Informational efficiency of loans versus bonds: Evidence from secondary market prices

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Abstract

This paper examines the informational efficiency of loans relative to bonds using a unique dataset of daily secondary market prices of loans. We find that the loan market is informationally more efficient than the bond market prior to and surrounding information intensive events, such as corporate (loan and bond) defaults, and bankruptcies. Specifically, we find that loan prices fall more than bond prices prior to an event, and less than bond prices of the same borrower during a short time period surrounding an event. This evidence is consistent with a monitoring advantage of loans over bonds. Our results are robust to a different empirical methodology (Vector Auto Regression based Granger causality), and to alternative explanations which control for security-specific characteristics, such as seniority, collateral, recovery rates, liquidity, covenants, and for multiple measures of cumulative abnormal returns.

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1. Introduction

The informational efficiency of the bond market relative to the stock market has received increasing attention in recent years. For example, Kwan (1996) finds, using daily data, that stock returns lead bond returns, suggesting that stocks may be informationally more efficient than bonds, while Hotchkiss and Ronen (2002) find, using higher-frequency (intra-day) data, that the informational efficiency of corporate bonds is similar to that of the underlying stocks.[1]

However, there is no study to date that examines the informational efficiency of the secondary market for loans relative to the market for bonds of the same corporation, largely due to the unavailability (at least until now) of secondary market prices of loans. Our study fills this gap in the literature. Specifically, we examine, using a unique dataset of secondary market daily prices of loans from November 1, 1999 through July 31, 2002, whether the loan market is informationally more efficient than the bond market. Given the nature of our sample period (i.e., a time of increasing level of defaults and corporate bankruptcies), we focus our analysis on corporate (loan and bond) defaults and bankruptcies. An additional consideration for choosing these events is that the monitoring advantage of loans over bonds (see below), which we show later has implications for the informational efficiency of loans versus bonds, is likely to be of the highest magnitude for such events.

Banks, who lend to corporations, are considered "special" for several reasons, including reducing the agency costs of monitoring borrowers.[2] Several theoretical models highlight the unique monitoring functions of banks (e.g., Diamond, 1984; Ramakrishnan and Thakor, 1984; Fama, 1985). These studies generally argue that banks have a comparative advantage as well as enhanced incentives (relative to bondholders) in monitoring debt contracts. For

[1]There is also a growing literature on institutional trading costs that indirectly contributes to this debate. Using a large dataset of corporate bond trades of institutional investors from 1995 to 1997, Schultz (2001) documents that the average round-trip trading costs of investment grade bonds is $0.27 per $100 of par value. Schultz also finds that large trades cost less, large dealers charge less than small dealers, and active institutions pay less than inactive institutions. In a related study, Hong and Warga (2000) employ a sample of 1,973 buy and sell trades for the same bond on the same day and estimate an effective spread of $0.13 for investment-grade bonds and $0.19 for non-investment grade bonds per $100 par value.

[2]See, Saunders (2002) for a comprehensive review of why banks are considered special.

example, Diamond (1984) contends that banks have scale economies and comparative cost advantages in information production that enable them to undertake superior debt-related monitoring. Ramakrishnan and Thakor (1984) show that banks as information brokers can improve welfare by minimizing the costs of information production and moral hazard. Fama (1985) argues that banks, as insiders, have superior information due to their access to inside information whereas outside (public) debt holders must rely mostly on publicly available information. Several empirical studies also provide evidence on the uniqueness of bank loans, e.g., James (1987), Lummer and McConnell (1989), and Billett, Flannery and Garfinkel (1995).[3]

We argue that the bank advantages and incentives to monitor are likely to be preserved even in the presence of loan sales in the secondary market.[4] First, the lead bank, which typically holds the largest share of a syndicated loan (see Kroszner and Strahan (2001)) rarely sells its share of a loan in order to preserve its banking relationship with the borrower. As a result, it continues to monitor its loans to the borrower. Second, not all participants in a loan syndicate sell their share of a loan, and therefore continue to have incentives to monitor. Finally, the changing role of banks, from loan originators to loan dealers and traders, which has facilitated the development of a secondary market for loans (See Taylor and Yang (2003)), may provide additional channels of monitoring. For example, a bank who serves as a loan dealer will have incentives to monitor loans that are in its inventory.

Given the continued incentives (and abilities as "insiders") of banks to monitor we test the following implications of the monitoring advantage of loans over bonds for the informational

[3] These studies examine the issue of whether bank lenders provide valuable information about borrowers. For example, James (1987) documents that the announcement of a bank credit agreement conveys positive news to the stock market about the borrowing firm's credit worthiness. Extending James' work, Lummer and McConnell (1989), show that only firms renewing a bank credit agreement have a significantly positive announcement period stock excess return. Billet, Flannery, and Garfinkel (1995) show that the impact of loan announcements is positively related to the quality of the lender.

[4] Possible reasons for loan sales include a bank's desire to mitigate "regulatory taxes" such as capital requirements (see, e.g., Pennacchi (1988)), to reduce the underinvestment problem of loans (see, e.g., James (1988)), and to enhance origination abilities of banks. The only study that empirically examines the impact of a loan sale on the borrower and on the selling bank is Dahiya, Puri, and Saunders (2003), who find, on average, that while the stock returns of borrowers are significantly negatively impacted, the stock returns of the selling banks are not significantly impacted surrounding the announcement of a loan sale.

efficiency of loans versus bonds. First, we examine whether loan prices, adjusted for risk, fall more than bond prices of the same borrower prior to an event, such as a loan default, bond default, or a bankruptcy date. Second, we examine whether loan prices, adjusted for risk, fall less than bond prices in periods directly surrounding the same event, the latter might be expected since the "surprise" or "unexpected" component of an event is likely to be smaller for loan investors (as inside monitors) relative to (outside) bond investors as we get closer to the event date.[5]

In general, we find that the loan market is informationally more efficient than the bond market prior to and in periods directly surrounding events, such as corporate (loan and bond) defaults, and bankruptcies. First, we find that loan prices fall more than bond prices of the same borrower prior to an event, even after adjusting for risk in an event study setting. Second, we find that loan prices fall less than bond prices of the same borrower on a risk-adjusted basis in the periods directly surrounding an event. Third, we find that our results are robust to alternative explanations which control for security-specific characteristics, such as seniority, collateral, recovery rates, liquidity, covenants, and for multiple measures of cumulative abnormal returns.[6] Fourth, we also find that our results are robust to a different empirical methodology (Vector Auto Regression based Granger causality). In particular, following Hotchkiss and Ronen (2002), we find evidence that loan returns "Granger cause" bond returns at higher lag lengths for firms that defaulted on their debt (loans or bonds) or went bankrupt in the sample period, whereas we find no evidence that bond returns "Granger cause" loan returns for these firms. Finally, we find evidence to suggest that our results regarding the relative informational efficiency of loans versus bonds extend to loans

[5]These implications assume a partial spillover of the loan monitoring benefits to bonds. That is, if bonds realize the full benefit of loan monitoring quickly (say through arbitrage), the information incorporated into loan and bond prices will be identical resulting in no difference in price reactions. Whether the spillover of loan monitoring benefits to bonds is full or partial is finally an empirical issue that we examine in this paper.

[6]The relevance of collateral in debt financing has been well-established in the literature. For example, Berger and Udell (1990) document that collateral plays an important role in more than two-thirds of commercial and industrial loans in the United States. John, Lynch, and Puri (2003) study how collateral affects bond yields. See Rajan and Winton (1995) who suggest that covenants and collateral are contractual devices that increase a lender's incentive to monitor. Also, see Dahiya, Saunders, and Srinivasan (2003) and Petersen and Rajan (1994) for more evidence on the value of monitoring to a borrower.

versus stocks.

Overall, the results of our paper have important implications regarding the impact of corporate events, such as defaults and bankruptcies on debt values, the relative monitoring advantage of loans (and bank lenders) versus bonds, the benefits of loan monitoring for other financial markets (such as the bond market and the stock market), and on the potential diversification benefits of including loans as an asset class in an investment portfolio along with stocks and bonds.

The remainder of the paper is organized as follows. Section 2 describes the growth of the secondary market for bank loans. Section 3 describes our data and sample selection. Section 4 presents our test hypotheses. Section 5 summarizes our empirical results and Section 6 concludes.

2. The growth of the loan sales market

Understanding the informational efficiency of loans is important because the secondary market for loans has grown rapidly during the past decade. The market for loans typically includes two broad categories, the first is the primary or syndicated loan market, in which portions of a loan are placed with a number of banks, often in conjunction with, and as part of, the loan origination process (usually referred to as the sale of participations). The second category is the seasoned or secondary loan sales market in which a bank subsequently sells an existing loan (or part of a loan).

Banks and other financial institutions have sold loans among themselves for over 100 years. Even though this market has existed for many years, it grew slowly until the early 1980s when it entered a period of spectacular growth, largely due to expansion in highly leveraged transaction (HLT) loans to finance leveraged buyouts (LBOs) and mergers and acquisitions (M&As). With the decline in LBOs and M&As in the late 1980s after the stock market crash of 1987, the volume of loan sales fell to approximately $10 billion in 1990. However, since then the volume of loan sales has expanded rapidly, especially as M&A

activity picked up again.[7] Figure 1 shows the rate of growth in the secondary market for loans from 1991-2002. Note that secondary market loan transactions exceeded $100 billion in 2000.

The secondary loan sales market is sometimes segmented based on the type of investors involved on the "buy-side", e.g., institutional loan market versus retail loan market. An alternative way of stratifying loan trades in the secondary market is to distinguish between the "par" loans (loans selling at 90% or more of face value) versus "distressed" loans (loans selling at below 90% of face value). Figure 1 also shows an increasing proportion of distressed loan sales, reaching 42% in 2002.

3. Data and sample selection

The sample period for our study is November 1, 1999 through July 31, 2002. Our choice of sample period was primarily driven by data considerations, i.e., our empirical analysis requires secondary market daily prices of loans, which were not available prior to November 1, 1999. The dataset we use is a unique dataset of daily secondary market loan prices from the Loan Syndications and Trading Association (LSTA) and Loan Pricing Corporation (LPC) mark-to-market pricing service, supplied to over 100 institutions managing over $200 billion in bank loan assets. This dataset consists of daily bid and ask price quotes aggregated across dealers. Each loan has a minimum of at least two dealer quotes and a maximum of over 30 dealers, including all top loan broker-dealers.[8] These price quotes are obtained on a daily basis by LSTA in the late afternoon from the dealers and the price quotes reflect the market events for the day. The items in this database include a unique loan identification number (LIN), name of the issuer (Company), type of loan, e.g., term loan (Facility), date of pricing (Pricing Date), average of bid quotes (Avg Bid), number of bid quotes (Bid Quotes), average of second and third highest bid quote (High Bid Avg), average of ask quotes (Avg

[7] Specifically M&A activity increased from$190 billion in 1990 to $500 billion in 1995, and to over $1,800 billion in 2000 (Source: Thomson Financial Securities Data Corporation).

[8] Since LSTA and LPC do not make a market in bank loans and are not directly or indirectly involved the buying or selling of bank loans, the LSTA/LPC mark-to-market pricing service is believed to be independent and objective.

Ask), number of ask quotes (Ask Quotes), average of second and third lowest ask quotes (Low Ask Avg), and a type of classification based on the number of quotes received, e.g., Class II if 3 or more bid quotes. We have 560,958 loan-day observations spanning 1,863 loans in our loan price dataset.

Our bond price dataset is from the *Salomon* (now Citigroup) Yield Book. We extracted daily prices for all the companies for which we have loans in the loan price dataset. We have 386,171 bond-day observations spanning 816 bonds. For robustness, we also created another bond price dataset from Datastream for a subset of bonds, containing 91,760 bond-day observations spanning 248 bonds.[9]

We received the loan defaults data from Portfolio Management Data (PMD), a business unit of Standard & Poors which has been tracking loan defaults in the institutional loan market since 1995. We verified these dates in Lexis/Nexis and confirmed that they correspond to a missed interest or a principal payment rather than a technical violation of a covenant.

Our bond defaults dataset is the "New York University (NYU) Salomon Center's Altman Bond Default Database", a comprehensive dataset of domestic corporate bond default dates starting from 1974.

Our bankruptcy dataset is from www.bankruptcydata.com. Specifically, we identified the firms in the loan price dataset that went bankrupt and the dates they went bankrupt on during the sample period from www.bankruptcydata.com. For completeness, we verified the bankruptcy dates on Lexis/Nexis.

Our sources for loan, bond and stock index returns are the S&P/LSTA Leveraged Loan Index from Standard & Poor's, the Lehman Brothers U.S. Corporate Intermediate Bond Index from Datastream, and the NYSE/AMEX/NASDAQ Value-weighted Index from the Center for Research in Securities Prices (CRSP).

Finally, security-specific characteristics, such as seniority, collateral and covenants were obtained from the Loan Pricing Corporation (LPC) for loans, the NYU Salomon Center's Altman Bond Default Database, and the Fixed Income Securities Database for bonds.

[9]We report results in this paper using the Yield Book data. However, the results are qualitatively similar with the Datastream data (not reported here).

Due to the absence of a unique identifier that ties all these datasets together, these datasets had to be manually matched based on the name of the company and other identifying variables, e.g., date (See Appendix 1 for more details on how these datasets were processed and combined).

4. Test hypotheses

For reasons discussed in Section 1, we seek to test the following hypotheses regarding the relative informational efficiency of loan markets versus bond markets around an information intensive event, such as a loan default, bond default, or a bankruptcy:

H1: Loan prices fall more than bond prices of the same borrower prior to an event date.

H2: Loan prices fall less than bond prices in periods directly surrounding an event date.

Consistent with hypothesis H1, we expect the price reaction of loans to be significantly more adverse than the price reaction of bonds during the period leading upto a loan default, bond default, or a bankruptcy date.

Similarly, consistent with hypothesis H2, we expect the price reaction of loans to be significantly less adverse than the price reaction of bonds surrounding a default or a bankruptcy date since the surprise or unexpected component of a default or a bankruptcy event is likely to be smaller for loan investors relative to bond investors around the event date.

5. Empirical results

In this section, we empirically test the hypotheses outlined in the previous section. We present results for loan default dates in Section 5.1, for bond default dates in Section 5.2, and for bankruptcy dates in Section 5.3.

We focus on the response of loan prices and bond prices to loan default, bond default, and bankruptcy events for the following reasons: First, our sample period corresponds to a time of increasing level of corporate defaults and bankruptcies. Second, events, such as loan defaults, bond defaults, and bankruptcies are precisely the events where the monitoring advantage of banks is likely to be of the highest importance to debt-holders/investors.

Table 1 presents descriptive statistics of matched loan-bond pair data (based on the name of the borrower) for the three sub samples of data, i.e., loan defaults sub sample, bond defaults sub sample, and bankruptcy sub sample. Loans typically have a shorter-maturity, and are larger (in terms of issue size) than bonds. Moreover, as is well-known, loans are generally more senior, more secured, and recover more than bonds (in default or a bankruptcy), attributes that we consider later in the regression analysis in Section 5.4.

We compute a daily loan return based on the mid-price quote of a loan, namely the average of the bid and ask price of a loan in the loan price dataset.[10] That is, a one day loan return is computed as today's mid-price divided by yesterday's mid-price of a loan minus one. The daily bond returns are computed based on the price of a bond in the Salomon Yield Book, or on Datastream, in an analogous manner.

5.1. Loan default dates

We start with event study analysis to examine the relative impact of loan defaults on secondary market loan versus bond prices. We measure return performance by cumulating daily abnormal returns during a pre-specified time period. Specifically, we present empirical evidence for three different windows surrounding the event: 3-day window [-1,+1], 11-day window [-5,+5] and a 21-day window [-10,+10], and for the estimation time period [-244,-11], where day 0 refers to the loan default date.

We use several different methods to compute daily abnormal returns. First, on an un-adjusted basis, i.e., using the raw returns, as a first-approximation of the magnitude of the return impact on a loan or a bond of the same corporation around an event date. Three other return measures are also examined based on test methodologies described in Brown and Warner (1985). Specifically and secondly, a mean-adjusted return, i.e., average daily return during the 234 day estimation time period ([-244,-11]), is subtracted from a loan or

[10]We calculate returns based on the mid-price to control for any bid-ask "bounce". See, for example, Stoll (2000) and Hasbrouck (1988) for more details.

bond daily return. The third and fourth measures are based on a single-factor market index (we use the S&P/LSTA Leveraged Loan Index as a market index for loans, and the Lehman Brothers U.S. Corporate Intermediate Bond Index as a market index for bonds).[11] Thus, the third measure is a market-adjusted return, i.e., the return on a market index is subtracted from a loan or bond daily return and the fourth is a market-model adjusted return, i.e., the predicted return based on a market-model regression is subtracted from a loan or bond return. We also used two different types of multi-factor models for estimating abnormal returns: (a) a three-factor model where the three factors are the return on a loan index, the return on a bond index, and the return on a stock index, and (b) the three-factor model of Fama and French (1993).[12] The predicted return from a multi-factor model is subtracted from a loan or bond daily return. More formally,

$$A_{i,t} = R_{i,t} - E[R_{i,t}], \tag{1}$$

where $A_{i,t}$ is the abnormal return, $R_{i,t}$ is the observed arithmetic return,[13] and $E[R_{i,t}]$ is the expected return for security i at date t. The six different methods of computing daily abnormal returns correspond to six different expressions for the expected return for security i at date t. That is,

$$E[R_{i,t}] = \begin{cases} 0 & \text{unadjusted} \\ \bar{R}_i & \text{mean-adjusted} \\ R_{MKT,t} & \text{market-adjusted} \\ \hat{\alpha}_i + \hat{\beta}_i R_{MKT,t} & \text{market-model adjusted} \\ \hat{\alpha}_i + \hat{\beta}_{i,1} R_{L,t} + \hat{\beta}_{i,2} R_{B,t} + \hat{\beta}_{i,3} R_{S,t} & \text{three-factor model adjusted} \\ \hat{\alpha}_i + \hat{\beta}_{i,1} R_{S,t} + \hat{\beta}_{i,2} R_{HML,t} + \hat{\beta}_{i,3} R_{SMB,t} & \text{three-factor model (Fama-French) adjusted} \end{cases}$$

[11] While the Lehman Brothers U.S. Corporate Intermediate Bond Index is a daily series, the S&P/LSTA Leveraged Loan Index is a weekly series during our sample period. For computing market-adjusted and market-model adjusted daily abnormal returns of loans around default dates, we converted the S&P/LSTA Leveraged Loan Index weekly series to a daily series through linear intrapolation.

[12] The returns on the Fama and French (1993) factors are obtained from Professor Kenneth French's website http://mba.dartmouth.edu/pages/faculty/ken.french/.

[13] That is, $R_{i,t} = P_{i,t}/P_{i,t-1} - 1$, where $P_{i,t}$ and $P_{i,t-1}$ denote the price for security i at time t and t-1.

where $\bar{R}_i$ is the simple average of security i's daily returns during the 234-day estimation period (i.e., [-244,-11]):

$$\bar{R}_i = \frac{1}{234} \sum_{t=-244}^{t=-11} R_{i,t}. \tag{2}$$

$R_{MKT,t}$ is the return on a market index defined as below:

$$R_{MKT,t} = \begin{cases} R_{L,t} & \text{loan index} \\ R_{B,t} & \text{bond index} \\ R_{S,t} & \text{stock index} \end{cases}$$

where $R_{L,t}$ is the return on the S&P/LSTA Leveraged Loan Index, $R_{B,t}$ is the return on the Lehman Brothers U.S. Corporate Intermediate Bond Index, $R_{S,t}$ is the return on NYSE/AMEX/NASDAQ value-weighted index, $R_{HML,t}$ is the return on a zero-investment portfolio based on book-to-market, and $R_{SMB,t}$ is the return on a zero-investment portfolio based on size for day t. The coefficients $\hat{\alpha}_i$ and $\hat{\beta}_i$ are Ordinary Least Squares (OLS) values from the market-model regression during the estimation time period. That is, we regress security i's returns on market index returns and a constant term to obtain OLS estimates of $\hat{\alpha}_i$ and $\hat{\beta}_i$ during the estimation time period. The intercept and slope coefficients for the multi-factor models are defined analogously to the single-factor models.[14]

The test statistic under the null hypothesis (of zero abnormal returns) for any event day and for multi-day windows surrounding loan default dates is described below.[15] The test statistic for any day t is the ratio of the average abnormal return to its standard error, estimated from the time-series of average abnormal returns. More formally,

[14]Where we do not have return data for the full estimation period, to ensure that we have reasonable estimates (e.g., lower standard errors), we require at least 50 observations to compute abnormal returns. While the unadjusted and market-adjusted abnormal return procedures do not need any minimum number of observations, we still employ the same criteria of requiring at least 50 observations to ensure comparability of the different abnormal return measures.

[15]Please see Brown and Warner (1985), pp. 7-8, and pp. 28-29 for more details.

$$\frac{\bar{A}_t}{\hat{S}(\bar{A}_t)} \sim N(0,1), \tag{3}$$

where $\bar{A}_t$ and $\hat{S}(\bar{A}_t)$ are defined as

$$\bar{A}_t = \frac{1}{N_t} \sum_{i=1}^{N_t} A_{i,t}, \tag{4}$$

$$\hat{S}(\bar{A}_t) = \sqrt{\frac{1}{233} \left(\sum_{t=-244}^{t=-11} (\bar{A}_t - A^*)^2 \right)}, \tag{5}$$

where A^* used in computing $\hat{S}(\bar{A}_t)$ is defined as

$$A^* = \frac{1}{234} \sum_{t=-244}^{t=-11} \bar{A}_t, \tag{6}$$

where N_t is the number of securities whose abnormal returns are available at day t. For tests over multi-day intervals, e.g., [-5,+5], the test statistic is the ratio of the cumulative average abnormal return (which we simply refer to as CAR) to its estimated standard error, and is given by

$$\sum_{t=-5}^{t=+5} \bar{A}_t \Bigg/ \sqrt{\sum_{t=-5}^{t=+5} \hat{S}^2(\bar{A}_t)} \sim N(0,1). \tag{7}$$

5.1.1. Univariate results

Table 2 presents the event study results for loan-bond pairs of the same company using the market-model adjusted method. We find evidence consistent with the hypotheses described in Section 4, namely that loans decline in price by a larger amount prior to a loan default date (i.e., in the estimation period [-244,-11]) as denoted by hypothesis H1, and by a smaller amount as compared to bonds surrounding an event as reflected in hypothesis H2.

Specifically, consistent with hypothesis H1, loans fell on average by 4.33% during the time period leading up to a loan default event [-244,-11], while bonds fell on average by only 0.23%, with the difference between the loan average CAR (loan ACAR) and the bond average CAR (bond ACAR) of -4.10% (i.e., -4.33%-(-0.23%)) being statistically significant at the 1% level (Z-stat -2.59).

Similarly, consistent with hypothesis H2, loans fell by 18.43% during the 21 day [-10,+10] window surrounding a loan default date, while bonds fell by 45.29%. The difference in the loan average CAR (loan ACAR) and the bond average CAR (bond ACAR) of 26.86% (i.e., -18.43%-(-45.29%)) is statistically significant at the 1% level (Z-stat 4.68).[16]

For robustness purposes, we also examined the event study results for hypotheses H1 and H2 using five other CAR measures: (a) unadjusted, (b) mean-adjusted, (c) market-adjusted, (d) Fama-French three-factor model adjusted, and (e) a loan-bond-stock three-factor model (i.e., where the three factors are the return on a loan index, the return on a bond index, and the return on a stock index) adjusted. The results, not reported here are qualitatively similar to those in Table 2.[17] Hence for the remainder of the paper, we present our event study results based on market-model adjusted CARs.

In summary (so far), we find support for our hypotheses H1 and H2 outlined in Section 4. That is, loan prices fall more than bond prices of the same borrower in the period prior to loan default dates after adjusting for risk in an event study setting. In contrast, in the event period, loan prices fall less than bond prices of the same borrower. Our results are robust to the choice of event window (i.e., 3-day, 11-day or 21-day event window), as well as the choice of the method of computing abnormal returns (i.e., unadjusted, mean-adjusted, market-adjusted, market-model adjusted, Fama-French three-factor model-adjusted, or a loan-bond-stock three-factor model adjusted). However, the event study results have (so far) controlled only for the company name, and not for security specific characteristics, such as maturity, and issue size. We next turn our attention to these issues.

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[16]The Z statistic for the difference in ACARs is based on a paired difference test of CARs of matched loan-bond pairs.

[17]These results are available from the authors on request.

5.1.2. Multivariate results

We define the dependent variable DCAR as simply the difference in CAR, i.e., CAR of a loan minus the CAR of a bond for each loan-bond pair observation. That is, if a loan price of a company falls more than the matched bond price of the same company on a risk-adjusted basis (hypothesis H1), DCAR is negative. For example, for a loan CAR of -4.33% relative to bond CAR of -0.23% for a loan-bond pair, the dependent variable DCAR takes a value of -4.10% (i.e., -4.33%-(-0.23%)) in the cross-sectional regressions. Analogously, if a loan price falls less than the bond price on a risk-adjusted basis (hypothesis H2), DCAR is positive. For example, for a loan CAR of -18.43% as compared to bond CAR of -45.29% for a loan-bond pair, the dependent variable DCAR takes a value of 26.86% (i.e., -18.43%-(-45.29%)) in the regressions. The independent variables, defined for a given loan-bond pair, used in the OLS regressions are:

DLN(MATURITY): Stands for the difference between the natural log of one plus remaining maturity (in years) of the loan and that of the bond, measured as of an event date.

DLN(AMOUNT): Stands for the difference between the natural log of one plus the amount of the loan issue (in $ millions) relative to that of the bond issue.

5.1.2.1. Discussion of the variables

We test hypotheses H1 and H2 by examining the predicted sign (and significance) of the INTERCEPT coefficient in a multivariate regression explaining the determination of DCAR. Consistent with hypothesis H1 (loan prices fall more than bond prices on a risk-adjusted basis leading up to an event period), we expect the INTERCEPT coefficient to be negative. Similarly, consistent with hypothesis H2 (loan prices fall less than bond prices on a risk-adjusted basis in the period immediately surrounding an event), we expect the INTERCEPT coefficient to be positive.

With respect to the control variables in our multivariate regressions, we expect DLN(maturity) to have a negative coefficient since longer-maturity issues are potentially subject to a greater interest-rate risk exposure than shorter-maturity issues, and can have a higher default risk

(Flannery, 1986).[18] Further, with respect to DLN(AMOUNT), we expect larger issues to be more liquid, and to have more publicly available information generated about them. However, on the other hand, larger issues may be more difficult to reorganize post-default. Whether the sign of the DLN(AMOUNT) coefficient is positive or negative is thus an empirical question.

5.1.2.2. Discussion of the results

The multivariate regression results are presented in Panel A in Tables 3 and 4. Table 3 Panel A tests hypothesis H1, and Table 4 Panel A tests hypothesis H2.

In Table 3 Panel A, we test two different model specifications for the period preceding the loan default event period. Consistent with hypothesis H1 (i.e., loan prices fall more than bond prices on a risk-adjusted basis leading up to an event), we find that the INTERCEPT has the expected negative sign, and is statistically significant at the 1% level in both specifications.

In Table 4 Panel A, we test H2 using the same two specifications as in Table 3 Panel A. Consistent with hypothesis H2 (i.e., loan prices fall less than bond prices on a risk-adjusted basis in the period immediately surrounding an event), we find that the INTERCEPT coefficient is positive and statistically significant at the 1% level in both specifications.

Overall, based on the regression results, we find evidence consistent with the hypotheses H1 and H2 described in Section 4. That is, we find that loan prices fall more than bond prices prior to a loan default date, and less than bond prices in short time periods surrounding a loan default date on a risk-adjusted basis after controlling for security-specific characteristics, such as maturity, and issue size. Nevertheless, neither maturity nor issue size appear to offer significant explanation for the determination of the size of DCAR and the explanatory power of 5% (in Table 3 Panel A) and 3% (in Table 4 Panel A) is rather low. This suggests that alternative factors need to be investigated to verify the robustness of the results. These factors are discussed in Section 5.4.

[18] However, since loans are typically floating rate instruments and bonds are fixed rate instruments, when we replaced DLN(maturity) with the difference in duration in our regressions, the results are qualitatively unchanged. We thank Mark Carey for this suggestion.

We next examine whether our hypotheses regarding superior monitoring of loan investors extend to other information intensive events, such as bond default dates and bankruptcies.

5.2. Bond default dates

The results in the previous section suggest that the monitoring advantage of loans over bonds may result in information being incorporated into loan prices faster than bond prices. One could argue that potentially bank loan default events are endogenous to a bank lender and it should not be surprising that loans seem to be informationally more efficient than bonds around loan default dates. To address this issue, we examine next whether we find similar results around events that are more exogenous to bank lenders, such as bond default dates.

These results are presented in Tables 3 Panel B (for hypothesis H1) and 4 Panel B (for hypothesis H2). We find results similar those ones documented in Section 5.1. Interestingly, this evidence suggests that lenders and loan investors are not only better monitors than bondholders in the case of loan defaults but this information advantage extends to bond default dates as well.

5.3. Bankruptcy dates

We examine next whether the evidence of superior monitoring of loan investors extends to bankruptcy dates. We find results similar to those found for bond defaults and loan defaults (see Table 3 Panel C for hypothesis H1, and Table 4 Panel C for hypothesis H2).

Overall, the evidence is generally consistent with loans being informationally more efficient than bonds around loan default, bond default, and bankruptcy dates. However, as stated above in all three cases: loan defaults, bond defaults, and bankruptcies, the explanatory power of the model is low. Consequently, we next test whether our results are robust to alternative explanations for these observed differences in the price reaction of loans versus bonds. These alternative explanations include differences among loan and bond seniority, collateral, recovery rates, liquidity, covenants, timing of defaults, and lender forbearance.

5.4. Alternative explanations

In this section we test for several alternative explanations for the results reported in Sections 5.1 through 5.3. For the sake of brevity, we discuss and present evidence on whether differences in seniority, collateral, recovery rates, liquidity and covenants between loans and bonds explain the difference in price declines prior to and surrounding loan default dates.[19] In addition, we also examine whether timing differences between loan and bond defaults or lender forbearance can explain away these differences.

5.4.1. Seniority, collateral, and recovery rates

In this sub-section we test whether a loan price decline continues to be larger than a bond price decline during the period preceding a loan default (hypothesis H1) after we control for seniority, collateral and recoveries. First, we construct DSENIOR, a variable that stands for the difference in seniority between a loan and a bond. This variable takes a value of one (minus one) if a loan is senior (junior) to a bond, and zero otherwise. Second, we construct DSECURED, a variable that stands for the difference between loan and bond collateral. This variable takes a value of one (minus one) if a loan is more (less) secured relative to a bond, and zero otherwise. Appendix 1 describes the DSENIOR and DSECURED variables in more detail. Finally, we measure the difference in loan-bond recovery rates as the difference in price of a loan and that of a matched bond on the loan default date.[20] See Altman and Kishore (1996) and Altman (1993) for more details. Prices at or soon after default are used in many credit-risk reports, e.g., Altman (annually), Moody's (annually), as well as in the settlement process in the credit default swap market (usually 30 days after default).[21]

One possible reason for a loan price decline being smaller than a bond price decline in

[19] The results are qualitatively similar for loan-bond pairs prior to, and surrounding bond default, and bankruptcy days as well.

[20] Implicitly, we are assuming that the expected recovery rates equal the actual recovery rates.

[21] An alternative measure for the recovery rate is the price at the end of the restructuring process, e.g., Chapter 11 emergence, discounted back to the default date (See Altman and Eberhart (1994)). We have not used this measure since many of the defaults in our study period have not been concluded and the data is not readily available even when completed.

the period immediately surrounding a loan default (hypothesis H2) is simply because loans are more senior or more secured or they tend to recover more than bonds post-bankruptcy (see, Altman (1993)). Hence, we also test whether the observed loan price declines are less than bond price declines in the loan default event period even after controlling for seniority, collateral, and recoveries.

5.4.2. Liquidity

To test whether differences in the liquidity of loans versus bonds explain the relative loan and bond price declines prior to and around a loan default date, we use the difference in the scaled frequency of price changes of a loan minus those on a matched bond as an additional proxy for liquidity. The "scaled" frequency of price changes is defined as the number of non-zero daily return observations, as a fraction of the number of daily return observations during the estimation period [-244,-11] divided by the standard deviation of daily returns during the same period.[22]

5.4.3. Covenants

To test whether differences in covenants of loans and bonds explain our earlier results, we construct a covenant score measure from a scale of 0 to 4 for each loan and bond in a matched loan-bond pair, and include the difference in the covenant score as an additional explanatory variable in a multivariate regression. To construct the covenant score measure for a loan or a bond, we follow Smith and Warner (1979) by classifying a covenant into one of four categories: The first category are investment covenants, such as restrictions on disposition of assets, and restrictions around a merger event in the future. The second category are dividend covenants, such as restrictions on dividends and other distributions to equity holders. The third category are financing covenants, such as restrictions on issuance of debt or equity in the future. Finally, the fourth category are payoff covenants, i.e., provisions that modify the

[22]This scaling allows for a consistent measurement of liquidity across securities of differential risk, where risk is proxied by the standard deviation of daily returns. However, our results are not dependent on this scaling. That is, the results are qualitatively similar (not reported here) if we use the frequency of price changes instead of scaled frequency of price changes.

payoffs to security holders, such as sinking funds, convertibility and callability provisions.

The data sources we used for covenants were the Dealscan database for loans and the Fixed Income Securities Database for bonds.[23] To measure the tightness of covenants we follow an approach similar to the one used by Bagnani et al (1994) by creating separate dummy variables for whether a loan or a bond has at least one covenant in each category type. Specifically, INVCOV = 1 for at least one investment covenant, DIVCOV = 1 for at least one dividend covenant, FINCOV = 1 for at least one financing covenant, and PAYCOV = 1 for at least one covenant modifying the payoff to investors. All dummy variables are zero otherwise. The variable COVENANT SCORE of a loan or bond is defined as the sum of these four dummy variables. Consequently, COVENANT SCORE can take the lowest value of zero for a loan or a bond that has no restrictive covenants in any of the four category types, and the highest value of four for a loan or a bond that has all the four category types. We calculate the difference in covenant scores DIFF COVENANT SCORE as the covenant score of a loan minus that of its matched bond.

5.4.4. Timing of defaults

To test whether the loan-bond price declines documented in Section 5.1 can be explained by the difference in timing of a loan default vis-à-vis a bond default of the same borrower, we construct an indicator variable BOND DEFAULT LEADS that takes a value of one if a bond default leads the loan default of the same borrower.

Overall, when we enter variables measuring differences in seniority, collateral, recovery rates, liquidity, covenants, and timing variables simultaneously in a regression in Tables 5 (see Model 2) for hypothesis H1 and 6 (see Model 2) for hypothesis H2, the INTERCEPT coefficient continues to have the correct sign in both instances and is statistically significant at the 5% level or better. Moreover, the explanatory power of the regression is far higher with an adjusted R^2 for the pre-event period regression of 37% and 57% for the event period regression

[23] We consider both the explicit information (e.g., a restriction on issuance of future debt) and implicit information (e.g., a leverage covenant due to which a firm cannot exceed a certain leverage, implies a restriction on future debt financing) in classifying covenants into the four category types − both these covenants are classified as financing covenants.

itself. With respect to the Table 5 (Model 2), we find that DSENIOR, DSECURED, DIFF RECOVERY RATE, DIFF SCALED FREQUENCY OF PRICE CHANGES, and PRIOR BOND DEFAULT have the expected sign (see below) and are all statistically significant. For example, as expected, we find a positive relationship between DSENIOR and DCAR since the greater the seniority of a loan relative to its matched bond, the lower is the price decline of a loan relative to the matched bond. Similarly, we expect a positive relationship between DSECURED and DCAR, and DIFF RECOVERY RATE and DCAR as well. With respect to the relationship between DIFF SCALED FREQUENCY OF PRICE CHANGES and DCAR, it could be either positive or negative – a more liquid security may have a lower price decline being less risky ex ante, or a higher price decline since it is easier to trade out of in the event of a default. To the extent that a prior bond default serves as an informative signal, we expect a negative relationship between this variable and DCAR. Finally, as expected, we find with respect to the event period tests (Table 6) DSENIOR, DSECURED, and DIFF COVENANT SCORE are all positive and significant.

This suggests that the loan-bond price declines are not fully explained by differences in seniority, collateral, recoveries, liquidity, covenants, and the timing of a loan default vis-à-vis a bond default of the same borrower, and hence the monitoring advantage of loans over bonds continues to be an important factor in determining observed price declines prior to, and in periods surrounding loan default dates.

5.5. Lender forbearance

A loan may not be considered to be in default when a company misses a promised payment but rather is only placed in default after a (certain) grace period granted by a bank lender. In contrast a bond is considered to be in default as soon as the company misses a promised payment, such as interest coupon (i.e., no grace period). This may bias the difference in CARs of loans versus bonds (DCAR) around loan default dates (H2). In other words, the CAR of loans could be smaller than that for bonds around loan default dates simply because the loan default dates may be biased due to bank forbearance on delinquent loans. We test this alternative explanation by examining whether the CAR results change if we expand the event window to include a possible forbearance period of 30-90 days − loans that fail to accrue interest for more than 90 days are generally considered non-performing assets while the Federal Reserve usually treats a loan as non-performing if the borrower does not pay interest on the loan for more than 30 days.

The results corresponding to Table 2 (not reported here), for three different expanded event windows employed to capture a possible forbearance period of one month, two months or three months (i.e., for windows [-20,+10], [-40,+10] and [-60,+10], assuming each month corresponds to approximately 20 business days based on an estimation window of [-244,-61]) reveal that the loan ACAR in the event period is smaller than the bond ACAR (and the difference is statistically significant at the 5% level) in each of these cases where we allow for a potential forbearance period of respectively one month, two months, and three months.

5.6. Robustness: An alternative empirical methodology

So far our tests have been based on the differences in cumulative abnormal returns between loans and bonds in the period leading up to and during a default or bankruptcy "event". An alternative methodology to investigate the relationship between loan and bond returns is to use Granger-causality tests (see, Granger (1969) and Sims (1972) for details). We follow the Hotchkiss and Ronen (2002) methodology, for testing the informational efficiency of bonds versus stocks, by conducting Granger-causality tests based on Vector-Auto Regression (VAR) models for loans versus bonds. Specifically, we equally weight loan returns and bond returns of matched loan-bond pairs (based on the name of the borrower) in event time, and examine whether loan returns "Granger cause" bond returns or bond returns "Granger cause" loan returns during the pre-event period [-244,-11] as well as the pre- and event period [-244,10], where day 0 refers to a loan default date, bond default date, or a bankruptcy date. To test the null that loan returns do not Granger cause bond returns, we rely on a bivariate VAR model (equation 8), and estimate by ordinary least squares (OLS):

$$RB_t = c_1 + \sum_{i=1}^{j} a_{1,i} RB_{t-i} + \sum_{i=1}^{j} b_{1,i} RL_{t-i} + \nu_{1,t}. \tag{8}$$

Similarly, to test the null that bond returns do not Granger cause loan returns, we rely on a similar bivariate VAR model (equation 9):

$$RL_t = c_2 + \sum_{i=1}^{j} a_{2,i} RL_{t-i} + \sum_{i=1}^{j} b_{2,i} RB_{t-i} + \nu_{2,t}, \tag{9}$$

where, RB_t is the equally-weighted bond return, RL_t is the equally-weighted loan return, and omitting the suffixes, a's and b's are OLS coefficient estimates, c's are the regression constants, ν_t's are the disturbance terms, and j is the lag length. We then conduct F-tests of the null hypothesis that loan returns do not Granger cause bond returns using equation (10), and for the null hypothesis that bond returns do not Granger cause loan returns using equation (11):

$$H_0 : b_{1,i} = 0, \forall i, \tag{10}$$

$$H_0 : b_{2,i} = 0, \forall i. \tag{11}$$

Following Hamilton (1994) we test equations (8) and (9) using lag lengths from 1 to 10 days. We consider three sub samples of data: (a) firms that defaulted on their loans, (b) firms that defaulted on their bonds, and (c) firms that went bankrupt, during the sample period.[24]

Table 7 summarizes the results of the Granger causality tests. As expected, consistent with our CAR results, we find strong evidence that loan returns "Granger cause" bond returns for all sub samples, especially at higher lag lengths. However, we find no evidence that bond returns "Granger cause" loan returns for any of the sub samples.

In summary, consistent with our results based on CARs, we find evidence that loan re-

[24]For a similar approach see Kwan (1996) who uses a lag length of one.

turns "Granger cause" bond returns for firms subject to high information intensity events, such as default and bankruptcy.

5.6. Loans versus stocks

We next examine whether our loan-bond results extend to loan-stock pairs. Moreover, comparing the price reaction of loans relative to stocks serves as a direct, rather than an indirect, test of the monitoring role of loans (see, James (1987), Lummer and McConnell (1989), and Billett, Flannery, and Garfinkel (1995)). Specifically, in previous empirical literature testing the specialness of banks and the monitoring role of loans, the stock price reaction of a borrower to the announcement of a new loan or a renewal of an existing loan were examined. Such tests may be viewed as indirect tests rather than direct tests, analyzing the behavior of loan prices, before and around default and bankruptcy events as described here.

Table 8 presents the results for matched loan-stock pairs where we were able to compute the CAR based on the market-model adjusted method for a [-10,+10] event window. That is, the return based on a market-model regression (using a market index such as the S&P/LSTA Leveraged Loan Index for loans, or a value-weighted NYSE/NASDAQ/AMEX index for stocks) is subtracted from the loan or stock daily return respectively.

We find evidence consistent with both hypotheses H1 and H2 as outlined in Section 4. In particular, consistent with hypothesis H1, loans fall by 3.66% during the time period leading up to a loan default event [-244,-11], while stocks rise by 1.09%. The difference in the loan average CAR (loan ACAR) and the stock average CAR (stock ACAR) of -4.75% (i.e., -3.66%-(1.09%)) is statistically significant at the 5% level (Z-stat -2.09). Similarly, consistent with hypothesis H2, loans fall by 13.16% during the 21 day [-10,+10] window surrounding loan default dates, while stocks fall by 52.14%. The difference in the loan average CAR (loan ACAR) and the stock average CAR (stock ACAR) of 38.98% (i.e., -13.16%-(-52.14%)) is statistically significant at the 1% level (Z-stat 5.08). The results are qualitatively similar for bond default days and bankruptcy dates (see, Table 8).

6. Conclusions

We find that the loan market is informationally more efficient than the bond market around events, such as loan default, bond default, and bankruptcy dates. Specifically, consistent with hypothesis H1, we find that risk-adjusted loan prices fall more than risk-adjusted bond prices of the same borrower prior to an event date. In addition, consistent with hypothesis H2, we find that risk-adjusted loan prices fall less than risk-adjusted bond prices of the same borrower in the periods surrounding an event date. Moreover, these results are robust to several alternative explanations. Controlling for security-specific characteristics, such as maturity, size, seniority, collateral, covenants, and for multiple measures of cumulative abnormal returns around loan default, bond default, and bankruptcy dates, we find that our initial results are highly robust. Further, our results are also robust to a different empirical methodology (Vector Auto Regression based Granger causality).

Overall, our results have important implications regarding the continuing specialness of banks and bank loans, for the benefits of loan monitoring for other financial markets (such as the bond market and the stock market), and for the benefits of including loans as a separate asset class in an investment portfolio since loan returns are generally not highly correlated with bond and stock returns.

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TABLE 1
Descriptive statistics

This table presents descriptive statistics of variables used in the regression models (see Tables 3 through 6) for loan-bond pairs (N) matched based on the name of the borrower for the loan default sub sample in Panel A, the bond default sub sample in Panel B, and the bankruptcy sub sample in Panel C of the same company. See Appendix 1 for variable definitions. In this table, superscripts a, b, and c stand for statistical significance at the 1%, 5%, and 10% levels using a two-tailed test, and nm refers to "not meaningful".

Panel A: Loan default dates (N=80)

	Loans		Bonds		Difference	
Variable	Mean	T-stat	Mean	T-stat	Mean	T-stat
Maturity (years)	5.91	34.14[a]	5.69	21.23[a]	0.22	0.61
Amount ($ million)	614.66	12.36[a]	440.72	12.41[a]	173.96	2.91[a]
Senior (fraction)	1.00	nm	0.88	23.52[a]	0.12	3.36[a]
Secured (fraction)	0.90	26.66[a]	0.31	5.99[a]	0.59	7.85[a]
Recovery rate (% of par value)	64.80	27.96[a]	29.79	14.85[a]	35.01	36.81[a]
Frequency of price changes	0.49	16.50[a]	0.29	13.12[a]	0.19	5.80[a]
Scaled frequency of price changes	95.69	11.17[a]	9.59	10.23[a]	86.11	10.70[a]
Covenant Score (0-4)	2.16	12.93[a]	3.35	54.13[a]	-1.19	-7.15[a]

Panel B: Bond default dates (N=109)

	Loans		Bonds		Difference	
Variable	Mean	T-stat	Mean	T-stat	Mean	T-stat
Maturity (years)	5.37	28.98[a]	6.25	19.80[a]	-0.88	-2.11[b]
Amount ($ million)	649.43	14.34[a]	422.64	14.91[a]	226.79	4.51[a]
Senior (fraction)	1.00	nm	0.83	22.62[a]	0.17	4.77[a]
Secured (fraction)	0.72	16.86[a]	0.24	5.82[a]	0.48	8.02[a]
Recovery rate (% of par value)	65.44	31.58[a]	28.97	14.85[a]	36.47	18.33[a]
Frequency of price changes	0.43	15.06[a]	0.23	12.14[a]	0.20	6.76[a]
Scaled frequency of price changes	84.14	10.73[a]	7.10	9.21[a]	77.04	10.38[a]
Covenant Score (0-4)	2.10	15.17[a]	3.33	45.13[a]	-1.23	-8.13[a]

Panel C: Bankruptcy dates (N=92)

	Loans		Bonds		Difference	
Variable	Mean	T-stat	Mean	T-stat	Mean	T-stat
Maturity (years)	5.42	25.79[a]	6.17	16.73[a]	-0.75	-1.51
Amount ($ million)	646.12	14.02[a]	417.80	13.13[a]	228.32	4.04[a]
Senior (fraction)	1.00	nm	0.88	25.89[a]	0.12	3.51[a]
Secured (fraction)	0.83	20.79[a]	0.27	5.83[a]	0.56	8.15[a]
Recovery rate (% of par value)	61.32	28.03[a]	31.25	15.08[a]	30.07	21.23[a]
Frequency of price changes	0.45	15.37[a]	0.27	13.08[a]	0.18	6.03[a]
Scaled frequency of price changes	80.89	12.37[a]	7.49	11.09[a]	73.40	11.84[a]
Covenant Score (0-4)	2.18	14.91[a]	3.22	39.46[a]	-1.04	-6.70[a]

TABLE 2
Average cumulative abnormal returns of matched loan-bond pairs surrounding loan default, bond default, and bankruptcy dates

This table presents the average cumulative abnormal return (ACAR) of matched loan-bond pairs (based on the name of the borrower) surrounding a loan default date in Panel A, a bond default date in Panel B, and a bankruptcy date in Panel C of the same company. This table includes matched loan-bond pairs where we are able to compute the CAR based on the market-model adjusted method for the [-10,+10] event window. That is, the return based on a market-model regression using a market index (such as the S&P/LSTA Leveraged Loan Index for loans, or the Lehman Brothers U.S. Corporate Intermediate Bond Index for bonds) is subtracted from the loan or bond daily return respectively. The Z statistics of ACARs in the event window (shown in parentheses) are computed using the methodology of Brown and Warner (1985) that considers both the time-series and cross-sectional dependence in returns. The Z statistics for the difference in ACARs are based on a paired difference test of CARs of matched loan-bond pairs (N), and are shown in parentheses, where a, b, and c stand for significance at the 1%, 5%, and 10% levels using a two-tailed test.

Panel A: Loan default dates (N=80)

	Loan ACAR (%) (1)	Bond ACAR (%) (2)	Difference in ACAR (%) (3) = (1) - (2)
Event window			
[-1,+1]	-3.74	-19.30	15.56
	(-4.43)^a	(-8.45)^a	(7.46)^a
[-5,+5]	-9.53	-36.83	27.30
	(-5.89)^a	(-8.42)^a	(6.80)^a
[-10,+10]	-18.43	-45.29	26.86
	(-8.25)^a	(-7.49)^a	(4.68)^a
Pre-estimation period	-4.33	-0.23	-4.10
[-244,-11]	(-2.84)^a	(-1.42)	(-2.59)^a

Panel B: Bond default dates (N=109)

	Loan ACAR (%) (4)	Bond ACAR (%) (5)	Difference in ACAR (%) (6) = (4) - (5)
Event window			
[-1,+1]	-3.23	-12.47	9.24
	(-5.36)^a	(-5.70)^a	(4.95)^a
[-5,+5]	-9.21	-25.40	16.19
	(-7.99)^a	(-6.07)^a	(4.83)^a
[-10,+10]	-14.71	-29.75	15.04
	(-9.24)^a	(-5.14)^a	(2.98)^a
Pre-estimation period	-3.12	0.00	-3.12
[-244,-11]	(-2.75)^a	(-0.01)	(-2.68)^a

Panel C: Bankruptcy dates (N=92)

	Loan ACAR (%) (7)	Bond ACAR (%) (8)	Difference in ACAR (%) (9) = (7) - (8)
Event window			
[-1,+1]	-3.87	-12.18	8.31
	(-5.37)[a]	(-4.68)[a]	(4.85)[a]
[-5,+5]	-9.95	-27.65	17.70
	(-7.21)[a]	(-5.55)[a]	(4.41)[a]
[-10,+10]	-16.93	-32.52	15.59
	(-8.88)[a]	(-4.72)[a]	(3.00)[a]
Pre-estimation period	-3.70	-0.11	-3.59
[-244,-11]	(-2.77)[a]	(-0.80)	(-2.60)[a]

TABLE 3
Linear regression of difference in cumulative abnormal return prior to loan default, bond default, and bankruptcy dates

This table presents OLS estimates of regression specifications determining the cumulative abnormal return (CAR) performance of loans and bonds prior to loan default, bond default, and bankruptcy dates of the same company. The dependent variable DCAR, measured as a percentage, equals loan CAR[-244,-11] minus bond CAR[-244,-11], where day [0] refers to an event date, namely the loan default date (in Panel A), the bond default date (in Panel B), and the bankruptcy date (in Panel C) of the same company. The CARs are computed based on market-model adjustment, i.e., the return based on a market-model regression (using a market index such as the S&P/LSTA Leveraged Loan Index for loans and the Lehman Brothers U.S. Corporate Intermediate Bond Index for bonds) is subtracted from the loan or bond daily return. The independent variables are as follows: DLN(MATURITY) stands for the difference in the natural log of one plus remaining maturity (in years) of the loan and that of the bond, as on a event date. DLN(AMOUNT) stands for the difference in natural log of one plus the amount of the loan issue (in $ millions) and that of the bond issue. To facilitate comparison with other tables in this paper, this table includes matched loan-bond pairs where we are able to compute the CAR based on the market-model adjusted method for the [-10,+10] event window. The t ratios shown in parentheses are adjusted for heteroskedasticity using White's (1980) variance-covariance matrix (a, b, and c stand for significance at the 1%, 5%, and 10% levels using a two-tailed test).

Panel A: Loan default dates

Dependent Variable: DCAR[-244,-11]		
Variable	Model 1	Model 2
INTERCEPT	-4.63	-5.09
	(-2.95)^a	(-2.77)^a
DLN(MATURITY)	5.34	2.87
	(2.38)^b	(0.95)
DLN(AMOUNT)		2.39
		(1.40)
Observations	80	80
Adjusted R^2	0.04	0.05

Panel B: Bond default dates

Dependent Variable: DCAR[-244,-11]		
Variable	Model 1	Model 2
INTERCEPT	-2.96	-3.78
	(-2.68)^a	(-2.74)^a
DLN(MATURITY)	1.79	1.17
	(1.59)	(1.21)
DLN(AMOUNT)		2.34
		(2.52)^a
Observations	109	109
Adjusted R^2	0.01	0.03

Panel C: Bankruptcy dates

Dependent Variable: DCAR[-244,-11]		
Variable	Model 1	Model 2
INTERCEPT	-3.47	-4.67
	(-2.62)^a	(-2.71)^a
DLN(MATURITY)	2.00	1.32
	(1.64)	(1.34)
DLN(AMOUNT)		2.85
		(2.54)^b
Observations	92	92
Adjusted R^2	0.00	0.05

TABLE 4
Linear regression of difference in cumulative abnormal return surrounding loan default, bond default, and bankruptcy dates

This table presents OLS estimates of regression specifications determining the cumulative abnormal return (CAR) performance of loans and bonds surrounding loan default, bond default, and bankruptcy dates of the same company. The dependent variable DCAR, measured as a percentage, equals loan CAR[-10,+10] minus bond CAR[-10,+10], where day [0] refers to an event date, namely the loan default date (in Panel A), the bond default date (in Panel B), and the bankruptcy date (in Panel C) of the same company. The CARs are computed based on market-model adjustment, i.e., the return based on a market-model regression (using a market index such as the S&P/LSTA Leveraged Loan Index for loans and the Lehman Brothers U.S. Corporate Intermediate Bond Index for bonds) is subtracted from the loan or bond daily return. The independent variables are as follows: DLN(MATURITY) stands for the difference in the natural log of one plus remaining maturity (in years) of the loan and that of the bond, as on a event date. DLN(AMOUNT) stands for the difference in natural log of one plus the amount of the loan issue (in $ millions) and that of the bond issue. To facilitate comparison with other tables in this paper, this table includes matched loan-bond pairs where we are able to compute the CAR based on the market-model adjusted method for the [-10,+10] event window. The t ratios shown in parentheses are adjusted for heteroskedasticity using White's (1980) variance-covariance matrix (a, b, and c stand for significance at the 1%, 5%, and 10% levels using a two-tailed test).

Panel A: Loan default dates

Dependent Variable: DCAR[-10,+10]		
Variable	Model 1	Model 2
INTERCEPT	26.34	24.52
	$(4.26)^a$	$(3.68)^a$
DLN(MATURITY)	5.36	-4.34
	(0.88)	(-0.59)
DLN(AMOUNT)		9.37
		$(1.80)^c$
Observations	80	80
Adjusted R^2	0.00	0.03

Panel B: Bond default dates

Dependent Variable: DCAR[-10,+10]		
Variable	Model 1	Model 2
INTERCEPT	16.18	17.49
	$(3.37)^a$	$(2.95)^a$
DLN(MATURITY)	12.44	13.44
	$(3.42)^a$	$(4.32)^a$
DLN(AMOUNT)		-3.75
		(-0.90)
Observations	109	109
Adjusted R^2	0.02	0.02

Panel C: Bankruptcy dates

Dependent Variable: DCAR[-10,+10]		
Variable	Model 1	Model 2
INTERCEPT	16.26	18.14
	$(3.26)^a$	$(2.87)^a$
DLN(MATURITY)	11.01	12.08
	$(2.91)^a$	$(3.70)^a$
DLN(AMOUNT)		-4.46
		(-1.06)
Observations	92	92
Adjusted R^2	0.02	0.02

TABLE 5
Robustness tests for alternative explanations of price declines leading upto loan default dates

This table presents robustness tests for alternative explanations of price declines around loan default dates. See TABLE 3 Model 2 for the regression specification and definitions of variables. Additional variables used in this table are: DSENIOR stands for the difference in seniority between a loan and a bond, and takes a value of one (minus one) if a loan is senior (junior) to a bond, and zero otherwise. DSECURED stands for the difference in loan-bond collateral, and takes a value of one (minus one) if a loan is more (less) secured relative to a bond, and zero otherwise. DIFF RECOVERY RATE refers to the recovery rate of a loan minus the recovery rate of a bond, where recovery rate is defined as the amount an investor expects from her investment in the loan or the bond subsequent to the loan default date, and is proxied by the price of the loan or the bond on the loan default date. DIFF SCALED FREQUENCY OF PRICE CHANGES refers to the scaled frequency of price changes of a loan minus the scaled frequency of price changes of a bond, where scaled frequency of price changes refers to the number of non-zero daily return observations as a fraction of the number of daily return observations during the estimation period [-244,-11], further scaled by the standard deviation of daily returns during the same period. DIFF COVENANT SCORE is the covenant score of a loan minus the covenant score of a bond, where covenant score is defined as the sum of four dummy variables that represent four loan/bond covenants as described in Smith and Warner (1979), namely, INVCOV = 1 for restrictions on investments, DIVCOV = 1 for restrictions on dividends, FINCOV = 1 for restrictions of financing, and PAYCOV = 1 for covenants modifying payoff to investors. The t ratios shown in parentheses are adjusted for heteroskedasticity using White's (1980) variance-covariance matrix (a, b, and c stand for significance at the 1%, 5%, and 10% levels using a two-tailed test).

Dependent Variable: DCAR[-244,-11]

	Benchmark model	Alternative explanations
Variable	Model 1	Model 2
INTERCEPT	-5.09	-29.82
	(-2.77)^a	(-3.90)^a
DLN(MATURITY)	2.87	-0.76
	(0.95)	(-0.34)
DLN(AMOUNT)	2.39	0.09
	(1.40)	(0.07)
DSENIOR		3.97
		(1.64)^c
DSECURED		10.51
		(3.33)^a
DIFF RECOVERY RATE		0.48
		(3.27)^a
DIFF SCALED FREQUENCY OF PRICE CHANGES		0.03
		(2.11)^b
DIFF COVENANT SCORE		-0.17
		(-0.19)
PRIOR BOND DEFAULT		-2.67
		(-1.66)^c
Observations	80	80
Adjusted R^2	0.05	0.37

TABLE 6
Robustness tests for alternative explanations of price declines around loan default dates

This table presents robustness tests for alternative explanations of price declines around loan default dates. See TABLE 4 Model 2 for the regression specification and the definitions of variables. Additional variables used in this table are: DSENIOR stands for the difference in seniority between a loan and a bond, and takes a value of one (minus one) if a loan is senior (junior) to a bond, and zero otherwise. DSECURED stands for the difference in loan-bond collateral, and takes a value of one (minus one) if a loan is more (less) secured relative to a bond, and zero otherwise. DIFF RECOVERY RATE refers to the recovery rate of a loan minus the recovery rate of a bond, where recovery rate is defined as the amount an investor expects from her investment in the loan or the bond subsequent to the loan default date, and is proxied by the price of the loan or the bond on the loan default date. DIFF SCALED FREQUENCY OF PRICE CHANGES refers to the scaled frequency of price changes of a loan minus the scaled frequency of price changes of a bond, where scaled frequency of price changes refers to the number of non-zero daily return observations as a fraction of the number of daily return observations during the estimation period [-244,-11], further scaled by the standard deviation of daily returns during the same period. DIFF COVENANT SCORE is the covenant score of a loan minus the covenant score of a bond, where covenant score is defined as the sum of four dummy variables that represent four loan/bond covenants as described in Smith and Warner (1979), namely, INVCOV = 1 for restrictions on investments, DIVCOV = 1 for restrictions on dividends, FINCOV = 1 for restrictions of financing, and PAYCOV = 1 for covenants modifying payoff to investors. The t ratios shown in parentheses are adjusted for heteroskedasticity using White's (1980) variance-covariance matrix (a, b, and c stand for significance at the 1%, 5%, and 10% levels using a two-tailed test).

Dependent Variable: DCAR[-10,+10]

	Benchmark model	Alternative explanations
Variable	Model 1	Model 2
INTERCEPT	24.52	55.15
	$(3.68)^a$	$(2.12)^b$
DLN(MATURITY)	-4.34	5.17
	(-0.59)	(0.88)
DLN(AMOUNT)	9.37	-15.58
	$(1.80)^c$	$(-3.91)^a$
DSENIOR		46.18
		$(3.67)^a$
DSECURED		72.41
		$(9.34)^a$
DIFF RECOVERY RATE		-1.41
		$(-2.17)^b$
DIFF SCALED FREQUENCY OF PRICE CHANGES		-0.19
		$(-3.09)^a$
DIFF COVENANT SCORE		5.42
		$(2.03)^b$
PRIOR BOND DEFAULT		-2.68
		(-0.26)
Observations	80	80
Adjusted R^2	0.03	0.57

TABLE 7
Granger causality tests using a bivariate vector auto regression (VAR)

This table summarizes the results of Granger causality tests. Following Hotchkiss and Ronen (2002), we use equally-weighted (in event time) loan returns and bond returns of matched loan-bond pairs (based on the name of the borrower) surrounding a loan default date in Panel A, a bond default date in Panel B, and a bankruptcy date in Panel C of the same company. Specifically, we conduct an F-test of the null hypothesis that loan returns do not Granger cause the bond returns by equation (10), and for the null hypothesis that bond returns do not Granger cause the loan returns by equation (11). Superscripts a, b, and c stand for statistical significance of the reported F-statistic (in rejecting the null hypothesis of no Granger causality) at the 1%, 5%, and 10% levels respectively.

Panel A: Loan default dates

	Pre-event period [-244,-11]		Pre- and event period [-244,10]	
	Loan returns Granger cause Bond returns	Bond returns Granger cause Loan returns	Loan returns Granger cause Bond returns	Bond returns Granger cause Loan returns
Lags	F-statistic	F-statistic	F-statistic	F-statistic
1	0.04	0.66	0.01	1.29
2	0.02	1.72	0.04	1.50
3	0.29	2.14	0.17	1.87
4	1.75	1.58	1.92	1.38
5	1.69	1.19	1.68	1.07
6	1.52	0.98	1.49	0.87
7	8.13^a	0.88	8.80^a	0.75
8	8.18^a	0.69	8.30^a	0.65
9	7.45^a	0.81	7.59^a	0.71
10	7.16^a	0.71	7.28^a	0.61

Panel B: Bond default dates

	Pre-event period [-244,-11]		Pre- and event period [-244,10]	
	Loan returns Granger cause Bond returns	Bond returns Granger cause Loan returns	Loan returns Granger cause Bond returns	Bond returns Granger cause Loan returns
Lags	F-statistic	F-statistic	F-statistic	F-statistic
1	0.03	0.83	0.10	1.50
2	0.05	1.14	0.05	1.24
3	0.24	1.42	0.17	1.35
4	1.64	1.08	1.83	1.00
5	1.37	0.82	1.51	0.78
6	1.28	0.66	1.36	0.63
7	6.66^a	0.67	7.28^a	0.64
8	6.17^a	0.51	6.63^a	0.46
9	5.49^a	0.64	5.91^a	0.53
10	4.98^a	0.66	5.33^a	0.54

Panel C: Bankruptcy dates

	Pre-event period [-244,-11]		Pre- and event period [-244,10]	
	Loan returns Granger cause Bond returns	Bond returns Granger cause Loan returns	Loan returns Granger cause Bond returns	Bond returns Granger cause Loan returns
Lags	F-statistic	F-statistic	F-statistic	F-statistic
1	0.00	0.86	0.06	1.79
2	0.14	1.36	0.09	1.30
3	0.37	1.79	0.23	1.48
4	1.95	1.42	2.07	1.14
5	1.83	1.02	1.81	1.14
6	1.62	0.83	1.57	0.85
7	7.22[a]	0.84	7.47[a]	0.69
8	6.63[a]	0.69	6.70[a]	0.66
9	5.95[a]	0.75	6.01[a]	0.54
10	5.39[a]	0.70	5.41[a]	0.51

TABLE 8
Average cumulative abnormal returns of matched loan-stock pairs surrounding loan default, bond default, and bankruptcy dates

This table presents the average cumulative abnormal return (ACAR) of matched loan-stock pairs (based on the name of the borrower) surrounding a loan default date in Panel A, a bond default date in Panel B, and a bankruptcy date in Panel C of the same company. This table includes matched loan-stock pairs where we are able to compute the CAR based on the market-model adjusted method for the [-10,+10] event window. That is, the return based on a market-model regression (using a market index such as the S&P/LSTA Leveraged Loan Index for loans, or a value-weighted NYSE/NASDAQ/AMEX index for stocks) is subtracted from the loan or stock daily return respectively. The t ratios of ACARs are computed using the methodology of Brown and Warner (1985) that considers both the time-series and cross-sectional dependence in returns. The t ratios for differences are based on pair-wise difference in the ACARs of matched loan-stock pairs (N). The t ratios are shown in parentheses, where a, b, and c stand for significance at the 1%, 5%, and 10% levels using a two-tailed test.

Panel A: Loan default dates (N=29)

	Loan ACAR (%) (1)	Stock ACAR (%) (2)	Difference in ACAR (%) (3) = (1) - (2)
Event window			
[-1,+1]	0.21	-30.77	30.98
	(0.17)	(-5.63)^a	(3.62)^a
[-5,+5]	-4.87	-32.84	27.97
	(-2.08)^a	(-3.14)^a	(2.94)^a
[-10,+10]	-13.16	-52.14	38.98
	(-4.93)^a	(-4.04)^a	(5.08)^a
Pre-estimation period	-3.66	1.09	-4.75
[-244,-11]	(-1.68)^c	(2.81)^a	(-2.09)^b

Panel B: Bond default dates (N=59)

Event window	Loan ACAR (%) (4)	Stock ACAR (%) (5)	Difference in ACAR (%) (6) = (4) - (5)
[-1,+1]	-0.38	-17.27	16.89
	(-0.76)	(-5.40)^a	(3.87)^a
[-5,+5]	-4.30	-25.39	21.09
	(-4.48)^a	(-4.14)^a	(4.57)^a
[-10,+10]	-6.38	-44.57	38.19
	(-4.76)^a	(-5.28)^a	(1.47)
Pre-estimation period	-1.62	1.35	-2.97
[-244,-11]	(-1.46)	(5.49)^a	(-2.59)^b

Panel C: Bankruptcy dates (N=27)

	Loan ACAR (%) (7)	Stock ACAR (%) (8)	Difference in ACAR (%) (9) = (7) - (8)
Event window			
[-1,+1]	-0.24	-28.47	28.23
	(-0.22)	(-6.04)^{a}	(2.82)^{a}
[-5,+5]	-5.78	-34.17	28.39
	(-2.75)^{a}	(-3.79)^{a}	(2.17)^{b}
[-10,+10]	-10.97	-39.04	28.07
	(-3.78)^{a}	(-3.13)^{a}	(2.67)^{a}
Pre-estimation period	-3.94	0.10	-4.04
[-244,-11]	(-3.11)^{a}	(6.39)^{a}	(-1.71)^{c}

Appendix 1
Datasets used in this study

This appendix outlines a brief overview of the datasets that we use in this study. We list the providers of this data, and how the data was processed into individual datasets used in this study.

Loan price dataset

The source for this data is the Loan Syndications and Trading Association (LSTA) and Loan Pricing Corporation (LPC) mark-to-market pricing service, an independent and objective pricing service to more than 100 institutions, managing almost 175 portfolios with over $200 billion in bank loan assets. This unique dataset consists of daily bid and ask price quotes aggregated across dealers. Each loan has a minimum of at least two dealer quotes and a maximum of over 30 dealers, including all top broker-dealers. At the time we received the dataset from LSTA, there were 33 dealers providing quotes to the LSTA/LPC mark-to-market pricing service. These price quotes are obtained on a daily basis by LSTA in the late afternoon from the dealers and the price quotes reflect the market events for the day. The data items in this database include a unique loan identification number (LIN), name of the issuer (Company), type of loan, e.g., term loan (facility), date of pricing (Pricing Date), average of bid quotes (Avg Bid), number of bid quotes (Bid Quotes), average of second and third highest bid quote (High Bid Avg), average of ask quotes (Avg Ask), number of ask quotes (Ask Quotes), average of second and third lowest ask quotes (Low Ask Avg), and a type of classification based on the number of quotes received, e.g., Class II if 3 or more bid quotes.

The daily data from 11/1999 thru 07/2002 in the form of individual excel spreadsheets were combined in SAS based on the unique loan identification number (LIN). We excluded loans with a missing LIN since there is no unique way of combining them. We have 560,958 loan-day observations in our loan price data spanning 1,863 loans.

Bond price (Yield Book) dataset

We extracted daily bond prices for the companies for which we have loans in the loan price dataset in the following manner: First, we found all the available matching Yield Book IDs from the Fixed Income Securities Database (FISD), namely the 9-digit identifiers comprising a 6 digit issuer cusip plus a 3 digit issue cusip for the bonds pertaining to the companies in the loan price dataset. The matching was done manually to ensure that we do not miss any bonds due to errors, such as an abbreviated company name in one database and its full name in another database. Second, we extracted daily prices of the bonds from the Salomon Yield Book based on their 9-digit identifiers. We have a total of 386,171 bond-day observations spanning 816 bonds.

Bond price (Datastream) dataset

We extracted daily bond prices for a subset of loans in the loan price dataset with a loan default date, bond default date or a bankruptcy in the following manner: First, we checked both the current list of Datastream codes of live bonds and the list on the Datastream Extranet which contains the dead bonds. Second, we extracted daily prices of the bonds from Datastream based on their 6-digit identifiers. We have a total of 91,760 bond-day observations spanning 248 bonds.

Stock price dataset

We extracted daily stock prices and returns for the companies for which we have loans in the loan price dataset in the following manner: First, we found all the available matching permnos for the stocks pertaining to the companies in the loan price dataset. The matching was done manually to ensure that we do not miss any stocks due to errors, such as an abbreviated company name in one database and its full name in another database, extra characters in one database as compared to the other. If we could still not find a match, we checked on Hoovers Online, Mergent Online and finally on Google. If the company is a subsidiary of a larger company we used the parent companys permno. Second, we extracted daily prices and stocks from the

CRSP stock files based on the permnos. We have a total of 21,741 stock-day observations spanning 75 stocks corresponding to a subset of loans in the loan price dataset with a loan default, bond default or a bankruptcy.

Loan defaults dataset

The loan defaults dataset consists of loan defaults from the institutional loans market. We received this data from Portfolio Management Data (PMD), a business unit of Standard & Poors (recently changed its name to "Standard & Poor's Leveraged Commentary & Data") which has been tracking loan defaults in the institutional loans market since 1995. We verified these dates in Lexis/Nexis and confirmed that they correspond to a missed interest or a principal payment rather than a technical violation of a covenant.

Bond defaults dataset

The source for our bond defaults dataset is the "New York University (NYU) Salomon Center's Altman Bond Default Database". It is a comprehensive dataset of domestic corporate bond default dates starting from 1974.

Bankruptcy dataset

The source for our bankruptcy dataset is www.bankruptcydata.com. We also verified these dates on Lexis/Nexis.

Loan characteristics dataset

The source for our loan characteristics dataset is the Loan Pricing Corporation, especially the Dealscan Database. We used the information we obtained from Loan Pricing Corproation for each loan in our loan price dataset, such as issue date, issue amount, and maturity, to best identify the relevant loan in Dealscan database. We used the information on Seniority, Collateral, Covenants of the best-matched loan to create independent variables, such as SENIOR, SECURED, COVENANT SCORE for each loan.

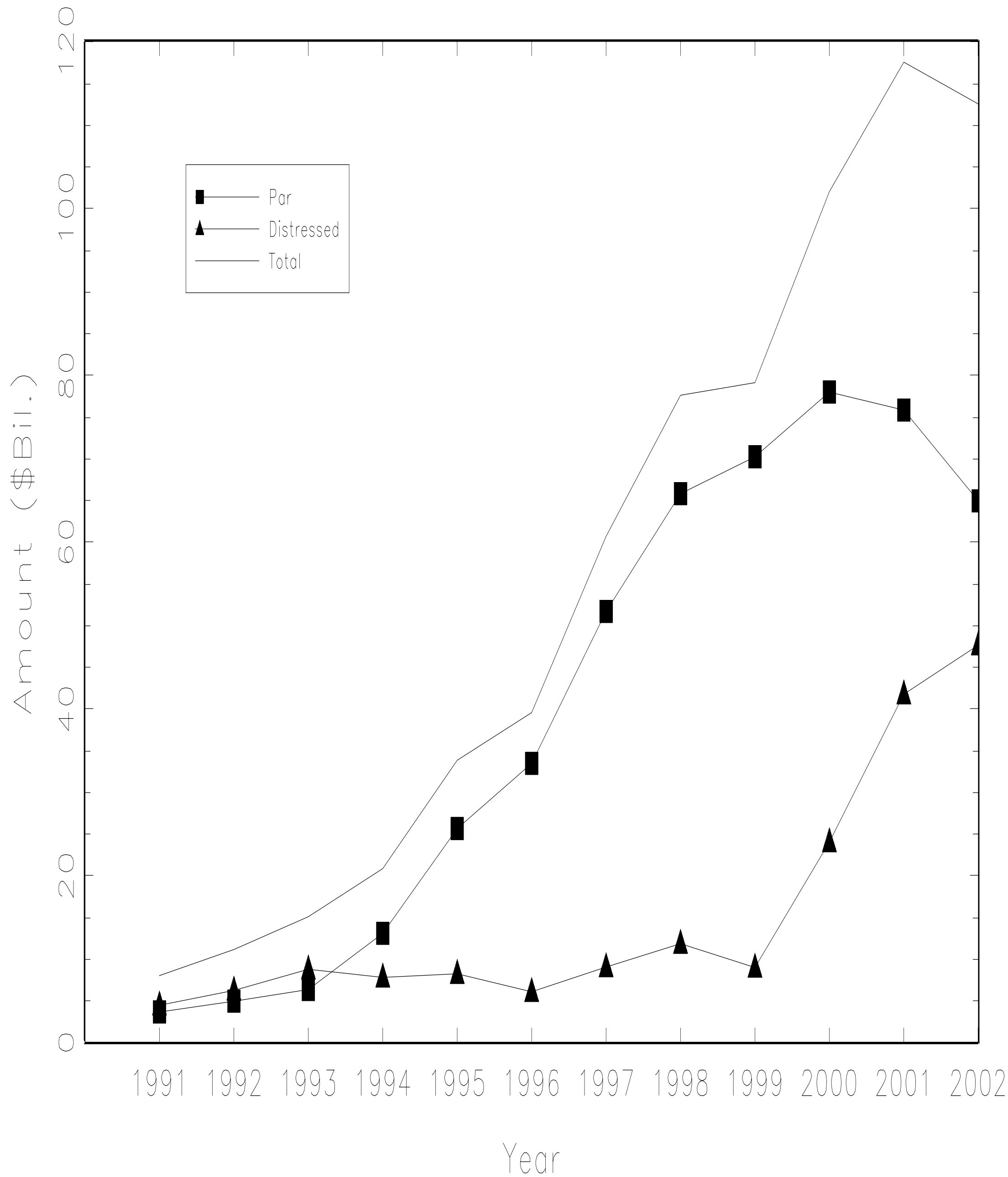
Bond characteristics dataset

The source for our bond defaults dataset is the Fixed Income Securities Database (FISD) and the "New York University (NYU) Salomon Center's Altman Bond Default Database". We incorporate seniority, collateral, and covenants information of a bond based on the issue description. For example, if a bond is described as senior secured or simply senior, we classify it as a senior bond. In defining the SECURED variable, we cross-reference the description of the bond issue with Fabozzi (2003) to infer if a particular issue can be classified as secured. For example, Equipment Trust Certificates are considered as secured. If a bond issue has a collaterlaized credit enhancement, we upgrade such a bond issue to being secured. In addition, we infer words such as collateralized, mortgage, gauaranteed, secured in the description of a bond issue to mean a secured bond. In classifying the structure of bond covenants, we follow Smith and Warner (1979).

Indices dataset

The sources for the indices dataset is the S&P/LSTA Leveraged Loan Index from the Standard & Poor's, the Lehman Brothers U.S. Corporate Intermediate Bond Index from the Datastream, and the NYSE/AMEX/NASDAQ Value-weighted Index from the Center for Research in Securities Prices (CRSP) for the loan, bond and stock index returns. While the Lehman Brothers U.S. Corporate Intermediate Bond Index and the NYSE/AMEX/NASDAQ Value-weighted Index are both daily series, the S&P/LSTA Leveraged Loan Index is a weekly series during our sample period. We converted the S&P/LSTA Leveraged Loan Index weekly series to a daily series through linear intrapolation wherever necessary.

Figure 1
Secondary Market for Loans



Source: Loan Syndications and Trading Association (LSTA).