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Does Poor Performance Damage the Reputation of Financial Intermediaries? Evidence from the Loan Syndication Market

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ABSTRACT

We investigate the effect of poor performance on financial intermediary reputation by estimating the effect of large-scale bankruptcies among a lead arranger's borrowers on its subsequent syndication activity. Consistent with reputation damage, such lead arrangers retain larger fractions of the loans they syndicate, are less likely to syndicate loans, and are less likely to attract participant lenders. The consequences are more severe when borrower bankruptcies suggest inadequate screening or monitoring by the lead arranger. However, the effect of borrower bankruptcies on syndication activity is not present among dominant lead arrangers, and is weak in years in which many lead arrangers experience borrower bankruptcies.

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)). A downside to such delegation is that it can introduce a layer of information and incentive problems between financial intermediaries and investors. A large theoretical literature on the role of reputation suggests that an intermediary's concern with maintaining its reputation for diligent screening and monitoring will mitigate such agency problems. The intermediary knows that poor performance on its part will hurt its reputation and lead to loss of future economic rents.[1] Despite the importance of this argument, there is little direct empirical evidence on whether poor performance imposes reputation-related costs on financial intermediaries, and how the costs vary across institutions and with market conditions. If anything, the revelation

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[1] See Klein and Leffler (1981), Kreps and Wilson (1982), Rogerson (1983), Allen (1984), Diamond (1989a), Diamond (1991), Boot, Greenbaum, and Thakor (1993), Chemmanur and Fulghieri (1994b), Pichler and Wilhelm (2001), and Gorton and Pennacchi (1995).

that in the years leading up to the recent financial crisis many "reputable" financial institutions assumed substantial exposure to risky assets without adequate screening (Kashyap, Rajan, and Stein (2008)) casts doubt on the validity of the reputation cost argument.

In this paper, we use the loan syndication market as a testing ground to explore whether loss of reputation is costly for financial intermediaries. A loan syndicate comprises a lead arranger that originates the loan and "participant" lenders that fund parts of the loan but delegate screening and monitoring of the borrower to the lead arranger. Our empirical strategy is to study the consequences of "shocks" to a lead arranger's reputation on its subsequent syndication activity. Specifically, using large-scale Chapter 11 bankruptcy filings by a lead arranger's borrowers as a signal of poor performance by the lead arranger, we examine the effect of such bankruptcies on the lead arranger's activity in the loan syndication market.[2] We therefore test a *necessary* condition for a reputation-based disciplining mechanism to work, namely, punishment for the agent following poor performance. Our strategy of relying on shocks to reputation allows us to test a rich set of predictions regarding the effectiveness, and limitations, of reputation-based disciplining 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. Adverse selection problems may arise because, unlike lead arrangers, participant lenders generally do not have direct lending relationships with borrowers. The syndicate structure also weakens the lead arranger's incentives to screen and monitor borrowers because it holds only a fraction of the loan. A prominent example that highlights these problems is the controversy surrounding a syndicated loan made to Enron just before its bankruptcy filing, when some of the participants accused the lead arranger, J.P. Morgan Chase & Co., of deliberately concealing Enron's perilous financial condition and of using part of the loan proceeds to lower its own exposure to Enron.[3] This controversy also highlights the limited legal recourse available to participants against the lead arranger in case of loan defaults. From a legal standpoint, syndicate participants are senior lenders that are counterparties to the loan contract, which makes it difficult to argue that they were misled by the lead arranger. Moreover, given the diversity of participants, many of which are foreign banks or nonbanking institutions, it is difficult to coordinate a legal response.

[2] Supporting our use of Chapter 11 bankruptcy filings by borrowers to identify poor performance by the lead arranger, Dahiya, Saunders, and Srinivasan (2003) find that the announcement of bankruptcy or default by a bank's borrowers has a significant negative effect on its market value. Although these findings are attributed in part to a loss of valuable relationships with borrowers, they may also reflect a loss of the bank's reputation and lower ability to syndicate loans in the future.

[3] 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 the *Wall Street Journal*, February 21, 2003.

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 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 rich data available on the loan syndication market also allow us to identify the channels through which the reputation mechanism works, and how its effectiveness varies in the cross-section of institutions as well as over time. In particular, 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 over 28,000 syndicated and nonsyndicated loans contracted over a period spanning 15 years.

We interpret a lead arranger's reputation in terms of market participants' perception of its innate ability to screen and monitor borrowers. If there is uncertainty among participants about a lead arranger's ability, and if its screening and monitoring actions are unobservable, then bankruptcy filings by its borrowers are likely to lower participants' assessment of its ability, thereby damaging its reputation.[4] The loss of reputation may in turn lower the lead arranger's ability to attract participants and to syndicate loans. We refer to this as the *reputation hypothesis*.

Apart from a loss of reputation, borrower bankruptcies may also lead to an erosion of the lead arranger's capital, which could affect its subsequent lending activity adversely. If borrower bankruptcies 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. Our rich data set allows us to design tests that explicitly control for these alternate hypotheses.

We begin our empirical analysis by investigating the effect of borrower bankruptcies on the fraction of subsequent loans retained by the lead arranger (henceforth, lead allocation). If borrower bankruptcies lower the lead arranger's reputation, then, all else equal, we expect an increase in lead allocation on its future loans. The larger lead allocation signals increased commitment by the lead arranger to screen and monitor the borrower, thus compensating for its loss of reputation, and also provides a stronger signal of borrower quality.[5]

[4] Even though bankruptcies are to some extent expected, not all participant lenders may have enough information on borrower characteristics and loan terms to distinguish between expected and unexpected bankruptcies. Information on recovery rates also takes time to realize, and may not be known to all lenders. Therefore, borrower bankruptcies are unconditionally likely to be viewed as bad news, and are likely to hurt the lead arranger's reputation.

[5] Theory suggests that the fraction of the loan financed by a lead arranger can signal its commitment to 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 (2007), and Ball, Bushman, and Vasvari

We test our predictions by combining the following 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, Compustat for financial information on borrowers, and the Federal Reserve's Y-9C database for financial information on lead arrangers. To identify lead arrangers that have large loan amounts outstanding to bankrupt borrowers, we construct the dummy variable *large bankruptcies*, which takes a value of 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 syndication volume of the lead arranger over the previous 2 years. The 10% cutoff allows for some expected level of borrower bankruptcies that are not punished by the market; our results are robust to alternative cutoffs. We test our predictions by estimating the effect of lagged values of *large bankruptcies* on the lead arranger's lending activity. By way of preview, our main findings are as follows.

Controlling for borrower characteristics, loan characteristics, and borrower and year fixed effects, we find that lead arrangers that experience large bankruptcies (instances in which the lagged value of *large bankruptcies* equals one) retain 4.95% more of the loans that they arrange. In comparison, the median loan fraction retained by lead arrangers in our sample is 38.56%. Thus, *large bankruptcies* result in a 12.8% increase in the loan fraction financed by the lead arranger. This result is consistent with the reputation hypothesis. The result is also robust to controlling for the lead arranger's capital and other financial characteristics, as well as for commonalities in industry and geography between the borrower and the bankrupt borrowers.

A striking finding is that the increase in lead allocation following large bankruptcies is absent for large lead arrangers (those within the top 5th percentile in terms of syndication volume) and is only present among small lead arrangers. This result could be due to the exercise of market power by large lead arrangers, who arrange close to half of the loans in our sample. Consistent with this explanation, we find no increase in lead allocation following large bankruptcies when the lead arranger is dominant in the borrower's industry or state.[6] These results highlight a key limitation of the reputation mechanism, and may also go some way toward explaining the concentrated nature of the loan syndication market.[7]

Bankruptcy filings that occur during periods of economic distress are likely to be less informative about the lead arranger's ability, because they are

(2007) find that the fraction of the loan financed by the lead arranger increases with the extent of the borrower's information opacity.

[6] We classify a lead arranger as dominant if its market share of the borrower's industry or state by total amount syndicated in the previous year exceeds 25%.

[7] They are also consistent with the anecdotal evidence that many banks that participated in the syndicated loan to Enron were reluctant to participate in possible legal action against J.P. Morgan, because they feared retribution from J.P. Morgan, which could use its dominance of the loan market to shut out any bank that questioned its dealings. 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 the *Wall Street Journal*, February 21, 2003.

more likely to be attributed to poor economic conditions. Consistent with this conjecture, we find that the increase in lead allocation following large bankruptcies is lower in years in which several other lead arrangers also experience large bankruptcies and during recession years. This result highlights another important limitation of a reputation-based disciplining mechanism. Because correlated bankruptcies are unlikely to be punished by market participants, it may provide incentives for lead arrangers to herd in their *ex ante* lending decisions (as suggested by Scharfstein and Stein (1990) and Rajan (1994)).

We also find that the increase in lead allocation following large bankruptcies is greater when the bankruptcies are more unexpected ex ante, especially if they occur soon after loan origination or if they involve low-yield loans. These findings are consistent with the reputation hypothesis, because such unexpected bankruptcies are more likely to suggest inadequate screening and monitoring by the lead arranger and thus lead to greater downward revision of its ability. These results also help distinguish the reputation hypothesis from alternative explanations.

Our results are robust to how we define large bankruptcies, and to alternate ways of measuring lead arranger size. To ensure that our reliance on the loan amount and maturity at the time of origination in defining *large bankruptcies* does not bias our conclusions, we also obtain the actual loan amounts outstanding to Compustat borrowers that file for bankruptcy after 1996 by examining their 10-Q statements before the bankruptcy filing.[8] We obtain similar results when we repeat our estimation after redefining *large bankruptcies* based on these actual outstanding loan amounts. We also perform tests to ensure that our results are not due to *large bankruptcies* selectively identifying lead arrangers that lend to risky borrowers or selectively identifying periods of credit distress. Our results are also not driven by a shift in lead arrangers' borrower profile following large bankruptcies.

For a reputation-based disciplining mechanism to be effective, it is necessary that participant lenders be willing and able to avoid participating in loans syndicated by a lead arranger that experiences large bankruptcies. One expects larger and more diversified participants to be less dependent on a single lead arranger and hence to find it easier to eschew syndicates of lead arrangers with a tarnished reputation. Consistent with this prediction, we find that while lenders are, on average, less likely to participate in loans syndicated by a lead arranger that experiences large bankruptcies, the effect is stronger in the case of large and diversified participants. The result highlights the importance of large participants in sustaining a reputation mechanism.

When we differentiate between syndicated and sole-lender loans, we find that lead arrangers are likely to both retain a larger fraction of syndicated loans and also syndicate loans less often following large bankruptcies. These effects are present for up to 2 years after large bankruptcies. We also find that large bankruptcies have a dramatic effect on the level of activity of a subset of lead arrangers. About 23 out of the 88 lead arrangers that experience large

[8] Our sample is restricted because electronic versions of 10-Q statements are only available for Compustat firms after 1996.

bankruptcies stop syndicating future loans completely within a year after they experience large bankruptcies for the first time. This also highlights that our estimates on the effect of large bankruptcies on lead allocation are likely to be a lower bound.

Overall, our results are broadly consistent with the reputation hypothesis, and indicate that large bankruptcies adversely affect the lead arranger's ability to syndicate loans and attract participants. A major contribution of our paper is also to highlight two key limitations of the reputation mechanism. First, large lead arrangers and those with dominant market shares are virtually unaffected by large bankruptcies. Second, correlated bankruptcies that occur during periods of credit crisis appear to have a minimal effect on lead arrangers, suggesting that reputation concerns may give them ex ante incentives to herd in lending decisions.

Existing literature on the loan syndication market uses a lead arranger's market share as a proxy for its reputation, and shows that lead arrangers with larger market shares retain smaller loan fractions (Dennis and Mullineaux (2000), Lee and Mullineaux (2004), and Sufi (2007)). Although this evidence is consistent with a reputation story, it is also consistent with alternative explanations based on matching between better quality borrowers and large lead arrangers, and the exercise of market power by large lead arrangers (Fang (2005) addresses these biases in the bond underwriting market). Unlike these papers, we do not assume the effectiveness of the reputation mechanism, but instead test for it in the cross-section and over time. As we mention in the first paragraph of the paper, the current financial crisis highlights the need to better understand the limitations of market-based disciplining mechanisms for financial intermediaries.

Our paper is also related to the literature examining the effect of investment bank reputation on underwriting spreads and returns. Chemmanur and Fulghieri (1994a) provide a model of endogenous reputation acquisition by investment banks, and show that investment banks with higher reputation charge higher underwriting spreads. Supportive evidence is provided in the case of initial public offerings (IPOs) by Carter and Manaster (1990), and in the case of corporate bonds by Fang (2005). Using underwriter tombstone position as a proxy for underwriter reputation, Carter and Manaster (1990) show that high reputation underwriters manage less risky issues associated with lower initial returns.[9] Using underwriter market share as a proxy for reputation, Fang (2005) shows that debt underwritten by more reputable underwriters carries lower yields but higher underwriting spreads. Other papers that examine the role of intermediary reputation are Beatty and Ritter (1986) and Nanda and Yun (1997) in the market for IPO underwriting, and Krishnan et al. (2011) in the venture capital market. In comparison, ours is the first study to examine the cost of lost reputation for financial intermediaries, and to analyze how this cost varies across the cross-section of institutions as well as over time.

[9] In related work, Logue et al. (2002) show that there are differences between high and low reputation underwriters in terms of their pre- and postissue activities around IPOs.

The remainder of the paper is organized as follows. We outline our main hypotheses in Section I, and describe our data and summary statistics in Section II. Our main results are presented in Section III. Section IV concludes the paper.

I. Hypotheses and Empirical Predictions

A. Reputation Hypothesis

A lead arranger's concern for maintaining its reputation can mitigate the potential information and incentive problems with participants in loan syndicates. To the extent that participants are uncertain about a lead arranger's ability, bankruptcy filings by the lead arranger's borrowers are likely to lower participants' assessment of the lead arranger's ability, damaging 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.[10]

If large bankruptcies damage a lead arranger's reputation, then the lead arranger should, ceteris paribus, retain a larger fraction of the loans it arranges in the future. Retaining a larger loan fraction will not only provide greater explicit incentives to the lead arranger to screen and monitor the borrower, thereby compensating for a decline in implicit reputation-based incentives, but will also act as a stronger signal of borrower quality. The increase in lead allocation may be greater for smaller lead arrangers, because there is greater uncertainty regarding their screening and monitoring abilities. Alternatively, it may be the case that the syndication ability of large lead arrangers is less affected by borrower bankruptcies because they are able to exercise greater market power over participant lenders.[11] "Unexpected" bankruptcies are likely to be more damaging for the lead arranger's reputation as compared to "expected" bankruptcies, because the former are more indicative of inadequate screening or monitoring by the lead arranger. Although bankruptcies should be more frequent during periods of economic distress, such bankruptcies are likely to be less informative about a lead arranger's ability, because participants are more likely to attribute such bankruptcies to the poor economic conditions. Thus, among bankruptcies, we expect idiosyncratic ones to have a greater effect on lead allocation.

[10] Although our subsequent results highlight the importance of lead arranger reputation, to the extent that loans can be linked to individual loan officers, their reputation may also be affected by borrower bankruptcies. Our results suggest, however, that replacing/reassigning these officers and making other organizational changes is unlikely to completely forestall adverse consequences to the lead arranger. This is reasonable because the poor performance of individual loan officers will be attributed at least in part to the inability of internal control systems to forestall poor performance in the first place.

[11] For diversification reasons, participating lenders may find it difficult to avoid participating in the loans syndicated by lead arrangers that are dominant in particular industries or geographic areas.

The reputation hypothesis also has predictions on how large bankruptcies may affect the nature of participants in future syndicates, the level of the lead arranger's activity, and future borrower and loan profiles. We discuss the specific predictions in greater detail before we present the results of our empirical tests.

B. Alternate Hypotheses

Borrower bankruptcies may also inflict substantial monetary loss on the lead arranger. Apart from the direct loss on account of its loan exposure to the bankrupt borrower,[12] the lead arranger may lose a valuable lending relationship with the bankrupt firm. If a lead arranger is constrained in raising fresh outside capital to bridge these losses, then bankruptcies may reduce the lead arranger's capital base and hence future lending activity.[13] A lower capital base may also hamper the lead arranger's ability to attract participants by increasing the uncertainty about its long-term viability.

Although the loss of capital combined with minimum capital requirements for lending predicts a decrease in lead allocation following large bankruptcies, the lower ability to attract participants predicts an increase in lead allocation. The adverse effects of loss of capital should be more severe for small lead arrangers that are likely to face greater constraints in raising fresh capital. In our empirical tests, we explicitly control for the level of bank capital to distinguish the reputation hypothesis from this alternative explanation.

Apart from lowering the lead arranger's reputation among market participants, large bankruptcies may also lead to a revision in the lead arranger management's assessment of the ability of its lending department. Such a revision would predict a more cautious approach to future lending. Note that this is complementary to the reputation hypothesis as it involves a loss of reputation within the organization. However, unlike the reputation hypothesis, the internal learning hypothesis predicts a decrease in lead allocation following large bankruptcies. Finally, if borrower bankruptcies 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. In our tests, we explicitly control for the bankrupt borrower's industry and geography to rule out this alternate explanation.

Although we employ a number of borrower, loan, and lead arranger controls in our model, to the extent that our controls for risk are inadequate, large bankruptcies and lead allocation may be spuriously correlated. This can happen if, say, lead arrangers that specialize in lending to riskier borrowers experience large bankruptcies more often and also retain a larger loan fraction. In our

[12] Gupton, Gates, and Carty (2000) estimate the recovery rates on senior secured loans and senior unsecured loans to be 69% and 52%, respectively.

[13] A lower capital base will reduce lending due to either minimum capital requirement regulations for lending or an increase in regulatory scrutiny (Dahiya, Saunders, and Srinivasan (2003)).

empirical analysis, we conduct a number of robustness tests in an attempt to rule out such risk-based explanations.

II. Data and Descriptive Statistics

A. Data Sources

We obtain data on individual loan contracts from a 2006 extract of LPC's Dealscan database. Dealscan provides information on loans made to medium- and large-sized U.S. and foreign firms. According to LPC, 70% of the data are gathered from the SEC filings (13-Ds, 14-Ds, 13-Es, 10-Ks, 10-Qs, 8-Ks, and Registration Statements), and the remaining data are collected directly from lenders and borrowers.[14] We extract information on all dollar-denominated loans made by U.S. lenders to U.S. borrowers during the period 1990 to 2006. There are 66,301 such loans reported on Dealscan.

The loans are financed either by a single lender or by a syndicate of lenders. When the loan is financed by a syndicate, Dealscan allows us to identify the lead arranger for the loan. Specifically, we use the variable *LeadArrangerCredit* to identify if a lender is also a lead arranger. We include all loans with at least one lead arranger in our sample. For loans with multiple lead arrangers, we have one observation corresponding to each lead arranger.[15] We also obtain information on loan contract terms such as the total loan amount, yield spread,[16] maturity, loan type, loan purpose, presence of security, and syndicate structure details, such as the percentage of the loan retained by the lead arranger.

Our data on bankruptcy filings come from the website 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 period 1990 to 2005. 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 do not have information on what triggered the bankruptcy filing or how much lenders were ultimately able to recover in bankruptcy. But as we note below, our empirical strategy only assumes that, on average, lenders recover less than 100% of their loan outstanding when the borrower declares bankruptcy. Prior research supports this assumption: Dahiya, Saunders, and Srinivasan (2003) find that the announcement of bankruptcy or default by a bank's borrowers has a significant negative effect on its stock price, suggesting

[14] 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.

[15] Of the total of 66,301 loans, we are unable to identify the lead arranger for 5,023 loans (7.58%) using this method, and hence exclude them from our analysis. We identify multiple lead arrangers for 6,023 loans (9.08%); of these, 5,986 loans have two lead arrangers, and 37 loans have more than two lead arrangers. These are included in our sample.

[16] 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 LIBOR.

that the bankruptcies were not fully anticipated by the market and are very costly. Gupton, Gates, and Carty (2000) estimate the average recovery rates on senior secured loans and senior unsecured loans in Chapter 11 bankruptcy to be 69% and 52%, respectively. By manually matching the firm names in our bankruptcy data with the borrower names in Dealscan, we are able to identify the loans obtained by 1,048 firms that subsequently file for bankruptcy.

We obtain detailed financial information on the borrowers in our sample from the Compustat database. We are able to match Compustat and Dealscan using the Compustat–Dealscan link made publicly available by Michael Roberts and Wharton Research and Data Services (Chava and Roberts (2008)).[17] The borrower's financial information corresponds to the beginning of the financial year in which the loan is originated. Finally, for a subset of lead arrangers that are either banks or subsidiaries of bank holding companies (BHCs), we obtain financial characteristics at the BHC level using the Federal Reserve's quarterly Y-9C reports. We obtain this information by manually matching the names of the parent organizations of the lead arrangers from Dealscan with the names of the BHCs in the FR Y-9C reports. Information on Tier-1 Capital is only available for 1997 and thereafter.

B. Key Independent Variable

The key independent variable that we employ in our baseline analysis is *large bankruptcies*, a dummy variable that identifies lead arrangers that have large loans outstanding to borrowers that file for Chapter 11 bankruptcy during the year. We construct this variable as follows. For the firms that file for Chapter 11 bankruptcy, we identify all loans outstanding at the time of the bankruptcy filing using the loan origination date and stated maturity in Dealscan. We aggregate all such outstanding loans for each lead arranger for each year. We code *large bankruptcies*$_{j,t}$ equal to one if the total loan amount lent by the lead arranger j and outstanding to borrowers that file for bankruptcy during year t exceeds 10% of the average annual amount syndicated by the lead arranger j over the previous 2 years. In our regressions, we use lagged values of *large bankruptcies* as our main independent variable. The 10% cutoff in the definition of *large bankruptcies* is designed to allow for some average expected level of bankruptcies that are unlikely to hurt a lead arranger's reputation. This is also consistent with theories of reputation that predict a discontinuous response to bad performance (Diamond (1989b)). However, for robustness we perform tests using a continuous measure of bankruptcies, *scaled bankruptcies*, which is the ratio of the aggregate loan outstanding to bankrupt borrowers over the annual average syndication volume of the lead arranger. Please refer to the Appendix for definitions of all the variables that we use in our analysis.

Although our method of coding large bankruptcies using the loan amount and stated maturity at origination is simple and generally applicable to both Compustat and non-Compustat firms, it may suffer from some shortcomings.

[17] We thank an anonymous referee for directing us to this link.

For example, for lines of credit that are drawn down only partially, and in the case of loans that are prepaid, the amount outstanding at the time of bankruptcy may be smaller than the loan amount at origination. To ensure that this does not bias our conclusions, for the subsample of Compustat firms that file for bankruptcy, we examine the 10-Q reports filed by each firm before its bankruptcy filing to identify the actual loan amount outstanding to the lead arranger at the time of bankruptcy.[18] We use the information obtained from the 10-Qs to define the dummy variable *large bankruptcies (Compustat)*, which identifies lead arrangers for which the total outstanding loan amount to Compustat firms that file for bankruptcy exceeds 10% of the average annual syndication volume of the lead arranger to Compustat firms over the previous 2 years. Note that while this is a more rigorous approach to identifying the actual amount outstanding at the time of bankruptcy, it can only be applied to Compustat firms that file for bankruptcy after 1996 and hence excludes 42% of our bankruptcy sample. However, as we discuss below, *large bankruptcies* and *large bankruptcies (Compustat)* are highly correlated, and our results are robust to both measures.

In constructing *large bankruptcies* and *large bankruptcies (Compustat)*, we do not differentiate bankruptcies based on how much lenders eventually recover or expect to recover in bankruptcy. This is reasonable because actual recovery rates take time to realize, and may not be observed by all participant lenders even after they are realized.[19] Moreover, not all participant lenders may have enough information on borrower risk characteristics and loan terms to be able to estimate recovery rates on the bankrupt loans. In the absence of such information, borrower bankruptcies will unconditionally be viewed as bad news by participant lenders and may hurt the lead arranger's reputation.[20] It is, however, reasonable to expect that the reaction of participants will be more severe for bankruptcies that are ex ante more unexpected, or that reflect egregious mistakes on the part of the lead arranger. In our empirical analysis we use a number of proxies to classify bankruptcies as expected and unexpected, and examine if the effects are stronger following unexpected bankruptcies.

C. Descriptive Statistics

Table I provides a year-wise summary of our loan and bankruptcy data for the period 1990 to 2006. We have information on 59,341 loans made to borrowers from 868 unique four-digit SIC industries. The increase in the number of loans

[18] We thank the editor for the suggestion to use the database made publicly available by Amir Sufi, which provides links to the 10-Q statements filed by firms with the SEC.

[19] Our empirical tests examine the impact of large bankruptcies on the lead arranger's lending activity in the following year. Because bankruptcy resolution in Chapter 11 takes more than 1 year, on average, the actual recovery rates may not even be known in the year following large bankruptcies.

[20] This is consistent with theoretical models of reputation, which assume some degree of unobservability of the agent's actions by investors and predict negative consequences after bad performance even if such bad performance is to some extent expected (Diamond (1989a)).

Table I

Summary Statistics on Loans and Bankruptcy Filings by Year

This table presents a year-wise summary of our loan data and bankruptcy data over the period 1990 to 2006. *Dealscan Loans* is the number of loans in Dealscan, and *Borrower Industries* is the number of unique four-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 four-digit SIC code industries of the bankrupt borrowers.

Year	Dealscan Loans (1)	Borrower Industries (2)	Bankruptcy Filings (3)	Bankrupt Loans (4)	Bankrupt Industries (5)
1990	1,937	387	84	61	24
1991	1,853	387	115	115	33
1992	2,017	405	84	79	23
1993	2,574	452	78	49	17
1994	3,219	509	54	32	16
1995	3,053	471	71	49	19
1996	3,898	546	62	54	24
1997	4,826	556	63	56	19
1998	3,831	511	106	69	28
1999	3,874	503	144	178	50
2000	4,409	529	191	269	71
2001	4,137	543	273	346	83
2002	4,401	572	233	290	62
2003	4,655	591	182	186	58
2004	5,624	632	98	86	26
2005	5,655	604	91	100	23
2006	1,315	293			
Overall	61,278	868	1,929	2,019	293

over the sample period is due in part to the growth in the syndicated loan market, and in part to improved coverage by Dealscan. Our bankruptcy data provide information on 1,929 Chapter 11 bankruptcy filings over the period 1990 to 2005. It is clear that there is a spurt in bankruptcy filings during the period 2000 to 2003 (column (3)) and, mirroring this spurt, there is also an increase in the number of loans outstanding to bankrupt borrowers during this period (column (4)).

Because we use the lagged value of *large bankruptcies* in our analysis, and have bankruptcy data for the period 1990 to 2005, our regressions are confined to loans originated during the period 1991 to 2006. Moreover, in most of our regressions we control for borrower financial characteristics, which are only available for borrowers covered by Compustat ("*Compustat firms*"). Therefore, to correspond to our regression sample, in Table II we provide summary statistics of our key variables only for the loans made to Compustat firms during the period 1991 to 2006.[21] As mentioned before, in the case of loans with

[21] Loans to non-Compustat firms constitute 53% of our loan sample. Our reported results are robust to including all loans and excluding borrower financial information as controls.

Table II

Summary Statistics, Key Loan Variables

This table reports summary statistics for the key variables in our sample of loans originated between 1991 and 2006. Each observation represents a loan. All variables are defined in the Appendix. Panel A summarizes the whole sample, while Panel B compares the subsample of loans identified using lagged values of *large bankruptcies*. *Only for syndicated loans.

			Percentile distribution			
	Mean	Std. Dev.	25^{th}	Median	75^{th}	*N*
Loan characteristics:						
Amount (in $ million)	271.56	634.45	20	90	270	28,043
Yield	169.15	121.27	75	150	250	21,217
Short term	0.23	0.42	0	0	0	28,043
Long term	0.16	0.37	0	0	0	28,043
Secured	0.76	0.43	1	1	1	19,415
Takeover	0.15	0.36	0	0	0	28,043
Working capital	0.55	0.50	0	1	1	28,043
Repayment	0.22	0.41	0	0	0	28,043
Syndicated	0.65	0.48	0	1	1	28,043
Lead allocation	52.75	38.56	15.00	41.15	100	11,940
Lead allocation*	25.93	19.31	11.00	20.00	37.50	7,409
Lenders in Loan*	7.00	6.00	3.00	6.00	9.00	18,296
Borrower characteristics:						
Assets_{t-1} (in $ billion)	4.81	22.25	0.11	0.49	2.46	28,043
High rated_{t-1}	0.04	0.20	0	0	0	28,043
Leverage_{t-1}	0.35	0.25	0.17	0.32	0.48	27,931
ROA_{t-1}	0.11	0.13	0.07	0.12	0.17	27,204
$(\text{Market to book})_{t-1}$	1.73	1.09	1.10	1.38	1.91	23,837
Lead arranger characteristics:						
Lead size_{t-1} (in $ billion)	48.19	76.61	0.91	9.54	55.49	24,912
Small lead_{t-1}	0.53	0.50	0	1	1	28,043
Large $\text{bankruptcies}_{t-1}$	0.07	0.25	0	0	0	27,930
BHC Size_{t-1}	19.11	1.46	18.35	19.29	20.28	22,672
$(\text{BHC Tier 1 Capital/Assets})_{t-1}$	6.21	0.91	5.60	6.11	6.59	16,022
BHC ROA_{t-1}	1.01	0.40	0.80	1.05	1.27	22,672
$(\text{BHC deposits/Assets})_{t-1}$	0.57	0.13	0.52	0.57	0.65	22,527
$(\text{BHC loans/Assets})_{t-1}$	0.53	0.14	0.45	0.54	0.62	22,672

multiple lead arrangers, we have one observation corresponding to each lead arranger.

As can be seen, there is large variation in loan size; the average loan amount is $272 million, while the median loan amount is only $90 million. Among the loans for which we have information on the yield spread, the average loan yield spread is 169 basis points over LIBOR. In terms of maturity, about 23% of the loans in our sample have a maturity of less than 1 year (*short term*), and 16% have a maturity greater than 5 years (*long term*). Among the loans for which security information is available, 76% are secured. Around 65% of the loans are syndicated, with an average syndicate size of seven lenders. On average, the lead arranger finances 52.75% of a loan, and 25.93% of a syndicated loan.

There is also large variation in borrower size. The average borrower has assets with book value of \$4.81 billion, while the median borrower only has assets of \$0.49 billion. Only 4% of the borrowers have an S&P credit rating of "A" or better (*high rated*). The average leverage ratio (book value of debt to assets) is 0.35, and the average return on assets (operating income to assets) is 0.11.

In seeking to characterize lead arrangers, we note that the loan syndication market is highly concentrated, with a sizable portion of the loans financed by a few large lead arrangers. This is highlighted by the fact that the average lead arranger syndicates loans worth \$49 billion per year (*lead size*), while the 25^{th} percentile and median lead arrangers only syndicate loans worth \$0.91 billion and \$9.54 billion, respectively, per year. Therefore, we classify a lead arranger as *small* if it is within the 95^{th} percentile in terms of number of loans syndicated during the year. Although small lead arrangers constitute 95% of all lead arrangers in any given year, they only originate about half (53%) of all loans in our sample. The mean value of *large bankruptcies*, 0.07, indicates that 7% of the loans in our sample are originated by lead arrangers that had large loan amounts outstanding to borrowers that file for bankruptcy the previous year. We now proceed to formal multivariate tests of our hypotheses.

III. Empirical Results

A. Lead Arranger Allocation

We begin our multivariate analysis by examining how large bankruptcies affect the *lead allocation* for loans arranged by the lead arranger in the subsequent year. As noted, the reputation hypothesis predicts an increase in *lead allocation* following large bankruptcies. To test this prediction, we estimate panel regressions that are variants of the following form:

$$\begin{aligned}\text{Lead allocation}_l = \beta_0 + \beta_1 \times \text{large bankruptcies}_{j,t-1} + \beta_2 \times X_i + \beta_3 \times X_l \\ + \beta_4 \times X_j + \mu_t + \mu_i,\end{aligned} \tag{1}$$

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. Our regression sample includes both syndicated and sole-lender loans; we discuss the results on subsamples of syndicated loans in Section III.A.2. Because *lead allocation* can depend on unobserved borrower characteristics, we include borrower fixed effects (μ_i) in the regression in addition to year fixed effects (μ_t). Inclusion of borrower fixed effects ensures that the effects we identify are within-borrower changes in *lead allocation* when the loan is financed by a lead arranger that experienced large bankruptcies in the previous year as compared to a lead arranger that did not. In all specifications, the standard errors are robust to heteroskedasticity and are clustered at the individual borrower level. The results of our estimation are presented in Panel A of Table III.

Table III

Percentage of Loan Financed by the Lead Arranger

This table reports the results of regressions investigating the impact of large bankruptcies on the percentage of loan retained by the lead arranger. In Panel A, we estimate the regression

$$lead\ allocation_l = \beta_0 + \beta_1 \times large\ bankruptcies_{j,t-1} + \beta_2 \times X_j + \beta_3 \times X_l + \mu_t + \mu_i,$$

We estimate this regression on all the loans in our sample originated during 1991 to 2006. All variables are defined in the Appendix. We include borrower fixed effects in all specifications except the Tobit specification in column (4), and year fixed effects in all specifications. The standard errors are robust and clustered at the individual borrower level. In Panel B, we investigate how the impact of large bankruptcies on *lead allocation* varies with the lead arranger's size and market power. In column (1), X is *small lead*, a dummy variable that identifies lead arrangers within the 95$^{\text{th}}$ percentile in terms of the number of loans syndicated during the year. In column (2), X is *dominant lead*, a dummy variable that identifies if the lead arranger syndicated more than 25% of the loan amount in either the borrower's two-digit SIC industry or the borrower's state during the year. In columns (3) and (4), we repeat our estimation with $X = small\ lead$ on the subsamples with $dominant\ lead = 0$ and $dominant\ lead = 1$, respectively. The empirical specification and control variables are the same as in column (1) of Panel A. In Panel C, we investigate how the impact of large bankruptcies on *lead allocation* varies with credit market conditions. In columns (1) and (2), X is *Other leads tainted*, a dummy variable that identifies years in which more than 7.5% of all lead arrangers experience large bankruptcies. In columns (3) and (4), X is *Recession*, a dummy variable that identifies recession years 1990, 1991, and 2001. Columns (1) and (3) implement an OLS specification; the specification and control variables are the same as in column (1) of Panel A. Columns (2) and (4) implement a Tobit specification.

In Panel D, we investigate how the impact of large bankruptcies on *lead allocation* varies with characteristics of the bankrupt loans. We split *large bankruptcies* into two variables, *X1* and *X2*, based on the characteristics of the bankrupt loans. In columns (1) and (2), the dummy variable *X1* (*X2*) identifies lead arrangers that experience large bankruptcies mainly on account of bankruptcies that occur before (after) one-fourth of the loans' stated maturity has elapsed. In columns (3) and (4), *X1* (*X2*) identifies lead arrangers that experience large bankruptcies mainly on account of high yield (low yield) loans. We classify a loan as high yield (low yield) if its yield spread at origination is higher (lower) than the median yield spread charged by the lead arranger on all its loans during that year. Columns (1) and (3) implement an OLS specification; the specification and control variables are the same as in column (1) of Panel A. Columns (2) and (4) implement a Tobit specification. In Panels B through D, we control for all variables that we used in Panel A, and also include borrower and year fixed effects. For brevity, we suppress the coefficients on the control variables.

Panel A: Impact of large bankruptcies on lead allocation

	Lead allocation					
	(1)	(2)	(3)	(4)	(5)	(6)
Large bankruptcies$_{t-1}$	4.949		5.429	11.056		
	(2.225)**		(3.076)*	(1.923)***		
Scaled bankruptcies$_{t-1}$		16.259				
		(5.749)***				
Large bankruptcies$_{t-1}$					4.471	4.222
(Compustat)					(2.385)*	(2.538)*
High rated$_{t-1}$	1.948	1.895	0.636	6.684	0.901	0.757
	(2.748)	(2.729)	(1.866)	(1.585)***	(1.733)	(1.872)
Market to book$_{t-1}$	1.229	1.273	1.894	1.533	1.477	0.463
	(0.821)	(0.823)	(1.231)	(0.338)***	(1.179)	(0.452)

(continued)

Table III—*Continued*

Panel A: Impact of large bankruptcies on lead allocation						
	Lead allocation					
	(1)	(2)	(3)	(4)	(5)	(6)
Leverage_{t-1}	−9.054	−9.293	−11.004	−9.948	−9.547	−11.609
	(4.360)**	(4.357)**	(5.469)**	(1.706)***	(5.234)*	(5.363)**
Size_{t-1}	−3.929	−3.842	−2.579	−1.391	−2.924	−3.189
	(1.358)***	(1.356)***	(2.763)	(0.330)***	(2.576)	(2.678)
ROA_{t-1}	−13.768	−13.383	−23.439	−35.329	−27.943	−20.729
	(8.767)	(8.774)	(11.101)**	(3.827)***	(10.487)***	(9.803)**
Lead's bankrupt industry	1.154	0.970	1.997	3.837	2.931	2.272
	(2.422)	(2.388)	(2.589)	(2.968)	(2.416)	(2.574)
Lead's bankrupt state	2.218	1.872	2.547	1.526	3.319	2.672
	(1.322)*	(1.331)	(1.493)*	(1.119)	(1.575)**	(1.489)*
Short term	3.831	3.847	2.632	5.092	2.639	2.660
	(0.897)***	(0.900)***	(0.924)***	(0.805)***	(0.937)***	(0.925)***
Long term	3.781	3.764	5.916	3.950	6.309	5.827
	(1.510)**	(1.511)**	(2.565)**	(1.291)***	(2.754)**	(2.555)**
Takeover	−3.317	−3.300	−2.513	−0.227	−1.874	−2.341
	(2.750)	(2.738)	(3.257)	(1.661)	(3.551)	(3.286)
Working capital	−1.684	−1.737	−3.943	2.257	−3.718	−3.660
	(2.490)	(2.474)	(2.738)	(1.528)	(3.191)	(2.773)
Repayment	−3.793	−3.819	−4.440	0.367	−4.578	−4.121
	(2.495)	(2.479)	(3.069)	(1.602)	(3.390)	(3.066)
Log(loan amount)	−7.973	−7.964	−5.555	−13.455	−5.760	−5.533
	(0.630)***	(0.628)***	(0.914)***	(0.374)***	(0.881)***	(0.915)***
$\text{Log(lead size)}_{t-1}$	−1.662	−1.626	−1.016	−1.497	−1.141	−1.063
	(0.277)***	(0.275)***	(0.348)***	(0.182)***	(0.307)***	(0.345)***
Avg. past yield (lead)			−0.0001	0.005	0.008	0.001
			(0.013)	(0.009)	(0.013)	(0.013)
BHC ROA_{t-1}			0.996	4.613		1.312
			(1.514)	(1.082)***		(1.516)
$\text{(BHC deposits/Assets)}_{t-1}$			3.658	3.025		4.041
			(10.428)	(4.659)		(10.529)
$\text{(BHC tier1 cap./Assets)}_{t-1}$			−0.930	−2.905		−0.902
			(1.088)	(0.503)***		(1.101)
$\text{(BHC loans/Assets)}_{t-1}$			2.521	−0.454		1.090
			(10.071)	(4.133)		(10.152)
Obs.	8,199	8,199	4,395	4,395	4,843	4,395
R^2 (or pseudo R^2)	0.892	0.892	0.914	0.136	0.910	0.914
Specification	OLS	OLS	OLS	Tobit	OLS	OLS
Borrower Fixed Effects	Yes	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

(continued)

In column (1) of Panel A, we estimate the regression on the subsample of loans made to Compustat firms. Apart from borrower fixed effects, our controls for borrower characteristics include *log(assets)* to proxy for size, *high rated* and *leverage* to proxy for risk, *ROA* to proxy for profitability, and *market to book* to proxy for growth opportunities. We control for lead arranger size using

Table III—*Continued*

Panel B: Variation with lead arranger size and market power

	X = Small lead	X = Dominant lead	X = small lead: Dominant lead = 0	X = small lead: Dominant lead = 1
	(1)	(2)	(3)	(4)
Large bankruptcies$_{t-1}$ × X$_{t-1}$ (β_1)	7.335	−7.205	7.060	−0.812
	(2.343)***	(6.650)	(2.514)***	(5.535)
Large bankruptcies$_{t-1}$ × [1 − X$_{t-1}$] (β_2)	−2.510	5.890	−0.233	−5.090
	(5.076)	(2.316)**	(6.757)	(6.833)
X$_{t-1}$	−0.468	0.357	−0.961	−1.325
	(1.306)	(1.117)	(1.404)	(5.836)
$\beta_2 - \beta_1$	−9.845	13.096	−7.293	−4.279
	(5.527)*	(7.025)*	(7.105)	(8.765)
Obs.	8,199	8,199	7,112	1,087
R^2	0.892	0.892	0.896	0.93
Borrower and Year FE	Yes	Yes	Yes	Yes

Panel C: Variation by credit market conditions

	X = Other leads tainted		X = Recession Year	
	(1)	(2)	(3)	(4)
Large bankruptcies$_{t-1}$ × X$_{t-1}$ (β_1)	3.261	2.486	4.329	1.860
	(2.949)	(1.849)	(3.176)	(1.948)
Large bankruptcies$_{t-1}$ × [1 − X$_{t-1}$] (β_2)	6.407	12.147	5.436	11.883
	(3.266)**	(1.765)***	(2.979)*	(1.701)***
X$_{t-1}$	−7.420	−7.666	3.382	0.459
	(3.327)**	(1.960)***	(3.241)	(4.504)
$\beta_2 - \beta_1$	3.146	9.660	1.107	10.024
	(4.402)	(2.535)***	(4.252)	(2.576)***
Obs.	8,199	8,199	8,199	8,199
R^2 or pseudo R^2	0.892	0.139	0.892	0.139
Specification	OLS	Tobit	OLS	Tobit
Borrower FE	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes

(continued)

Log(lead size). We include the dummy variables *lead's bankrupt industry* and *lead's bankrupt state* to control for coincident increases in both lead allocation and bankruptcy filings in distressed industries and states, respectively. We also control for loan amount (*Log(loan amount)*), loan maturity (*short term* and *long term*), and loan purpose (*takeover*, *working capital*, and *repayment*).

The identifying assumption in our empirical analysis is that, after the inclusion of all the above controls, *large bankruptcies* is exogenous. This assumption may not be valid if some unobserved time-varying omitted variable affects both the incidence of large bankruptcies and lead allocation in subsequent loans.

Table III—*Continued*

Panel D: Variation by characteristics of loans outstanding to bankrupt borrowers

	X1 = Quick Bankruptcies X2 = Delayed Bankruptcies		X1 = High Yield Loans X2 = Low yield Loans	
	(1)	(2)	(3)	(4)
$X1_{t-1}$ (β_1)	6.858	14.931	1.100	0.244
	(3.093)**	(2.459)***	(3.521)	(1.945)
$X2_{t-1}$ (β_2)	4.256	5.097	6.159	9.777
	(2.811)	(1.458)***	(3.423)*	(1.983)***
$\beta_2 - \beta_1$	−2.602	−9.834	5.059	9.534
	(4.143)	(2.790)***	(4.754)	(2.720)***
Obs.	8,199	8,199	8,026	8,026
R^2 or pseudo R^2	0.892	0.138	0.892	0.138
Specification	OLS	Tobit	OLS	Tobit
Borrower FE	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes

We discuss some such possible omitted factors in Section A.1, and perform a number of robustness tests to rule them out.

The positive and significant coefficient on *large bankruptcies* in column (1) indicates that, ceteris paribus, lead arrangers that experience large bankruptcies retain 4.95% more of the loans they arrange in the subsequent year. The coefficient is also economically significant, and represents a 12.8% increase in *lead allocation* with respect to its sample median of 38.56% (Table II). This result is consistent with the reputation hypothesis. The sample size in this regression is only 8,199 because we restrict the sample to loans to Compustat firms.

The coefficients on the control variables indicate that *lead allocation* is lower in loans to large borrowers and borrowers with high leverage ratios; the latter result may be due to the fact that larger firms typically have higher leverage ratios. We also find that *lead allocation* is lower for loans arranged by large lead arrangers, large loans, and medium-term loans (positive coefficients on *short term* and *long term*), and is higher if the borrower is from the same state as a bankrupt borrower of the lead arranger.

In column (2), we repeat the regression with a continuous measure of bankruptcies, *scaled bankruptcies*. The coefficient on *scaled bankruptcies* is again positive and significant.

To ensure that the increase in lead allocation following large bankruptcies is not due to some unobserved risk factor that is also present in the past loans originated by the lead arranger, in column (3) we repeat our estimation after controlling for the average risk of the lead arranger's past loans using the variable *Avg. past yield*, defined as the average yield spread on all loans originated by the lead arranger in years $t-1$ and $t-2$.[22] We also include additional controls for the lead arranger's financial health. As we mentioned before, these variables are only available for lead arrangers that are either banks or subsidiaries of BHCs; even for this subsample, information on Tier-1 capital is available only from 1997 onward. As a result, our sample size in column (3) decreases to 4,395. For this subsample, we are able to control for the lead arranger's profitability (*BHC ROA*), regulatory capital (*BHC tier-1 cap. / Assets*), and balance sheet characteristics (*BHC deposits / Assets* and *BHC loans / Assets*) at its parent company.

As can be seen in column (3), the coefficient on *large bankruptcies* continues to be positive and significant even after we include these additional controls. Thus, the increase in lead allocation is not explained by the average risk of the lead arranger's past loans. The negative coefficient on *BHC tier-1 cap. / Assets* indicates that *lead allocation* is higher when the parent BHC has a low Tier-1 capital ratio. This result may reflect the reluctance of participant lenders to participate in syndicates arranged by BHCs with poor financial health.

As we mentioned before, the sample for our regression includes nonsyndicated loans as well. As a result, the dependent variable, *lead allocation*, takes a value 100 for 28.4% of the loans in our sample. To control for this, in column (4) we estimate a Tobit model with the same set of control variables as in column (3). We do not include borrower fixed effects in this specification to avoid the incidental parameters problem (Neyman and Scott (1948)). As can be seen, the coefficient on *large bankruptcies* continues to be positive and significant.

To ensure that our use of loan amount and maturity at origination in defining *large bankruptcies* does not bias our results, in columns (5) and (6) we repeat our estimation using *large bankruptcies (Compustat)* instead of *large bankruptcies*. Recall that we construct *large bankruptcies (Compustat)* based on the *actual* loan amounts outstanding to Compustat firms (as listed in their 10-Q statements) that file for bankruptcy after 1996. We find that *large bankruptcies (Compustat)* and *large bankruptcies* are quite similar. When we reconstruct *large bankruptcies* using only the loans to Compustat firms, we find that the correlation between the two is 89.52%. This offers some preliminary evidence that our use of loan amount and maturity at origination is unlikely to bias our conclusions.

Our sample size drops to 4,843 in column (5) because we only use loans made to Compustat firms after 1996 for this regression. As can be seen, the coefficient on *large bankruptcies (Compustat)* is positive and significant, and is comparable to the coefficient on *large bankruptcies* in column (1). In column (6), we repeat our estimation after including the BHC-level control variables that

[22] We do not adjust this measure for the average yield spread across all loans by all lead arrangers during the year because the year fixed effects, which we include in all of our specifications, do so in effect. Alternative measures for the average risk of the lead's past loans were considered as well, such as the yield spread on all loans originated by the lead arranger in year $t-1$, the average lead allocation and fraction of loans secured on all loans originated by the lead arranger in year $t-1$. The results are similar to those reported using *Avg. past yield*.

we employ in column (3), and find that the coefficient on *large bankruptcies (Compustat)* continues to be positive and significant.

We conduct a number of additional robustness tests whose results are available upon request. To control for correlated standard errors across borrowers within an industry, we repeat our estimation in column (1) after clustering the standard errors at the three-digit SIC industry level, instead of at the borrower level. To avoid double counting of loans from a lead arranger to a borrower, we repeat our estimation after redefining *large bankruptcies* using only the most recent loan package before a borrower declares bankruptcy, and, alternatively, by redefining *large bankruptcies* after dropping all loans taken by a bankrupt borrower prior to a loan whose purpose is to repay an earlier loan. Our finding of an increase in *lead allocation* following large bankruptcies is robust to all these specifications.

Overall, the results in Panel A indicate that, ceteris paribus, lead arrangers that experience large bankruptcies retain a larger fraction of the loans that they arrange in the subsequent year. This evidence is consistent with the reputation hypothesis. In the remaining panels of Table III, we run a number of cross-sectional tests to examine whether the increase in lead allocation is larger for certain institutions or during certain time periods.

Variation by lead arranger size and market power. In Panel B of Table III, we investigate whether the effect of large bankruptcies on *lead allocation* varies with the lead arranger's size and market power. To do so, we estimate regression model (1) after replacing $large\ bankruptcies_{t-1}$ with two interaction terms, namely, $large\ bankruptcies_{t-1} \times X_{t-1}$ and $large\ bankruptcies_{t-1} \times [1 - X_{t-1}]$, where X is a measure of the lead arranger's size or market power. We also include X as an additional control. The empirical specification and other control variables are the same as in column (1) of Panel A. For brevity, we suppress the coefficients on the control variables.

In column (1), X is *small lead*, a dummy variable that identifies lead arrangers within the 95$^{\text{th}}$ percentile in terms of the number of loans syndicated during the previous year. As can be seen, the increase in *lead allocation* following large bankruptcies is essentially confined to small lead arrangers. The coefficient estimates indicate that small lead arrangers retain an additional 7.2% of the loan that they arrange in the year after they experience large bankruptcies.

There are three possible nonmutually exclusive explanations for this cross-sectional finding, the first one is consistent with the reputation hypothesis, while the other two are not. First, our results may reflect greater uncertainty regarding the screening and monitoring abilities of small lead arrangers, which causes participants to react more severely to bankruptcy filings by borrowers of small lead arrangers. Second, large lead arrangers may evade the consequences of large bankruptcies because of their market power.[23] We perform additional tests of this explanation in columns (2) to (4). Third, if

[23] The first and second explanations are not mutually exclusive because market power may itself arise due to low uncertainty about the screening and monitoring abilities of large lead arrangers.

small lead arrangers are more likely to lend to risky firms, and hence both retain a larger loan fraction and experience bankruptcies more often, then our results may reflect unobserved loan risk. We address this third interpretation in Section III.A.1.

In column (2), we examine whether the effect of large bankruptcies on *lead allocation* varies with the lead arranger's dominance in the borrower's industry or geographical area. In column (2), X is *lead dominant*, a dummy variable that takes the value of one if the lead arranger syndicated more than 25% of the aggregate loan amount to firms in the borrower's two-digit SIC industry or state during the previous year.[24] Although small lead arrangers are less likely to be dominant in an industry or state, we find that the correlation between our dominance measure and lead arranger size is a modest 37%. Consistent with column (1), our results indicate that the effect of *large bankruptcies* on lead allocation is confined to lead arrangers that are not dominant.

In columns (3) and (4), we conduct subsample tests to better understand whether it is a lead arranger's size or dominance in an industry/geographic area (or both) that shields it from the effects of large bankruptcies. To do so, we partition the sample based on the dummy variable *lead dominant* and rerun the specification in column (1) separately for the two subgroups. As indicated in column (3), when the sample is restricted to *lead dominant* = 0, the results are similar to those for the full sample: the increase in *lead allocation* following large bankruptcies is mainly confined to small lead arrangers. On the other hand, column (4) indicates that when *lead dominant*=1, lead arrangers (small and large) do not exhibit a significant increase in *lead allocation* following large bankruptcies. These results imply that it is primarily small lead arrangers that are also not dominant in an industry/geographic area that suffer negative consequences on account of borrower bankruptcies. The reputation mechanism appears ineffectual when it comes to lead arrangers that either dominate an industry/geographic area or have a large share of the overall market.[25]

Variation by credit market conditions. In Panel C of Table III, we use a similar approach as in Panel B to investigate whether the effect of large bankruptcies on *lead allocation* varies with credit market conditions. In columns (1) and (2), X is *Other leads tainted*, a dummy variable that identifies years in which more than 7.5% of all lead arrangers experience large bankruptcies.[26] In column (1), we implement an OLS specification similar to that in column (1) of Panel A, while in column (2) we implement a Tobit specification similar to that in

[24] To ensure that we do not pick industries and states with very few loans, we confine this to industries and states in which at least five loan packages were contracted during the year.

[25] It is worth pointing out that the lack of adverse consequences for large/dominant leads in the loan syndication market may not carry over to other markets such as the underwriting market given, for instance, differences in the structure of the markets and institutional arrangements. Hence, while the literature finds negative consequences for underwriters (on average) when the IPOs they manage are poorly priced (Beatty and Ritter (1986)), it is not clear whether top-tier investment banks are also subject to these negative consequences or can largely escape them.

[26] The 7.5% cutoff represents the 75$^{\text{th}}$ percentile in terms of the annual fraction of lead arrangers that experience large bankruptcies.

column (4) of Panel A. The coefficient estimates indicate that correlated bankruptcies among the borrowers of lead arrangers do not significantly affect *lead allocation* (insignificant coefficient on *large bankruptcies*$_{j,t-1} \times X_{t-1}$). On the other hand, large bankruptcies that occur in relatively benign credit market conditions are associated with an increase in *lead allocation* (positive coefficient on *large bankruptcies*$_{j,t-1} \times [1 - X_{t-1}]$). This result is consistent with the reputation hypothesis because, when several lead arrangers experience borrower bankruptcies, market participants are less likely to attribute bankruptcies to inadequate screening or monitoring by the lead arranger. This result highlights another important limitation of the reputation mechanism, as it suggests that correlated defaults among lenders are not punished.

We explore this idea further in columns (3) and (4), where X is *Recession*, a dummy variable that identifies recession years 1990, 1991, and 2001. Once again, we find that the effect of large bankruptcies on *lead allocation* is largely confined to bankruptcies that occur in nonrecession years.

Variation by characteristics of loans outstanding to bankrupt borrowers. As we have discussed, it is reasonable to expect that the reaction of participants will be more severe for bankruptcies that are ex ante unexpected, or that reflect egregious mistakes on the part of the lead arranger. We explore this idea in Table III, Panel D, where we examine whether the effect of large bankruptcies on *lead allocation* varies with the characteristics of the loans outstanding to the bankrupt borrowers. We do so by splitting *large bankruptcies* into two dummy variables—*X1* and *X2*—based on some characteristic of the loans outstanding to bankrupt borrowers. Thus, our methodology in this panel is slightly different from that in Panels B and C.

In columns (1) and (2), we examine whether the effect of large bankruptcies is greater when most of the bankruptcies happen early in the loan's life, because such cases are more likely to reflect inadequate screening on the part of the lead arranger. Specifically, for each loan outstanding to a bankrupt borrower, we classify the bankruptcy filing as quick if it occurs before one-fourth of the loan's stated maturity has elapsed. The dummy variable *X1* (*X2*) identifies lead arrangers that experience large bankruptcies, such that more than half of the loan amount outstanding to bankrupt borrowers is on account of quick (not quick) bankruptcies. Column (1) employs an OLS specification while column (2) employs a Tobit specification. The positive and significant coefficient on $X1_{j,t-1}$ and the insignificant coefficient on $X2_{j,t-1}$ in column (1) indicate that the effect of large bankruptcies on *lead allocation* is mainly felt when most of the bankruptcies are quick bankruptcies. This result is consistent with the reputation hypothesis.

In columns (3) and (4), we examine whether the adverse effect of large bankruptcies is greater when most of the loans outstanding to the bankrupt borrowers are low yield loans, because such bankruptcies are more unexpected and reflect poorly on the lead arranger's ability to price credit risk. We classify loans as "high yield" ("low yield") if the yield spread on the loan at origination is higher (lower) than the median yield spread on all loans made by the lead arranger during the year. The dummy variable *X1* (*X2*) identifies lead arrangers that experience large bankruptcies, such that more than half of the loan amount outstanding to the bankrupt borrowers is on account of high yield (low yield) loans. Consistent with the reputation hypothesis, we find that the effect of large bankruptcies on *lead allocation* is only present for bankruptcies that primarily involve low yield loans.

A.1. Ruling Out Alternative Explanations

The identifying assumption in our empirical analysis thus far is that, after controlling for borrower, lead arranger, and loan characteristics, *large bankruptcies* is exogenous. This allows us to interpret our findings as arising from a loss of the lead arranger's reputation following large bankruptcies. However, our identifying assumption may not be valid if some unobserved time-varying omitted variable—notably risk—affects both the incidence of large bankruptcies and lead allocation. Note that any such alternate explanation must not only be consistent with our results in Panel A of Table III but also with the cross-sectional results in Panel D. In this section, we perform a number of robustness tests to rule out these alternate explanations. For expositional convenience, we list each possible alternative explanation for our results, and describe the test we conduct to rule it out.

Do our results reflect a coincident increase in bankruptcies and lead allocation during periods of credit distress for certain categories of lead arrangers? Note that while we include year fixed effects in all our specifications to control for any average trends that occur during the year, they are inadequate if the increase in bankruptcies and lead allocation is concentrated among a subset of lead arrangers. For example, small lead arrangers are more likely to lend to small and risky firms. Such firms are likely to be disproportionately adversely affected during periods of credit crisis. This in turn can result in a spike in both bankruptcies and lead allocation among lead arrangers that specialize in lending to such borrowers. To address this alternative explanation, we create a dummy variable *(placebo) large bankruptcies* that identifies lead arrangers that do not experience large bankruptcies themselves, but are closest in terms of volume of syndication activity (size) to a lead arranger that experiences large bankruptcies during the year. In other words, for each "affected" lead arranger (i.e., *large bankruptcies* = 1), we identify a "control" lead arranger (*large bankruptcies* = 0) that is closest in size during the year. Highlighting the closeness of the match, we find that, on average, the size of the "control" lead arranger is within 3% of the size of the "affected" lead arranger that it is matched with.

We next repeat our estimation after replacing *large bankruptcies* with *(placebo) large bankruptcies*. The underlying assumption behind this test is that lead arrangers of similar size are likely to have loan portfolios with similar characteristics and hence are likely to be subject to similar risk factors. The result of this estimation is presented in column (1) of Table IV. If the increase in lead allocation following large bankruptcies is due to some common risk factor affecting the borrowers of lead arrangers of a particular size during the

Table IV

Robustness Tests

This table presents the results of robustness tests that aim to address alternative explanations for our results. In column (1), the dummy variable *(placebo) large bankruptcies* identifies lead arrangers that do not experience large bankruptcies themselves, but are closest in terms of volume of syndication activity to a lead arranger that experiences large bankruptcies during the year. In column (2), the dummy variable *prelarge bankruptcies* identifies lead arrangers in the year before they experience large bankruptcies. In column (3), the dummy variable *repeat* identifies loans involving repeat relationships between the borrower and the lead arranger. The empirical specification and control variables are the same as in column (1) of Panel A in Table III. To conserve space, we do not report the coefficients on the other control variables in this table.

	Lead allocation		
	(1)	(2)	(3)
(Placebo) large bankruptcies$_{t-1}$	0.228		
	(1.463)		
Prelarge bankruptcies		1.745	
		(1.914)	
Large bankruptcies$_{t-1}$			5.622
			(2.884)*
Repeat			2.675
			(0.879)***
Large bankruptcies$_{t-1}$ × Repeat$_{t-1}$			−1.747
			(4.323)
Obs.	8,199	7,265	7,513
R^2	0.891	0.898	0.898
Specification	OLS	OLS	OLS
Borrower and Year FE	Yes	Yes	Yes

year, then the lead allocations on loans arranged by the "control" lead arrangers should also increase, that is, the coefficient on *(placebo) large bankruptcies* should be positive and significant. The statistically insignificant coefficient on *(placebo) large bankruptcies* in column (1) indicates otherwise and hence does not support this alternative explanation.

Is large bankruptcies selectively identifying lead arrangers that lend to risky firms? As we show in column (3) of Panel A, this is unlikely to be the case because the increase in lead allocation following large bankruptcies cannot be explained by any risk that is present in the lead arranger's past loans. Another way to confront this alternative explanation is to implement the preprogram estimator (Heckman and Hotz (1989)) and examine whether lead arrangers originate "abnormally" high risk loans in the year *before* they experience large bankruptcies. In this test, we use *lead allocation* as a proxy for risk because it is likely to reflect the risks known to the lenders. Specifically, we define the dummy variable *prelarge bankruptcies* to identify lead arrangers in the year before they experience large bankruptcies, and then repeat our estimation after replacing *large bankruptcies*$_{t-1}$ with *prelarge bankruptcies*. Note that we are able to design this test only because of our empirical strategy of using shocks to reputation to identify the effect of reputation. The result of this estimation is presented in column (2) of Table IV. If our results are due to the fact that *large bankruptcies* selectively identifies lead arrangers that lend to risky firms, then we should expect a positive and significant coefficient on *prelarge bankruptcies*. The insignificant coefficient on *prelarge bankruptcies* indicates otherwise and does not support this alternative explanation.

Are our results due to a change in borrower profile following large bankruptcies? To test for this possibility, we repeat our estimation after including two new variables: *repeat*, a dummy variable that identifies loans involving repeat relationships between the borrower and the lead arranger, and the interaction term *large bankruptcies* $\times$ *repeat*. The positive and significant coefficient on *large bankruptcies* and the insignificant coefficient on the interaction term in column (3) in Table IV indicate that the increase in lead allocation after large bankruptcies occurs for both new and repeat borrowers. This ensures that our results are not due to a change in the borrower profile following large bankruptcies.

Overall, the results in Table IV indicate that the increase in *lead allocation* following large bankruptcies is not driven by a coincident increase in both bankruptcies and lead allocations during certain time periods or for certain categories of lenders, or because of a switch in the lead arranger's borrower profile following large bankruptcies. In the Internet Appendix (available on the *Journal of Finance* website of http://www.afajof.org/supplements.asp), we also show that our results are robust to implementing the switching regression model (see Fang (2005)) to control for the endogenous matching between lead arrangers and borrowers.

A.2. Increase in Lead Allocation versus Drop in Syndication Propensity

The increase in *lead allocation* following large bankruptcies can occur either because the lead arranger retains a larger fraction of the loans that it syndicates or because it shifts some of its lending from syndicated to sole-lender loans (which will cause the *lead allocation* on these loans to increase to 100). Although both effects are consistent with the reputation hypothesis, it is interesting to distinguish between the two effects and to quantify their relative importance. We do this in Panel A of Table V.

In column (1), for ease of comparison, we replicate our results from column (1) of Panel B, Table III, which shows that small lead arrangers retain 7.335% more of the loans they syndicate in the year after they experience large bankruptcies. Note that the sample for this regression includes both syndicated and sole-lender loans.

In column (2), we repeat our estimation from column (1) after limiting the sample to syndicated loans.[27] Our results indicate that the *lead allocation* increases by 4.094% among syndicated loans arranged by small arrangers in

[27] Because the decision to syndicate a loan is endogenous, confining the sample to syndicated loans may lead to sample selection bias. Nevertheless, we do so to obtain an estimate of the increase in lead allocation for syndicated loans.

Table V

Syndication Propensity and Lead Allocation for Syndicated Loans

In Panel A, we separately examine the impact of large bankruptcies on syndication propensity and *lead allocation* on syndicated loans for small and large lead arrangers. The dependent variable in columns (1) and (2) is *lead allocation*. In column (1), the regression is estimated on both syndicated and nonsyndicated loans (this is a replication of column (1) in Panel B of Table III), while in column (2) the regression is estimated only on syndicated loans. The dependent variable in column (3) is *Syndicate*, a dummy variable that identifies syndicated loans. In Panel B, we examine the persistence of the effect of large bankruptcies on syndication propensity and lead allocation over a 3-year horizon. In column (1), the dependent variable is *lead allocation*, and the regression is confined to syndicated loans. The dependent variable in column (2) is *Syndicate*, a dummy variable that identifies syndicated loans.

Panel A: Effect of large bankruptcies on syndication propensity and lead allocation

	Lead allocation		
	(All Loans)	(Syndicated Loans)	*Syndicate*
	(1)	(2)	(3)
Large bankruptcies × Small lead	7.335	4.094	−0.087
	(2.343)***	(1.895)**	(0.022)***
Large bankruptcies × [1 − small lead]	−2.510	−4.382	0.068
	(5.076)	(3.286)	(0.039)*
Small	−0.468	−0.317	0.040
	(1.306)	(0.943)	(0.013)***
Obs.	8,199	5,867	19,970
R^2	0.892	0.788	0.706
Firm and Year FE	Yes	Yes	Yes

Panel B: Persistence of the effect of large bankruptcies

	Lead allocation	*Syndicate*
	(1)	(2)
Large bankruptcies$_{t-1}$ × Small lead	3.680	−0.072
	(1.824)**	(0.020)***
Large bankruptcies$_{t-2}$ × Small lead	2.853	−0.034
	(1.484)*	(0.020)*
Large bankruptcies$_{t-3}$ × Small lead	0.425	−0.010
	(1.773)	(0.020)
Large bankruptcies$_{t-1}$ × [1 − small lead]	−2.791	0.070
	(3.233)	(0.035)**
Large bankruptcies$_{t-2}$ × [1 − small lead]	−2.114	0.022
	(2.445)	(0.036)
Large bankruptcies$_{t-3}$ × [1 − small lead]	−1.775	0.029
	(1.545)	(0.028)
Obs.	6,744	23,434
R^2	0.777	0.706
Firm & Year FE	Yes	Yes

the year after they experience large bankruptcies. This shows that part of the effect we document is due to an increase in the lead allocation among syndicated loans.

In column (3), we estimate the change in syndication likelihood following large bankruptcies for small and large lead arrangers. The dependent variable in this specification is *Syndicate*, a dummy variable that identifies syndicated loans. Note that the sample size for this regression is much larger than in any of our earlier specifications because, in Dealscan, information on syndication status is more widely available than the information on lead allocation. The negative and significant coefficient of -0.087 on *large bankruptcies* $\times$ *small lead* indicates that small lead arrangers are 8.7% less likely to syndicate a loan in the year after they experience large bankruptcies. Note that we include *small lead* as a control variable to take into account any average difference in the syndication likelihood between small and large lead arrangers. The effect we document is economically significant given that, on average, the syndication likelihood for small lead arrangers in our sample is 57%.

In the Internet Appendix, we repeat our estimation in all the panels of Table III with *Syndicate* as the dependent variable, and find that the decrease in the propensity to syndicate a loan following large bankruptcies is larger when the lead arranger is small and not dominant in an industry/geographic area, when few other lead arrangers experience large bankruptcies, and when bankruptcies are more unexpected. All the results using *Syndicate* are also robust to using a logistic specification instead of the OLS specification.

A.3. Persistence of the Effect of Large Bankruptcies

A natural question that arises is whether the effect of large bankruptcies on *lead allocation* and *Syndicate* persists beyond 1 year. Our ability to test for such persistence is significantly affected by the fact that, at least for a subset of lead arrangers, *large bankruptcies* has a significant negative effect on their activity level in the loan syndication market. For example, 23 out of the 88 lead arrangers that experience large bankruptcies drop completely out of the loan syndication market within a year after experiencing large bankruptcies for the first time.[28] Even the lead arrangers that continue to syndicate loans experience a large drop in activity in terms of both the number of loans they syndicate and the number of loans syndicated by other lead arrangers that they participate in. The tests of persistence therefore look at the lead arrangers that continue to syndicate loans, that is, the ones less affected by large bankruptcies. As a result, our estimates should be interpreted as lower bounds on the effect of large bankruptcies.

In Panel B of Table V, we examine the effect of large bankruptcies for small and large lead arrangers after 1, 2, and 3 years. We do so by including

[28] In the Internet Appendix, we show that our main results continue to hold even if we drop from our sample all loans arranged by lead arrangers that stop syndicating altogether within a year of experiencing large bankruptcies.

interaction terms involving multiple lags of *large bankruptcies*. The empirical specification is similar to that employed in Panel A of Table V, except that we drop *market to book* as a control variable because it is insignificant in the earlier specifications and also because it is missing for a large number of observations.

In column (1), the dependent variable is *lead allocation* and the regression is confined to syndicated loans. As can be seen, the coefficient on *large bankruptcies*$_{t-2}$ $\times$ *small lead* is positive and significant, but is smaller in magnitude as compared to the coefficient on *large bankruptcies*$_{t-1}$ $\times$ *small lead*. The coefficient on *large bankruptcies*$_{t-3}$ $\times$ *small*, while positive in sign, is not significant. In column (2), we repeat our regression with *Syndicate* as the dependent variable and again find that the effect of *large bankruptcies* lasts up to 2 years for small lead arrangers.

Overall, the results in Panel B indicate that large bankruptcies have a persistent negative effect on the lead arranger's ability to syndicate loans, with the effect gradually tapering off in 3 years.

B. Lead Arranger's Ability to Attract Participants

The reputation hypothesis predicts that lenders that depend on lead arrangers to screen and monitor borrowers should be reluctant to participate in syndicates arranged by a lead arranger that experiences large bankruptcies. Because participants depend on lead arrangers for access to loans, avoiding certain lead arrangers may impose costs on them. Thus, not all participants may be willing or able to avoid a lead arranger that experiences large bankruptcies. In this section, we examine how participants' characteristics, such as size and past relationship with the lead arranger, affect their propensity to participate in syndicates of lead arrangers that experience large bankruptcies. These tests provide additional insights into how a reputation-based disciplining mechanism that relies on coordinated actions by participants works in the loan syndication market.

To do so, we create a lead arranger-participant panel data set with one observation for each lead arranger–participant–year combination. The panel includes all pairs of lead arrangers and participants that ever syndicated a loan together. We then estimate the following panel regression:

$$\begin{aligned}\text{Log}(1+\text{Loans together})_{jkt} = \beta_0 &+ \beta_1 \times [\text{large bankruptcies}_{j,t-1} \times X_{k,t-1}] \\ &+ \beta_2 \times [\text{large bankruptcies}_{j,t-1} \times [1 - X_{k,t-1}]] \\ &+ \beta_3 \times X_j + \mu_{jk} + \mu_t, \end{aligned} \tag{2}$$

where *Loans together*$_{jkt}$ is the number of loans syndicated by lead arranger j during year t in which participant lender k participated. We use *Log(1 + Loans together)* as a measure of activity between a lead arranger and participant, because the raw measure of activity, *Loans together*, is highly skewed. Moreover, because *Loans together* can take the value of zero, we add one to it before computing the logarithm so as to avoid missing values. Because Dealscan does not provide a comprehensive listing of all private debt transactions in the United States and the extent of coverage is known to have increased after 1995 (Carey and Hrycray (1999)), we confine the sample to the post-1995 period, although all our results hold even if we use the full sample period of 1990 to 2005. We also exclude observations pertaining to 2006 because we do not have the full year's data for 2006.[29] To avoid multiple zero observations in the dependent variable, we include each lead arranger until 1 year after the last year in which it syndicates at least one loan, and each participant lender until 1 year after the last year in which it participates in at least one loan.

To control for lead arranger size, we include in the regression the total number of loans syndicated by the lead arranger in the previous year. Further, to control for any unobserved lead-participant pair characteristics that may affect their activity together, we include lead arranger-participant pair fixed effects (μ_{jk}). We additionally control for year fixed effects (μ_t). The results of our estimation are presented in Table VI.

Consistent with large bankruptcies affecting the lead arranger's ability to attract participants and hence its level of activity in the loan syndication market, we find that the coefficient on *large bankruptcies* in column (1) is negative and significant. The coefficient on *large bankruptcies* (-0.144) is also economically significant, indicating that a lead arranger experiences a 29% decrease in activity between itself and a given participant in the year after the lead arranger experiences large bankruptcies.

In columns (2) through (4), we estimate our model after replacing *large bankruptcies*$_{t-1}$ with two interaction terms, namely, *large bankruptcies*$_{t-1} \times X_{k,t-1}$ and *large bankruptcies*$_{t-1} \times [1 - X_{k,t-1}]$, where $X_{k,t-1}$ is the participant characteristic of interest.

In column (2), X equals *Large participant*, a dummy variable that identifies participants that are in the top quartile in terms of the number of loans they participate in during the year. In column (3), X equals *Diversified participant*, a dummy variable that identifies participants that are in the top quartile in terms of the number of lead arrangers whose syndicates they participate in during the year. The results in columns (2) and (3) indicate that large participants and diversified participants are less likely to participate in a lead arranger's syndicates after it experiences large bankruptcies (the difference $\beta_1 - \beta_2$ is negative and significant in both columns). These results highlight that, among participants, large and diversified ones are more likely to avoid a lead arranger that experiences large bankruptcies. This highlights the importance of large and diversified participants in sustaining a reputation mechanism.

In column (4), we examine whether a participant's reaction to a lead arranger that experiences large bankruptcies depends on the strength of their relationship. In this column, X equals *Favorite lead*, a dummy variable that

[29] We also do not adjust our activity measures to account for mergers among lead arrangers and lenders. As long as mergers are not systematically correlated with large bankruptcies, this is unlikely to bias our results.

Table VI

Lead Arranger's Ability to Attract Participants

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

$$\text{Log}(1 + \textit{Loans together})_{jkt} = \beta_0 + \beta_1 \times (\textit{large bankruptcies}_{j,t-1} \times X_{k,t-1}) + \beta_2 \times (\textit{large bankruptcies}_{j,t-1} \times [1 - X_{k,t-1}]) + \beta_3 \times X_j + \mu_{jk} + \mu_t,$$

where $\textit{Loans together}_{jkt}$ is the number of loans syndicated together by lead arranger j and participant k in year t. The panel includes all pairs of lead arrangers and participants that syndicated a loan together. The overall panel spans the period 1995 to 2005. In column (1), X equals one. In column (2), X is *Large participant*, a dummy variable that identifies participants that are in the top quartile in terms of the number of loans they participated in during the previous year. In column (3), 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. In column (4), X is *Favorite lead*, a dummy variable that identifies whether the lead arranger was the participant's preferred lead arranger in the previous year in terms of the number of loans that the participant participated in. We control for lead arranger–participant fixed effects and year fixed effects. In all specifications, the standard errors are robust and clustered at the lead arranger–participant level.

	Log(1 + Loans together)			
	(1)	(2)	(3)	(4)
X=	1	Large participant	Diversified participant	Favorite lead
Large bankruptcies$_{t-1}$ × X$_{t-1}$ (β_1)	−0.144	−0.182	−0.186	−0.027
	(0.009)***	(0.011)***	(0.011)***	(0.015)*
Large bankruptcies$_{t-1}$ × [1 − X$_{t-1}$] (β_2)		−0.040	.036	−0.140
		(0.012)***	(0.014)***	(0.011)***
Loans by lead$_{t-1}$ (in '000s)	0.608	0.680	0.682	0.808
	(0.053)***	(0.058)***	(0.058)***	(0.070)***
$\beta_1 - \beta_2$	NA	−0.142	−0.221	0.114
		(0.015)***	(0.016)***	(0.016)***
Obs.	120,766	115,853	115,853	95,735
R^2	0.562	0.576	0.576	0.642
Pair FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

identifies the lead arranger with whom the participant did the most number of deals during the year. According to the reputation hypothesis, the decrease in a participant's activity after a lead arranger experiences large bankruptcies should be less severe in cases in which the participant has a strong relationship with the lead arranger. This is because such participants are less likely to lower their assessment of the lead arranger following large bankruptcies. Our results in column (4) are consistent with this hypothesis, and indicate that the decline in activity after large bankruptcies is indeed less pronounced if the lead arranger is the participant's favorite lead arranger.

C. Borrower Characteristics and Loan Characteristics

In our final set of tests, we investigate the effect of large bankruptcies on the type of borrowers that the lead arranger lends to in the subsequent year, and the risk characteristics of the loans it finances. In general we would expect the changes to reflect factors such as the degree of difficulty the lead might face in syndicating loans and its loss of wealth from borrower bankruptcies. We estimate 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), *Size* in column (2), *leverage* in column (3), and *market to book* in column (4). We use *Non Compustat* and *log(assets)* as measures of the extent of information asymmetry regarding the borrower. The notion is that lead arrangers are more likely to be informed about firms with financial information in Compustat and about larger firms. We use *leverage* and *market to book* as additional proxies for a firm's risk. We further control 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. Note that our sample in column (1) includes loans to both Compustat and non-Compustat firms.

The negative coefficient on *large bankruptcies* in column (1) indicates that a lead arranger that experiences large bankruptcies is 7.9% less likely to lend to a *Non Compustat* firm the following year. This is consistent with the lead arranger wishing to move toward more transparent borrowers after it experiences large bankruptcies. This could be due to the lead arranger having lower risk tolerance following large bankruptcies, or lower ability to syndicate loans of opaque borrowers.

The negative coefficient on *large bankruptcies* in column (2) indicates that, following large bankruptcies, the lead arranger shifts its lending to smaller borrowers. Although this result is somewhat inconsistent with the lead arranger's preference for more transparent borrowers, it is consistent with reduced syndication ability for the lead arranger. Because loans to large borrowers are more likely to be large and require syndication, a loss of syndication ability may reduce the extent of such loans made by the lead arranger.

We fail to find any evidence that lead arrangers switch to borrowers with lower leverage levels following large bankruptcies (insignificant coefficient on *large bankruptcies* in column (3)). However, the negative and significant coefficient on *large bankruptcies* in column (4) indicates that lead arrangers are less likely to lend to growth firms following large bankruptcies.

In Panel B of Table VII, we investigate the extent to which large bankruptcies affect the risk characteristics and other features of the loans arranged by the lead arranger in the subsequent year. We include borrower financial characteristics as controls in these regressions, and hence confine the sample to loans to Compustat firms. Apart from borrower characteristics, in these regressions we control for lead arranger size, loan maturity, loan purpose, loan size, borrower fixed effects, and year fixed effects. The standard errors are robust to heteroskedasticity and clustered at the level of the individual borrower.

Table VII

Borrower and Loan Characteristics

Panel A of the table reports the results of regressions investigating the impact of large bankruptcies on the type of borrowers that the lead arranger lends to in the subsequent year. We estimate OLS regressions that are variants of the form:

$$y_l = \beta_0 + \beta_1 \times large\ bankruptcies_{j,t-1} + \beta_2 \times X_j + \mu_t + \mu_j.$$

In column (1), y_l is *Non Compustat*, a dummy variable that identifies borrowers for which financial information is not available in the Compustat database. The dependent variable is *Size* in column (2), *leverage* in column (3), and *market to book* in column (4). Definitions of these variables are available in the Appendix. We estimate the regression on all the loans in our sample originated over 1991 to 2006. We include lead arranger fixed effects and year fixed effects in all specifications, and the standard errors are robust and clustered at the individual lead arranger level.
Panel B reports the results of regressions investigating the impact of large bankruptcies on the characteristics of loans arranged by the lead arranger in the subsequent year. We estimate OLS regressions that are variants of the following form:

$$y_l = \beta_0 + \beta_1 \times large\ bankruptcies_{j,t-1} + \beta_2 \times X_i + \beta_3 \times X_l + \beta_4 \times X_j + \mu_t + \mu_i.$$

In column (1), y_l is *low yield*, a dummy variable that identifies loans whose yield spread at origination is lower than the median yield spread charged by the lead arranger during that year. In column (2), y_l is *secured*, a dummy variable that identifies secured loans. In column (3), y_l is *Covenants*, a dummy variable that identifies whether the loan includes any restrictive covenants. We estimate the regression on all the loans in our sample originated over 1991 to 2006 and that are made to borrowers for which financial information is available in the Compustat database. We include borrower fixed effects and year fixed effects in all specifications, and the standard errors are robust and clustered at the individual borrower level.

Panel A: Borrower characteristics

	Non Compustat	Size	Leverage	Market to book
	(1)	(2)	(3)	(4)
Large bankruptcies$_{t-1}$	−0.079	−0.197	−0.005	−0.150
	(0.021)***	(0.067)***	(0.012)	(0.058)***
Log(lead size)$_{t-1}$	−0.002	0.027	0.010	−0.011
	(0.007)	(0.029)	(0.003)***	(0.014)
Obs.	57,687	24,235	24,140	20,625
R^2	0.1	0.458	0.107	0.075
Specification	OLS	OLS	OLS	OLS
Lead FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

(continued)

Table VII—*Continued*

Panel B: Loan characteristics

	Low yield	Secured	Covenants
	(1)	(2)	(3)
Large bankruptcies$_{t-1}$	0.078	0.021	0.034
	(0.030)**	(0.019)	(0.020)*
Log(lead size)$_{t-1}$	−0.024	−0.003	0.010
	(0.003)***	(0.003)	(0.003)***
High rated$_{t-1}$	−0.013	0.110	−0.158
	(0.021)	(0.047)**	(0.115)
Size$_{t-1}$	0.107	−0.068	−0.038
	(0.017)***	(0.014)***	(0.016)**
ROA$_{t-1}$	0.641	−0.315	−0.038
	(0.126)***	(0.083)***	(0.114)
Leverage$_{t-1}$	−0.353	0.243	0.171
	(0.053)***	(0.048)***	(0.042)***
Market to book$_{t-1}$	0.035	−0.026	−0.016
	(0.010)***	(0.010)**	(0.012)
Short term	0.067	−0.093	−0.022
	(0.010)***	(0.013)***	(0.015)
Long term	−0.078	0.056	0.014
	(0.017)***	(0.015)***	(0.012)
Takeover	−0.053	0.003	0.023
	(0.029)*	(0.027)	(0.031)
Working capital	0.066	−0.096	−0.099
	(0.025)***	(0.026)***	(0.030)***
Repayment	0.061	−0.080	−0.018
	(0.027)**	(0.026)***	(0.029)
Log(loan amount)	0.042	−0.023	−0.0008
	(0.006)***	(0.005)***	(0.006)
Obs.	16,309	13,362	11,524
R^2	0.643	0.769	0.626
Specification	OLS	OLS	OLS
Borrower FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

In column (1), we proxy for low risk loans using *low yield*, a dummy variable that identifies loans for which the yield spread over the LIBOR is lower than the median yield spread charged by the lead arranger in the sample. Consistent with a move toward safer loans, the positive coefficient on *large bankruptcies* in column (1) indicates that a lead arranger that experiences large bankruptcies is 7.8% more likely to make *low yield* loans in the following year. As against this, the unconditional probability of a loan in our sample having a low yield is 46%.[30] Turning to the coefficients on the control variables, we observe that loans are more (less) likely to be *low yield* loans if they are made to large

[30] 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.

and profitable borrowers (borrowers with high leverage), if their maturity is less than a year (more than 5 years), and if their stated purpose is to finance working capital or to repay an earlier loan (finance a takeover).

In column (2), the dependent variable is *secured*, a dummy variable that identifies secured loans. Although the coefficient on *large bankruptcies* is positive, indicating that lead arrangers are more likely to include security in their loans following large bankruptcies, the coefficient is not statistically significant. In column (3), the dependent variable is *Covenants*, a dummy variable that identifies loans that include restrictive covenants. The positive and significant coefficient on *large bankruptcies* indicates that lead arrangers are 3.4% more likely to include restrictive covenants in the loans they arrange following large bankruptcies.

Overall, our results in Table VII indicate that lead arrangers that experience large bankruptcies are likely to switch to less opaque borrowers and to less risky loans. As noted, this may reflect the lead arranger's lower appetite for risk following the large bankruptcies as well as greater difficulty in syndicating the loans of opaque borrowers.

IV. Concluding Remarks

We use the loan syndication market as a testing ground to examine whether loss of reputation is costly for financial intermediaries, and how this cost varies across the cross-section of institutions and over time. Our empirical strategy is to study the consequences of shocks to lead arranger reputation from large-scale Chapter 11 bankruptcy filings by its borrowers, and to examine the effect of such shocks on the lead arranger's subsequent loan syndication activity. Our empirical strategy is similar to that in papers that examine how performance affects mutual fund flows (Gruber (1996), Sirri and Tufano (1998), and Zheng (1999)) and job terminations of mutual fund managers (Chevalier and Ellison (1999)) and security analysts (Hong and Kubik (2003)). However, the focus of our paper and its key findings are very different from these papers, which have little to say about the effectiveness of reputation-based disciplining mechanisms. In particular, unlike the earlier literature on financial intermediary reputation, we do not assume that reputation-based disciplining mechanisms are effective, but instead use shocks to lead arranger reputation to test if loss of reputation has consequences.

Consistent with large-scale bankruptcies of its borrowers damaging a lead arranger's reputation, we find that, all else equal, the lead arranger retains a significantly larger fraction of the loans it arranges in the subsequent year. We also find that the consequences of large bankruptcies are stronger for bankruptcies that are more unexpected ex ante, that is, bankruptcies that occur soon after loan origination and bankruptcies involving low yield loans. These findings support the reputation hypothesis because unexpected bankruptcies are more likely to suggest inadequate screening and monitoring by the lead arranger.

A striking finding of the paper is that not every lead arranger appears to suffer reputation-related costs following poor performance. Borrower bankruptcies appear to have little effect on large lead arrangers and on lead arrangers with a dominant market position. Also, the adverse consequences of large bankruptcies are less severe when several other lead arrangers also experience borrower bankruptcies. These results highlight significant limitations of reputation-based disciplining mechanisms, at least in the context of the loan syndication market. An implication of these findings is that smaller lead arrangers may be at a competitive disadvantage relative to large lead arrangers: not only are smaller lenders more likely to lend to small and risky firms that are more prone to bankruptcy, but borrower bankruptcies also have a more adverse consequence for such lenders. This may help explain why loan syndication activity tends to be dominated by a relatively small number of large lead arrangers.

The findings in our paper raise several related questions: If poor performance by large and dominant lead arrangers is not punished by market participants, then what disciplines their behavior? How does the lack of ex post punishment change the ex ante incentives of large lead arrangers to screen and monitor borrowers? Do large lead arrangers exhibit a greater appetite for risk than smaller competitors that are more sensitive to the risk of loss in reputation? Finally, does the lack of punishment for correlated bad performance provide incentives for lead arrangers to take correlated risks ex ante? We hope that future research will shed more light on these questions.

Appendix: Variable Definitions

Lead arranger characteristics:

Lead size: The average annual amount syndicated by the lead arranger over the past 2 years.

Small: A dummy variable that identifies lead arrangers whose size is within the 95th percentile in terms of the number of deals syndicated during the previous year.

Scaled bankruptcies: The total syndicated and nonsyndicated loan amount lent by the lead arranger and outstanding to borrowers who file for bankruptcy during the year, divided by *lead size*.

Large bankruptcies: A dummy variable that takes the value one if the total syndicated and nonsyndicated loan amount lent by the lead arranger and outstanding to borrowers who file for bankruptcy during the year exceeds 10% of *lead size* (i.e., *large bankruptcies* = 1 if *scaled defaults* > 0.1). The dummy variable *Prelarge bankruptcies* identifies lead arrangers in the year before they experience large bankruptcies.

Loan Characteristics:

Syndicate: A dummy variable that identifies loans involving more than one lender.
Lead allocation: The percentage of the loan financed by the lead arranger; it equals 100 for nonsyndicated loans.
Lenders in loan: The number of lenders involved in financing a loan; it equals one for nonsyndicated loans.
Amount: The size of the loan in $million.
Yield: The loan yield expressed as the basis point spread over LIBOR.
Short term: A dummy variable that identifies loans with stated maturity less than or equal to 12 months.
Medium term: A dummy variable that identifies loans with stated maturity between 1 and 5 years.
Long term: A dummy variable that identifies loans with maturity greater than 5 years.
Secured: A dummy variable that identifies loans that are secured.
Takeover, working capital, and repayment: Dummy variables that identify if the main purpose of the loan is to finance a takeover, finance working capital, or to repay debt, respectively.

Borrower Characteristics:

Non Compustat: A dummy variable that identifies borrowers for which financial information is not available in the Compustat database.
Assets: The book value of assets.
Size: The natural logarithm of the book value of assets.
Rated: A dummy variable that identifies borrowers that have an unsecured long-term credit rating. *High rated* is a dummy variable that identifies borrowers with a debt rating of *A* and higher.
Leverage: The ratio of the book value of total debt to the book value of total assets.
Market to book: The ratio of the sum of the market value of equity and the book value of debt to the book value of total assets.
ROA: The ratio of earnings before interest, depreciation, and taxes (EBITDA) to total assets.

Bank Characteristics: These variables are available only for those lead arrangers whose parent organizations are BHCs that file FR Y-9C Reports (i.e., financial information on a consolidated basis) with the Federal Reserve System.

BHC size: The natural logarithm of the BHC's book value of total assets.
BHC ROA: The ratio of the BHC's income before extraordinary items to its total assets.

BHC deposits/Assets: The ratio of the BHC's total deposits to its total assets.
BHC loans/Assets: The ratio of the BHC's total loans to its total assets.
BHS tier1 cap./Assets: The ratio of the BHC's Tier-1 capital to its total assets.

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