How do Defaults Affect Lead Arranger Reputation in the Loan Syndication Market?[*]

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Abstract

Does a financial intermediary's concern with maintaining its reputation help alleviate agency problems between the financial intermediary and investors? We investigate this question in the context of the loan syndication market by measuring how defaults by a lead arranger's borrowers affect its subsequent lending activity. Defaults appear to diminish a lead arranger's ability to syndicate loans: the lead arranger syndicates 8% fewer loans and retains 15.3% more of the loans it does syndicate. This is consistent with a loss of lead arranger reputation, and contrary to defaults affecting subsequent lending only via a reduction in lead arranger capital. The effects are stronger when the lead arranger is small, when few other lead arrangers experience defaults and when defaults suggest poor screening or monitoring by the lead arranger. Lenders continuing to participate in the lead arranger's syndicates tend to be those with a strong prior relationship with the lead arranger. Overall, there is a significant decline in the lead arranger's syndicated lending activity following defaults. Our results support the disciplining role of reputation concerns in the loan syndication market, and also highlight the limitations of a reputation-based disciplining mechanism.

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Introduction

Investors delegate the task of screening and monitoring firms to specialized financial intermediaries such as banks and underwriters (Leland and Pyle (1977) and Diamond (1984)). This, in turn, may give rise to information and incentive problems between financial intermediaries and investors. Economic theory suggests that these agency problems can be mitigated by the financial intermediary's concern with maintaining its reputation for diligent screening and monitoring.[1] Empirical testing of the role of intermediary reputation is made difficult, however, by the lack of exogenous proxies for a financial intermediary's reputation. Also, reputation mechanisms, even if they are effective in certain situations, may be subject to significant limitations. This is suggested, for instance, by recent revelations of prolonged misbehavior by reputable institutions such as Bear Sterns, Lehman Brothers and AIG.

In this paper, we use the loan syndication market as a testing ground to examine if reputation concerns can be effective in mitigating the agency problems that arise between lead arrangers, who originate syndicated loans, and "participant" lenders that fund parts of the loan and are counter-parties to the loan contract. We use Chapter 11 bankruptcy filings by a lead arranger's borrowers as evidence of poor performance by the lead arranger, and examine how its future activity in the loan syndication market is affected by such poor performance. Our empirical strategy allows us to test a rich set of predictions regarding the effectiveness and limitations of reputation mechanisms.

Apart from the fact that it is a large and important source of corporate finance worldwide, our focus on the loan syndication market is motivated by three important considerations: First, agency problems between the lead arranger and the participants can be potentially severe. Participants face an adverse selection problem because the lead arranger may have private information about the borrower. Also, by lowering its exposure to the borrower, syndication may weaken the lead arranger's incentives to screen and monitor the borrower. These problems were famously highlighted following the bankruptcy of Enron when some of the participants in Enron's syndicated loans accused the lead arrangers, JP Morgan and Citigroup, of helping Enron conceal its perilous financial condition and of using part of the loan proceeds to lower their own exposure.[2] The Enron affair also highlighted the limited legal recourse available to participants against the lead arranger in case of a loan default.[3]

[1]See Klein and Leffler (1981), Rogerson (1983), Allen (1984)), Diamond (1989), Diamond (1991), Boot, Greenbaum, and Thakor (1993), Chemmanur and Fulghieri (1994), Pichler and Wilhelm (2001) and Gorton and Pennacchi (1995).

[2]See "Enron Ties May Haunt J.P. Morgan Anew — Finance Firm Could Face Action By Banks That Joined in Loan To Failed Houston Energy Trader" in Wall Street Journal February 21, 2003.

[3]The courts tend to view participants in syndicated loans as senior lenders that are privy to borrower

Second, reputation considerations are likely to play an important role in the loan syndication market because lead arrangers and participant lenders are repeat players with long organizational memories. Information on the past performance of lead arrangers is readily available to the participant lenders through a variety of data sources. Anecdotal evidence suggests that participants use this information to maintain internal rankings of lead arrangers that guide their future participation decisions.

Third, the richness of data available on the loan syndication market also makes it an ideal testing ground to study the effectiveness of reputation mechanisms. We are able to obtain information on loan contract terms, borrower characteristics, syndicate structure of loans, and identities of the lead arranger and participants for more than 50,000 syndicated and non-syndicated loans contracted over a period spanning 15 years. We complement the loan data with Chapter 11 bankruptcy data which lets us identify a relatively clean proxy for shocks to lead arranger reputation. As we explain below, our data allows us to identify the channels through which the reputation mechanism works, how reputation effects vary in the cross section, and important limitations of a reputation-based disciplining mechanism.

We interpret a lead arranger's reputation in terms of the market's perception of its innate ability and willingness to screen and monitor borrowers. To the extent that there is uncertainty among market participants about a lead arranger's ability, Chapter 11 bankruptcy filings by a lead arranger's borrowers ("loan defaults") are likely to lower the market's assessment of the lead arranger's ability and damage its reputation. If lead arranger reputation matters in the loan syndication market, then such a loss of reputation should reduce the lead arranger's ability to attract participants and syndicate loans. We refer to this as the *reputation hypothesis*.

Apart from a loss of reputation, loan defaults may also lead to a significant erosion of the lead arranger's capital, which, in turn, could affect its subsequent lending activity adversely. We refer to this as the *loss of capital hypothesis*. If the loan defaults are due to wider economic problems in the borrowers' geographic area or industry, then a lead arranger that specializes in that geographic area or industry could suffer additional loss of future business. We refer to this as the *specialization hypothesis*. While these three hypotheses are not mutually exclusive, their different predictions enable us to uncover their empirical importance in the context of the loan syndication market.

We begin our empirical analysis by investigating two predictions that help distinguish the reputation hypothesis from the alternate hypotheses. If defaults lower the lead arranger's reputation, then, all else equal, the lead arranger should retain a larger fraction of the loans it syndicates in the future, in order to compensate for its lower reputation.[4] Moreover, the

information, and hence, responsible for their lending decisions.

[4]Theory suggests that the fraction of the loan financed by a lead arranger can signal its commitment to

lead arranger should also be less likely to syndicate a loan in the future. On the other hand, if the lead arranger is more capital constrained as a result of the defaults, it should reduce the fraction of the loan it finances and syndicate more often. The primary implication of the specialization hypothesis that we test is that the changes in the syndicate structure of loans should be largely driven by commonalities in either industry or geographic location between the lead arranger's bankrupt borrowers and the current borrower.

We test our predictions by combining three data sources: Loan Pricing Corporation's (LPC) Dealscan database for loan information, New Generation Research's bankruptcy database for information on Chapter 11 bankruptcy filings, and Compustat. To identify lead arrangers that experience large defaults, we construct a dummy variable *Large Defaults* that takes a value one if the total loan amount lent by the lead arranger and outstanding to borrowers that file for bankruptcy during the year exceeds 10% of the average annual amount it has syndicated over the previous two years. We test our predictions by estimating the effect of lagged values of *Large Defaults* on the lead arranger's lending activity. By way of preview, our main findings are as follows.

Controlling for borrower fixed effects and loan characteristics, we find that lead arrangers that experience large defaults (instances when lagged values of *Large Defaults* is one) finance 4.3% more of the loans that they syndicate in the subsequent year. Moreover, lead arrangers that experience large defaults are 5.3% less likely to syndicate a loan the following year. Both these results are economically significant, and are consistent with the reputation hypothesis. They also indicate that loss of capital is not the main driver of the changes in the syndicate structure of loans after a lead arranger experiences large defaults. There is little support for the specialization hypothesis either, because these effects do not appear to depend on whether the borrower shares the same industry or geographic location with the lead arranger's defaulted borrowers.

We do a number of additional tests to understand how these effects vary in the cross-section. In terms of lead arranger size, we find that both the increase in the fraction of syndicated loans financed by the lead arranger and the fall in the likelihood of syndication are confined only to small lead arrangers (lead arrangers within the 95^{th} percentile in terms of syndication volume). This result is consistent with the reputation hypothesis because there is likely to be greater uncertainty regarding the ability of small lead arrangers to begin with. It also highlights the difficulties small lead arrangers face in establishing themselves in the loan syndication market, and may go some way towards explaining the concentrated

providing due diligence and monitoring, and hence, should increase with the severity of agency problems between the arranger and the participants (see Leland and Pyle (1977) and Holmstrom and Tirole (1997)). Consistent with the theory, Dennis and Mullineaux (2000), Lee and Mullineaux (2004), Jones, Lang, and Nigro (2000), Sufi (2006) and Ball, Bushman, and Vasvari (2007) find that the fraction of the loan financed by the lead arranger increases with the extent of the borrower's information opacity.

nature of the loan syndication market. The lack of adverse consequences for large lead arrangers may also reflect their market power, and highlights a limitation of the reputation mechanism in disciplining them.

Our results indicate that the adverse consequences of large defaults are weaker in years in which several other lead arrangers also experience large defaults. This is consistent with the reputation hypothesis, because during such years, the defaults are more likely to be attributed to poor economic conditions rather than poor performance by the lead arranger. This result too highlights an important limitation of a reputation-based disciplining mechanism. Since correlated defaults are unlikely to be punished by the market participants, it may provide incentives for lead arrangers to herd in their lending decisions.

In terms of defaulted loan characteristics, we find that the consequences of large defaults are stronger for unexpected defaults – specifically, for defaults that occur soon after origination and for defaults of low-yield loans. Since unexpected defaults suggest inadequate screening and monitoring by the lead arranger, these findings are consistent with the reputation hypothesis. The alternate hypotheses do not have any specific cross-sectional predictions in this regard.

Our results are robust to how we define large defaults and to alternate ways of measuring lead arranger size. They are also robust to controlling for the lead arranger's capital and credit rating. When we use lead arranger credit rating as an alternate proxy for lender reputation, we find that while lead arrangers with a higher rating do finance a smaller fraction of the syndicated loan, there is no corresponding effect on the syndication likelihood.

With regard to syndicate participants, we find that while participants are, on average, less likely to participate in loans syndicated by a lead arranger that experiences large defaults, the effect is weaker in case of participants that have a strong relationship with the lead arranger. This is consistent with the reputation hypothesis because participants that know the lead arranger well are less likely to update their assessment of its abilities following large defaults. Again, the alternate hypotheses do not have any specific predictions in this regard.

After experiencing large defaults, lead arrangers tend to shift their lending to less opaque and less risky borrowers, and to less risky loans. Lead arrangers also experience a large drop in their aggregate level of syndicated loan activity following large defaults. In fact, close to 40% of lead arrangers that experience large defaults completely drop out of the syndicated loan market within a year. There is also a drop in the number of loans originated by other lead arrangers in which the lead arranger participates. The drop in the lead arranger's syndicated loan activity is consistent with a significant erosion of the lead arranger's capital as well as with a loss of reputation.

Overall, our results support the idea that poor performance by a lead arranger damages its reputation and lowers its ability to syndicate loans in the future. At the same time, poor performance by large lead arrangers with market power and correlated poor performance are less likely to be punished. These are important limitations of a reputation-based disciplining mechanism as highlighted by our results.

Our paper is closely related to existing empirical papers on the loan syndication market (Dennis and Mullineaux (2000), Lee and Mullineaux (2004) and Sufi (2006)) which typically use a lead arranger's past level of activity as a proxy for its reputation, and show that reputable lead arrangers are more likely to syndicate loans and to hold smaller fractions of the loans that they do syndicate. We contribute to this literature in several ways. Unlike the cross-sectional approach in existing studies, we investigate a necessary condition for the effectiveness of a reputation based disciplining mechanism, namely, loss of economic rents following a poor performance. Since our empirical design is based on shocks to a lead arranger's reputation, it is less subject to selection biases in the loan syndication market where better quality firms, which are more likely to have their loans syndicated, tend to borrow from the "more reputable" lenders.[5] We also provide a number of interesting cross-sectional tests on how the impact of a loss of reputation varies based on lead arranger size and performance of other lead arrangers.

Our paper is also related to papers that examine the role of reputation in other financial markets, such as IPO underwriting (Beatty and Ritter (1986) and Nanda and Yun (1997)), funds management (Chevalier and Ellison (1999)), security analysis (Hong and Kubik (2003)), and venture capital (Krishnan, Masulis, and Singh (2007)). Our identification strategy is closest to Chevalier and Ellison (1999) and Hong and Kubik (2003) in the sense that we use poor performance by a lead arranger to identify a shock to its reputation. Another related paper is by Dahiya, Saunders, and Srinivasan (2003) who find that the announcement of bankruptcy or default by a bank's borrowers has a significant negative effect on its market value. While these findings are attributed, in part, to a loss of valuable relationships, they may also reflect a loss of the bank's reputation and lower ability to syndicate loans in future.

The remainder of the paper is organized as follows. We outline our main hypotheses in Section 1, and describe our data and summary statistics in Section 2. Our main results are presented in Section 3. We discuss robustness of our results in Section 4. Section 5 concludes the paper.

[5] See Fernando et al. (2005) for evidence of such matching in the equity underwriting market.

1 Hypotheses and Empirical Predictions

In this section, we discuss the key hypotheses regarding the impact of large loan defaults by a lead arranger's borrowers on its future lending activity, and outline their testable predictions. The three hypotheses – *reputation*, *loss of capital* and *specialization* – are not mutually exclusive. Our tests are intended to help understand their empirical relevance in the context of the loan syndication market.

Reputation hypothesis In the introduction, we outlined the information and incentive problems that can arise between the lead arranger and participants in a loan syndicate. A non-contractual mechanism that can mitigate these agency problems is the lead arranger's concern for its own reputation. Because lead arrangers and participants are repeat players in the loan syndication market and are likely to have relatively long organizational memories, lead arrangers have an incentive to develop and maintain a reputation for diligent screening and monitoring. To the extent that participants are uncertain about a lead arranger's ability and willingness to screen and monitor borrowers, large loan defaults are likely to lower the participants' assessment of the lead arranger's ability, and hence, damage its reputation. Such a loss of reputation could negatively affect the lead arranger's ability to attract participants and syndicate loans in the future. We refer to this as the reputation hypothesis.[6] We now outline the predictions of the reputation hypothesis starting with key predictions that help distinguish it from the alternate hypotheses.

If large defaults damage a lead arranger's reputation, then we expect it to hold a larger fraction of the loans it syndicates in the future, to compensate for its loss of reputation and to reassure syndicate participants about borrower quality and its own intention to monitor the loan. The lead arranger should, ceteris paribus, also be less likely to syndicate a loan after it experiences large defaults. These effects should be stronger for small lead arrangers because there is likely to be greater uncertainty about their screening and monitoring abilities. The effects should also be stronger when defaults are ex-ante "unexpected," e.g., when defaults occur soon after origination, because participants are more likely to attribute these defaults to inadequate screening and monitoring by the lead arranger. We describe how we identify unexpected defaults in Section 3.

Other lenders should, in general, be less willing to participate in loans syndicated by the lead arranger after large defaults. However, this effect should be weaker for participants

[6]While our subsequent results highlight the importance of lender reputation, to the extent loans can be identified to individual loan officers, their reputation may also be affected by defaults. Our results suggest that replacing/reassigning these officers and making other organizational changes is, however, unlikely to completely forestall adverse consequences to the lead arranger. This is reasonable because lack of adverse consequences will reduce incentives for the lead arranger to put in place control systems, checks and balances to prevent bad performance by individual loan officers.

that have a strong relationship with the lead arranger because, given their past information and experience with the lead arranger, these participants are less likely to update their view of the lead arranger.

If participants lower their assessment of the lead arranger's ability to screen and monitor borrowers following large defaults, then it should cause the lead arranger to switch to more transparent and less risky borrowers that require less screening and monitoring. However, at the same time, given its lower ability to syndicate loans, the lead arranger may be less able to lend to large firms that rely primarily on syndicated loans. Finally, the lead arranger's overall activity in the loan syndication market should drop after it experiences large defaults.[7]

Loss of capital hypothesis A lead arranger may suffer substantial losses when its borrowers default and file for bankruptcy. Apart from the direct loss on account of the lead arranger's loan exposure to the bankrupt borrower,[8] the lead arranger also stands to lose future business with the borrower. If a lead arranger is constrained in raising fresh outside capital, then a fall in its capital should result in a reduction in its future lending activity, because bank regulations typically stipulate minimum capital requirements for lending. Moreover, as Dahiya, Saunders, and Srinivasan (2003) note, defaults may also increase regulatory scrutiny. The loss of capital combined with the increased regulatory scrutiny could also cause the lead arranger to become more risk averse in its lending.

In sharp contrast to the reputation hypothesis, the loss of capital hypothesis predicts that the lead arranger will hold smaller fractions of loans it syndicates following large defaults. This is because the loss of capital, and the risk-averse behavior it engenders, will induce the lead arranger to lower its loan exposure to its borrowers. By a similar logic, the lead arranger should also, ceteris paribus, be more likely to syndicate a loan following large defaults. These effects should be more severe for small lead arrangers that are likely to face greater constraints in raising fresh capital. The loss of capital hypothesis does not have any specific cross-sectional predictions regarding the lead arranger's ability to attract other lenders to participate in its syndicates.

[7]The reputation hypothesis does not have any clear predictions for whether the lead arranger's participation activity in loans originated by other lead arrangers should increase or decrease. On the one hand, it might seem reasonable that the lead arranger will participate in more loans to compensate for its reduced ability to syndicate loans. However, it is well known that lead arrangers in the syndication market ride off each other's syndication abilities, i.e., they participate in each other's deals. So a lead arranger that has lost the ability to syndicate loans might not be invited to participate in loans of other lead arrangers, causing its participation activity to drop.

[8]Empirical studies that examine loan recovery rates in Chapter 11 bankruptcy report somewhat different figures. Franks and Torous (1994), using a sample from 1983 to 1989, find recovery rates on bank debt, non-bank secured debt, and senior debt to be 86%, 80%, and 47%, respectively. However, in a more recent study, Gupton, Gates, and Carty (2000) estimate the recovery rates on senior secured loans and senior unsecured loans to be 69% and 52%, respectively.

To the extent that the loss of capital makes the lead arranger more risk averse, the lead arranger should shift to safer borrowers and safer loans. However, loss of capital could also translate into a shift towards smaller borrowers, because the lead arranger may not be able to fund the loan amounts sought by bigger firms. The loss of capital hypothesis also predicts a drop in syndicated lending activity of the lead arranger. Moreover, the loss of capital is also likely to reduce the number of loans (syndicated by other lead arrangers) in which the lead arranger participates.

Specialization hypothesis Bankruptcy filing by a firm may portend economic distress in the firm's industry or local economy. This could be a problem for lead arrangers that specialize in lending to specific industries or geographical areas. For such specialized lead arrangers, large borrower bankruptcies may mean poor future investment opportunities, which in turn may affect their ability and willingness to make loans. We refer to this as the specialization hypothesis.

As per the specialization hypothesis, the impact of large defaults on syndicate structure of future loans should depend on whether the borrower is from the same industry or geographic area as any of the lead arranger's bankrupt borrowers. We use this sector-specific prediction of the specialization hypothesis to distinguish it from the reputation hypothesis. The predictions of the specialization hypothesis are otherwise very similar to those of the loss of capital hypothesis.

2 Sample Construction, Empirical Specification and Preliminary Results

2.1 Sample Construction

We obtain the data on individual loan contracts from a 2006 extract of the Loan Pricing Corporation's (LPC) Dealscan database. Dealscan provides information on loans made to medium and large sized US and foreign firms. According to LPC, 70% of the data is gathered from SEC filings (13-Ds, 14-Ds, 13-Es, 10-Ks, 10-Qs, 8-Ks, and Registration Statements), and the remaining portion is collected directly from lenders and borrowers.[9] We extract information on all dollar-denominated loans made by US lenders to US borrowers during the 1990–2006 period.

The loans are financed either by a single lender or by a syndicate of lenders. When

[9] All public firms and all firms that have public debt outstanding are required to file details of their loans with the SEC. Lenders who may use the Dealscan league tables as a marketing tool also have incentives to voluntarily report their loans to Dealscan.

the loan is financed by a syndicate, Dealscan allows us to identify the lead arranger for the loan. Specifically, Dealscan lists the role of each lender in the syndicate and we designate a lender as the lead arranger if its role is listed as any of the following: Agent, Admin Agent, Arranger, Co-arranger, Lead Bank, or Lead Manager. We drop the loans for which we are either unable to identify any lead arranger or identify multiple lead arrangers.[10] We also obtain the loan contract terms such as the total loan amount, yield spread,[11] maturity, loan type, loan purpose, presence of security, and syndicate structure details such as the fraction of the loan financed by the lead arranger from Dealscan.

Our data on bankruptcy filings is from the web site www.bankruptcydata.com maintained by New Generation Research. We obtain data on all Chapter 11 bankruptcy filings by firms with total liabilities greater than \$50 million over the 1990–2005 period. Among other things, this database provides information on the name of the company filing for bankruptcy and the date of the filing. We have information on 1,929 bankruptcy filings by 1,869 firms. We then manually match the bankruptcy data with the Dealscan data using the company's name to identify all loans contracted by the company filing for bankruptcy. By this method, we are able to identify loans obtained by 1,048 firms that subsequently file for bankruptcy.

Finally, we use the Compustat database to obtain detailed financial information on the borrowers in our sample. Again, to avoid errors, we manually match the Dealscan data with Compustat using firm name. For the borrowers with coverage in Compustat, we obtain the borrower's financial information at the end of the financial year in which the loan is originated.

2.2 Empirical Specifications and Key Variables

We begin our empirical analysis by analyzing the fraction of the loan financed by the lead arranger and the probability the lead arranger syndicates a loan. We model these syndicate characteristics by estimating panel regressions that are variants of the following form:

$$\begin{aligned} y_l = {} & \beta_0 + \beta_1 \times \text{Large Defaults}_{j,t-1} + \beta_2 \times X_j + \beta_3 \times X_l + \beta_4 \times X_i \\ & + \mu_t + \text{Borrower or Lead Arranger FE}, \end{aligned} \tag{1}$$

where subscript 'l' denotes the loan, subscripts 'i' and 'j' denote the borrower and lead arranger respectively, and subscript 't' denotes the year in which the loan is originated.

[10] Out of 71,825 loans, we could not identify the lead arranger using the above method for 4,145 loans (5.7%), and we identified multiple lead arrangers for 3,285 loans (4.6%).

[11] Specifically, Dealscan provides a variable called "all-in-drawn spread" which denotes the cost to the borrower per dollar of loan amount withdrawn. The all-in-drawn spread is provided as a basis-point spread above the London Interbank Offer Rate (LIBOR).

The two dependent variables that we model are *Lead Allocation*, which is the fraction of the syndicated loan financed by the lead arranger, and *Syndicate*, a dummy variable that identifies instances when the loan is financed by a syndicate of lenders. For the regressions with *Lead Allocation* as the dependent variable, the sample is restricted to syndicated loans only. We do this because *Lead Allocation*, by definition, equals 100% for non-syndicated loans. For the regressions with *Syndicate* as the dependent variable, the sample consists of all the loans originated during 1991–2006. These regressions are estimated with year fixed effects (μ_t), and borrower or lead arranger fixed effects. In all specifications, the standard errors are robust and are clustered at the same level as the fixed effects employed. For the regressions with *Syndicate* as the dependent variable, we also use a logistic panel specification as an alternative to model (1).[12]

The main independent variable in all our specifications is *Large Defaults*, a dummy variable that identifies lead arrangers that experience large loan defaults during the year as a result of bankruptcy filings by their borrowers. We construct this variable as follows: We match the bankruptcy data with Dealscan data to identify all the loans obtained by firms that subsequently file for Chapter 11 bankruptcy. We then use the loan origination date and its stated maturity reported in Dealscan to identify loans outstanding at the time of the bankruptcy filing. We aggregate all such outstanding loans for each lead arranger for each year. We code $Large\ Defaults_{j,t}$ equal to one if the total loan amount lent by the lead arranger j and outstanding to borrowers who file for bankruptcy during year t exceeds 10% of the average annual amount syndicated by the lead arranger j over the previous two years. In our regressions, we use lagged values of *Large Defaults* as our main dependent variable.

We also do robustness tests with a continuous measure of the magnitude of defaults, which we refer to as *Scaled Defaults*. This is defined as the total loan amount lent by lead arranger j and outstanding to borrowers who file for bankruptcy during year t, scaled by the average annual amount syndicated by the lead arranger j over the previous two years. Note that $Large\ Defaults_{j,t}$ equals one if *Scaled Defaults* exceeds 10%.

A couple of comments on the definition of *Large Defaults* are in order: First, because we do not observe a loan's actual repayment and instead use the loan's stated maturity to identify if it is outstanding at the time of the bankruptcy filing, some loans may be misclassified. In practice, the actual maturity of a loan may be shorter than the stated maturity if either the borrower voluntarily pre-pays the loan,[13] or is forced to do so following a covenant violation or a default. Similarly, a loan's maturity may be extended beyond its

[12] We do not employ the logistic specification for our main analysis that employs fixed effects due to the incidental parameters problem (Wooldridge (2002)).

[13] We believe that the number of such loans is likely to be limited because firms that file for bankruptcy are likely to be liquidity constrained prior to the filing and hence are less likely to pre-pay outstanding loans.

original maturity as a result of a renegotiation between the borrower and the lender (Gilson (1989) and Roberts and Sufi (2007)). Also, since Dealscan is not a comprehensive listing of all US private debt,[14] we may not identify all the defaulted loans. These issues are only likely to attenuate our results by introducing noise into our independent variable, *Large Defaults*. Since Dealscan significantly increased its coverage after 1995, we repeat our tests after confining the sample to post-1995 loans to partly control for any potential biases arising from our inability to identify all the defaulted loans.

We also control these regressions for lead arranger characteristics, borrower characteristics, and loan characteristics. The lead arranger characteristics include, *Log(Lead Size)*, the natural logarithm of the average annual loan amount syndicated by the lead arranger over the previous two years, *Lead's Bankrupt Industry* (*Lead's Bankrupt State*), a dummy variable that identifies if the borrower of a loan is from the same industry (state) as any of the lead arranger's borrowers who declare bankruptcy the previous year. Among the loan characteristics, X_l, that we control for, *Short Term* (*Long Term*) is a dummy variable that identifies loans with maturity of less than one year (greater than five years); *Takeover*, *Working Capital*, and *Repayment* are dummy variables that identify loans whose main purpose is to finance takeovers, to finance working capital or to repay debt, respectively; *Log(Loan Amount)* is the logarithm of the size of the loan in \$ million.

In the next set of tests, we investigate how large loan defaults affect the lead arranger's ability to attract other lenders to participate in its syndicates. For this, we create a panel data set with one observation for every lead arranger-participant-year combination. The panel includes all pairs of lead arrangers and participants that ever syndicate a loan together. We then estimate the following model:

$$y_{jkt} = \beta_0 + \beta_1 \times \text{Large Defaults}_{j,t-1} + \beta_2 \times X_{j,k} + \mu_t + \text{Arranger-Participant Pair FE}, \tag{2}$$

where y_{jkt} is *Log(1+Loans Together)*. *Loans Together* is the number of loans syndicated by the lead arranger j and in which participant k participated during the year t. $X_{j,k}$ is a set of lead arranger-participant pair characteristics. We control these regressions for year fixed effects and lead arranger-participant pair fixed effects.

Next, we conduct tests using a variant of (1) to examine how large loan defaults affect the type of borrowers the lead arranger lends to and the risk characteristics of the loans contracted by the lead arranger. We control these regressions for lead arranger characteristics and lead arranger fixed effects.

[14]According to Carey and Hrycray (1999), the database contains between 50% and 75% of all commercial loans in the US during the early 1990s. From 1995 onwards, Dealscan contains the "large majority" of sizeable commercial loans.

In our final set of tests, we use a model similar to (2) to examine the impact of large loan defaults on the lead arranger's overall level of lending activity. To this end, we create a panel data set with one observation for every lead arranger-year combination. We control these regressions for lead arranger characteristics and lead arranger fixed effects.

2.3 Summary Statistics and Univariate Tests

Table I provides an year-wise summary of our loan and bankruptcy data. We have information on 57,502 loans made to borrowers from 865 unique 4-digit SIC industries. There is clearly an increase in the number of loans over the sample period. While part of the increase is due to the growth in the syndicated loan market, part of it is also due to improved coverage by Dealscan. Our bankruptcy data provides information on 1,929 Chapter 11 bankruptcy filings over the period 1991–2006. From Column (3) it is clear that there is a spurt in bankruptcy filings during the years 2000 through 2003 and mirroring this spurt, there is also an increase in the number of loan defaults during the 2000–2003 period [Column (4)].

In Panel A of Table II, we provide descriptive statistics of our key loan variables for the sample of loans originated during 1991–2006 for which we can identify a lead arranger. As indicated, the average loan amount is $179 million and the median is $55 million. Among the loans for which we have information on the yield spread, the average loan yield spread is 200 basis points over LIBOR. In terms of maturity, about 20% of the sample loans have a maturity of less than one year, as indicated by the mean value of *Short Term*, while 21% have a maturity greater than five years. Among the loans for which security information is available, 80% are secured. Around 65% of the loans are syndicated, with an average syndicate size of 5.5 lenders. On average, the lead arranger finances 29% of a syndicated loan.

In terms of borrower characteristics, financial data from the Compustat database is not available for borrowers involved in 73% of the loans (as indicated by the mean value of *Non Compustat*). For borrowers in the Compustat database, the median book value of total assets is $553 million, with an average leverage ratio (book value of debt to assets) of 0.31. Around 41% of these borrowers have bond ratings from Standard and Poor.

In seeking to characterize lead arrangers, we note that the loan syndication market is concentrated, with a sizable portion of the loans financed by a few large lead arrangers. We classify a lead arranger as *Small* in a given year if it is within the 95^{th} percentile in terms of number of loans syndicated during the previous year. While small lead arrangers constitute 95% of all lead arrangers in any given year, they only originate about half (52%) of all loans in our sample. In terms of defaults, the mean value of $Large\ Defaults_{t-1}$ indicates that

6.4% of the loans in our sample are originated by lead arrangers that experience large loan defaults in the previous year.

In Panel B of Table II, we offer a univariate perspective on the impact of borrower defaults. The table provides the means of key variables in sub-samples identified based on whether the lagged value of *Large Defaults* is one or not.[15] Panel B indicates that lead arrangers with large defaults are more likely to be small lead arrangers and are likely to finance smaller loans with higher yield spreads in the following year. Also, lead arrangers that experience large defaults are less likely to syndicate loans the following year, and are likely to retain a larger fraction of the loans they do syndicate. While these findings are consistent with the reputation hypothesis, they do not control for various loan, borrower, and lead arranger characteristics. Our subsequent multi-variate analysis shows that these differences persist even after we explicitly control for lead arranger size and include lead arranger fixed effects. In terms of borrower characteristics, lead arrangers that experience large defaults are less likely to lend to the more opaque, Non Compustat firms. However, among firms with Compustat data, they are more likely to lend to smaller firms.

We now proceed to formal multivariate tests of our hypotheses.

3 Empirical Results

In this section we present our main empirical findings on the effect of large loan defaults on the lead arranger's lending activity. We divide the discussion into four sub-sections. In Section 3.1, we discuss our results on the syndicate structure of future loans financed by the lead arranger following large defaults. We then present our findings on the lead arranger's ability to attract participants following large defaults in Section 3.2. These two sets of tests help distinguish between the three hypotheses. In Section 3.3, we discuss our findings regarding the type of borrowers that the lead arranger lends to and the type of loans it finances after it experiences large defaults. Finally, in Section 3.4, we present our findings regarding the impact of large defaults on the aggregate level of the lead arranger's activity in the syndicated and non-syndicated loan markets.

3.1 Syndicate Structure of Loans

We begin by investigating how large loan defaults affect the syndicate structure of loans made by the lead arranger in the following year. Specifically, we examine the impact on the

[15] To correspond to our subsequent regression analysis with lead arranger fixed effects, we confine the sample to loans originated by lead arrangers that have *Large Defaults* equal to one for at least one year.

fraction of the loan financed by the lead arranger and on the lead arranger's propensity to syndicate a loan.

3.1.1 Lead Arranger Allocation

Panel A of Table III presents the results of regression (1) with *Lead Allocation* as the dependent variable. The sample for these regressions is confined to syndicated loans only because, by definition, *Lead Allocation* equals 100 for non-syndicated loans. Recall that the reputation hypothesis predicts that following large defaults, the lead arranger is likely to finance a larger fraction of the loans it syndicates, to compensate for its lower syndication ability and to send a stronger signal to syndicate participants regarding the quality of the loans and its commitment to monitor. On the other hand, the loss of capital hypothesis predicts a fall in the fraction financed because the lead arranger has less capital to lend. The specialization hypothesis predicts that any change in the fraction of loan financed by the lead arranger should depend on whether the borrower is in the same industry or same state as any of the lead arranger's bankrupt borrowers.

The positive coefficient on *Large Defaults* in Column (1) indicates that the percentage of loan financed by the lead arranger increases by 4.3% in the year following large defaults. Note that the regression includes borrower fixed effects. Hence, the coefficient on *Large Defaults* measures the within-borrower difference in the fraction of the loan financed by a lead arranger that experiences large defaults as compared to a lead arranger that does not. The economic significance of this coefficient can be gauged by the fact that the average value of *Lead Allocation* for the syndicated loans in our sample is 28.8% (see Panel A of Table II). In other words, in the year following large defaults, the fraction of the loan financed by the lead arranger increases by 15%. This result is consistent with the reputation hypothesis but not with the loss of capital hypothesis. Moreover, notice that the coefficients on both the dummy variables *Lead's Bankrupt Industry* and *Lead's Bankrupt State* are not significant, indicating little support for the specialization hypothesis.

We next examine if our result is robust to alternate specifications and to variations in data quality. From Table I (Panel B) we know that small lead arrangers are more likely to experience large defaults. So one concern with our result in Column (1) is that the positive coefficient on *Large Defaults* may be the result of unobserved lead arranger characteristics. To check this, in Column (2), we repeat our estimation after including lead arranger fixed effects. Apart from controlling for time-invariant lead arranger characteristics, inclusion of lead arranger fixed effects lets us understand how the fraction of the loan financed by a given lead arranger changes when it experiences large defaults. The coefficient on *Large Defaults* continues to be positive and significant suggesting that our results are not being driven by unobserved lead arranger characteristics, although the magnitude of the coefficient drops by 50%. A possible reason for the fall in magnitude is that the specification with lead arranger fixed effects does not control for any change in borrower profile following large defaults. As we show in Section 3.3, following large defaults, the lead arranger shifts lending to safer borrowers. It is well known that the lead arrangers retain a lower fraction of the loan in the case of such borrowers (Sufi (2006)).

In Column (3) we investigate whether our results are robust to using an alternative variable to indicate large defaults. Specifically, we repeat our allocation regression after replacing the dummy variable, *Large Defaults*, with a continuous measure of the magnitude of default, *Scaled Defaults*. Consistent with earlier results, our finding is that the fraction of the loan retained by the lead arranger increases with the size of the defaults that it experiences.

Since Dealscan's coverage improved significantly after 1995, in Column (4), we repeat our estimation after confining the sample to post-1995 loans only. As we noted previously, Dealscan's poor coverage before 1995 is likely to add noise to our main independent variable, *Large Defaults*, because we are unlikely to identify all the lead arrangers that have loans outstanding to firms that file for bankruptcy. Consistent with this conjecture, we find that the coefficient on *Large Defaults* in Column (4) is 10% bigger (as compared to Column (1)). Finally, in Column (5), we repeat our estimation after re-defining *Large Defaults* only in terms of defaults on syndicated loans. That is, for this Column, we let *Large Defaults* take a value one if the total amount outstanding on *syndicated* loans to borrowers that file for bankruptcy during the year exceeds 10% of the average annual amount syndicated by the lead arranger over the previous two years. Our results in this column are consistent with our earlier results.

Overall, the results in Panel A show that a lead arranger that experiences large defaults is likely to retain a larger fraction of any loan it syndicates, and this finding is not driven by whether the borrower is from the same industry or same state as any of the defaulting borrowers. This evidence is supportive of the reputation hypothesis. In the next few panels, we investigate additional predictions of the reputation hypothesis. Specifically we examine the effect of lead arranger characteristics, syndicate market characteristics, and defaulted loan characteristics on the fraction of the loan retained by the lead arranger following large defaults.

In Panel B, we investigate if the impact of large defaults on the fraction of the loan retained by the lead arranger depends on lead arranger size. To do this, we estimate regression model (1) after replacing *Large Defaults* with two interaction terms namely, *Large Default*$\times$*Small* and *Large Default*$\times$*[1-Small]*. For brevity, we suppress the coefficients on the control variables, and only report the coefficient estimates on the interaction terms. Recall that the reputation hypothesis predicts that the impact of large defaults will be more severe for small lead arrangers because there is likely to be greater uncertainty about their screening and monitoring abilities. On the other hand, to the extent small lead arrangers face greater difficulty in raising new capital, the loss of capital hypothesis predicts that such arrangers should retain a smaller fraction of the loan. Our results [Columns (1) and (2)], consistent with the reputation hypothesis, indicate that the increase in fraction of the loan retained by the lead arranger following large defaults is essentially confined to small lead arrangers. Small lead arrangers retain 6.6% more of the loan following large loan defaults. As reported in Column (3), the coefficients on the interaction terms are significantly different from each other.

In Panel C, we investigate if the impact of large defaults on the fraction of the loan retained by the lead arranger depends on whether several other lead arrangers also experience large defaults. The reputation hypothesis predicts that the adverse impact of large defaults should be less severe during such times as market participants are more likely to attribute defaults to poor economic conditions. Note that the prediction does not follow in any obvious way from the alternative hypotheses. To test the prediction, we estimate (1) after replacing *Large Defaults* with two interaction terms namely, *Large Default*$\times$*Other Leads Tainted* and *Large Default*$\times$*[1-Other Leads Tainted]*, where *Other Leads Tainted* is a dummy variable that identifies years in which more than 7.5% of all lead arrangers experience large defaults. The 7.5% cutoff represents the 75^{th} percentile in terms of the annual fraction of lead arrangers that experience large defaults. The coefficients reported in Panel C indicate that while the estimated effects are less severe in years in which several other lead arrangers also experience large defaults (3.058 as compared to 6.557), due to the noise in our estimation the coefficients are not significantly different from each other.

In Panels D through F, we investigate if the impact of large defaults depends on the characteristics of the loans that default. In Panel D, we examine if the adverse impact of loan defaults is greater when most of the defaults happen soon after the loan origination, because such cases are more likely to reflect inadequate screening on the part of the lead arranger. To test this, we classify all defaults that occur within two years of the loan origination as quick defaults. We then split *Large Defaults* into two dummy variables, one representing instances when the majority of the defaults (greater than half by loan amount) are quick defaults and the other representing instances when the majority are *not* quick defaults. We then estimate (1) after replacing *Large Defaults* with these two dummy variables. The results in Panel D [Columns (1) and (2)] show that the increase in the loan fraction retained by the lead arranger is evident mainly when the majority of the defaults are quick defaults. The difference between the coefficients on the two dummy variables is also statistically significant [Column (3)].

In Panel E, we investigate if the increase in the loan fraction retained by the lead arranger varies with the risk of the defaulted loans. Since low risk loans are expected to default at a lower rate, and as such defaults are likely to impose a greater loss on market participants, we expect the adverse impact of loan defaults to be more severe when the majority of the defaults involve low-risk loans. To test this prediction, we use the loan yield spread as a proxy for risk and classify loans as 'low-yield' if the yield spread on the loan is lower than the median yield spread on all loans made by the lead arranger. We then split *Large Defaults* into two dummy variables, one representing instances when most of the defaults (by loan amount) are on account of low-yield loans, and the other representing the instances when the majority of the defaults are *not* on account of low-yield loans. We then estimate (1) after replacing *Large Defaults* with these two dummy variables. The results in Panel E [Columns (1) and (2)] show that the increase in the loan fraction retained by the lead arranger is largely confined to the instances when most of the defaults are on account of low-yield loans. Once again, the difference between the coefficients on the two dummy variables is statistically significant.

In Panel F, we investigate if the impact on the fraction of loan retained by the lead arranger varies with the distance between the lead arranger and its defaulted borrowers. The reputation hypothesis predicts that the effects are likely to be stronger for defaults involving borrowers located closer to the lead arranger, because the lead arranger is expected to engage in more intense monitoring and have more information about such borrowers. Accordingly, we classify loans as 'close' if the distance between the lead arranger and the borrower is lower than the sample median distance of five hundred miles. We measure the distance between a borrower and a lead arranger as the distance in miles between the centroids of the zipcodes of their respective head offices. To the extent that lead arranger-borrower interaction occurs through branch offices, our measure is likely to overestimate the distance between the lead arranger and the borrower. To test our prediction, we split *Large Defaults* into two dummy variables, one representing instances when most of the defaults (by loan amount) are on account of close loans, and the other representing instances when most of the defaults are *not* on account of close loans. We then estimate (1) after replacing *Large Defaults* with these two dummy variables. The results in Panel F [Columns (1) and (2)] do not provide consistent evidence that the effects are stronger for distant defaults. One reason for lack of consistent evidence may be the noise in our distance measure.

Summarizing the results in Panels B through F, we find that the increase in the fraction of the loan retained by the lead arranger following large defaults is bigger for small lead arrangers, and smaller in the years when several other lead arrangers experience large defaults. The effects are also larger for defaults that happen within two years of the loan origination, and for defaults involving low-yield loans. Overall, these results are consistent with the reputation hypothesis.

A key implication of our results in Table III is that reputation concerns are likely to be far more important for small lead arrangers as compared to large lead arrangers. We investigate this cross-sectional result further in Table IV to ensure that it is not simply an artifact of the way we identify large defaults or the way we measure bank size.

A potential concern stems from the finding that the consequences of defaults are more severe for larger values of *Scaled Defaults* (see Column (3) of Table III, Panel A), coupled with the observation that small lead arrangers typically have higher values of *Scaled Defaults* (due to their lower syndication volume) as compared to large lead arrangers. Hence, using *Large Defaults* in Panel B may bias our results towards finding stronger effects for small lead arrangers. To ensure that our cross-sectional result on small versus large lead arrangers is not driven by lead arrangers with extreme values of *Scaled Defaults*, we repeat our estimation after excluding the loans financed by lead arrangers with *Scaled Defaults* greater than 20%. Our results, in Column (1) of Table IV, are consistent with those in Panel B of Table III, and confirm that large defaults primarily affect small lead arrangers.

In Column (2), we repeat our estimation after replacing the dummy variable *Small* with a continuous measure of lead arranger size. This serves as a robustness check to ensure that our results in Panel B are not driven by how we identify small and large lead arrangers. Our results in Column (2) confirm that the fraction retained by the lead arranger following large defaults increases more for small lead arrangers as compared to large lead arrangers.

It could be argued that our cross-sectional results in Panel B are due to systematic differences in the type of loans syndicated by small and large lead arrangers, which our empirical specification does not fully control for. For instance, screening and monitoring may be less important in case of loans made by large lead arrangers because they typically lend to large informationally transparent firms, while small lead arrangers lend to informationally opaque firms (see Berger et al. (2005)). Alternatively, it could be that large lead arrangers are more likely to finance high-risk takeover deals, where the loss of reputation in case of failure is minimal because participants are aware of the risks ex ante. To investigate this further, in Columns (3) and (4), we repeat our estimation after confining our sample to a more homogenous set of loans. In Column (3), we confine the sample to loans made to firms for which financial information is not available in the Compustat database, because screening and monitoring is likely to be more important for such informationally opaque firms. In Column (4), we confine our sample to loans where the main purpose is not to finance takeovers. We do this because loans to finance takeovers are typically high levered transactions which are only syndicated by large lead arrangers. By excluding such loans we obtain a sample of loans that are similar across small and large lead arrangers. In both cases we obtain results that indicate that large defaults primarily affect small lead arrangers.

3.1.2 Probability of Syndication

Panel A of Table V presents the results of the regressions that examine how large defaults affect the lead arranger's propensity to syndicate a loan. These tests have *Syndicate* as the dependent variable. Because the likelihood of syndication can depend on unobserved borrower characteristics, we include borrower fixed effects in the regression in addition to year fixed effects and the loan amount. Inclusion of borrower fixed effects and loan amount ensures that the effects we identify are within-borrower changes in the syndication likelihood when the loan is financed by a lead arranger that experiences large defaults as compared to a lead arranger that does not. As can be seen from Column (1), the coefficient on *Large Defaults* is negative and significant. Since this is a linear probability model, the coefficient is also equal to the marginal effect. The coefficient indicates that a lead arranger that experiences large defaults is 5.3% less likely to syndicate a loan in the following year. The result is economically significant, with the average probability of a loan being syndicated in our sample at 65% (see Panel A of Table I). This result is consistent with the reputation hypothesis but not with the loss of capital hypothesis, which predicts an increase in the propensity to syndicate. There is also little support for the specialization hypothesis: The coefficients on the dummy variables *Lead's Bankrupt Industry* and *Lead's Bankrupt State* are not significantly different from zero, indicating that the lead arranger's propensity to syndicate a loan does not depend on whether the borrower is from the same industry or state as any of its bankrupt borrowers. From the coefficients on the control variables, we find that a loan is more likely to be syndicated if its maturity is between one and five years (negative coefficients on *Short Term* and *Long Term*), if it is a large loan (positive coefficient on *Log(Loan Amount)*), and if the lead arranger is large in terms of its volume of syndication (positive coefficient on *Log(Lead Size)*).

In the next few Columns, we test the robustness of our findings. To control for unobserved lead arranger characteristics, in Column (2) we repeat our estimation after including lead arranger fixed effects. As can be seen, the coefficient on *Large Defaults* continues to be negative and significant, although its magnitude reduces by 32%. Here again, we believe that the fall in magnitude may be because of the lead arranger switching to safer borrowers following large defaults, an effect which we document in Section 3.3.

In Column (3), we repeat our estimation with a logistic specification. In Column (4), we repeat our estimation with a continuous measure of defaults. In Column (5), we confine the sample to loans originated after 1995, because Dealscan's coverage improved significantly after 1995. Finally, in Column (6), we repeat our estimation after defining *Large Defaults* only in terms of defaults on syndicated loans. In all specifications, the coefficient on the default measure is negative and significant.

Overall, the results in Panel A suggest that a lead arranger that experiences large defaults is less likely to syndicate a loan in the following year, and this finding is not driven by whether the borrower is from the same industry or same state as any of the defaulting borrowers. This evidence is supportive of the reputation hypothesis. In the next few panels, we investigate additional predictions of the reputation hypothesis. The tests in these Panels are similar to the ones in Panels B-F in Table III.

Panel B examines if our results vary with lead arranger size. As can be seen from Columns (1) through (3), the decrease in the syndication likelihood is confined to small lead arrangers. There is no significant decrease in the syndication likelihood for large lead arrangers. This evidence is consistent with the reputation hypothesis.

In Panel C, we investigate if the decrease in syndication likelihood depends on whether other lead arrangers also experience large defaults in the same year. The results in Columns (1)-(3) indicate that the fall in syndication likelihood is much greater in the years in which other lead arrangers do not experience large defaults as compared to when they do (7.5% in comparison to 3.3%), and the two coefficients are statistically different from each other.

In Panels D-F, we examine if the decrease in the syndication likelihood depends on the defaulted loan characteristics. In Panel D, we examine if the impact is more severe when most of the defaults are on account of loans defaulting within two years of their origination. The results in Columns (1)-(3) indicate that the decrease in the syndication likelihood is confined to cases where most of the defaults occur within two years of the loan origination. This result is strongly supportive of the reputation hypothesis.

In Panel E, we examine if the decrease in the syndication likelihood is more when most of the defaults are on account of low-risk loans. Recall that we use the yield spread on the loan at the time of its origination as a measure of risk. The results in Columns (1)-(3) of Panel E show that, as predicted by the reputation hypothesis, the decrease in the syndication likelihood is confined to cases where most of the defaults are on account of low-yield loans.

Finally, in Panel F, we examine if the decrease in the syndication likelihood following large defaults depends on the distance between the lead arranger and the defaulting borrowers. The results in Panel F indicate that the decrease in syndication likelihood occurs only when defaults are due to "close" borrowers. Possibly due to the noise in our estimation, we find that the coefficients are not significantly different from each other.

In unreported tests, we find that we obtain qualitatively similar results when we employ the logistic specification instead of the linear probability model.

Summarizing the results in Tables III, IV, and V, we find that lead arrangers that experience large loan defaults are likely to finance a larger fraction of the loans that they syndicate and are less likely to syndicate loans the following year. Both these effects are larger for small lead arrangers, and are smaller in years in which several other lead arrangers also experience large defaults. Examining the characteristics of the defaulted loans, we find that the effects are larger for defaults occurring soon after the loan origination and for defaults involving low-risk loans. There is also some evidence that the probability of syndication result is stronger for defaults involving loans to borrowers that are located close to the lead arranger. Overall, these results provide strong support for the reputation hypothesis.

3.2 Lead arranger's ability to attract participants

In this section, we investigate the impact of large defaults on the lead arranger's ability to attract other lenders to participate in its future syndicates. We specifically focus on the cross-sectional variation across participant lenders in terms of their propensity to participate in loans syndicated by a lead arranger that has experienced large defaults. The reputation hypothesis is the only hypothesis that has specific predictions in this regard, and so we use these tests to distinguish the reputation hypothesis from the alternate hypotheses.

We create a panel data set in which each observation represents a lead arranger-participant-year combination. The dependent variable in these regressions is *Log(1+Loans Together)*, where *Loans Together* is the number of loans in the year that are syndicated by the lead arranger and in which the participant is involved. We must point out that our measures of loan activity are noisy because Dealscan is not a comprehensive listing of all private debt transactions in the US, although the extent of coverage is known to have increased after 1995 (Carey and Hrycray (1999)). To account for this, we confine the sample to the post-1995 period for these tests.[16] We also exclude observations pertaining to 2006 because we do not have the full year's data for 2006.[17] To avoid multiple zero observations in the dependent variable, we include each lender in the panel till one year after the last year in which it either syndicates or participates in at least one loan.

In this sample, we estimate the panel regression model (2) and present the results in Table VI. We control the regression for lead arranger size as measured by the total number of loans syndicated by the lead arranger in the previous year. To control for any unobserved

[16] All our results hold even if we use the full sample period of 1990–2005.

[17] We also do not adjust our activity measures to account for mergers among lead arrangers. As long as mergers are not systematically correlated with loan defaults, this is unlikely to bias our results.

lead-participant pair characteristics, we include lead arranger-participant pair fixed effects in our regression, in addition to year fixed effects.

Consistent with large defaults affecting the lead arranger's level of activity in the loan syndication market, the results in Column (1) indicate a fall in the number of loans syndicated between a lead arranger and a participant in the year after the lead arranger experiences large defaults. The coefficient estimates are also economically significant. The coefficient of -0.068 in Column (1) represents a 9.1% drop in activity between the pair in the year after the lead arranger experiences large defaults.

In Column (2), we examine if a participant's reaction to a lead arranger that has experienced large defaults depends on the strength of the relationship between them. As a proxy for relationship strength, we construct a dummy variable *Favorite Lead* that identifies the lead arranger with whom the participant did the most number of deals during the previous year. As per the reputation hypothesis, the drop in a participant's activity after a lead arranger experiences large loan defaults should be less severe in cases where the participant has a strong relationship with the lead arranger. To test this, we estimate our model after replacing *Large Defaults* with two interaction terms, namely *Large Defaults*×*Favorite Lead* and *Large Defaults*×*[1-Favorite Lead].* Our results in Column (2) indicate that the fall in activity after large defaults is indeed less if the lead arranger is the participant's favorite lead arranger.

In Column (3), we examine if the drop in participation in a lead arranger's syndicates after it experiences large defaults vary with participant size. To do this we estimate our model after replacing *Large Defaults* with two interaction terms, namely *Large Defaults*×*Large Participant* and *Large Defaults*×*[1-Large Participant].* The idea of this test is to see if large participants (i.e., participants in the top quartile in terms of the number of loans they participate in during the previous year), who are more likely to have other options when it comes to choosing among lead arrangers, are more likely to shift away from a lead arranger who suffers large defaults. The results in Column (3) are consistent with our conjecture: the drop in syndication activity between the lead arranger and participants is confined to large participants. Moreover, the difference between the two interaction terms is statistically significant. This result highlights the importance of large participants in sustaining a reputation mechanism, because their willingness and ability to abandon poorly performing lead arrangers could be crucial to disciplining lead arrangers.

In Column (4), we examine if participants that are more diversified, in terms of the number of lead arrangers they participate in syndicates with, are less likely to stay with a lead arranger that experiences large loan defaults. While we would expect this variable to be related to participant size, it is possible that large participants are those affiliated with larger leads and are not substantially more diverse than smaller participants. To test this, we define *Diversified Participant*, a dummy variable that identifies participants that are in the top quartile in terms of the number of lead arrangers with which they syndicate a loan during the previous year. We then estimate our model after replacing *Large Defaults* with two interaction terms, namely *Large Defaults*×*Diversified Participant* and *Large Defaults*×*[1-Diversified Participant]*. The coefficients on the interaction terms indicate that diversified participants are less likely to participate in syndicates of lead arrangers that experience large loan defaults. There is no corresponding decline in the participation activity of other lenders. The difference between the coefficients on the interaction terms is statistically significant.

Overall, our findings in Section 3.2 indicate that participants that have a strong relationship with the lead arranger are more likely to continue participating in its syndicates even after the lead arranger experiences large defaults. On the other hand, larger and well-diversified participants are less likely to participate in loans syndicated by a lead arranger that experiences large defaults. These results are consistent with the reputation hypothesis, and highlight the importance of larger and more diversified participants in sustaining a reputation-based disciplining mechanism.

3.3 Borrower Characteristics and Loan Characteristics

In this section, we investigate the impact of large defaults on the type of borrowers that the lead arranger lends to and the risk characteristics of the loans it finances in the following year. We proceed by estimating regressions that are variants of regression model (1), with various borrower and loan characteristics as dependent variables. Our findings are presented in Table VII.

In Panel A, we present the results with borrower characteristics as the dependent variable. The borrower characteristics that we examine are, *Non Compustat* in Column (1), *Repeat Borrower* in Column (2), *Log (Assets)* in Column (3), and *Leverage* in Column (4). *Non Compustat* is a dummy variable that identifies borrowers for which financial information is not available in the Compustat database; *Repeat Borrower* is a dummy variable that identifies firms that have borrowed from the lead arranger in the past; *Log(Assets)* is the natural logarithm of the book value of total assets of the borrower; and *Leverage* is the ratio of the book value of total debt to the book value of assets of the borrower. *Non Compustat*, *Repeat Borrower*, and *Log(Assets)* are measures of the extent of information asymmetry regarding the borrower. The idea is that the lead arranger is more likely to be informed about firms with financial information in Compustat, firms that the lead arranger has lent to in the past, and larger firms. We use *Leverage* as a proxy for the firm's risk. We control all these regressions for the size of the lead arranger, and include year fixed effects. Apart from its size, a lead arranger's choice of borrower may also depend on other factors such as its location, industry specialization, portfolio of services offered, etc. To control for these unobserved lead arranger characteristics, we also include lead arranger fixed effects.

All three hypotheses predict that, in order to limit its risk exposure and/or attract participants to its syndicates, the lead arranger will seek to move towards more transparent and less risky borrowers after it experiences large loan defaults. However, the reputation and the loss of capital hypotheses predict that, despite the desire to reduce information asymmetry, the lead arranger may be forced to switch to smaller borrowers, either because of an inability to syndicate loans which large borrowers demand or because of a loss of capital.

The negative coefficient on *Large Defaults* in Column (1) indicates that a lead arranger that experiences large loan defaults is 4.4% less likely to lend to a Non Compustat firm the following year. Similarly, the positive coefficient on *Large Defaults* in Column (2) implies that the lead arranger is more likely to lend to a repeat borrower following large defaults. Both these results are consistent with the lead arranger's preference for borrowers about which it has fewer information asymmetry concerns after it experiences large defaults. However, the negative coefficient on *Large Defaults* in Column (3) indicates that following large defaults, the lead arranger shifts its lending to smaller borrowers. While this result is generally inconsistent with lead arranger's preference for more transparent borrowers, it is consistent with the lead arranger's lower ability to lend to large borrowers, which is predicted by both the reputation hypothesis and the loss of capital hypothesis. In Column (4), we repeat the regression with *Leverage* as the dependent variable. The negative coefficient on *Large Defaults* indicates that a lead arranger is likely to lend to less risky borrowers following large defaults. This is consistent with all our hypotheses.

In Panel B, we investigate how large defaults affect the risk characteristics and other features of the loans contracted by the lead arranger the following year. We use two important measures of loan risk, namely the loan's yield spread at origination, *Low Yield*, and its security status *Secured*. *Low Yield* is a dummy variable that identifies loans for which the yield spread over the London Interbank Offer Rate (LIBOR) is lower than the median yield spread charged by the lead arranger. We control these regressions for lead arranger size, loan maturity, loan purpose, loan size, borrower fixed effects and time fixed effects.

Consistent with a move towards safer loans, the positive coefficient on *Large Defaults* in Column (1) indicates that a lead arranger that experiences large defaults is 6.5% more likely to make *Low Yield* loans the following year. As against this, the unconditional probability of a loan in our sample being low yield is 46%.[18] From the coefficients on the control variables, we observe that loans are more (less) likely to be *Low Yield* loans if their maturity is less than a year (more than five years), and if their stated purpose is to finance working capital or to repay an earlier loan (finance a takeover).

The positive coefficient on *Large Defaults* in Column (2) indicates that a lead arranger that experiences large defaults is 3.5% more likely to include security in the loans that it makes in the following year. From the coefficients on the control variables, we find that loans are more (less) likely to be secured if they have longer (shorter) maturities, if the loan amount is smaller (larger) and if the purpose of the loan is to finance a takeover (finance working capital or to repay an earlier loan).

Overall, our results in Table VII indicate that lead arrangers that experience large defaults are likely to switch to less opaque and less risky borrowers, and to less risky loans. These results are broadly consistent with the three hypotheses.

3.4 Lead arranger's aggregate level of syndicated loan activity

In Section 3.2, we showed that the number of loans syndicated by a lead arranger-participant pair decreases in the year after the lead arranger experiences large loan defaults. This suggests an overall drop in the activity level of the lead arranger. In this section, we formally investigate the impact of large loan defaults on the lead arranger's aggregate level of syndicate lending activity. Recall that the hypotheses have somewhat different predictions in this regard: All three hypotheses predict a decrease in syndicated loan activity; the loss of capital hypothesis predicts a drop in participation activity as well, while the specialization hypothesis predicts a possible increase in participation activity to compensate for the lower origination. While the reputation hypothesis does not have a clear prediction in this regard, a drop in participation activity would be consistent with implicit reciprocity in syndicate formation; i.e., a lead arranger that has lost the ability to syndicate loans is also less likely to be invited to participate in syndicates arranged by other lead arrangers.

To test these predictions, we assemble a lead arranger panel in which each observation represents a lead arranger-year combination. The panel includes all lead arrangers with at least one syndicated loan reported in Dealscan, and has 706 lead arrangers and 3469 lead arranger-year observations. Each lead arranger enters the panel in the first year in which it syndicates a loan. To avoid multiple zero observations in the aggregate activity variable, we include each lead arranger in the panel till one year after the last year in which it syndicates at least one loan. For reasons outlined earlier in Section 3.2, we restrict the sample time

[18] The median is not exactly 50% because we classify a loan as 'Low Yield' only if its yield spread is *strictly less* than the median yield spread charged by the lead arranger.

period to 1995–2005.

Note that by dropping lead arrangers from our panel one year after they cease to be active in the loan syndication market, we are potentially under-estimating the negative consequences of large defaults. An idea of the adverse consequences of large defaults on syndication activity of lead arrangers can be derived from the fact that 40 out of the 98 lead arrangers that experience large defaults, completely drop out of the loan syndication market within a year after they experience large defaults.

Table VIII presents the results of the regression model (2). The dependent variable in Column (1) is *Lead Active*, a dummy variable that identifies if the lead arranger syndicated at least one loan during the year. As before, our main independent variable is lagged *Large Defaults*. To control for unobserved lead arranger characteristics, we also include lead arranger fixed effects in addition to year fixed effects. As expected, the coefficient on *Large Defaults* is negative and significant. A lead arranger that experiences large defaults is 10% less likely to be active in the loan syndication market in the following year. As against this, the lead arrangers in our sample have a 65% chance of syndicating at least one loan in a year. In Column (2), we interact *Large Defaults* with *Small* to see if the drop in the overall syndicated loan activity is greater for small lead arrangers. The negative coefficient on the interaction term suggests that this is indeed so.

In Column (3), we repeat the regression with *Log(1+Loans)* as the dependent variable, where *Loans* is the number of loans syndicated by the lead arranger during the year. As expected, the coefficient on *Large Defaults* is negative and significant. The negative coefficient in Column (3) translates to 1.62 fewer loans in the year following large defaults, which is economically significant given that the average number of loans syndicated by a lead arranger in a year is 11.Thus, there is a 14.75% drop in the number of loans syndicated by the lead arranger in the year following large defaults. The findings in Columns (1) through (3) are consistent with the reputation hypothesis as well as with the alternate hypotheses. Since we define *Small* using the number of loans syndicated by the lead arranger in the previous year, we do not estimate a regression with an interaction term between *Large Defaults* and *Small* in the specifications with *Log(1+Loans)* as the dependent variable.

In Column (4), we examine if the lead arranger's participation in loans syndicated by other lead arrangers is affected by large loan defaults. The dependent variable to test these predictions in Column (4) is *Log(1+Loans Participated)*, where *Loans Participated* is the number of loans, originated by other lead arrangers, that the lead arranger participates in during the year. Consistent with all three hypotheses, we find that the number of loans participated by the lead arranger falls in the year following large defaults.

Overall, the results in Table VIII suggest that large loan defaults lead to a significant decline in the lead arranger's activity in the syndicated loan market. Moreover, the lead arranger also participates in fewer loans syndicated by other lead arrangers. The drop in aggregate syndication activity is consistent with the reputation hypothesis as well as the alternate hypotheses.

4 Robustness Tests

In this section, we discuss additional robustness tests for our key results. To conserve space, we do not report the results of these tests in the paper. They are available upon request.

A direct way to distinguish the reputation hypothesis from the loss of capital hypothesis is to show that our results are robust to controlling for the level of the lead arranger's capital. Although we do not have information on capital for all lead arrangers, we are able to obtain this information for the commercial banks in our sample, by name-matching them with the Call Reports database. For these lead arrangers, we measure bank capital as the ratio of the sum of the book values of Tier-1 and Tier-2 capital to the book value of total assets. We first examine if large defaults impair bank capital. Somewhat surprisingly, we are unable to show that large defaults have a significant effect on bank capital. There are two possible explanations for this result: First, banks may experience limited losses in Chapter 11 bankruptcy filings because bank debt is usually senior and secured. Second, it could be that banks are able to offset lost capital either by generating internal profits or by raising outside capital. In additional tests, we find that our main results, on the fraction of loan retained by the lead arranger and the lead arranger's propensity to syndicate a loan, are qualitatively similar when we control for the level of the lead arranger's capital.

Prior literature has used lender credit ratings as a proxy for lender reputation (see Billet et al. (1995)). In our next set of tests, we examine if a lead arranger's credit rating can proxy for its reputation in the loan syndication market. To do this, we name-match the lead arrangers in the Dealscan database with the Compustat database and obtain their credit rating information. We are able to obtain credit rating information for only 236 lead arrangers in our sample.[19] Interestingly, only 15 out of these 236 lead arrangers had below investment grade ratings. Moreover, small lead arrangers are more likely to have a better credit rating than large lead arrangers. Highlighting the benign credit environment for banks during our sample period, we find only 17 instances of lead arrangers experiencing a credit rating downgrade. We find that lead arranger's credit rating does not fully capture lender reputation in the loan syndication market. While lenders with better credit rating, do finance a smaller fraction of the syndicated loan, there is no evidence that such lenders are

[19]These 236 lead arrangers finance 21,517 loans out of the total of 57,502 loans in our sample.

more likely to syndicate a loan. We also do not find any significant impact of large defaults on the probability of the lead arranger suffering a credit rating downgrade. (This result is consistent with our earlier result that large defaults do not have a significant negative impact on bank capital.) Our results on the fraction of loan held by the lead arranger and the lead arranger's propensity to syndicate a loan are robust to controlling for the lead arranger's credit rating.

One concern with our results showing an increase in the fraction of loan held by the lead arranger (Table III) and a fall in the likelihood of syndication (Table V) following large defaults is that they may be biased by lead arrangers shifting to new borrowers. Since lead arrangers are likely to know less about new borrowers, they may optimally retain a large loan fraction and syndicate less often. We believe that this is unlikely to be the case because our results in Table VII indicate that, after they experience large defaults, lead arrangers are more likely to lend to repeat borrowers. Nonetheless, to address this concern more directly, we re-estimate the regressions in Tables III and V after including an additional control variable, *New Borrower*, which is a dummy variable that identifies first-time borrowers of a lead arranger. We find that while lead arrangers do retain larger fraction of their loans to new borrowers, and are less likely to syndicate such loans, the coefficient on *Large Defaults* continues to be statistically and economically significant. Thus, our results in Table III and V are not being driven solely by a switch to new borrowers.

5 Concluding Remarks

We use Chapter 11 bankruptcy filings by a lead arranger's borrowers as indicative of poor performance, and examine how such poor performance affects the lead arranger's future lending activity. Loan defaults are not only likely to damage the lead arranger's reputation by lowering market participants' assessment of its ability to screen and monitor borrowers, but may also erode its capital significantly. Our empirical design thus allows us to test both the importance of lead arranger reputation and also the effects of loss of capital on the lead arranger's lending activity, while controlling for any lending specialization in terms of industry or geography.

Consistent with loan defaults damaging the lead arranger's reputation, we find that following large defaults, the lead arranger syndicates loans less often and holds a larger fraction of the loans that it does syndicate. These effects are larger for small lead arrangers, and are smaller in years in which several other lead arrangers also experience large defaults. The effects are also larger for loan defaults that occur relatively quickly after the loan origination, and for defaults of low-risk loans.

We find further evidence consistent with a loss of reputation for the lead arranger when we examine the propensity of participant lenders to continue participating in loans syndicated by the lead arranger after it experiences large defaults. Participants with strong relationships with the lead arranger are more likely to continue participating in its syndicates even after it experiences large defaults, while large and diversified participants are more likely to leave.

The lead arranger is more likely to lend to safer and more transparent borrowers, and to also finance more low-risk loans following large defaults. Consistent with a loss of reputation as well as a significant erosion of the lead arranger's capital, we find a significant decrease in the lead arranger's overall syndicated lending activity, as well as a reduction in the number of loans syndicated by other lead arrangers that it participates in.

Overall, our results highlight both the importance of lead arranger reputation in the loan syndication market and also the adverse effects of loss of capital. The fact that small lead arrangers experience tougher punishment following poor performance highlights the difficulty these lenders face in establishing themselves in the loan syndication market, and might partly explain the highly concentrated nature of the loan syndication market. Another interesting result is that the negative consequences of loan defaults are weaker in years when several other lead arrangers also experience loan defaults. This result highlights an important limitation of the reputation channel. If correlated defaults among lenders, such as the ones during the recent sub-prime loan crisis, are not punished by the market, then it may encourage herding behavior among lenders.

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Table I: Summary Statistics on Loans and Bankruptcy Filings by Year

This table presents an year-wise summary of our loan data and bankruptcy data over the period 1991–2006. *Dealscan Loans* is the number of loans in Dealscan, and *Borrower Industries* is the number of unique 4-digit SIC code industries of the borrowers. *Bankruptcy Filings* is the number of Chapter 11 bankruptcy filings reported on www.bankruptcydata.com. *Bankrupt Loans* is the number of loans to bankrupt borrowers that are outstanding at the time of the company's bankruptcy filing, and *Bankrupt Industries* is the number of unique 4-digit SIC code industries of the bankrupt borrowers.

Year	Dealscan Loans	Borrower Industries	Bankruptcy Filings	Bankrupt Loans	Bankrupt Industries
	(1)	(2)	(3)	(4)	(5)
1991	1833	382	115	105	32
1992	1946	398	84	79	23
1993	2436	440	78	48	17
1994	3041	506	54	30	16
1995	2927	461	71	50	19
1996	3841	543	62	57	24
1997	4923	561	63	59	19
1998	4390	533	106	70	29
1999	3677	496	144	189	49
2000	4109	521	191	278	70
2001	3855	536	273	352	87
2002	4157	558	233	292	61
2003	4399	585	182	170	59
2004	5335	624	98	87	27
2005	5388	594	91	87	24
2006	1245	285			
Overall	57502	865	1929	2009	300

Table II: Summary Statistics- Key Loan Variables

This table reports the summary statistics for the key variables in our sample of loans originated between 1991 and 2006. Each observation represents a loan. Under loan characteristics, *Amount* is the size of the loan in $ million; *Yield* is the loan yield expressed as a basis point spread over LIBOR; *Short Term* and *Long Term* are dummy variables that identify loans with average maturity of less than one year, and greater than five years, respectively; *Secured* is a dummy variable that identifies loans that are secured; *Takeover*, *Working Capital*, and *Repayment* are dummy variables that identify if the main purpose of the loan is to finance a takeover, working capital, or to repay debt, respectively. *Syndicate* is a dummy variable that identifies loans involving more than one lender; *Lenders in Loan* is the number of lenders involved in financing a syndicated loan; and *Lead Allocation* is the percentage of the syndicated loan financed by the lead arranger. Among borrower characteristics, *Non Compustat* is a dummy variable that identifies borrowers for which financial information is not available in the Compustat database; *Assets* is the book value of assets; *Rated* is a dummy variable that identifies borrowers that have an unsecured long-term credit rating; *Leverage* is the ratio of book value of total debt to book value of total assets. Among lead arranger characteristics, *Lead Size* is the average annual amount syndicated by the lead arranger over the past two years; *Small* is a dummy variable that identifies lead arrangers whose size is within the 95^{th} percentile in terms of the number of deals syndicated during the previous year; *Large Defaults* is a dummy variable that takes the value one if the total syndicated and non-syndicated loan amount lent by the lead arranger and outstanding to borrowers who file for bankruptcy during the year exceeds 10% of *Lead Size*. Panel A summarizes the whole sample, while Panel B compares the sub-sample of loans identified using lagged values of *Large Defaults*.

Panel A: Summary Statistics

	Mean	**Median**	**Std. dev**	**Min**	**p25**	**p75**	**Max**	**N**
Loan Characteristics								
Amount (in $ million)	178.696	55	446.338	0.010	17.200	165	24000	57502
Yield	200.858	200	128.519	6	100	275	1500	41546
Short Term	0.199	0	0.400	0	0	0	1	57502
Long Term	0.212	0	0.409	0	0	0	1	57502
Secured	0.803	1	0.398	0	1	1	1	30761
Takeover	0.183	0	0.387	0	0	0	1	57502
Working Capital	0.527	1	0.499	0	0	1	1	57502
Repayment	0.181	0	0.385	0	0	0	1	57502
Syndicate	0.653	1	0.476	0	0	1	1	57502
Lenders in Loan[1]	5.465	4	4.975	2	2	7	173	37530
Lead Allocation[1]	28.843	23.606	19.817	0	12.5	42	100	10854
Borrower Characteristics								
Non Compustat	0.734	1	0.442	0	0	1	1	48720
Assets (in $ million)	4242.60	553.05	22802.29	1.24	134.63	2472.03	902210	12965
Rated	0.413	0	0.492	0	0	1	1	13048
Leverage	0.311	0.297	0.229	0	0.153	0.431	4.320	12917
Lead Arranger Characteristics								
Lead Size (in $ million)	32029.62	6814.013	49252.27	0	974.25	43518.82	195530.5	51155
Small	0.518	0	0.500	0	0	1	1	57502
Large Defaults$_{t-1}$	0.064	0	0.246	0	0	0	1	57327

[1] Only for syndicated loans.

Panel B: Univariate Tests

	Large Defaults$_{t-1}$=0	Large Defaults$_{t-1}$=1	Difference
Large Lead	0.539	0.172	-0.367***
Syndicated	0.673	0.533	-0.140***
Lead Allocation[1]	25.802	36.917	11.114^{*n**}
Amount	205.031	102.423	-102.609***
Yield	194.970	270.410	75.440^{*n**}
Non Compustat	0.733	0.716	-0.017*
Log(Assets)	1.613	0.613	-1.001^{**n*}
Leverage	0.332	0.303	-0.029***

[1] Only for syndicated deals.

Table III: Percentage of loan financed by the lead arranger

This table reports the results of regressions investigating the impact of large loan defaults on the percentage of loan financed by the lead arranger. In Panel A, we estimate the following OLS regression:

$$\text{Lead Allocation}_l = \beta_0 + \beta_1 \times \textit{Large Defaults}_{j,t-1} + \beta_2 \times X_j + \beta_3 \times X_l + \mu_t + \mu_i,$$

where *Lead Allocation* is the percentage of the loan financed by the lead arranger. We estimate this regression on all the syndicated loans in our sample originated during 1991–2006. Among lead arranger characteristics, X_j, *Lead Size* is the average annual amount (in \$ million) syndicated by the lead arranger over the past two years; *Large Defaults* is a dummy variable that takes the value one if the total syndicated and non-syndicated loan amount lent by the lead arranger and outstanding to borrowers who file for bankruptcy during the year exceeds 10% of *Lead Size*, *Scaled Defaults* is the ratio of the total syndicated and non-syndicated loan amount lent by the lead arranger and outstanding to borrowers who file for bankruptcy during to *Lead Size*. *Lead's Bankrupt Industry* (*Lead's Bankrupt State*) is a dummy variable that takes the value one if the borrower is in the same industry (state) as any of the lead arranger's bankrupt borrowers. Among the loan characteristics, X_l, *Short Term* (*Long Term*) is a dummy variables that identifies loans with maturity of less than one year (greater than five years); *Takeover*, *Working Capital* and *Repayment* are dummy variables that identify if the main purpose of the loan is to finance a takeover, working capital, or to repay debt, respectively; *Log(Loan Amount)* is the logarithm of the size of the loan in \$ million. We include borrower fixed effects and year fixed effects. In Column (2), we repeat the estimation after including lead arranger fixed effects instead of borrower fixed effects. In Column (3), we employ *Scaled Defaults* as our measure of defaults, while in Column (4), the sample is confined to post-1995 loans. In Column (5), we estimate the regression after defining *Large Defaults* only in terms of defaults on syndicated loans. In all specifications, the standard errors are robust and clustered at the individual borrower level.

	Lead Allocation				
	(1)	(2)	(3)	(4)	(5)
Large Defaults$_{t-1}$	4.317	2.158		4.727	4.352
	(1.386)***	(1.055)**		(1.675)***	(1.517)***
Scaled Defaults$_{t-1}$			11.596		
			(3.893)***		
Lead's Bankrupt Industry	2.870	.446	2.833	2.607	3.051
	(2.723)	(2.693)	(2.707)	(3.168)	(2.711)
Lead's Bankrupt State	.762	1.054	.519	.755	.743
	(.853)	(.817)	(.868)	(.985)	(.861)
Short Term	1.475	-.404	1.464	1.873	1.454
	(.429)***	(.478)	(.430)***	(.446)***	(.430)***
Long Term	2.532	.146	2.501	5.240	2.546
	(1.021)**	(.603)	(1.020)**	(1.189)***	(1.019)**
Takeover	-.125	-1.855	-.150	-.037	-.135
	(1.243)	(.976)*	(1.247)	(1.440)	(1.247)
Working Capital	-1.689	-1.567	-1.711	-2.556	-1.704
	(1.013)*	(.893)*	(1.010)*	(1.189)**	(1.011)*
Repayment	-2.468	-2.985	-2.526	-2.662	-2.468
	(1.049)**	(.893)***	(1.051)**	(1.253)**	(1.052)**
Log(Loan amount)	-3.227	-7.049	-3.217	-3.252	-3.218
	(.312)***	(.175)***	(.312)***	(.347)***	(.312)***
Log(Lead Size)	-1.301	-.055	-1.300	-1.205	-1.315
	(.188)***	(.250)	(.189)***	(.188)***	(.189)***
Const.	56.041	63.056	55.635	55.941	56.225
	(2.863)***	(2.459)***	(2.883)***	(2.641)***	(2.856)***
Obs.	10163	10163	10163	8203	10163
R^2	.777	.442	.777	.793	.777
Fixed Effects	Firm	Lead	Firm	Firm	Firm
Year FE	Yes	Yes	Yes	Yes	Yes

In Panels B through F, we investigate if the impact of large loan defaults on the fraction of loan financed by the lead arranger varies with lead arranger, loan market, and the defaulted loan characteristics. Specifically, we estimate the following OLS regression:

$$y_l = \beta_0 + \beta_1 \times X1_{j,t-1} + \beta_2 \times X2_{j,t-1} + \beta_3 \times X_j + \beta_4 \times X_l + \mu_t + \mu_i,$$

where y_l is *Lead Allocation*. We control these regressions for all variables that we use in Panel A, and also include borrower and year fixed effects. For brevity we suppress the coefficients on the control variables.

In Panel B, we investigate how the impact of large loan defaults on *Lead Allocation* varies with the size of the lead arranger. In this panel, *X1* is *Large Defaults*Small*, where *Small Lead* is a dummy variable that identifies lead arrangers within the 95^{th} percentile in terms of the number of loans syndicated during the year; *X2* is *Large Defaults*[1-Small]*.

In Panel C, we investigate how the impact of large loan defaults on *Lead Allocation* varies with whether or not other lead arrangers also experience large defaults. In this panel, *X1* is *Large Defaults*Other leads tainted*, where *Other Leads Tainted* is a dummy variable that identifies years in which more than 7.5% of all lead arrangers experience large defaults; *X2* is *Large Defaults*[1-Other leads tainted]*.

In Panel D, we investigate how the impact of large loan defaults on *Lead Allocation* varies with the time between the loan origination and its subsequent default. To do this, we split *Large Defaults* into two variables: one identifying large defaults in which most of the loans (by amount) default within two years of their origination (*X1*), and the other identifying large defaults in which most of the loans default beyond two years of their origination (*X2*).

In Panel E, we investigate how the impact of large loan defaults on *Lead Allocation* varies with the yield on the defaulted loan. To do this, we split *Large Defaults* into two variables: one identifying large defaults in which most of the defaulted loans (by amount) are low yield loans (*X1*), and the other identifying large defaults in which most of the defaulted loans are not-low yield loans (*X2*). We define a loan to be low-yield if its yield spread is lower than the median yield spread charged by the lead arranger on all its loans.

In Panel F, we investigate how the impact of large loan defaults on *Lead Allocation* varies with the distance between the lead arranger and its bankrupt borrowers. To do this, we split *Large Defaults* into two variables: one identifying large defaults in which most of the defaults (by amount) are by borrowers who are within the median distance of 500 miles of the lead arranger (*X1*), and the other identifying large defaults in which most of the defaults are by borrowers who are beyond 500 miles of the lead arranger (*X2*).

Panel B: Variation with lead arranger size

Large Defaults × Small Lead (β_1)	Large Defaults × [1- Small Lead] (β_2)	$\beta_1 - \beta_2$	Firm FE	Year FE	R^2	Obs.
(1)	(2)	(3)	(4)	(5)	(6)	(7)
6.654 (1.593)***	-.325 (2.296)	6.979 (2.665)***	Yes	Yes	.778	10163

Panel C: Variation with large defaults among other lead arrangers

Large Defaults × Other Leads Tainted (β_1)	Large Defaults × [1-Other Leads Tainted] (β_2)	$\beta_1 - \beta_2$	Firm FE	Year FE	R^2	Obs.
(1)	(2)	(3)	(4)	(5)	(6)	(7)
3.058 (1.608)*	6.557 (2.493)***	-3.499 (2.939)	Yes	Yes	.777	10163

Panel D: Variation with time between loan origination and default

Quick Defaults (β_1) (Most defaults within two years)	Delayed Defaults (β_2) (Most defaults beyond two years)	$\beta_1 - \beta_2$	Firm FE	Year FE	R^2	Obs.
(1)	(2)	(3)	(4)	(5)	(6)	(7)
7.560 (1.884)***	.895 (1.789)	6.665 (2.469)***	Yes	Yes	.778	10163

Panel E: Variation with loan yield

Low Yield Defaults (β_1) (Most defaults are below-median yield loans)	High Yield Defaults (β_2) (Most defaults are above-median yield loans)	$\beta_1 - \beta_2$	Firm FE	Year FE	R^2	Obs.
(1)	(2)	(3)	(4)	(5)	(6)	(7)
7.160 (2.347)***	1.068 (1.620)	6.092 (2.711)***	Yes	Yes	.777	10045

Panel F: Variation with distance between lead arranger and bankrupt borrower

Close Borrowers (β_1) (Most defaults involve close borrowers)	Distant Borrowers (β_2) (Most defaults do not involve close borrowers)	$\beta_1 - \beta_2$	Firm FE	Year FE	R^2	Obs.
(1)	(2)	(3)	(4)	(5)	(6)	(7)
3.505 (2.792)	4.266 (3.600)	-.761 (4.477)	Yes	Yes	.783	9691

Table IV: Robustness Tests - Percentage of Loan Financed by the Lead Arranger

This table reports the results of regressions investigating the impact of large loan defaults on the percentage of loan financed by the lead arranger. We estimate the following OLS regression:

$$\text{Lead Allocation}_l = \beta_0 + \beta_1 \times \textit{Large Defaults}_{j,t-1} + \beta_2 \times X_j + \beta_3 \times X_l + \mu_t + \mu_i,$$

where *Lead Allocation* is the percentage of the loan financed by the lead arranger. We estimate this regression on all the syndicated loans in our sample originated during 1991–2006. Among lead arranger characteristics, X_j, *Lead Size* is the average annual amount (in $ million) syndicated by the lead arranger over the past two years; *Large Defaults* is a dummy variable that takes the value one if the total syndicated and non-syndicated loan amount lent by the lead arranger and outstanding to borrowers who file for bankruptcy during the year exceeds 10% of *Lead Size*. *Scaled Defaults* is the ratio of the total syndicated and non-syndicated loan amount lent by the lead arranger and outstanding to borrowers who file for bankruptcy during the year and *Lead Size*. *Small Lead* is a dummy variable that identifies lead arrangers within the 95^{th} percentile in terms of the number of loans syndicated during the year. Among the loan characteristics, X_l, *Short Term* (*Long Term*) is a dummy variables that identifies loans with maturity of less than one year (greater than five years); *Takeover*, *Working Capital* and *Repayment* are dummy variables that identify if the main purpose of the loan is to finance a takeover, working capital, or to repay debt, respectively; *Log(Loan Amount)* is the logarithm of the size of the loan in $ million. We include borrower fixed effects and year fixed effects. In Column (1) we confine the sample to instances when *Scaled Defaults* is less than 20%, in Column (3), we confine the sample to loans to firms that do not have financial information in Compustat while in Column (4) we confine the sample to loans whose main purpose is not to finance takeovers. In all specifications, we include borrower fixed effects and the standard errors are robust and clustered at the individual borrower level.

	Lead Allocation			
	(1)	(2)	(3)	(4)
Large Default$_{t-1}$*Small Lead	4.647		8.560	5.890
	(2.393)*		(2.687)***	(1.555)***
Large Default$_{t-1}$*[1-Small Lead]	-.938		.311	-2.745
	(2.574)		(3.198)	(2.490)
Large Defaults$_{t-1}$		2.578		
		(1.860)		
Large Defaults$_{t-1}$ X Log(Lead Size)		-1.305		
		(.787)*		
Short Term	1.703	1.461	1.593	.664
	(.428)***	(.430)***	(.759)**	(.431)
Long Term	2.319	2.543	3.143	2.131
	(1.050)**	(1.018)**	(1.379)**	(1.193)*
Takeover	.441	-.167	-1.993	
	(1.235)	(1.243)	(2.021)	
Working Capital	-1.385	-1.729	-3.504	-1.456
	(.995)	(1.009)*	(1.571)**	(1.043)
Repayment	-1.991	-2.544	-4.429	-3.325
	(1.023)*	(1.049)**	(1.619)***	(1.094)***
Log(Loan amount)	-3.122	-3.233	-2.327	-3.227
	(.320)***	(.312)***	(.367)***	(.342)***
Log(Lead Size)	-1.185	-1.223	-1.628	-1.026
	(.185)***	(.187)***	(.368)***	(.194)***
Const.	54.048	55.736	62.509	55.842
	(2.971)***	(2.850)***	(3.975)***	(2.973)***
Obs.	9792	10163	5307	8513
R^2	.78	.777	.82	.814
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table V: Probability of Syndication

This table reports the results of regressions investigating how large loan defaults affect a lead arranger's propensity to syndicate loans in the following year. In Panel A, we estimate the following OLS regression

$$\text{Syndicate}_l = \beta_0 + \beta_1 \times \textit{Large Defaults}_{j,t-1} + \beta_2 \times X_j + \beta_3 \times X_l + \mu_t + \mu_i,$$

where *Syndicate* is a dummy variable that identifies syndicated loans. We estimate this regression on all the loans in our sample originated during 1991–2006. Among lead arranger characteristics, X_j, *Lead Size* is the average annual amount (in $ million) syndicated by the lead arranger over the past two years; *Large Defaults* is a dummy variable that takes the value one if the total syndicated and non-syndicated loan amount lent by the lead arranger and outstanding to borrowers who file for bankruptcy during the year exceeds 10% of *Lead Size*. *Scaled Defaults* is the ratio of the total syndicated and non-syndicated loan amount lent by the lead arranger and outstanding to borrowers who file for bankruptcy during to *Lead Size*. *Lead's Bankrupt Industry* (*Lead's Bankrupt State*) is a dummy variable that takes the value one if the borrower is in the same industry (state) as any of the lead arranger's bankrupt borrowers. Among the loan characteristics, X_l, *Short Term* (*Long Term*) is a dummy variables that identifies loans with maturity of less than one year (greater than five years); *Takeover*, *Working Capital*, and *Repayment* are dummy variables that identify if the main purpose of the loan is to finance a takeover, working capital, or to repay debt, respectively; *Log(Loan Amount)* is the logarithm of the size of the loan in $ million. We include borrower fixed effects and year fixed effects. In Column (2), we repeat the estimation after including lead arranger fixed effects instead of borrower fixed effects. In Column (3), we estimate a Logit specification. In Column (4), we use *Scaled Defaults* instead of *Large Defaults* as our measure of defaults, while in Column (5), the sample is confined to post-1995 loans. In Column (6), we estimate the regression after defining *Large Defaults* only in terms of defaults on syndicated loans. In all specifications, the standard errors are robust and clustered at the individual borrower level.

	Syndicate					
	(1)	(2)	(3)	(4)	(5)	(6)
Large Defaults$_{t-1}$	-.053 (.012)***	-.036 (.012)***	-.477 (.084)***		-.085 (.014)***	-.037 (.014)***
Scaled Defaults$_{t-1}$				-.139 (.032)***		
Lead's Bankrupt Industry	-.0002 (.024)	-.022 (.023)	.133 (.255)	.003 (.024)	-.009 (.022)	-.003 (.024)
Lead's Bankrupt State	-.008 (.009)	-.018 (.009)*	-.082 (.090)	-.005 (.010)	-.014 (.010)	-.010 (.010)
Short Term	-.058 (.006)***	-.090 (.006)***	-.567 (.062)***	-.058 (.006)***	-.057 (.007)***	-.057 (.006)***
Long Term	-.023 (.007)***	.027 (.006)***	-.209 (.059)***	-.023 (.007)***	-.022 (.007)***	-.023 (.007)***
Takeover	.049 (.012)***	.035 (.009)***	.575 (.094)***	.049 (.012)***	.032 (.013)**	.049 (.012)***
Working Capital	-.022 (.011)**	-.046 (.008)***	-.098 (.081)	-.022 (.011)**	-.033 (.011)***	-.022 (.011)**
Repayment	.029 (.012)**	.016 (.009)*	.310 (.089)***	.030 (.012)**	.011 (.013)	.029 (.012)**
Log(Loan amount)	.069 (.003)***	.095 (.002)***	.682 (.024)***	.069 (.003)***	.059 (.003)***	.069 (.003)***
Log(Lead Size)	.021 (.002)***	.004 (.003)	.179 (.012)***	.021 (.002)***	.017 (.002)***	.022 (.002)***
Const.	.192 (.028)***	.169 (.028)***		.196 (.028)***	.253 (.024)***	.186 (.028)***
Obs.	50011	50011	19204	50011	43003	50011
R^2 (or pseudo R^2)	.704	.328	.218	.705	.725	.704
Spec.	OLS	OLS	Logit	OLS	OLS	OLS
Fixed Effects	Firm	Lead	Firm	Firm	Firm	Firm
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

In Panels B through F, we investigate if the impact of large loan defaults on the lead arranger's propensity to syndicate loans varies with lead arranger, loan market, and the defaulted loan characteristics. Specifically, we estimate the following OLS regression:

$$y_l = \beta_0 + \beta_1 * X1_{j,t-1} + \beta_2 \times X2_{j,t-1} + \beta_3 \times X_j + \beta_4 \times X_l + \mu_t + \mu_i,$$

where y_l is a dummy variable that identifies syndicated loans. We control these regressions for all variables that we use in Panel A, and also include borrower and year fixed effects. For brevity, we suppress the coefficients on the control variables.

In Panel B, we investigate how the impact of large loan defaults on *Syndicate* varies with the size of the lead arranger. In this panel, *X1* is *Large Defaults*Small*, where *Small* is a dummy variable that identifies lead arrangers within the 95^{th} percentile in terms of number of loans syndicated during the previous year; *X2* is *Large Defaults*[1-Small].*

In Panel C, we investigate how the impact of large loan defaults on *Syndicate* varies with whether or not other lead arrangers also experience large defaults. In this panel, *X1* is *Large Defaults*Other leads tainted*, where *Other Leads Tainted* is a dummy variable that identifies years in which more than 7.5% of all lead arrangers experience large defaults; *X2* is *Large Defaults*[1-Other leads tainted].*

In Panel D, we investigate how the impact of large loan defaults on *Syndicate* varies with the time between the loan origination and its subsequent default. To do this, we split *Large Defaults* into two variables: one identifying large defaults in which most of loans (by amount) default within two years of their origination (*X1*), and the other identifying large defaults in which most of the loans default beyond two years of their origination (*X2*).

In Panel E, we investigate how the impact of large loan defaults on *Syndicate* varies with the yield on the defaulted loan. To do this, we split *Large Defaults* into two variables: one identifying large defaults in which most of the defaulted loans (by amount) are low yield loans (*X1*), and the other identifying large defaults in which most of the defaulted loans are not low yield loans (*X2*). We define a loan to be low-yield if its yield spread is lower than the median yield spread charged by the lead arranger on all its loans.

In Panel F, we investigate how the impact of large loan defaults on *Syndicate* varies with the distance between the lead arranger and its bankrupt borrowers. To do this, we split *Large Defaults* into two variables: one identifying large defaults in which most of defaults (by amount) are by borrowers who are within 500 miles (sample median) of the lead arranger (*X1*), and the other identifying large defaults in which most of the defaults are by borrowers who are beyond 500 miles of the lead arranger (*X2*).

Panel B: Variation with lead arranger size

Large Defaults × Small (β_1)	Large Defaults × [1- Small] (β_2)	$\beta_1 - \beta_2$	Firm FE	Year FE	R^2	Obs.
(1)	(2)	(3)	(4)	(5)	(6)	(7)
-.072 (.014)***	.029 (.025)	-.101 (.028)***	Yes	Yes	.705	50011

Panel C: Variation with large defaults among other lead arrangers

Large Defaults × Other Leads Tainted (β_1)	Large Defaults × [1-Other Leads Tainted] (β_2)	$\beta_1 - \beta_2$	Firm FE	Year FE	R^2	Obs.
(1)	(2)	(3)	(4)	(5)	(6)	(7)
-.033 (.015)**	-.075 (.019)***	.042 (.023)*	Yes	Yes	.705	50011

Panel D: Variation with time between loan origination and default

Quick Defaults (β_1)	Delayed Defaults (β_2)	$\beta_1 - \beta_2$	Firm FE	Year FE	R^2	Obs.
(Most defaults within two years)	(Most defaults beyond two years)					
(1)	(2)	(3)	(4)	(5)	(6)	(7)
-.091 (.016)***	-.004 (.017)	-.087 (.022)***	Yes	Yes	.705	50011

Panel E: Variation with loan yield

Low Yield Defaults (β_1)	High Yield Defaults (β_2)	$\beta_1 - \beta_2$	Firm FE	Year FE	R^2	Obs.
(Most defaults are below-median yield loans)	(Most defaults are above-median yield loans)					
(1)	(2)	(3)	(4)	(5)	(6)	(7)
-.068 (.018)***	-.027 (.019)	-.041 (.024)*	Yes	Yes	.704	49101

Panel F: Variation with distance between lead arranger and bankrupt borrower

Close Borrowers (β_1)	Distant Borrowers (β_2)	$\beta_1 - \beta_2$	Firm FE	Year FE	R^2	Obs.
(Most defaults involve close borrowers)	(Most defaults do not involve close borrowers)					
(1)	(2)	(3)	(4)	(5)	(6)	(7)
-.066 (.030)**	-.034 (.022)	-.032 (.036)	Yes	Yes	.709	47543

Table VI: Lead arranger's ability to attract participants

This table reports the results of regressions investigating how large defaults affect the lead arranger's ability to attract participants in the syndication market. Specifically, we estimate the panel OLS regression

$$y_{jkt} = \beta_0 + \beta_1 \times (LargeDefaults_{j,t-1} \times X_{j,t-1}) + \beta_2 \times (LargeDefaults_{j,t-1} \times [1 - X_{j,t-1}]) + \beta_3 \times X_j + \mu_t + \mu_{j \times k},$$

where y_{jkt} is the logrithm of one plus the number of loans syndicated together by the lead arranger 'j' and participant 'k' in year 't'. The panel includes all pairs of lead arrangers and participants that ever syndicate a loan together. The overall panel spans the time period 1995–2005. *Large Defaults* is a dummy variable that takes the value one if the total syndicated and non-syndicated loan amount lent by the lead arranger and outstanding to borrowers who file for bankruptcy during the year exceeds 10% of the average annual loan amount syndicated by it over the previous two years. In Column (1), X equals one. In Column (2), X is *Favorite Lead*, a dummy variable that identifies that the lead arranger was the participant's most preferred lead arranger in the previous year in terms of the number of loans that the participant participated in. In Column (3), X is *Large Participant*, a dummy variable that identifies participants that are in the top quartile in terms of the number of loans participated during the previous year. In Column (4), X is *Diversified Participant*, a dummy variable that identifies participants that are in the top quartile in terms of the number of lead arrangers with which they syndicated loans during the previous year. We control for lead arranger-participant pair fixed effects and year fixed effects. In all specifications, the standard errors are robust and clustered at the lead arranger-participant pair level.

	Log(1+ Loans Together)			
	(1)	(2)	(3)	(4)
X=	**1**	***Favorite Lead***	***Large Participant***	***Diversified Participant***
Large Defaults$_{t-1}\times$ X$_{t-1}$ (β_1)	-.068	-.010	-.095	-.099
	(.008)***	(.013)	(.011)***	(.010)***
Large Defaults$_{t-1}\times$ [1-X$_{t-1}$] (β_2)		-.070	.001	.060
		(.010)***	(.010)	(.013)***
Loans by lead$_{t-1}$	.0007	.001	.0008	.0008
	(.00006)***	(.00008)***	(.00007)***	(.00007)***
$\beta_1 - \beta_2$		.060	-.097	-.159
		(.014)***	(.013)***	(.015)***
Obs.	101077	80930	97005	97005
R^2	.551	.628	.565	.565
Pair FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table VII: Borrower and Loan Characteristics

This table reports the results of regressions investigating the impact of large loan defaults on the borrower characteristics (Panel A) and loan characteristics (Panel B) of future loans financed by the lead arranger. Specifically, we estimate OLS regressions that are variants of the following form:

$$y_l = \beta_0 + \beta_1 \times \textit{Large Defaults}_{j,t-1} + \beta_2 \times X_j + \beta_3 \times X_l + \mu_t + \mu_j \text{ or } \mu_i,$$

where y_l in Panel A is *Non Compustat* in Column (1), *Repeat Borrower* in Column (2), *Log(Assets)* in Column (3), and *Leverage* in Column (4). *Non Compustat* is a dummy variable that identifies firms for which financial information is not available on the Compustat database; *Repeat Borrower* is a dummy variable that takes the value one if the firm has borrowed from the lead arranger in the past, and the value zero otherwise; *Log(Assets)* is the logarithm of the book value of assets of the firm; and *Leverage* is the ratio of the book value of total debt to the book value of total assets. Among lead arranger characteristics, X_j, *Lead Size* is the average annual amount syndicated (in $million) by the lead arranger over the previous two years; *Large Defaults* is a dummy variable that takes the value one if the total syndicated and non-syndicated loan amount lent by the lead arranger and outstanding to borrowers who file for bankruptcy during the year exceeds 10% of *Lead Size*. We estimate the regression on our sample of loans originated after the year 1991. We include lead arranger fixed effects and year fixed effects, and the standard errors are robust and clustered at the individual lead arranger level.

Panel A: Borrower Characteristics

	Non Compustat	Repeat Borrower	Log(Assets)	Leverage
	(1)	(2)	(3)	(4)
Large Defaults$_{t-1}$	-.044	.034	-.253	-.042
	(.024)*	(.014)**	(.084)***	(.017)**
Log(Lead Size)	.007	.027	.026	.009
	(.008)	(.006)***	(.037)	(.004)**
Const.	.724	.049	.576	.235
	(.069)***	(.047)	(.366)	(.030)***
Obs.	42840	48624	11410	11375
R^2	.121	.06	.405	.121
Lead FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

This Panel reports the results of regressions investigating the impact of large loan defaults on the characteristics of the loans financed by the lead arranger in the following year. We use a model similar to the one in Panel A. The dependent variable y_l is *Low Yield* in Column (1), and *Secured* in Column (2). *Low Yield* is a dummy variable that identifies loans with an yield spread lower than the median yield spread charged by the lead arranger on all its loans. *Secured* is a dummy variable that identifies secured loans. Among the loan characteristics, X_l, that we control for, *Short Term* (*Long Term*) is a dummy variable that identifies loans with maturity of less than one year (greater than five years); *Takeover*, *Working Capital* and *Repayment* are dummy variables that identify if the main purpose of the loan is to finance a takeover, working capital, or to repay debt, respectively; *Log(Loan Amount)* is the logarithm of the size of the loan in $ million. We include borrower fixed effects and year fixed effects, and the standard errors are robust and clustered at the individual borrower level.

Panel B: Loan Characteristics

	Low Yield	Secured
	(1)	(2)
Large Defaults$_{t-1}$	.065	.035
	(.021)***	(.014)**
Log(Lead Size)	-.023	-.001
	(.003)***	(.003)
Short Term	.049	-.060
	(.009)***	(.010)***
Long Term	-.099	.034
	(.010)***	(.009)***
Takeover	-.076	.029
	(.018)***	(.016)*
Working Capital	.040	-.067
	(.017)**	(.016)***
Repayment	.040	-.035
	(.018)**	(.016)**
Log(Loan amount)	.056	-.028
	(.004)***	(.004)***
Const.	.382	.993
	(.045)***	(.046)***
Obs.	38619	25116
R^2	.704	.753
Firm FE	Yes	Yes
Year FE	Yes	Yes

Table VIII: Lead arranger's activity in the syndicated loan market

This table reports the results of regressions relating a lead arranger's activity in the syndicated loan market to large loan defaults. Specifically, we estimate the panel OLS regression

$$y_{jt} = \beta_0 + \beta_1 \times \textit{Large Defaults}_{j,t-1} + \beta_2 \times X_j + \beta_3 \times X_m + \mu_t + \mu_j,$$

where y_{jt} measures the lending activity of lead arranger 'j' in year 't'. Each observation in the panel is a lead arranger-year observation. The panel spans the time period 1995-2005, and includes all lead arrangers that have at least one syndicated loan reported in Dealscan during this period. *Large Defaults* is a dummy variable that takes the value one if the total syndicated and non-syndicated loan amount lent by the lead arranger and outstanding to borrowers who file for bankruptcy during the year exceeds 10% of the average annual loan amount syndicated by it over the previous two years. *Small* is a dummy variable that identifies lead arrangers that are within the 95^{th} percentile in terms of the number of loans syndicated during the year. We control for lead arranger fixed effects and year fixed effects. In all specifications, the standard errors are robust and clustered at the individual lead arranger level.

The dependent variable in Columns (1) and (2) is *Lead Active*, a dummy variable that identifies if the lead arranger syndicated at least one loan during the year. The dependent variable in Column (3) is *Log(1+Loans)*, where *Loans* is the number of loans syndicated by the lead arranger during the year. The dependent variable in Column (4) is *Log(1+Loans Participated)*, where *Loans Participated* is the number of loans syndicated by other lead arrangers that the lead arranger participates in during the year.

Lead arranger's activity in the syndicated loan market

	Lead Active	Lead Active	Log(1+Loans)	Log(1+Loans Participated)
	(1)	(2)	(3)	(4)
Large Defaults$_{t-1}$	-.101	.056	-.484	-.390
	(.049)**	(.073)	(.169)***	(.187)**
Small Lead$_{t-1}$		-.116		
		(.043)***		
Large Default$_{t-1}\times$ Small Lead$_{t-1}$		-.163		
		(.087)*		
Const.	.501	.837	1.496	2.909
	(.047)***	(.062)***	(.140)***	(.134)***
Obs.	2370	1962	2370	2370
R^2	.31	.448	.66	.765
Lead FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes