers can credibly use their reputation as a commitment device. While the coefficient of the high-reputation lead arranger dummy is insignificant in regression 2, the coefficient of the top 100 and top 20 lead arranger dummies in regressions 3 and 4 are negative and significant, while the lead arranger reputation proxy (LR) becomes (almost) insignificant. Thus, we conclude that Sufi's (2007) results are driven by his sample of top 100 lead arrangers and that his findings cannot be generalized. Similarly, while our baseline results of lead arranger reputation in Table II are substantially driven by the most reputable lead arrangers, the results have a strong enough reputation to credibly signal their monitoring commitment to the participating banks.

Regarding the arranger-borrower relationship, it appears that the effects of the arranger-borrower relationship on the lead arranger's lending share also depend on the reputation of the lead arrangers. We now add interaction effects for the effect that the former lead status of a highly reputable arranger has for an opaque borrower such that we have FL*opaque*$LR_{high,D}$ in regression 2, FL*opaque*$LR_{high,D}$ in regression 3 and FL*opaque*$LR_{20,D}$ in regression 4. This interaction effect has a negative and significant impact on the arranger's lending share only in regressions 3 and 4, and the impact is more substantial for the top 20 arrangers. Overall, we interpret the findings for the arranger-borrower relationship as follows. There is evidence for moral hazard aspects of the information asymmetry problem for all borrowers, both transparent and opaque, and all lead arrangers, independent of their reputation. In contrast, the adverse selection problem is associated only with opaque borrowers. However, the most reputable former lead arrangers can counteract the adverse selection effect. Accordingly, our results are consistent with Sufi (2007), who finds a positive but insignificant adverse selection effect for loans to opaque borrowers arranged by the 100 most reputable lead arrangers.[6] In general, participants require all former lead arrangers to hold a higher lending share for opaque borrowers where lead arrangers may be most likely tempted to syndicate out 'lemons'. The most reputable lead arrangers – but only the top 20 and, to a lesser extent, the top 100 lead arrangers – can counteract this increase in lending share.

[Insert Table V about here]

5.5. Borrower-Lead Arranger Relationship

In Table VI, we further disaggregate our basic borrower-lead arranger results of regression 8 in Table II with specific attention to the timeliness of the former lead's interaction with the borrower. Similar to our proxies for the previous borrower, we distinguish two situations. First, we consider borrowers who have at least one loan with the same lead arranger in the one year prior to loan signing ($FL_{D,1}$), three years prior to loan signing ($FL_{D,3}$) or five years prior to loan signing ($FL_{D,5}$). Second, we more specifically distinguish borrowers who have at least one loan with the same lead arranger in the 2nd or 3rd year before loan signing but no such loans in the year immediately prior to loan signing ($FL_{D,2+3\ only}$) and borrowers who have at least one loan with the same lead arranger in the 4th or 5th year before loan signing but no such loans in the first 3 years prior to loan signing ($FL_{D,4+5\ only}$). Regressions 1 to 3 show similar effects across the different time horizons. The coefficients are negative for the former lead proxy and positive for the interaction term – just as in our baseline specification – but no clear patterns can be observed over time. However, as

[6] Regarding regression 3, an F-test on whether the sum of both coefficients of FL*opaque and FL*opaque*$LR_{high,D}$ is different from zero results in a value of 0.60, which is insignificant. Similarly, the corresponding F-test for regression 4 results in a value of 0.51, which is insignificant. This indicates that there is no statistically significant adverse selection effect for the most reputable lead arrangers.

Table A-III in the appendix shows, for borrowers who do have a former lead arranger, the average number of prior loans with the same former lead arranger increases over time from 1.52 in the prior one year to 1.95 in the prior three years and, finally, to 2.25 in the prior five years. If borrowers repeatedly interact with the same lead arranger, our simple proxies are not mutually exclusive. The more specific proxies used in regression 4 are mutually exclusive and do reveal a time pattern such that the one-year effects reflected by $FL_{D,1}$ hardly differ from the two- and three-year effect reflected by $FL_{D,2+3\ only}$ – a finding that can be explained by the fact that, on average, the maturity of our loans is just under 3.5 years. Thus, when the current loan is signed, the lead arranger is still actively monitoring a prior loan, even if this prior loan was signed three years ago. However, with an average maturity of less than four years, many of the loans signed even earlier are no longer outstanding, and the lead arranger is not necessarily monitoring the borrower. Thus, the effect diminishes for $FL_{D,4+5\ only}$.

[Insert Table VI about here]

6. Robustness Checks

To check whether our main results – regression 8 of Table II and regression 4 of Table V – are robust to different specifications and data samples, we perform a number of tests in Table VII. For ease of comparison, we replicate our benchmark regressions as regressions 1 and 2. Our first set of robustness checks focuses on different samples. We then begin to investigate whether the inclusion of sole lenders affects our results. Despite the fact that there is no involvement of funds from participants, we view these bilateral loans as a corner solution to the information asymmetry problem in syndicated lending. To assess the influence of this assumption, we exclude bilateral loans from our sample. As regressions 3 and 4 reveal, our results are robust to this exclusion. We can, therefore, satisfactorily conclude that there is no difference between sole lenders and other lenders as far as the syndicate structure relationship is concerned.

Next, we consider specific types of loans in regressions 5 and 6. As described in the introduction, among the three different types of syndications, club deals were usually small deals, and the borrower generally selects the syndicate members. Hence, as these types of deals involve lenders selected by the borrower, they lack typical information asymmetry problems associated with a typical syndicated loan structure. However, though only 27 deals in our sample are club deals, we nevertheless exclude them. Additionally, we exclude project finance deals due to their different characteristics. As noted by Esty and Megginson (2003) and Kleimeier and Megginson (2000), project finance loans differ from syndicated loans in terms of syndicate structure and loan pricing. Project finance loans are repaid by the cash flow of the project itself, and project finance companies are often highly leveraged. Considering the different

features of project finance loans, we exclude the 116 project finance loans from our sample. Furthermore, we exclude 1,180 loans to financial firms from our sample. The three categories overlap and we overall exclude 1,206 observations. Our results are robust to the exclusion of these deals, as can be evidenced in regressions 5 and 6. Our results, therefore, suggest that club deals, project finance deals and loans to financial firms do not unduly influence our main results.

In regressions 7 and 8, we restrict our sample to loans signed between 1992 and 2007. As the Dealscan database goes back only to 1986, our proxies for previous borrower, former lead and arranger-borrower relationships may be understated for loans signed before 1992. The results indicate that this is indeed the case. With the exception of our previous borrower (PB) proxy, which now is insignificant compared to a 10% significance in our benchmark regressions, all proxies are more significant in regressions 7 and 8.

Finally, rather than using loan deals as the unit of observation in our analysis, we replicate the analysis on a tranche level. This increases our sample size to 23,588 observations. Regressions 9 and 10 confirm our benchmark results, and the reported effects for lead arranger reputation are both statistically and economically stronger. Hence, our results are strongly robust on the tranche level.

[Insert Table VII about here]

7. Summary and Conclusion

This paper studies the influence of information asymmetry on the structure of lending syndicates. We extend the existing literature and gain additional insights by using a range of different and specific proxies for borrower reputation, lead arranger reputation and the length of the relationship between lead arrangers and borrowers. We show that only the most reputable lead arrangers are able to use their reputation as a credible commitment device for participating banks, thereby reducing the moral hazard problem resulting from asymmetric information between themselves and the participating banks. Furthermore, we show stronger effects of information asymmetry mitigation for borrowers whose reputations are established relatively recently or more persistently. We support the moral hazard aspect of information asymmetry for borrowers, in general, and document an adverse selection effect only for opaque borrowers. This adverse selection effect is stronger for short- to medium-term relationships between borrowers and lead arrangers, and only the most reputable former lead arrangers can counteract it. In this sense, the most reputable lead arrangers are different.

Overall, our results show that information asymmetry has a substantial impact on the structure of loan syndicates. In particular, both the degree of information asymmetry by itself and its timing are important in determining the type of financial contract signed between the bank and the borrower.

Reputation – of both the borrower and the lead arranger – is crucial in overcoming these information asymmetry problems. Our findings imply that reputation eases access to finance as participating banks are more willing to lend. This should be particularly valuable for financially constraint firms or during times of credit rationing.

Our finding that only the most reputable lead arrangers can overcome the adverse selection problem that arises from their former lead activities with opaque borrowers has important implications for participating banks and policy makers. Participating banks need to correctly read the lead arranger's behavior and appropriately manage their risk exposure in syndicated lending. Policy makers have to realize that the contribution of lead arrangers to the overall systemic risk depends on the lead arranger's reputation. A uniform policy to mitigate such risk may thus have asymmetric effects and a policy to limit opportunistic behavior of the average, low-reputation lead arrangers may not be effective.

Appendix

[Insert Tables A-I to A-III here]

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Table I
Descriptive Statistics

This table presents summary statistics for a sample of 17,839 syndicated loan deals to 8,701 borrowers signed between 1986 and 2007. Borrowers are classified into three categories based on their opactiy. A transparent borrower has both, a S&P senior debt rating and a ticker. A very opaque borrower has neither a rating nor a ticker. The remaining borrowers are categorized as semi opaque because they have either a rating or a ticker. The 8,701 different borrowers in our sample are divided into three groups of small, mid-sized, and large borrowers based on their sales size with each group containing either 2,900 or 2,901 borrowers. The 17,839 loans are arranged by 1,080 different lead arrangers. These lead arrangers are categorized into top-, mid- and low-reputation arrangers based on their annual market share with each group containing 360 arrangers. The top-100 lead arrangers include those 100 arrangers with the highest market share. Panel A reports general borrower and loan characteristics whereas Panel B reports information about the syndicate structure. Variable definitions can be found in Table A-I of the appendix. The unit of observation is the deal level.

Panel A: Loan and borrower characteristics

	Loans to borrowers that are											
	Very opaque				Semi opaque				Transparent			
	Fraction of loans (%)	Mean	Median	Standard deviation	Fraction of loans (%)	Mean	Median	Standard deviation	Fraction of loans (%)	Mean	Median	Standard deviation
Loan characteristics												
Deal size ($ million)		101.00	25.00	257.00		130.00	30.30	483.00		621.00	275.00	1,330.00
Maturity (days)		1,191.05	1,080.00	907.00		1,273.95	1,080.00	8,429.00		1,275.72	1,140.00	792.80
Multiple tranche deal	26.68				24.02				25.26			
Deal containing term loan	20.76				16.30				7.08			
Borrower characteristics												
Total sales ($ million)		526.00	93.90	3,770.00		635.00	140.00	3,970.00		4,680.00	1,400.00	13,800.00
Number of previous syndicated loans		0.66	0.00	1.45		1.20	0.00	2.10		2.57	1.00	3.39
Purpose of the loan												
Acquisition line	4.18				4.66				3.50			
Corporate purpose	32.76				31.67				32.90			
Debt repayment	24.33				22.10				17.70			
Working capital	18.50				25.90				17.80			
Other	20.00				15.67				27.90			
Industry of the borrower												
Financial services	7.20				5.83				7.71			
General manufacturing	12.65				13.59				10.37			
Healthcare	7.10				8.04				5.33			
Oil and gas	5.21				5.89				8.88			
Retail & supermarkets	7.70				6.79				6.49			
Technology	9.59				11.98				3.72			
Other	50.50				47.80				57.20			

Table I (continued)
Descriptive Statistics

Panel B: Syndicate structure characteristics	Loans to borrowers that are											
	"Highly opaque"				"Semi opaque"				"Transparent"			
	Number of loans	Mean	Median	Standard deviation	Number of loans	Mean	Median	Standard deviation	Number of loans	Mean	Median	Standard deviation
Number of participants	5,038	2.06	0.00	4.24	7,430	2.22	0.00	4.21	5,371	7.76	6.00	8.33
Total number of lenders	5,038	3.13	1.00	4.28	7,430	3.28	1.00	4.24	5,371	8.95	7.00	8.43
Market share of lead arranger (%)												
Average market share across all lead arrangers in syndicate	5,038	0.54	0.03	1.50	7,430	0.67	0.04	1.62	5,371	1.18	0.40	1.94
Lending share of lead arranger (%)												
All loans & all lead arrangers	5,038	69.35	100.00	35.18	7,430	65.71	71.43	35.81	5,371	27.67	16.67	27.39
Loans arranged by top-20 lead arrangers	1,394	56.48	50.00	35.46	2,144	53.71	44.44	35.74	2,615	24.60	14.67	24.87
Loans arranged by top-100 lead arrangers	2,023	62.34	59.22	36.52	3,132	56.69	50.00	36.27	3,412	24.37	14.29	24.76
Loans arranged by top-reputation lead arrangers	2,648	65.33	70.00	35.97	4,002	59.97	50.00	36.40	3,837	24.67	14.64	25.00
Loans arranged by mid-reputation lead arrangers	1,078	74.99	100.00	33.60	1,499	73.00	100.00	33.60	678	36.48	23.89	32.03
Loans arranged by low-reputation lead arrangers	1,344	72.75	100.00	33.86	1,939	71.92	100.00	34.16	867	34.06	21.31	30.77
Loans raised by small borrowers	2,547	86.70	100.00	25.72	3,066	86.13	100.00	26.20	251	49.99	36.00	34.13
Loans raised by mid-sized borrowers	1,726	58.18	50.00	34.02	2,824	59.31	50.00	34.05	1,330	38.01	26.08	30.74
Loans raised by large borrowers	797	38.07	25.00	32.32	1,550	36.99	25.00	31.00	3,801	22.59	13.50	23.63
Concentration of the syndicate (HHI)												
All loans & all lead arrangers	5,038	8,550	10,000	2,584	7,430	8,196	10,000	2,891	5,371	5,091	4,624	3,372
Loans arranged by top-20 lead arrangers	1,394	4,871	3,025	4,282	2,144	4,449	2,500	4,248	2,615	1,454	256	2,821
Loans arranged by top-100 lead arrangers	2,023	8,169	10,000	2,759	3,132	7,626	10,000	3,148	3,412	4,735	4,064	3,330
Loans arranged by top-reputation lead arrangers	2,648	8,300	10,000	2,725	4,002	7,810	10,000	3,091	3,837	4,686	3,949	3,327
Loans arranged by mid-reputation lead arrangers	1,078	8,937	10,000	2,256	1,499	8,730	10,000	2,503	678	6,093	6,400	3,293
Loans arranged by low-reputation lead arrangers	1,344	8,734	10,000	2,492	1,939	8,581	10,000	2,615	867	6,098	6,566	3,255
Loans raised by small borrowers	2,547	9,411	10,000	1,833	3,066	9,463	10,000	1,741	251	7,304	8,356	3,106
Loans raised by mid-sized borrowers	1,726	8,168	10,000	2,711	2,824	7,979	10,000	2,906	1,330	6,176	6,469	3,326
Loans raised by large borrowers	797	6,628	7,079	3,080	1,550	6,087	6,543	3,322	3,801	4,565	3,851	3,253

Table II
Main Effects of Information Asymmetry

This table presents tobit regression results. The dependent variable is the lead arranger's lending share defined as the average lending share across all lead arrangers who participate in the loan's syndicate. The independent variables are defined in Table A-I of the appendix. Subscript D indicates a dummy variable. All regressions include loan purpose, loan size, borrower industry and year dummies. For each independent variable, the top row reports the estimated coefficient and the bottom row reports the t-statistic. Standard errors are heteroskedasticity robust and clustered at the borrower-level. ***, **, and * indicate significance at the 1%, 5% and 10% level, respectively.

	Lead arranger's lending share							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Very opaque$_D$	3.34 ***							
	3.80							
Semi opaque$_D$	2.62 ***							
	3.39							
Opaque$_D$		2.70 ***	8.63 ***	3.77 ***	3.67 ***	4.34 ***	4.34 ***	3.25 ***
		3.75	10.09	4.46	4.36	4.94	4.94	3.27
Previous borrower (PB$_{\#,5}$)			-1.24 ***	0.42	0.34	0.38	0.72	1.16 *
			-2.59	0.76	0.62	0.69	1.27	1.92
PB$_{\#,5}$*opaque$_D$				-2.00 **	-1.92 **	-1.94 **	-1.88 **	-2.64 ***
				-2.49	-2.39	-2.43	-2.35	-3.08
Lead arranger reputation (LR)					-77.87 ***	-41.91 **	-43.20 **	-46.56 **
					-7.32	-1.96	-2.02	-2.19
LR*opaque						-63.14 ***	-63.97 ***	-57.53 **
						-2.65	-2.69	-2.42
Former lead (FL$_{D,5}$)							-1.62 ***	-3.61 ***
							-3.05	-4.69
FL$_{D,5}$*opaque								3.19 ***
								2.98
Borrower size	-0.70 **	-0.73 ***	1.61 ***	-0.69 **	-0.63 **	-0.64 **	-0.64 **	-0.64 **
	-2.53	-2.64	5.14	-2.49	-2.28	-2.31	-2.33	-2.35
Loan size	-22.26 ***	-22.24 ***	-4.84 ***	-22.23 ***	-22.09 ***	-22.03 ***	-22.00 ***	-22.00 ***
	-49.41	-49.42	-5.18	-49.52	-49.25	-49.20	-49.25	-49.41
Loan size*mid$_D$	-2.91 ***	-2.94 ***	-14.32 ***	-2.92 ***	-2.91 ***	-2.92 ***	-2.91 ***	-2.88 ***
	-5.39	-5.46	-17.02	-5.42	-5.06	-5.01	-4.98	-4.94
Loan size*large$_D$	15.03 ***	15.00 ***	1.35	14.95 ***	14.99 ***	14.92 ***	14.90 ***	14.93 ***
	32.09	32.12	1.53	31.95	32.19	31.97	31.97	31.99
Loan maturity	-4.53 ***	-4.54 ***	-1.69 ***	-4.57 ***	-4.52 ***	-4.52 ***	-4.54 ***	-4.55 ***
	-10.07	-10.08	-3.43	-10.15	-10.07	-10.06	-10.13	-10.17
Term loan$_D$	5.82 ***	5.88 ***	7.66 ***	5.88 ***	5.85 ***	5.85 ***	5.82 ***	5.82 ***
	6.33	6.41	7.52	6.41	6.18	6.14	6.11	6.12
Multiple tranches$_D$	-0.02	-0.03	-0.37	-0.02	-0.02	-0.05	-0.07	-0.06
	-0.03	-0.04	-0.54	-0.03	-0.03	-0.07	-0.11	-0.10
Pseudo R^2	0.150	0.152	0.150	0.151	0.151	0.152	0.152	0.153
Number of observations	17,839	17,839	17,839	17,839	17,839	17,839	17,839	17,839

Table III
Borrower Reputation

This table presents tobit regression results. The dependent variable is the lead arranger's lending share defined as the average lending share across all lead arrangers who participate in the loan's syndicate. The independent variables are defined in Table A-I of the appendix. Subscript D indicates a dummy variable. All regressions include loan purpose, loan size, borrower industry and year dummies. For each independent variable, the top row reports the estimated coefficient and the bottom row reports the t-statistic. Standard errors are heteroskedasticity robust and clustered at the borrower-level. ***, **, and * indicate significance at the 1%, 5% and 10% level, respectively.

	Lead arranger's lending share		
	(1)	(2)	(3)
$Opaque_D$	2.51 ***	2.72 ***	3.25 ***
	2.70	2.81	3.27
Previous borrower ($PB_{\#,1}$)	1.91		
	1.55		
$PB_{\#,1}$*$opaque_D$	-1.92		
	-1.22		
Previous borrower ($PB_{\#,3}$)		0.67	
		0.97	
$PB_{\#,3}$*$opaque_D$		-1.74 *	
		-1.78	
Previous borrower ($PB_{\#,5}$)			1.16 *
			1.92
$PB_{\#,5}$*$opaque_D$			-2.64 ***
			-3.08
Lead arranger reputation (LR)	-46.19 **	-46.55 **	-46.56 **
	-2.16	-2.18	-2.19
LR*opaque	-59.34 **	-58.21 **	-57.53 **
	-2.50	-2.45	-2.42
Former lead ($FL_{D,5}$)	-3.42 ***	-3.34 ***	-3.61 ***
	-4.39	-4.30	-4.69
$FL_{D,5}$*opaque	2.47 **	2.72 **	3.19 ***
	2.28	2.52	2.98
Borrower size	-0.68 **	-0.65 **	-0.64 **
	-2.52	-2.40	-2.35
Loan size	-21.98 ***	-22.01 ***	-22.00 ***
	-49.38	-49.36	-49.41
Loan size*mid_D	-2.90 ***	-2.89 ***	-2.88 ***
	-4.97	-4.94	-4.94
Loan size*$large_D$	14.96 ***	14.97 ***	14.93 ***
	32.13	32.04	31.99
Loan maturity	-4.50 ***	-4.56 ***	-4.55 ***
	-10.12	-10.18	-10.17
Term $loan_D$	5.80 ***	5.82 ***	5.82 ***
	6.09	6.12	6.12
Multiple $tranches_D$	-0.09	-0.07	-0.06
	-0.14	-0.12	-0.10
Pseudo R^2	0.150	0.150	0.150
Number of observations	17,839	17,839	17,839

Table IV
Borrower Reputation

This table presents tobit regression results. The dependent variable is the lead arranger's lending share defined as the average lending share across all lead arrangers who participate in the loan's syndicate. The independent variables are defined in Table A-I of the appendix. Subscript D indicates a dummy variable. All regressions include loan purpose, loan size, borrower industry and year dummies. For each independent variable, the top row reports the estimated coefficient and the bottom row reports the t-statistic. Standard errors are heteroskedasticity robust and clustered at the borrower-level. ***, **, and * indicate significance at the 1%, 5% and 10% level, respectively.

	Lead arranger's lending share			
	(1)	(2)	(3)	(4)
$Opaque_D$	2.60 ***	2.87 ***	3.17 **	3.15 ***
	2.78	2.95	3.16	3.12
Previous borrower ($PB_{D,1}$)	1.93 *			1.92
	1.87			1.64
$PB_{D,1}$*$opaque_D$	-2.64 *			-3.40 **
	-1.89			-2.26
Previous borrower ($PB_{D,3}$)		0.71		
		0.83		
$PB_{D,3}$*$opaque_D$		-2.38 **		
		-2.14		
Previous borrower ($PB_{D,5}$)			0.84	
			0.97	
$PB_{D,5}$*$opaque_D$			-2.81 ***	
			-2.57	
Previous borrower ($PB_{D,2+3\ only}$)				-0.27
				-0.28
$PB_{D,2+3\ only}$*$opaque_D$				-2.10
				-1.58
Previous borrower ($PB_{D,4+5\ only}$)				0.79
				0.63
$PB_{D,4+5\ only}$*$opaque_D$				-3.10 *
				-1.71
Lead arranger reputation (LR)	-46.37 **	-47.03 **	-46.75 **	-46.90 **
	-2.17	-2.21	-2.20	-2.20
LR*opaque	-59.20 **	-57.41 **	-58.84 **	-56.93 **
	-2.49	-2.42	-2.48	-2.40
Former lead ($FL_{D,5}$)	-3.49 ***	-3.33 ***	-3.09 ***	-3.47 ***
	-4.49	-4.20	-4.44	-4.27
$FL_{D,5}$*opaque	2.66 **	2.88 ***	2.13 **	3.10 ***
	2.47	2.62	2.15	2.78
Borrower size	-0.68 **	-0.65 **	-0.67 **	-0.64 **
	-2.50	-2.37	-2.42	-2.36
Loan size	-21.99 ***	-22.01 ***	-22.00 ***	-21.97 ***
	-49.41	-49.31	-49.29	-49.38
Loan size*mid_D	-2.88 ***	-2.88 ***	-2.90 ***	-2.89 ***
	-4.94	-4.94	-4.97	-4.95
Loan size*$large_D$	14.98 ***	14.98 ***	14.99 ***	14.94 ***
	32.19	32.20	32.23	32.08
Loan maturity	-4.51 ***	-4.56 ***	-4.55 ***	-4.52 ***
	-10.12	-10.20	-10.14	-10.13
Term $loan_D$	5.79 ***	5.81 ***	5.84 ***	5.78 ***
	6.08	6.10	6.14	6.08
Multiple $tranches_D$	-0.07	-0.10	-0.08	-0.09
	-0.11	-0.15	-0.13	-0.15
Pseudo R^2	0.150	0.150	0.150	0.150
Number of observations	17,839	17,839	17,839	17,839

Table V

Moral Hazard versus Adverse Selection

This table presents tobit regression results. The dependent variable is the lead arranger's lending share defined as the average lending share across all lead arrangers who participate in the loan's syndicate. The independent variables are defined in Table A-I of the appendix. Subscript D indicates a dummy variable. All regressions include loan purpose, loan size, borrower industry and year dummies. For each independent variable, the top row reports the estimated coefficient and the bottom row reports the t-statistic. Standard errors are heteroskedasticity robust and clustered on the borrower-level. ***, **, and * indicate significance at the 1%, 5% and 10% level, respectively.

	Lead arranger's lending share			
	(1)	(2)	(3)	(4)
$Opaque_D$	3.25 ***	3.24 ***	3.16 ***	3.18 ***
	3.27	3.25	3.15	3.19
Previous borrower ($PB_{\#,5}$)	1.16 *	1.16 *	1.05 *	1.15 *
	1.92	1.92	1.74	1.92
$PB_{\#,5}$*$opaque_D$	-2.64 ***	-2.65 ***	-2.56 ***	-2.73 ***
	-3.08	-3.08	-2.99	-3.18
Lead arranger reputation (LR)	-46.56 **	-43.96 **	-15.64	-38.91 *
	-2.19	-2.00	-0.70	-1.81
High-reputation arrangers ($LR_{high,D}$)		-0.38		
		-0.55		
Top-100 arrangers ($LR_{100,D}$)			-2.93 ***	
			-3.64	
Top-20 arrangers ($LR_{20,D}$)				-2.07 ***
				-3.31
LR*opaque	-57.53 **	-54.55 **	-56.94 **	-44.60 *
	-2.42	-2.29	-2.36	-1.87
Former lead ($FL_{D,5}$)	-3.61 ***	-3.60 ***	-2.64 ***	-3.58 ***
	-4.69	-4.69	-2.87	-4.65
$FL_{D,5}$*opaque	3.19 ***	3.73 ***	2.86 ***	4.27 ***
	2.98	2.93	2.65	3.74
$FL_{D,5}$*opaque*$LR_{high,D}$		-0.95		
		-0.82		
$FL_{D,5}$*opaque*$LR_{100,D}$			-1.67 *	
			-1.69	
$FL_{D,5}$*opaque*$LR_{20,D}$				-3.31 ***
				-2.78
Borrower size	-0.64 **	-0.64 **	-0.63 **	-0.57 **
	-2.35	-2.32	-2.31	-2.08
Loan size	-22.00 ***	-21.98 ***	-21.83 ***	-21.92 ***
	-49.41	-49.24	-49.07	-49.26
Loan size*mid_D	-2.88	-2.89	-2.93	-2.91
	-4.94	-4.95	-5.02	-4.98
Loan size*$large_D$	14.93	14.92	14.84	14.84
	31.99	31.91	31.95	31.80
Loan maturity	-4.55 ***	-4.55 ***	-4.53 ***	-4.57 ***
	-10.17	-10.16	-10.13	-10.22
Term $loan_D$	5.82 ***	5.82 ***	5.79 ***	5.85 ***
	6.12	6.12	6.09	6.15
Multiple $tranches_D$	-0.06	-0.06	-0.04	-0.05
	-0.10	-0.10	-0.06	-0.08
Pseudo R^2	0.151	0.158	0.158	0.158
Number of observations	17,839	17,839	17,839	17,839

Table VI
Borrower-Lead Arranger Relationship

This table presents tobit regression results. The dependent variable is the lead arranger's lending share defined as the average lending share across all lead arrangers who participate in the loan's syndicate. The independent variables are defined in Table A-I of the appendix. Subscript D indicates a dummy variable. All regressions include loan purpose, loan size, borrower industry and year dummies. For each independent variable, the top row reports the estimated coefficient and the bottom row reports the t-statistic. Standard errors are heteroskedasticity robust and clustered at the borrower-level. ***, **, and * indicate significance at the 1%, 5% and 10% level, respectively.

	Lead arranger's lending share			
	(1)	(2)	(3)	(4)
$Opaque_D$	4.03 ***	3.64 ***	3.25 ***	3.91 ***
	4.55	4.03	3.27	4.26
Previous borrower ($PB_{\#,5}$)	0.87	1.22 **	1.16 *	1.31 **
	1.49	2.00	1.92	2.06
$PB_{\#,5}$*$opaque_D$	-2.57 ***	-2.86 ***	-2.64 ***	-2.95 ***
	-3.04	-3.27	-3.08	-3.29
Lead arranger reputation (LR)	-42.16 **	-44.68 **	-46.56 **	-42.98 **
	-1.97	-2.09	-2.19	-2.01
LR*opaque	-61.81 ***	-58.94 **	-57.53 **	-61.17
	-2.60	-2.48	-2.42	-2.57
Former lead ($FL_{D,1}$)	-3.07 ***			-3.02 ***
	-3.99			-3.96
$FL_{D,1}$*opaque	3.75 ***			3.69 ***
	3.19			3.15
Former lead ($FL_{D,3}$)		-3.93 ***		
		-5.15		
$FL_{D,3}$*opaque		4.10 ***		
		3.70		
Former lead ($FL_{D,5}$)			-3.61 ***	
			-4.69	
$FL_{D,5}$*opaque			3.19 ***	
			2.98	
Former lead ($FL_{D,2+3\ only}$)				-1.19 ***
				-3.36
$FL_{D,2+3\ only}$*opaque				1.07 **
				2.05
Former lead ($FL_{D,4+5\ only}$)				0.45
				1.07
$FL_{D,4+5\ only}$*opaque				-0.48
				-0.86
Borrower size	-0.63 **	-0.63 **	-0.64 **	-0.64 **
	-2.31	-2.30	-2.35	-2.34
Loan size	-22.02 ***	-22.00 ***	-22.00 ***	-21.98 ***
	-49.29	-49.35	-49.41	-49.27
Loan size*mid_D	-2.92 ***	-2.91 ***	-2.88 ***	-2.93 ***
	-5.00	-4.99	-4.94	-5.02
Loan size*$large_D$	14.94 ***	14.94 ***	14.93 ***	14.93 ***
	32.06	32.06	31.99	32.09
Loan maturity	-4.55 ***	-4.58 ***	-4.55 ***	-4.56 ***
	-10.13	-10.20	-10.17	-10.17
Term $loan_D$	5.86 ***	5.87 ***	5.82 ***	5.87 ***
	6.15	6.17	6.12	6.17
Multiple $tranches_D$	-0.06	-0.07	-0.06	-0.06
	-0.10	-0.12	-0.10	-0.10
Pseudo R^2	0.151	0.152	0.151	0.151
Number of observations	17,839	17,839	17,839	17,839

Table VII

Robustness Checks Regarding the Composition of the Sample

This table presents tobit regression results. The dependent variable is the lead arranger's lending share defined as the average lending share across all lead arrangers who participate in the loan's syndicate. The independent variables are defined in Table A-I of the appendix. Subscript D indicates a dummy variable. All regressions include loan purpose, loan size, borrower industry and year dummies. For each independent variable, the top row reports the estimated coefficient and the bottom row reports the t-statistic. Standard errors are heteroskedasticity robust and clustered at the borrower-level. ***, **, and * indicate significance at the 1%, 5% and 10% level, respectively.

	Lead arranger's lending share									
	Benchmark		Excluding sole lenders		Excluding project finance loans, club deals and loans to financial institutions		Sample period from 1992 to 2007 only		Tranche level analysis	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Opaque_D$	3.25 ***	3.18 ***	5.07 ***	5.01 ***	3.33 ***	3.25 ***	14.28 ***	14.15 ***	2.47 **	2.35 **
	3.27	3.19	5.33	5.28	3.17	3.10	13.46	13.41	2.32	2.21
Previous borrower ($PB_{\#,5}$)	1.16 *	1.15 *	0.90 *	0.90	1.13 *	1.12 *	1.32 *	1.31 *	-0.31	-0.33
	1.92	1.92	1.66	1.65	1.76	1.75	1.91	1.90	-0.50	-0.52
$PB_{\#,5}$*$opaque_D$	-2.64 ***	-2.73 ***	-2.58 ***	-2.64 ***	-2.43 ***	-2.51 ***	-4.92 ***	-5.09 ***	-1.68 *	-1.77 **
	-3.08	-3.18	-3.12	-3.19	-2.70	-2.79	-5.07	-5.24	-1.86	-1.96
Lead arranger reputation (LR)	-46.56 **	-38.91 *	-49.36 ***	-45.83 **	-46.26 **	-37.97	-52.82 **	-42.90 *	-48.62 ***	-39.43 **
	-2.19	-1.81	-2.70	-2.49	-2.01	-1.64	-2.04	-1.65	-3.04	-2.44
LR*opaque	-57.53 **	-44.60 *	-62.72 **	-55.16 **	-56.31 **	-43.22 *	-208.22 ***	-183.30 ***	-83.06 ***	-70.60 ***
	-2.42	-1.87	-2.44	-2.14	-2.23	-1.70	-5.73	-5.05	-4.27	-3.61
Former lead ($FL_{D,5}$)	-3.61 ***	-3.58 ***	-2.48 ***	-2.46 ***	-3.73 ***	-3.70 ***	-2.40 ***	-2.39 ***	-3.45 ***	-3.40 ***
	-4.69	-4.65	-3.50	-3.48	-4.57	-4.53	-2.97	-2.96	-4.38	-4.32
$FL_{D,5}$*opaque	3.19 ***	4.27 ***	1.84 *	2.75 **	3.02 ***	4.11 ***	2.02 *	4.07 ***	2.33 **	3.17 ***
	2.98	3.74	1.75	2.41	2.68	3.43	1.81	3.39	2.04	2.61
Top-20 arrangers ($LR_{20,D}$)		-2.07 ***		-0.96 *		-2.21 ***		-2.65 ***		-2.31 ***
		-3.31		-1.72		-3.36		-3.87		-3.58
$FL_{D,5}$*opaque*$LR_{20,D}$		-3.31 ***		-2.48 **		-3.33 ***		-6.64 ***		-2.49 **
		-2.78		-2.15		-2.68		-4.95		-1.96
Borrower size	-0.64 **	-0.57 **	0.32	0.35	-0.59 **	-0.51 *	2.24 ***	2.32 ***	-1.03 ***	-0.95 ***
	-2.35	-2.08	1.16	1.30	-1.98	-1.72	8.63	8.89	-3.53	-3.25
Loan size	-22.00 ***	-21.92 ***	3.88 ***	3.86 ***	-21.74 ***	-21.68 ***	-0.39	-0.43	-14.87 ***	-14.85 ***
	-49.41	-49.26	9.50	9.45	-45.84	-45.75	-1.05	-1.16	-33.12	-33.07
Loan size*mid_D	-2.88 ***	-2.91 ***	-19.08 ***	-19.03 ***	-3.04 ***	-3.04 ***	-14.32 ***	-14.27 ***	0.35	0.37
	-4.94	-4.98	-26.41	-26.31	-4.98	-4.99	-20.52	-20.53	0.53	0.55
Loan size*$large_D$	14.93 ***	14.84 ***	-11.97 ***	-11.95 ***	14.77 ***	14.70 ***	2.63 ***	2.50 ***	8.15 ***	8.13 ***
	31.99	31.80	-23.03	-23.03	29.98	29.85	4.63	4.45	17.24	17.18
Loan maturity	-4.55 ***	-4.57 ***	-2.76 ***	-2.79 ***	-4.52 ***	-4.54 ***	1.73 ***	1.69 ***	-3.87 ***	-3.88 ***
	-10.17	-10.22	-5.89	-5.96	-9.55	-9.59	3.73	3.65	-8.84	-8.86
Term $loan_D$	5.82 ***	5.85 ***	4.48 ***	4.50 ***	5.80 ***	5.82 ***	6.38 ***	6.35 ***	3.04 ***	3.04 ***
	6.12	6.15	4.54	4.56	5.90	5.93	6.10	6.09	3.73	3.74
Multiple $tranches_D$	-0.06	-0.05	1.42 **	1.44 **	0.00	0.01	-0.73	-0.71	-4.72 ***	-4.67 ***
	-0.10	-0.08	2.37	2.40	0.00	0.01	-1.04	-1.01	-6.91	-6.85
Pseudo R^2	0.153	0.158	0.158	0.164	0.151	0.152	0.164	0.164	0.162	0.162
Number of observations	17,839	17,839	12,511	12,511	16,633	16,633	13,782	13,782	23,588	23,588

Table A-I
Variable Definitions

Dependent variables	**Description**
Lead arranger's lending share	Percentage share kept by lead arranger (1 = 1%). In case of multiple lead arrangers, the average across all lead arrangers is used.
Independent variables	**Description**
Very $opaque_D$	Dummy = 1 if the borrower has no S&P senior debt rating and no ticker.
Semi $opaque_D$	Dummy = 1 if the borrower has either a S&P senior debt rating or a ticker.
$Opaque_D$	Dummy = 1 if the borrower is either very or semi opaque.
$Transparent_D$	Dummy = 1 if the borrower has both a S&P senior debt rating and a ticker.
Previous borrower ($PB_{\#,i}$)	The natural log of number of prior loans rasied by a borrower in the i= 1, 3, or 5 years prior to loan signing.
Previous borrower ($PB_{D,i}$)	Dummy=1 if the borrower raised at least one other loan in the i= 1, 3, or 5 years prior to loan signing.
Previous borrower ($PB_{D,i+j\ only}$)	Dummy=1 if the borrower raised at least one other loan in the i+j years prior to loan signing. We consider (1) i+j=2+3 when the borrower raised a loan 2 or 3 years prior to loan signing but not 1 year prior, and (2) i+j=4+5 when the borrower raised a loan 4 or 5 years prior to loan signing but not 1 to 3 years prior.
Lead arranger reputation (LR)	Lead arranger reputation measured by the market share of the lead arranger in the year prior to loan signing (0.01=1%).
High-reputation arrangers ($LR_{high,D}$)	Dummy=1 if lead arranger belongs to the top 33% of lead arrangers with respect to market share.
Top-100 arrangers ($LR_{100,D}$)	Dummy=1 if lead arranger belongs to the top-100 lead arrangers with respect to market share.
Top-20 arrangers ($LR_{20,D}$)	Dummy=1 if lead arranger belongs to the top-20 lead arrangers with respect to market share.
Former $lead_D$ ($FL_{D,i}$)	Dummy=1 if if the lead arranger has been a lead arranger to the same borrower in the i=1, 3, or 5 years prior to loan signing.
Former $lead_D$ ($FL_{D,i+j\ only}$)	Dummy=1 if lead arranger has been a lead arranger to the same borrower in i+j years prior to loan signing. We consider (1) i+j=2+3 when the lead arranger has been a lead arranger to the same borrower 2 or 3 years prior but not 1 year prior, and (2) i+j=4+5 when the lead arrnager has been a lead arrnger to the same borrower 4 or 5 years prior to loan signing but not 1 to 3 years prior.
Borrower size	Natural logarithm of the borrower's sales volume in millions of dollars at the time of loan signing.
Loan size	Natural logarithm of the deal amount in millions of dollar.
Mid_D	Dummy=1 for loans that belong to the mid-33% of the sample in terms of loan size for any particular year.
$Large_D$	Dummy=1 for loans that belong to the top-33% of the sample in terms of loan size for any particular year.
Loan maturity	Natural logarithm of average maturity across all tranches belonging to the same deal, measured in days.
Term $loan_D$	Dummy=1 if at least one tranche in the deal is a term loan.
Multiple $tranche_D$	Dummy=1 if the deal consists of more than one tranche.
Year dummies	Dummies indicating in which year the loan was signed. Individual dummies for each year from 1986 to 2007 are created. The dummy for year 1986 is excluded as the benchmark year.
Loan purpose dummies	Dummies indicating the different reasons why borrowers raised funds based on Dealscan's "Primary Loan Purpose" field. Individual dummies for acquisition, corporate purpose, and debt repayment are created. The dummy for working capital is excluded as the benchmark loan purpose.
Industry dummies	Dummies for the industry of the borrower based on Dealscan's "Major Industry Group" field. Individual dummies for financial services, general manufacturing, healthcare, oil and gas, retail & supermarkets, and technology are created. The dummy for aerospace is excluded as the benchmark industry.

Table A-II
League Table for the Top-20 Lead Arrangers from 1986 to 2007

This table shows the market shares of the 20 most-reputable lead arrangers. Market shares are based on the loan volume arranged by the lead arranger in the syndicated loan market between 1986 and 2007.

Lead arrangers	Market Share
JP Morgan Chase	10.56
Bank of America	9.20
Citigroup	6.33
Wells Fargo	5.97
Chemical	5.57
Chase Manhattan	4.45
Wachovia Corp	4.03
Deutsche	3.53
Merrill Lynch	3.30
Royal Bank of Canada	2.82
US Bancorp	2.28
Credit Suisse	2.26
PNC	1.95
BNP Paribas	1.86
Barclays	1.78
General Electric Capital Corp	1.67
Lehman Brothers	1.51
Goldman Sachs	1.42
Bank of New York	1.09
Bank of Montreal	0.77
Total	**72.38**

Table A-III

Borrowers' History in the Syndicated Loan Market

This table presents summary statistics for our sample of 17,839 syndicated loan deals.

	Number of prior loans				
	Maximum	Minimum	Mean	Mean excluding zeros	Standard deviation
Loans raised by the borrower					
Number of loans in 5 years prior to loan signing	32	0	1.01	2.44	1.73
Number of loans in 3 years prior to loan signing	31	0	0.73	2.05	1.34
Number of loans in 1 year prior to loan signing	12	0	0.30	1.55	0.75
Loans raised by the borrower with the same lead arranger					
Number of loans in 5 years prior to loan signing	15	0	1.00	2.25	1.60
Number of loans in 3 years prior to loan signing	14	0	0.71	1.95	1.25
Number of loans in 1 year prior to loan signing	12	0	0.29	1.52	0.73

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