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INFORMATIONAL EFFICIENCY OF LOANS VERSUS BONDS: EVIDENCE FROM SECONDARY MARKET PRICES

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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 surrounding loan default dates and bond default dates. We examine this issue using a unique dataset of daily secondary market prices of loans over the 11/1999-06/2002 period. We find evidence consistent with a monitoring role of loans. First, consistent with a view that the monitoring role of loans should be reflected in more precise expectations embedded in loan prices, we find that the price reaction of loans is less adverse than that of bonds around loan and bond default dates. Second, we find evidence that the difference in price reaction of loans versus bonds is amplified around loan default dates that are not preceded by a bond default date of the same company. Finally, we find a higher recovery rate for loans as compared to bonds, suggesting that the monitoring role of loans does not diminish significantly in the post default period. Our results are robust to controlling for security-specific characteristics, such as seniority, and collateral, and for multiple measures of cumulative abnormal returns around default dates. Overall, we find that the loan market is informationally more efficient than the bond market around default dates.

JEL Classification Codes: G21, G24, N22

Key Words: loans, bonds, monitoring, default, event study

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1. Introduction

The monitoring role of bank lending has been well documented in the literature. Several theoretical models highlight the unique monitoring function of banks (see for example, Diamond, 1984; Ramakrishnan and Thakor, 1984; Fama, 1985). These studies generally argue that banks have a comparative cost advantage in monitoring loan agreements. For example, 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. Diamond (1984) contends that banks have scale economies and comparative cost advantages in information production that enable them to undertake superior debt-related monitoring.[1]

It may be noted that the incentives to monitor are likely to be preserved even when a loan is sold in the secondary market. First, a loan buyer may have an implicit recourse to the bank selling the loan. Gorton and Pennacchi (1989) document evidence consistent with the presence of implicit guarantees to loan buyers to sell the loans back to the selling bank if the underlying borrower performs worse than anticipated. Second, the lead bank, which typically holds the largest share of a syndicated loan (see Kroszner and Strahan (2001) for details) rarely sells its share of a loan. Third, 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 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. Consequently, the monitoring role of loans has important implications for the informational efficiency of the loan market versus

[1]Several empirical studies also provide evidence on the uniqueness of bank loans. These studies examine the issue of whether bank lenders provide valuable information about borrowers. For example, James (1987) and Mikkelson and Partch (1986) document 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. More recently, Dahiya, Saunders, and Srinivasan (2003) document a significant negative announcement return for the lead lending bank when a major corporate borrower announces default or bankruptcy.

the bond market. That is, as skilled loan monitors − so called delegated monitors, banks collect information on a frequent basis, and should be able to reflect such information in the secondary market loan prices in a timely manner. Hence, the surprise or unexpected component of a loan default or a bond default is likely to be smaller for banks than for bond investors because banks are continuous monitors as compared to investors in the bond markets where monitoring tends to be more diffuse and subject to free rider problems.

The informational efficiency of the bond market relative to the stock market has received increasing attention. For example, using a dataset based on daily and hourly transactions for 55 high-yield bonds on the National Association of Securities Dealers (NASD) electronic fixed income pricing system (FIPS) between January 3, 1995 and October 1, 1995, Hotchkiss and Ronen (2002) find that the informational efficiency of corporate bond prices is similar to that of the underlying stocks. Specifically, they document that the information in earnings news is quickly incorporated into both bond and stock prices, even on an intraday level. Other studies have found a strong contemporaneous relationship between corporate bond returns and stock returns.[2]

There is also a growing literature that indirectly contributes to the informational efficiency debate by examining institutional bond trading costs, trading volumes, and the dynamics of price formation. 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. Interestingly, Schultz finds that bond ratings have little effect on trading costs.[3]Alexander et al (2000) use the NASD FIPS data to study the determinants of bond trading volume. They cite anecdotal evidence that bonds initially trade often but

[2]See, Blume et al. (1991), Cornell and Green (1991), and Kwan (1996) for details.

[3]Two other studies also examine bond trading costs. 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. Chakravarty and Sarkar (1999), using a methodology similar to Hong and Warga (2000) find that trading costs, on the basis of $100 par value, are highest for municipal bonds (mean spread of $0.22), followed by corporate bonds ($0.21), and treasury bonds ($0.11).

that trading declines as the bonds fall into the hands of institutions who hold them to maturity. Saunders, Srinivasan, and Walter (2002) analyze the dynamics of price formation in the corporate bond market. They study the bids (and offers) received by one anonymous asset manager who solicited offers to buy or sell from bond dealers on behalf of institutional clients from January to November 1997. Typically, these quotes were received within two minutes of a request for a price. The authors find that about 70 percent of the time, more than one bid (or offer) was received, and on average, for investment grade bonds, the winning bid price was 12.0 basis points better than the second best price and 20.5 basis points better than the average price.

However, there is no study to date that examines the pricing efficiency of the (secondary) market for loans nor on the informational efficiency of the market for loans relative to the market for bonds of the same corporation, largely due to unavailability (at least until now) of secondary market prices of loans. The market for loans 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). In addition, 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. A final 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 shows the rate of growth in the secondary market for loans, stratified by this last categorization from 1991-2002. Note the growth in the market upto 2000 when the level of secondary loan transactions topped $100 billion for the first time. Note also the increasing proportion of distressed loan sales reached 42% in 2002.

Our study focuses on the informational efficiency of the loan market relative to the bond market around default dates, using a unique dataset of secondary market daily prices of loans. Our sample period covers more than two years, namely November 1, 1999 through June 30, 2002, a time of increasing level of corporate defaults.[4]

We hypothesize and test the following implications of a monitoring role of loans: First, loans are likely to have timely and superior expectations built into their prices because banks are continuous monitors as compared to investors in the bond markets where monitoring tends to be more diffuse and subject to free rider problems. This implies the unexpected (or surprise) component of a default event is likely to be lower for loans than for bonds. Consequently, one would expect the price reaction of loans to be significantly lower than the price reaction of bonds around both loan and bond default dates. Second, to the extent that the monitoring advantage of loans over bonds is likely to continue post-default, one would expect a higher recovery rate for loans as compared to that of bonds, controlling for different attributes, such as, size, maturity, and seniority of both instruments.

Specifically, we pursue the following objectives: First, we examine return and price correlations of loans and bonds around loan and bond default dates. Second, we empirically test hypotheses on the return performance and recovery rates of loans versus bonds around loan and bond default dates as outlined above. Finally, to benchmark our results, we extend our analysis to the return performance of loans versus stocks. To the best of our knowledge, ours is the first study to examine these issues using secondary market loan price data.

Our main findings can be summarized as follows: First, while a positive correlation exists between daily bond returns and loan returns, it is relatively low. However, the return correlation is considerably higher during a 21 day event window [-10,+10], day 0 being the default date, as compared to other times in our sample. This finding reflects the increasing importance of default risk premiums in explaining loan and bond returns as compared to other factors[5] as we approach a default date. The price correlations are significantly higher

[4] According to Standard & Poors, corporate defaults set a record in 2002, for the fourth consecutive year. The 234 companies and $178 billion of debt that defaulted during 2002 was the largest number and amount ever, exceeding the previous records of 220 companies and $119 billion in 2001. In 2000 there were 132 companies and $44 billion as compared to 107 companies and $40 billion in 1999. See Brady, Vazza and Bos (2003) for a historical summary of corporate defaults since 1980.

[5] See Elton et al (2001) for an analysis of the determinants of corporate bond spreads (relative to Treasuries). The authors find that in addition to the expected default loss, other factors, such as taxes and risk

than the return correlations, and exhibit a similar pattern of an increase in magnitude during the 21 day event window surrounding a default date. Second, consistent with a view that the monitoring role of loans should reflect in more precise expectations embedded in loan prices, e.g., the surprise or unexpected component of a default is likely to be smaller for banks than for bond investors because banks are continuous monitors whereas monitoring in the bond market is more diffuse, we find that the price reaction of loans is less adverse than that of bonds around loan and bond default dates. Third, where a loan default date is not preceded a bond default date of the same company, we find that the differential price reaction of loans versus bonds is higher around such a loan default date since it also acts as a first signal of distress. Fourth, we find a higher recovery rate for loans as compared to bonds post-default, consistent with a view that the monitoring advantage of loans over bonds is likely to continue post-default. Our results are robust to controlling for security-specific characteristics, and for multiple measures of cumulative abnormal returns around default defaults. Finally, our results also extend to stocks, allowing us to make a similar assessment of the return performance of loans versus stocks. Overall, we find that the loan market is informationally more efficient than the bond market around default dates.

The results of our paper have important implications especially in terms of the impact of defaults on loans and bonds, the monitoring of loans versus bonds, and the benefits of loan monitoring role for other financial markets, such as the bond market and the stock market.

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

2. Data and sample selection

The sample period for our study is November 1, 1999 through June 30, 2002. Our choice of the sample period was driven by data considerations, i.e., our empirical analysis requires

premiums associated with Fama-French factors are important in determining corporate bond spreads.

secondary market daily prices of loans, which was not available prior to November 1, 1999.

We use several different data sources in this study. First, our loan price dataset is 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.[6] 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 loan broker-dealers.[7] 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 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 543,526 loan-day observations spanning 1,863 loans in our loan price dataset.

Second, the primary source for our bond price dataset is 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 371,797 bond-day observations spanning 816 bonds. Third, for robustness, we also created another bond price dataset from Datastream for a subset of loans with a bond default date or a loan default date (the primary focus of our study), containing 91,760 bond-day observations spanning 248 bonds.

Fourth, the source for our stock return dataset is the Center for Research in Securities Prices (CRSP) daily stock return and daily index return files.

Fifth, our loan defaults dataset consists of loan defaults from the institutional loan mar-

[6]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 expected to be independent and objective.

[7]At the time we received the dataset from LSTA, there were 33 loan dealers providing quotes to the LSTA/LPC mark-to-market pricing service.

ket. We received these 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.[8]

Sixth, 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.

Finally, the source for security-specific characteristics is the Loan Pricing Corporation (LPC).

Due to an absence of a unique identifier that ties all these datasets together, we manually matched these datasets based on 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).

3. Test hypotheses

In this section, we develop test hypotheses pertaining to the informational efficiency of the loan market as compared to that of the bond market surrounding loan default dates and bond default dates. Our central premise is that loans have a monitoring advantage over bonds. Several theoretical models highlight the unique monitoring function of banks (see for example, Diamond, 1984; Ramakrishnan and Thakor, 1984; Fama, 1985). These studies generally argue that banks have a comparative cost advantage in monitoring loan agreements which helps reduce the moral hazard costs of new debt financing. For example, Fama (1985) argues that banks, as insiders, have access to inside information whereas outside (public) debt holders must rely mostly on publicly available information, such as new bank loan agreements.[9] Diamond (1984, 1991) contends that banks have scale economies and comparative cost advantages in information production that enable them to undertake superior debt-related monitoring. Further, diffused public debt ownership and associated free-rider problem diminish bondholder' incentive to engage in costly information produc-

[8]Portfolio Management Data, a unit of Standard & Poor's has recently changed its name to "Standard & Poor's Leveraged Commentary & Data".

[9]James (1987) finds evidence that support an informational role that links loan agreements to favorable stock price reactions.

tion and monitoring. This results in higher agency costs relative to bank debt, which is typically concentrated. Several empirical studies, such as James (1987), Mikkelson and Partch (1986), Lummer and McConnell (1989), Dahiya, Saunders, and Srinivasan (2003) also provide evidence on the uniqueness of bank loans.

We argue that the incentives to monitor are likely to be preserved even when a loan is sold in the secondary market. First, a loan buyer may have an implicit recourse to the bank selling the loan. Gorton and Pennacchi (1989) document evidence consistent with the presence of implicit guarantees to loan buyers to sell the loans back to the selling bank. Second, the lead bank, which typically holds the largest share of a syndicated loan (see Kroszner and Strahan (2001) for details) rarely sells its share of a loan. Third, not all participants in a loan syndicate sell their share of a loan, and therefore continue to have incentives to monitor. Finally, a bank who serves as a loan dealer will have incentives to monitor loans that are in its inventory. Consequently, the monitoring role of loans has important implications for the informational efficiency of the loan market versus the bond market.

We next hypothesize two testable implications of the monitoring role of loans; the first one relates to the return performance around default dates, and the second one relates to the recovery rates around default dates.

3.1. Return performance around default dates

The monitoring advantage of loans over bonds implies that loans are likely to have timely and superior expectations built into their prices because banks are continuous monitors as compared to investors in the bond markets where monitoring tends to be more diffuse and subject to free rider problems. Hence, the unexpected (or surprise) component of a loan default event or a bond default is likely to be lower for loans than for bonds.[10] This leads to our first hypothesis:

Hypothesis 1 (Default expectation). The unexpected (or surprise) component of a

[10] This assumes a partial spillover of the loan monitoring benefits to bonds − if bonds realize the full benefit of loan monitoring, the information used in forming loan and bond prices is likely to be identical. Whether the spillover is full or only partial is finally an empirical issue. Our results, discussed in Section 4 are consistent only with a partial spillover of the benefit of loan monitoring from loans to bonds.

default event is likely to be lower for loans relative to bonds.

Consistent with Hypothesis 1, we expect the price reaction of loans to be significantly lower than the price reaction of bonds around loan default dates and bond default dates.

3.2. Recovery rates around default dates

A related issue is whether the monitoring advantage of loans over bonds is likely to continue post-default. We conjecture this to be the case based on the view that loans will continue to have a stronger incentive to monitor and reorganize post-default as compared to publicly issued bonds. This leads to our second hypothesis:

Hypothesis 2 (Post-default monitoring). The recovery rate is likely to be higher for loans as compared to bonds post-default after controlling for contractual differences.

Consistent with Hypothesis 2, one would expect a higher recovery rate for loans as compared to bonds, post-default, after controlling for contractual or security-specific attributes, such as, maturity, size, and seniority of both instruments.

4. Empirical results

We begin this section with an analysis of the return and price correlations of loans and bonds. We follow this analysis with the results from testing the hypotheses outlined in Section 3. We end this section with a discussion of whether our results also extend to markets other than loans and bonds, such as stocks.

4.1. Return and price correlations of loans and bonds

Table 1 presents the average price correlation, return correlation, and t-statistic of loan-bond pairs of the same company around loan and bond default dates. 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.[11] That is, a one day loan return is computed as

[11] We calculate returns based on the mid price, i.e., the quote mid point to abstract away from the bid-ask bounce. See, for example, Stoll (2000) and Hasbrouck (1988) for more details.

today's mid price divided by yesterday's mid price of the loan minus one. The daily bond returns are computed based on the price of a bond in the Salomon Yield Book in an analogous manner. A correlation coefficient and a t-statistic (of whether the correlation coefficient is statistically different from zero) is computed for each loan-bond pair of the same company as long as we have at least five observations during the time period of interest.[12] While the return correlations are generally low − as we approach closer to a significant event, such as a default, a loan-bond pair shows a greater commonality or positive correlation in returns. For example, the average return correlation between loan-bond pairs of the same company is 0.43 (average t-statistic on the correlations is 2.64, significant at the 1% level) during the 21 day event window surrounding a loan default date as compared to 0.12 (average t-statistic 1.97, significant at the 5% level) during the 234 day estimation window preceding the 21 day event window. The corresponding loan-bond pair correlations around bond default dates are 0.15 during the 21 day event window as compared to 0.01 during the 234 day estimation window − however, the average t-statistics on the correlations are not statistically significant at any meaningful level of significance. This finding reflects the increasing importance of default risk premiums in explaining loan and bond returns as compared to other factors (see footnote 5) as we approach a default date.

The price correlations in Table 1 are significantly higher than the return correlations, and exhibit a similar pattern of an increase in magnitude during the 21 day event window surrounding a default date. For example, the average price correlation of a loan-bond pair of the same company is 0.82 (average t-statistic 11.30, significant at the 1% level) during the 21 day event window surrounding a loan default date as compared to 0.57 (average t-statistic 13.94, also significant at the 1% level) during the 234 day estimation window preceding the 21 day event window. The corresponding loan-bond pair correlations around bond default dates are 0.61 (average t-statistic 5.39, significant at the 1% level) during the 21 day event

[12] We test whether a specific correlation coefficient is statistically different from zero by comparing $\frac{r_{xy}\sqrt{N-2}}{\sqrt{1-r_{xy}^2}}$, where r_{xy} is the correlation coefficient, N is the number of observations, with the critical value from a t-distribution with $N-2$ degrees of freedom at the desired level of significance based on a two-tailed test. See SAS Procedures guide (Version 8) for more details.

window as compared to 0.46 (average t-statistic 9.97, also significant at the 1% level) during the 234 day estimation window.

For robustness purposes, we also used daily prices and returns from Datastream instead of the Salomon Yield Book. These correlations are shown in Table 2. Clearly, the correlations in Table 2 are quite similar to the ones in Table 1, albeit marginally lower. Hence for the remainder of the paper, we present our results using bond price and return data from the Salomon Yield Book.

Correlations such as those presented in Tables 1 and 2 provide useful information about the commonality of returns and prices. However, to understand the magnitude of the difference in return performance, one needs to examine the cumulative abnormal returns surrounding default dates. We turn our attention to these measures in the following subsections.

4.2. Return performance around default dates

In this section, we empirically test the default expectation hypothesis. First, we present univariate comparisons of cumulative abnormal returns of loan-bond pairs, matched initially based on the name of the borrower, and later on based on additional attributes such as maturity and issue size. Next, we follow our univariate analysis with evidence from multivariate tests where we simultaneously control for security specific characteristics, such as maturity, issue size, seniority, and collateral of loans and bonds.

4.2.1. Univariate results

We conduct an event study analysis to examine the impact of corporate defaults on secondary market loan prices and bond prices. We examine two types of default, namely loan defaults, and bond defaults. We measure return performance surrounding default dates by cumulating daily abnormal returns during a pre-specified window surrounding a default date. We present empirical evidence for three different event windows: 3-day window [-1,+1], 11-day window [-5,+5] and a 21-day window [-10,+10], where day 0 refers to the default date.

We use several different methods to compute daily abnormal returns. First, on an unadjusted 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 default dates. 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 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).[13] 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).[14] 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,[15] 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,

[13] 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.

[14] 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/.

[15] 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.

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

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 return based on book-to-market, and $R_{SMB,t}$ is the return on a zero-investment portfolio return 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.[16] The intercept and slope

[16]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 the mean-adjusted and market-model adjusted abnormal returns. While the unadjusted and market-adjusted abnormal return

coefficients for the multi-factor models are defined analogously to the single-factor models.

The test statistic under the null hypothesis (of zero abnormal returns) for any event day and for multi-day windows surrounding default dates is described below.[17] 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,

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

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

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

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

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

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

Table 3 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 default expectation hypothesis described in Section 3.1, namely that loan returns decline by a smaller amount compared to bonds around default days. Specifically, loans fall by 19.51% during the 21 day

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.

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

[-10,+10] window surrounding loan default dates, while bonds fall by 47.40%. The difference in the loan average CAR (loan ACAR) and the bond average CAR (bond ACAR) of 27.89% (i.e., -19.51%-(-47.40%)) is statistically significant at the 1% level (Z-stat 4.51).[18] Similar results are found surrounding bond default dates as well. That is, loans fall by 20.00% during the 21 day window surrounding bond default dates, as compared to the 33.73% fall for bonds. The difference in ACARs of 13.73% is statistically significant at the 10% level (Z-stat 1.72). Other event windows, namely 3 day [-1,+1] window, and 11 day [-5,+5] window surrounding loan default days and bond default dates produce similar results.[19] So, while firms typically show signs of operating and financial problems prior to default, there is significant price deterioration just prior to and just after the event date as evidenced in the larger event window, e.g., 21 day window.

For robustness purposes, we also present the event study results for loan-bond pairs of the same company using the Fama-French three-factor model in Table 4. Clearly, the results in Table 4 are quite similar to the ones in Table 3. We also examined the event study results using the remaining four measures: (a) unadjusted, (b) mean-adjusted, (c) market-adjusted, and (d) 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) adjusted CARs. The results, reported in Appendices 2, 3, 4 and 5 are qualitatively similar. 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 the default expectation hypothesis. That is, the price reaction of loans is less adverse as compared to that of bonds around loan default dates and bond default dates. Our results are generally 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, or market-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, issue size, seniority, and

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

[19] The only exception is that the difference in ACARs for the 3 day window around bond default dates has the predicted sign but is not statistically significant.

collateral information underlying a loan or a bond. We next turn our attention to these issues.

Table 5 presents the event study analysis for loan-bond pairs of the same company, also matched on the maturity of the loan or bond. Table 6 presents a similar analysis of loan-bond pairs of the same company, also matched on the size of the loan or bond. We consider as matches a loan and a bond of the same company provided the difference in the attribute that we additionally match on (such as maturity, or size) is less than 25%. The results in these tables are qualitatively similar to the ones discussed above.[20]

We next test the robustness of these results using multivariate tests that better control for security specific characteristics, such as maturity, issue size, seniority, and collateral.

4.2.2. Multivariate results

For ease of interpretation, we define the dependent variable as the negative cumulative abnormal return (NCAR), i.e., NCAR = -CAR, which we simply refer to as "price decline". We focus on market-model adjusted NCAR during the 21-day event window, i.e., [-10,+10]. To measure the priority structure of loans and bonds, we incorporate the seniority and collateral information of a loan or a bond, using the classification of Altman and Kishore (1996). We classify the loans and bonds into four different categories (see Appendix 1 for details) based on security-specific information from the Loan Pricing Corporation (LPC) for loans, and the description of a bond in the bond default dataset, i.e., (a) Senior secured, (b) Senior unsecured, (c) Senior subordinated, and (d) Subordinated and others.[21] We categorize these descriptive variables into three separate dummy variables corresponding to: Senior secured, Senior unsecured, and Senior subordinated types.[22] The independent

[20] It may be noted that the number of observations in Tables 5 and 6 are significantly lower than in Tables 3 and 4 due to the additional restriction of matching on maturity or issue size − this should not be surprising considering that loans and bonds have significantly different dispersion around widely different mean levels on attributes such as maturity and issue size.

[21] We combine others, such as discount and junior subordinated categories (since there were relatively few such loans and bonds) with the Subordinated into a single category.

[22] To avoid the problem of linear dependence of the independent variables in an OLS regression, we can only include three dummy variables (of the four). We drop the dummy corresponding to "Subordinated and others".

variables used in some or all of the OLS regressions are:

LOAN DUMMY: An indicator variable that takes a value of one for a loan, and zero otherwise.

LOAN DEFAULT DUMMY: An indicator variable that takes a value of one if it is a loan default, and zero otherwise.

LOAN DUMMY x LOAN DEFAULT LEADS: An interactive indicator variable that takes a value of one if it is a loan and if the loan default is not preceded by a bond default date of the same loan-bond pair, and zero otherwise.

LN(MATURITY): Stands for natural log of one plus remaining maturity (in years) as on a default date.

LN(AMOUNT): Stands for natural log of one plus amount of the loan or bond issue (in $ millions).

SENIOR SECURED: An indicator variable that takes a value of one if a loan or a bond is senior secured, and zero otherwise.

SENIOR UNSECURED: An indicator variable that takes a value of one if a loan or a bond is senior unsecured, and zero otherwise.

SENIOR SUBORDINATED: An indicator variable that takes a value of one if a loan or bond is senior subordinated, and zero otherwise.

4.2.2.1. Discussion of the variables

We test the default expectation hypothesis described in Section 3.1 by examining the predicted sign of the LOAN DUMMY coefficient. We expect the LOAN DUMMY coefficient to be negative and statistically significant.

We include the following variables as control variables: First, LOAN DEFAULT DUMMY, an indicator variable for the type of default, namely whether it is a loan default or a bond default. On one hand, as delegated monitors, banks are expected to be better able to distinguish ex ante among good and bad borrowers relative to investors in the bond markets where monitoring tends to be diffuse and subject to free rider problems. Strictly interpreted, this implies that loan defaults should be rare events. Consequently, a loan default, when it does occur, is likely to be more surprising than a bond default, and may reflect the potential loss of reputation of the bank (see Dahiya, Saunders, and Srinivasan (2003)). However, on the other hand, it can be argued that loan defaults are, by definition, less surprising than bond defaults since there is more information associated with loans. Whether the LOAN DEFAULT DUMMY will have a positive coefficient or a negative coefficient depends on which of these two effects dominate. Second, LOAN DUMMY x LOAN DEFAULT LEADS, an interactive indicator variable that reflects the timing of a default date and additionally serves as the first signal of financial distress.[23] As a result, the measured effect of the LOAN DUMMY is expected to be amplified when a loan default leads or a bond default leads, i.e., we expect the interactive indicator variable to have a negative sign. Third, LN(MATURITY). We expect this variable to have a positive coefficient since longer-maturity debt issues are potentially subject to a greater interest-rate risk exposure, and can have a higher default risk (Flannery, 1986). Fourth, LN(AMOUNT). Larger issues, on one hand, are likely to be associated with less uncertainty, and have more public information associated with them. However, on the other hand, larger issues may be more difficult to reorganize post-default. Whether the sign of the LN(AMOUNT) coefficient is positive or negative is an empirical question as to which of these two effects dominates. Finally, the priority structure reflects the protection or safety cushion to the loan or bond holder in the event of default. For example, we expect the price decline for a SENIOR SECURED security to be the least, followed by that of a SENIOR UNSECURED security, which in turn is lower than that of a SENIOR SUBORDINATED security. Accordingly, we expect the coefficient of the SENIOR SECURED variable to be smaller than that of the SENIOR UNSECURED variable, which in turn should be smaller than that of the SENIOR SUBORDINATED variable.

[23]Of the 74 loan-bond pairs in Table 3, 43 cases are when the loan default leads, 5 cases are when the bond default leads, and the remaining 26 loan-bond pairs comprise simultaneous loan-bond defaults, i.e., loan and bond defaults within two days of each other. Since there are relatively few instances (five) where a bond default leads, we did not include an additional interactive indicator variable due to concerns of multicollinearity.

4.2.2.2. Multivariate regression results

The multivariate regression results are presented in Tables 7-9.[24] Table 7 presents the regression results on loan default dates only. Table 8 presents the regression results on bond default days only. Table 9 presents the results for loan and bond default days. The details of these regressions are discussed below.

Specifically in Table 7, we test six different specifications. We start with Model 1 where we regress NCAR on LOAN DUMMY. The coefficient on the LOAN DUMMY is negative and statistically significant, suggesting that the price decline is 27.89% lower for loans as compared to bonds.[25] Next, we augment Model 1 with the LOAN DUMMY x LOAN DEFAULT LEADS indicator variable to run the regression Model 2. The coefficient on LOAN DUMMY x LOAN DEFAULT LEADS variable is negative and statistically significant, suggesting that the price decline is 29.66% lower for loans as compared to bonds around loan default dates that are not preceded by a bond default of the same company. Following regression Model 2, we augment Model 1 with LN(MATURITY) and LN(AMOUNT) as additional control variables to run the regression Model 3. The LOAN DUMMY continues to be negative and statistically significant. Next, we augment Model 1 with the indicator variables for the priority structure, namely SENIOR SECURED, SENIOR UNSECURED, and SENIOR SUBORDINATED to run the regression Model 4. The LOAN DUMMY continues to be statistically significant and the coefficients on the priority structure variables have the correct sign and the correct relative magnitudes. We next augment Model 4 with LN(MATURITY) and LN(AMOUNT) to run the regression Model 5. The LOAN DUMMY continues to be negative and statistically significant. Finally, we augment Model 5 with the LOAN DUMMY x LOAN DEFAULT LEADS indicator variable. Interestingly, both the LOAN DUMMY and LOAN DUMMY x LOAN DEFAULT LEADS variables are each negative and statistically significant.

Table 8 presents the regression results around bond default dates only. The LOAN

[24] The results are qualitatively unchanged when the inference is based on White (1980)'s heteroskedasticity adjusted t-statistics (not reported here).

[25] This is exactly the difference in loan and bond ACARs from Table 3, i.e., -19.51 - (-47.40) = 27.89%.

DUMMY is negative in all six specifications, and statistically significant in the last three cases (Models 4-6). The LOAN DUMMY x LOAN DEFAULT LEADS is negative and statistically significant around loan default dates but is insignificant around bond default dates.

Finally, Table 9 combines the loan-bond pairs around loan default dates with the loan-bond pairs around bond default dates. By combining, we are able to augment each of the six regression specifications with a LOAN DEFAULT DUMMY which has the expected sign.

Overall, based on the regression results, we find evidence consistent with the default expectation hypothesis described in Section 3.1. Specifically, we find that the price reaction of loans is less adverse than that of bonds around both loan and bond default dates – our results are robust to controlling for security-specific characteristics, such as maturity, seniority, and for a variety of methods to measure price declines around default dates. Interestingly, the price decline is significantly much lower for loans as compared to bonds around loan default dates that are not preceded by a bond default date.

4.2.2. Results of simultaneous loan-bond defaults

In the multivariate regression results in Section 4.2.1., we controlled for the difference in timing of loan defaults and bond defaults through the indicator variable LOAN DUMMY x LOAN DEFAULT LEADS. As an additional robustness test, we focus our attention on the 26 loan-bond pairs with simultaneous loan-bond defaults. This subsample of 26 loan-bond pairs is not influenced by any timing differences between loan and bond default days, and hence can be used to test our monitoring story more directly. However given the small size of this sample, we need to be cautious in the interpretation of the results.

The univariate results of the raw unadjusted returns (our first measure of cumulative abnormal returns) are shown in Appendix 6. We find evidence consistent with the default expectation hypothesis described in Section 3.1. That is, we find that the LOAN ACAR is significantly lower than the BOND ACAR for the [-5,+5] and [-10,+10] event windows. The results are qualitatively similar with the market-model adjusted CARs (see Appendix

7), albeit marginally weaker.

We also ran the regression specifications in Table 7 for the sample of 26 loan-bond pairs with simultaneous loan-bond defaults. The results are shown in Appendix 8.[26] Once again, the results are qualitatively similar – the LOAN DUMMY coefficient has the predicted negative sign in all the regression specifications, and is statistically significant in the more complete models, i.e., Models 3-4.

4.3. Recovery rates around default dates

A related issue is whether we find a higher expected recovery rate for loans as compared to bonds. Specifically, we examine the determinants of recovery rates of loans versus bonds around default dates in this section.

4.3.1. Univariate results

As hypothesized in Section 3.2 (post-default monitoring hypothesis), to the extent that the monitoring advantage of loans over bonds is likely to continue post-default, one would expect a higher recovery rate for loans as compared to that of bonds.

Table 10 presents the correlation between cumulative returns and two traditional measures of recovery rates, namely, the trading price immediately at default, and the trading price one month after default.[27] The correlations with the two traditional measures of recovery rates are positive and relatively high for both loans (0.80-0.85 for loan default dates and 0.59-0.60 for bond default dates) and bonds (0.46-0.65 for loan default dates and 0.28-0.47 for bond default dates). This evidence, together with the evidence presented in Section 4.1

[26]Since the subsample of 26 loan-bond pairs contains only simultaneous loan-bond defaults, we cannot include the LOAN DUMMY x LOAN DEFAULT LEADS interactive variable in all the regression specifications. That is, Model 2 and Model 6 are identical to Model 1 and Model 5 respectively (in Table 7) for our subsample. Consequently, Appendix 8 contains only four specifications.

[27]See Altman and Kishore (1996) and Altman (1993) for more details. A useful proxy for the expected recovery rate in default is the average price around default. Prices at or soon after default are used in many default studies and 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). 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.

suggests that the recovery rates for loans can be expected to be higher than that of bonds.[28]

The univariate results presented here, while consistent with the post-default monitoring hypothesis, do not explicitly control for security specific characteristics, such as maturity, issue size, seniority etc. We examine this issue next through multivariate analysis.

4.3.2. Multivariate results

The dependent variable is the recovery rate of a loan or a bond, as proxied by the price at default. For example, when measuring the dependent variable on a loan default date, we use the loan price on the loan default date, and the matched bond price also on the same loan default date. We follow a similar procedure for bond default dates. The independent variables are as defined in Section 4.1.3.

Table 11 presents the regression results. We find evidence consistent with the post-default monitoring hypothesis described in Section 3.2. Of particular interest is the coefficient on LOAN DUMMY which is positive and statistically significant at the 1% level in all the six different specifications. It may also be noted that in our more complete specifications, i.e., in Models 5 and 6 where we have the highest explanatory power (as measured by Adjusted R^2), neither the timing of the loan default nor the type of default (i.e., whether it is a loan default or a bond default) is statistically significant from zero at any meaningful level of significance.

4.4. Extensions

In this section we examine whether our results also extend to stocks, allowing us to make a similar assessment of the return performance of loans and stocks. This will also allow us to benchmark our loan-bond results.

Table 12 presents event study results for loan-stock pairs. 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

[28] See Appendix 9 for a summary of recovery rates by debt type and seniority from 1988-2Q 2003.

a value-weighted NYSE/NASDAQ/AMEX index for stocks) is subtracted from the loan or stock daily return respectively.

We find evidence consistent with the default expectation hypothesis described in Section 3.1, namely that loan returns fall by a smaller amount as compared to stocks around default days. In particular, loans fell by 4.87% during the 11 day [-5,+5] window surrounding loan default dates, while stocks fell by 32.84%. The difference in the loan average CAR (loan ACAR) and the stock average CAR (stock ACAR) of 27.97% (i.e., -4.87%-(-32.84%)) is statistically significant at the 1% level (Z-stat 2.94). Similar results are found surrounding bond default dates as well. Specifically, loans fell by 4.30% during the 11 day window surrounding bond default dates, as compared to the 25.39% fall for stocks. The difference in ACARs of 21.09% is statistically significant at the 1% level (Z-stat 4.57). Other event windows, namely 3 day [-1,+1] window, and 21 day [-10,+10] windows produce similar results with the exception of the 21 day window around bond default dates (has the predicted sign but is not statistically significant).

5. Conclusions

This paper examines the information efficiency of loans relative to bonds surrounding loan default dates and bond default dates using a unique dataset of daily secondary market prices during 11/1999-06/2002. We find that the return correlation between loans and bonds is relatively low for the entire sample period but is considerably higher during a 21-day event window surrounding a default date. The price correlations are significantly higher than the return correlations, and exhibit a similar pattern of an increase in magnitude during the 21 day event window surrounding a default date.

Consistent with a view that the surprise or unexpected component of a default is likely to be smaller for banks than for bond investors because banks are continuous monitors whereas monitoring in the bond market is more diffuse, we find that the price reaction of loans is less adverse than that of bonds around loan and bond default dates. Interestingly, where a loan default date is not preceded a bond default date of the same company, we find that the differential price reaction of loans versus bonds is higher around such a loan default date since it also acts as a first signal of distress. Finally, we find a higher recovery rate for loans as compared to bonds post-default, consistent with a view that the monitoring advantage of loans over bonds is likely to continue post-default. Overall, we find that the loan market is informationally more efficient than the bond market around default dates.

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TABLE 1
Average return and price correlations between loans and bonds around default dates (matched by borrower name)

This table presents the average correlation and the average t-statistic (of testing whether the correlation coefficient is significantly different from zero) between: (a) daily returns of loans and bonds, and (b) daily prices of loans and bonds of the same company around default dates. The price and return data for loans is from the Loan Syndications and Trading Association (LSTA) and the price and return data for bonds is from the *Salomon* Yield Book. The average correlations are presented for the overall sample period and for several segments of time periods: (a) Pre-estimation period: on or preceding day -245, (b) Estimation period: [-244,-11], which is further broken down into sub periods as shown below, (c) Event window: [-10,+10], and (d) Post-event period: on or following day +11, where day 0 refers to the loan default date in Panel A, and to the bond default date in Panel B. The superscripts a, b, and c stand for significance at the 1%, 5%, and 10% levels using a two-tailed test.

Panel A: Loan Default Dates

	Return correlation		Price correlation	
Time Period	Mean	T-statistic	Mean	T-statistic
Pre-estimation period [≤-245]	-0.00	-0.22	0.50	9.27[a]
Estimation period [-244,-11]	0.12	1.97[b]	0.57	13.94[a]
– Subsegment [-244,-121]	0.02	0.29	0.55	7.50[a]
– Subsegment [-61,-120]	0.02	0.10	0.38	4.81[a]
– Subsegment [-31,-60]	0.03	0.14	0.46	5.07[a]
– Subsegment [-11,-30]	0.26	1.34	0.70	4.68[a]
Event window [-10,+10]	0.43	2.64[a]	0.82	11.30[a]
Post-event period [≥ +11]	0.02	0.34	0.42	6.81[a]

Panel B: Bond Default Dates

	Return correlation		Price correlation	
Time Period	Mean	T-statistic	Mean	T-statistic
Pre-estimation period [≤-245]	0.01	0.01	0.48	9.11[a]
Estimation period [-244,-11]	0.01	0.13	0.46	9.97[a]
– Subsegment [-244,-121]	0.01	0.19	0.56	8.56[a]
– Subsegment [-61,-120]	-0.02	-0.25	0.25	3.62[a]
– Subsegment [-31,-60]	0.03	0.24	0.27	2.52[b]
– Subsegment [-11,-30]	-0.00	-0.00	0.49	2.90[a]
Event window [-10,+10]	0.15	0.93	0.61	5.39[a]
Post-event period [≥ +11]	0.04	0.44	0.37	6.55[a]

TABLE 2
Average return and price correlations between loans and bonds around default dates (matched by borrower name)

This table presents the average correlation and the average t-statistic (of testing whether the correlation coefficient is significantly different from zero) between: (a) daily returns of loans and bonds, and (b) daily prices of loans and bonds of the same company around default dates. The price and return data for loans is from the Loan Syndications and Trading Association (LSTA) and the price and return data for bonds is from the Datastream. The average correlations are presented for the overall sample period and for several segments of time periods: (a) Pre-estimation period: on or preceding day -245, (b) Estimation period: [-244,-11], which is further broken down into sub periods as shown below, (c) Event window: [-10,+10], and (d) Post-event period: on or following day +11, where day 0 refers to the loan default date in Panel A, and to the bond default date in Panel B. The superscripts a, b, and c stand for significance at the 1%, 5%, and 10% levels using a two-tailed test.

Panel A: Loan Default Dates

	Return correlation		Price correlation	
Time Period	Mean	t-statistic	Mean	t-statistic
Pre-estimation period [≤-245]	0.02	0.07	0.29	5.61[a]
Estimation period [-244,-11]	0.19	3.00[a]	0.53	14.79[a]
– Subsegment [-244,-121]	0.03	0.34	0.35	5.77[a]
– Subsegment [-61,-120]	0.10	0.78	0.38	5.53[a]
– Subsegment [-31,-60]	0.15	1.01	0.42	5.60[a]
– Subsegment [-11,-30]	0.15	0.96	0.10	0.26
Event window [-10,+10]	0.22	1.16	0.59	7.55[a]
Post-event period [≥ +11]	0.04	0.44	0.31	8.73[a]

Panel B: Bond Default Dates

	Return correlation		Price correlation	
Time Period	Mean	t-statistic	Mean	t-statistic
Pre-estimation period [≤-245]	0.07	2.25[b]	0.20	5.71[a]
Estimation period [-244,-11]	0.07	0.96	0.46	11.93[a]
– Subsegment [-244,-121]	0.01	0.23	0.43	9.06[a]
– Subsegment [-61,-120]	0.06	0.50	0.21	3.52[a]
– Subsegment [-31,-60]	0.05	0.60	0.36	3.53[a]
– Subsegment [-11,-30]	0.01	0.07	-0.08	-1.55
Event window [-10,+10]	0.20	1.04	0.40	3.40[a]
Post-event period [≥ +11]	0.02	0.20	0.30	10.12[a]

TABLE 3
Average cumulative abnormal returns of matched loan-bond pairs around default dates (matched by borrower name)

This table presents the average cumulative abnormal return (ACAR) of matched loan-bond pairs (based on the name of the borrower) surrounding a default date (day 0), namely a loan default date or a bond default date 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 (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, 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

Event window	Loan ACAR (%) (1)	Bond ACAR (%) (2)	Difference in ACAR (%) (3) = (1) - (2)
[-1,+1]	-4.06	-20.92	16.86
	(-4.48)^a	(-9.13)^a	(7.71)^a
[-5,+5]	-9.82	-38.16	28.34
	(-5.67)^a	(-8.69)^a	(6.56)^a
[-10,+10]	-19.51	-47.40	27.89
	(-8.15)^a	(-7.82)^a	(4.51)^a
Obs	74	74	

Panel B: Bond default dates

Event window	Loan ACAR (%) (4)	Bond ACAR (%) (5)	Difference in ACAR (%) (6) = (4) - (5)
[-1,+1]	-3.37	-5.43	2.06
	(-3.51)^a	(-2.09)^b	(0.83)
[-5,+5]	-12.98	-28.84	15.86
	(-7.07)^a	(-5.81)^a	(2.99)^a
[-10,+10]	-20.00	-33.73	13.73
	(-7.88)^a	(-4.92)^a	(1.72)^c
Obs	69	69	

TABLE 4
Average cumulative abnormal returns of matched loan-bond pairs around default dates (matched by borrower name)

This table presents the average cumulative abnormal return (ACAR) of matched loan-bond pairs (based on the name of the borrower) surrounding a default date (day 0), namely a loan default date or a bond default date of the same company. This table includes matched loan-bond pairs where we are able to compute the CAR based on the Fama-French three factor model adjusted method for the [-10,+10] event window. That is, the return based on the Fama-French three-factor market-model regression is subtracted from the loan or bond daily return respectively. The Z statistics of ACARs (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, 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

Event window	Loan ACAR (%) (1)	Bond ACAR (%) (2)	Difference in ACAR (%) (3) = (1) - (2)
[-1,+1]	-4.57	-21.09	16.52
	$(-4.99)^a$	$(-9.14)^a$	$(7.56)^a$
[-5,+5]	-11.42	-38.39	26.97
	$(-6.51)^a$	$(-8.69)^a$	$(5.99)^a$
[-10,+10]	-21.58	-47.16	25.58
	$(-8.91)^a$	$(-7.73)^a$	$(3.90)^a$
Obs	74	74	

Panel B: Bond default dates

Event window	Loan ACAR (%) (4)	Bond ACAR (%) (5)	Difference in ACAR (%) (6) = (4) - (5)
[-1,+1]	-3.98	-5.74	1.76
	$(-4.04)^a$	$(-2.21)^b$	(0.70)
[-5,+5]	-14.64	-28.09	13.45
	$(-7.75)^a$	$(-5.65)^a$	$(2.54)^b$
[-10,+10]	-22.46	-34.11	11.65
	$(-8.61)^a$	$(-4.97)^a$	(1.41)
Obs	69	69	

TABLE 5
Average cumulative abnormal returns of matched loan-bond pairs around default dates (matched by borrower name, and maturity)

This table presents the average cumulative abnormal return (ACAR) of matched loan-bond pairs (based on the name of the borrower and maturity) surrounding a default date (day 0), namely a loan default date or a bond default date 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 (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, 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

Event window	Loan ACAR (%) (1)	Bond ACAR (%) (2)	Difference in ACAR (%) (3) = (1) - (2)
[-1,+1]	-3.24	-16.34	13.10
	(-1.94)^c	(-4.26)^a	(2.16)^b
[-5,+5]	-12.67	-55.38	42.71
	(-3.96)^a	(-7.54)^a	(3.04)^a
[-10,+10]	-30.41	-55.92	25.51
	(-6.88)^a	(-5.51)^a	(1.10)
Obs	15	15	

Panel B: Bond default dates

Event window	Loan ACAR (%) (4)	Bond ACAR (%) (5)	Difference in ACAR (%) (6) = (4) - (5)
[-1,+1]	-0.44	-17.07	16.63
	(-0.32)	(-3.78)^a	(2.15)^b
[-5,+5]	-9.32	-49.12	39.80
	(-3.61)^a	$(-5.68)^a$	(3.51)^a
[-10,+10]	-20.93	-47.80	26.87
	(-5.86)^a	$(-4.00)^a$	(1.46)
Obs	19	19	

TABLE 6
Average cumulative abnormal returns of matched loan-bond pairs around default dates (matched by borrower name, and amount)

This table presents the average cumulative abnormal return (ACAR) of matched loan-bond pairs (based on the name of the borrower and amount) surrounding a default date (day 0), namely a loan default date or a bond default date 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 (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, 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

Event window	Loan ACAR (%) (1)	Bond ACAR (%) (2)	Difference in ACAR (%) (3) = (1) - (2)
[-1,+1]	-4.05	-20.91	16.86
	(-6.72)^a	(-10.29)^a	(3.60)^a
[-5,+5]	-7.98	-42.89	34.91
	(-6.90)^a	(-11.02)^a	(3.06)^a
[-10,+10]	-21.47	-72.07	50.60
	(-13.45)^a	(-13.40)^a	(3.66)^a
Obs	15	15	

Panel B: Bond default dates

Event window	Loan ACAR (%) (4)	Bond ACAR (%) (5)	Difference in ACAR (%) (6) = (4) - (5)
[-1,+1]	-0.32	-11.62	11.29
	(-0.55)	(-3.34)^a	(1.49)
[-5,+5]	-6.25	-38.67	32.42
	(-5.58)^a	(-5.81)^a	(2.39)^b
[-10,+10]	-20.25	-65.97	45.72
	(-13.08)^a	(-7.17)^a	(2.40)^b
Obs	13	13	

TABLE 7

Linear regression of negative cumulative abnormal return around loan default dates

This table presents OLS estimates of regression specifications determining the cumulative abnormal return (CAR) performance of loans and bonds surrounding loan default dates. This table includes loans, and bonds where we are able to compute the CAR based on the market-model adjusted method for the [-10,+10] event window. The dependent variable NEGATIVE CUMULATIVE ABNORMAL RETURN, NCAR[-10,+10] equals -CAR[-10,+10], where day [0] refers to a default date, namely the loan default date or the bond default date 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: LOAN DUMMY takes a value of one if it is a loan, and zero otherwise. LOAN DUMMY x LOAN DEFAULT LEADS is an interactive dummy variable that takes a value of one if it is a loan and if the loan default date is not preceded by a bond default date for the same loan-bond pair, and zero otherwise. LN(MATURITY) stands for natural log of one plus remaining maturity (in years) as on a default date. LN(AMOUNT) stands for natural log of one plus amount of the loan or bond issue (in $ millions). SENIOR SECURED, SENIOR UNSECURED, and SENIOR SUBORDINATED each take a value of one if a loan or bond is classified like-wise and zero otherwise. The *t* ratios are shown in parentheses (a, b, and c stand for significance at the 1%, 5%, and 10% levels using a two-tailed test).

Dependent Variable: -CAR[-10,+10], Market-model adjusted (%)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
INTERCEPT	47.40	46.80	12.81	88.46	-14.23	-6.98
	(8.85)^a	(9.68)^a	(0.38)	(8.68)^a	(-0.44)	(-0.22)
LOAN DUMMY	-27.89	-3.84	-17.28	-41.54	-34.53	-19.01
	(-3.68)^a	(-0.29)	(-2.15)^b	$(-5.34)^a$	(-4.67)^a	(-1.82)^c
LOAN DUMMY x						
LOAN DEFAULT LEADS		-29.66				-24.46
		(-2.20)^b				(-2.07)^b
LN(MATURITY)			30.88		29.98	26.36
			(3.49)^a		(4.17)^a	(3.60)^a
LN(AMOUNT)			-3.54		7.69	8.52
			(-0.60)		(1.51)	(1.68)^c
SENIOR SECURED				-100.58	-105.99	-111.62
				(-7.42)^a	(-8.31)^a	(-8.66)^a
SENIOR UNSECURED				-38.60	-22.33	-23.22
				(-3.73)^a	(-2.15)^b	(-2.26)^b
SENIOR SUBORDINATED				-22.27	-16.86	-24.16
				(-2.16)^b	(-1.73)^c	(-2.35)^b
Observations	148	148	148	148	148	148
Adjusted R^2	0.08	0.10	0.14	0.38	0.46	0.47

TABLE 8
Linear regression of negative cumulative abnormal return around bond default dates

This table presents OLS estimates of regression specifications determining the cumulative abnormal return (CAR) performance of loans and bonds surrounding loan default dates. This table includes loans, and bonds where we are able to compute the CAR based on the market-model adjusted method for the [-10,+10] event window. The dependent variable NEGATIVE CUMULATIVE ABNORMAL RETURN, NCAR[-10,+10] equals -CAR[-10,+10], where day [0] refers to a default date, namely the loan default date or the bond default date 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: LOAN DUMMY takes a value of one if it is a loan, and zero otherwise. LOAN DUMMY x LOAN DEFAULT LEADS is an interactive dummy variable that takes a value of one if it is a loan and if the loan default date is not preceded by a bond default date for the same loan-bond pair, and zero otherwise. LN(MATURITY) stands for natural log of one plus remaining maturity (in years) as on a default date. LN(AMOUNT) stands for natural log of one plus amount of the loan or bond issue (in $ millions). SENIOR SECURED, SENIOR UNSECURED, and SENIOR SUBORDINATED each take a value of one if a loan or bond is classified like-wise and zero otherwise. The *t* ratios are shown in parentheses (a, b, and c stand for significance at the 1%, 5%, and 10% levels using a two-tailed test).

Dependent Variable: -CAR[-10,+10], Market-model adjusted (%)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
INTERCEPT	33.73	33.73	-67.70	78.10	-45.35	-40.71
	(4.76)^a	(4.74)^a	(-1.35)	(6.58)^a	(-0.90)	(-0.80)
LOAN DUMMY	-13.73	-13.70	-6.38	-34.47	-27.27	-23.04
	(-1.37)	(-1.21)	(-0.53)	$(-3.42)^a$	(-2.28)^b	(-1.72)^c
LOAN DUMMY x						
LOAN DEFAULT LEADS		-0.09				-10.39
		(-0.01)				(-0.71)
LN(MATURITY)			14.39		16.44	18.06
			(1.05)		(1.22)	(1.32)
LN(AMOUNT)			12.19		14.52	13.64
			(2.02)^b		(2.29)^a	(2.11)^b
SENIOR SECURED				-91.06	-93.64	-95.81
				(-5.43)^a	(-5.45)^a	(-5.48)^a
SENIOR UNSECURED				-47.90	-32.69	-35.78
				(-2.66)^a	(-1.72)^c	(-1.83)^c
SENIOR SUBORDINATED				-31.99	-25.44	-29.45
				(-2.76)^a	(-1.91)^c	(-2.03)^b
Observations	138	138	138	138	138	138
Adjusted R^2	0.01	0.01	0.02	0.16	0.19	0.19

TABLE 9
Linear regression of negative cumulative abnormal returns

This table presents OLS estimates of regression specifications determining the cumulative abnormal return (CAR) performance of loans and bonds surrounding default dates. This table includes loans, and bonds where we are able to compute the CAR based on the market-model adjusted method for the [-10,+10] event window. The dependent variable NEGATIVE CUMULATIVE ABNORMAL RETURN, NCAR[-10,+10] equals -CAR[-10,+10], where day [0] refers to a default date, namely the loan default date or the bond default date 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: LOAN DEFAULT DUMMY takes a value of one if it is a loan default, and zero otherwise. LOAN DUMMY takes a value of one if it is a loan, and zero otherwise. LOAN DUMMY x LOAN DEFAULT LEADS is an interactive dummy variable that takes a value of one if it is a loan and if the loan default date is not preceded by a bond default date for the same loan-bond pair, and zero otherwise. LN(MATURITY) stands for natural log of one plus remaining maturity (in years) as on a default date. LN(AMOUNT) stands for natural log of one plus amount of the loan or bond issue (in $ millions). SENIOR SECURED, SENIOR UNSECURED, and SENIOR SUBORDINATED each take a value of one if a loan or bond is classified like-wise and zero otherwise. The *t* ratios are shown in parentheses (a, b, and c stand for significance at the 1%, 5%, and 10% levels using a two-tailed test).

Dependent Variable: -CAR[-10,+10], Market-model adjusted (%)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
INTERCEPT	37.39	35.62	-48.02	78.01	-43.38	-36.18
	$(6.85)^a$	$(6.41)^a$	$(-1.69)^c$	$(9.58)^a$	(-1.51)	(-1.25)
LOAN DEFAULT DUMMY	6.60	10.01	11.80	12.39	15.77	19.09
	(1.06)	(1.52)	$(1.86)^c$	$(2.17)^b$	$(2.79)^a$	$(3.25)^a$
LOAN DUMMY	-21.06	-12.39	-11.17	-38.18	-30.92	-22.22
	$(-3.38)^a$	(-1.49)	(-1.61)	$(-6.17)^a$	$(-4.80)^a$	$(-2.84)^a$
LOAN DUMMY x LOAN DEFAULT LEADS		-14.76				-17.07
		(-1.56)				$(-1.95)^c$
LN(MATURITY)			19.48		20.38	20.65
			$(2.59)^a$		$(3.05)^a$	$(3.10)^a$
LN(AMOUNT)			7.67		13.13	12.19
			$(1.89)^c$		$(3.26)^a$	$(3.02)^a$
SENIOR SECURED				-96.74	-101.75	-105.03
				$(-8.84)^a$	$(-9.56)^a$	$(-9.79)^a$
SENIOR UNSECURED				-43.99	-29.41	-30.06
				$(-4.81)^a$	$(-3.05)^a$	$(-3.13)^a$
SENIOR SUBORDINATED				-27.78	-22.60	-28.15
				$(-3.58)^a$	$(-2.81)^a$	$(-3.31)^a$
Observations	286	286	286	286	286	286
Adjusted R^2	0.04	0.04	0.07	0.26	0.31	0.31

TABLE 10
Correlation between cumulative returns and recovery rates around default dates

This table presents correlation between return performance, as measured by cumulative returns around default dates, and proxies for recovery rates. We use two proxies for recovery rates, namely the price at default, and the price a month after default. Panel A presents this information around loan default dates, and Panel B presents this information around bond default dates.

Panel A: Loan Default Dates

	Correlation with cumulative returns of	
Proxy for recovery rate	Loans	Bonds
Price at default	0.80	0.46
Price one month after default	0.85	0.65

Panel B: Bond Default Dates

	Correlation with cumulative returns of	
Proxy for recovery rate	Loans	Bonds
Price at default	0.59	0.28
Price one month after default	0.60	0.47

TABLE 11
Linear regression of recovery rates

This table presents OLS estimates of regression specifications determining the recovery rates of loans and bonds subsequent to a default date, namely a loan default date or a bond default date. For comparison with our tables, we include in this table the loan-bond pairs of Table 9. The dependent variable, RECOVERY RATE refers to the amount an investor expects from her investment in the loan or the bond subsequent to the default date. We use the price at default as a proxy for the recovery rate. The independent variables are as follows: LOAN DEFAULT DUMMY takes a value of one if it is a loan default, and zero otherwise. LOAN DUMMY takes a value of one if it is a loan, and zero otherwise. LOAN DUMMY x LOAN DEFAULT LEADS is an interactive dummy variable that takes a value of one if it is a loan and if the loan default date is not preceded by a bond default date for the same loan-bond pair, and zero otherwise. LN(MATURITY) stands for natural log of one plus remaining maturity (in years) as on a default date. LN(AMOUNT) stands for natural log of one plus amount of the loan or bond issue (in $ millions). SENIOR SECURED, SENIOR UNSECURED, and SENIOR SUBORDINATED each take a value of one if a loan or bond is classified like-wise and zero otherwise. The *t* ratios are shown in parentheses (a, b, and c stand for significance at the 1%, 5%, and 10% levels using a two-tailed test).

Dependent Variable: Recovery rate

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
INTERCEPT	21.13	20.81	110.18	7.82	68.98	69.15
	(9.27)^a	(8.93)^a	(10.27)^a	(2.24)^b	(5.88)^a	(5.84)^a
LOAN DEFAULT DUMMY	10.33	10.95	5.48	6.41	3.34	3.42
	(3.97)^a	(3.97)^a	(2.28)^b	(2.61)^a	(1.45)	(1.42)
LOAN DUMMY	35.33	36.92	26.29	32.43	25.89	26.10
	(13.59)^a	(10.57)^a	(10.00)^a	(12.22)^a	(9.87)^a	(8.14)^a
LOAN DUMMY x						
LOAN DEFAULT LEADS		-2.68				-0.42
		(-0.68)				(-0.11)
LN(MATURITY)			-16.86		-18.37	-18.36
			(-5.94)^a		(-6.75)^a	(-6.73)^a
LN(AMOUNT)			-9.17		-4.17	-4.19
			(-5.98)^a		(-2.54)^b	(-2.54)^b
SENIOR SECURED				5.92	9.08	9.00
				(1.26)	(2.10)^c	(2.05)^c
SENIOR UNSECURED				28.40	22.51	22.50
				(7.24)^a	(5.74)^a	(5.72)^a
SENIOR SUBORDINATED				20.54	20.86	20.72
				(6.17)^a	(6.37)^a	(5.95)^a
Observations	286	286	286	286	286	286
Adjusted R^2	0.41	0.41	0.53	0.52	0.60	0.60

TABLE 12
Average cumulative abnormal returns of matched loan-stock pairs around default dates (matched by borrower name)

This table presents the average cumulative abnormal return (ACAR) of matched loan-stock pairs surrounding a default date (day 0), namely a loan default date or a bond default date 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 number of observations is shown for the estimation window [-10,+10]. 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. 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

Event window	Loan ACAR (%) (1)	Stock ACAR (%) (2)	Difference in ACAR (%) (3) = (1) - (2)
[-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]
Obs	29	29	

Panel B: Bond default dates

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)
Obs	59	59	

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 06/2002 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, e.g., if a company has three loans, and the LIN is missing on two of them. We have 543,526 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 371,797 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 or a bond default date (the primary focus of this study) in the following manner: First, we found all the available matching Datastream IDs, namely the 6 digit Datastream codes 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. We check 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 2002 CRSP stock files based on the permnos. We have a total of 21,510 stock-day observations spanning 75 stocks corresponding to a subset of loans in the loan price dataset with a loan default date or a bond default date (the primary focus of this study).

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. During our sample period we had 90 loan defaults.

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. During our sample period we had 765 bond defaults pertaining to 366 companies.

Loan characteristics dataset

The source for our loan characteristics dataset is the Loan Pricing Corporation. The key data items are: (a) Name of the borrower, (b) Facility type: information on seniority of a facility, and whether it is a term loan or revolver facility, (c) Facility amount, (d) Facility date, (e) Final maturity, (f) Security, e.g., Secured or Unsecured or what type of specific collateral (All assets, or Capital Stock of Operating Units etc.), (g) Loan Identification Number. We first matched the details of the loan from the loan price dataset, e.g., LIN, name of the borrower, and we created variables that denote the priority structure of a loan, e.g., SENIOR SECURED, SENIOR UNSECURED, and SENIOR SUBORDINATED (see Section 4.2.2.) based on Facility type and Security information.

Bond characteristics dataset

The source for our bond defaults dataset is the "New York University (NYU) Salomon Center's Altman Bond Default Database". To measure the priority structure of bonds, we incorporate the seniority and collateral information of a bond, using the classification of Altman and Kishore (1996). We classify bonds into four different categories based on the description of a bond in the bond defaults dataset: (a) Senior secured, (b) Senior unsecured, (c) Senior subordinated, and (d) Subordinated and others.

Appendix 2
Unadjusted returns of matched loan-bond pairs
(matched by borrower name)

This table presents the average cumulative abnormal return (ACAR) of matched loan-bond pairs (based on the name of the borrower) surrounding a default date (day 0), namely a loan default date or a bond default date of the same company. This table includes matched loan-bond pairs where we are able to compute the CAR based on the unadjusted method for the [-10,+10] event window. That is, the unadjusted loan or bond daily return respectively. The *Z* statistics of ACARs (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, 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

Event window	Loan ACAR (%) (1)	Bond ACAR (%) (2)	Difference in ACAR (%) (3) = (1) - (2)
[-1,+1]	-4.86	-21.94	17.08
	(-5.32)^a	(-9.51)^a	(7.90)^a
[-5,+5]	-12.61	-42.25	29.64
	(-7.21)^a	(-9.56)^a	(6.73)^a
[-10,+10]	-23.92	-55.38	31.46
	(-9.91)^a	(-9.07)^a	(5.14)^a
Obs	74	74	

Panel B: Bond default dates

Event window	Loan ACAR (%) (4)	Bond ACAR (%) (5)	Difference in ACAR (%) (6) = (4) - (5)
[-1,+1]	-4.29	-7.05	2.76
	(-4.31)^a	(-2.72)^a	(1.09)
[-5,+5]	-16.23	-35.18	18.95
	(-8.52)^a	(-7.10)^a	(3.55)^a
[-10,+10]	-25.55	-45.96	20.41
	(-9.71)^a	(-6.71)^a	(2.58)^a
Obs	69	69	

Appendix 3
Mean-adjusted average cumulative abnormal returns of matched loan-bond pairs (matched by borrower name)

This table presents the average cumulative abnormal return (ACAR) of matched loan-bond pairs (based on the name of the borrower) surrounding a default date (day 0), namely a loan default date or a bond default date of the same company. This table includes matched loan-bond pairs where we are able to compute the CAR based on the mean adjusted method for the [-10,+10] event window. That is, the average daily return during a 234 day estimation time period (from day -244 to -11 relative to the default date) is subtracted from the loan or bond daily return. The Z statistics of ACARs (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, 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

Event window	Loan ACAR (%) (1)	Bond ACAR (%) (2)	Difference in ACAR (%) (3) = (1) - (2)
[-1,+1]	-4.54	-20.83	16.29
	(-4.99)[a]	(-9.06)[a]	(7.28)[a]
[-5,+5]	-11.44	-38.18	26.74
	(-6.56)[a]	(-8.67)[a]	(6.14)[a]
[-10,+10]	-21.70	-47.62	25.92
	(-9.00)[a]	(-7.83)[a]	(4.01)[a]
Obs	74	74	

Panel B: Bond default dates

Event window	Loan ACAR (%) (4)	Bond ACAR (%) (5)	Difference in ACAR (%) (6) = (4) - (5)
[-1,+1]	-3.88	-5.32	1.44
	(-3.91)[a]	(-2.06)[b]	(0.58)
[-5,+5]	-14.72	-28.83	14.11
	(-7.75)[a]	(-5.82)[a]	(2.67)[a]
[-10,+10]	-22.67	-33.83	11.16
	(-8.64)[a]	(-4.94)[a]	(1.37)
Obs	69	69	

Appendix 4
Market-adjusted average cumulative abnormal returns of matched loan-bond pairs (matched by borrower name)

This table presents the average cumulative abnormal return (ACAR) of matched loan-bond pairs (based on the name of the borrower) surrounding a default date (day 0), namely a loan default date or a bond default date of the same company. This table includes matched loan-bond pairs where we are able to compute the CAR based on the market adjusted method for the [-10,+10] event window. That is, the return based on 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 (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, 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

Event window	Loan ACAR (%) (1)	Bond ACAR (%) (2)	Difference in ACAR (%) (3) = (1) - (2)
[-1,+1]	-4.76	-22.21	17.45
	(-5.19)^a	(-9.42)^a	(8.14)^a
[-5,+5]	-12.26	-42.79	30.53
	(-7.00)^a	(-9.48)^a	(6.88)^a
[-10,+10]	-23.78	-56.34	32.56
	(-9.82)^a	(-9.03)^a	(5.28)^a
Obs	74	74	

Panel B: Bond default dates

Event window	Loan ACAR (%) (4)	Bond ACAR (%) (5)	Difference in ACAR (%) (6) = (4) - (5)
[-1,+1]	-4.29	-7.37	3.08
	(-4.34)^a	(-2.84)^a	(1.21)
[-5,+5]	-16.24	-36.11	19.87
	(-8.57)^a	(-7.27)^a	(3.72)^a
[-10,+10]	-25.63	-47.31	21.68
	(-9.79)^a	(-6.89)^a	(2.72)^a
Obs	69	69	

Appendix 5
Three-factor model adjusted average cumulative abnormal returns of loan-bond pairs (matched by borrower name)

This table presents the average cumulative abnormal return (ACAR) of matched loan-bond pairs (based on the name of the borrower) surrounding a default date (day 0), namely a loan default date or a bond default date of the same company. This table includes matched loan-bond pairs where we are able to compute the CAR based on a three-factor model adjusted method for the [-10,+10] event window. That is, the return based on a three-factor model regression (the three factors being the return on the S&P/LSTA Leveraged Loan Index, the return on the Lehman Brothers U.S. Corporate Intermediate Bond Index, and the return on the NYSE/AMEX/NASDAQ value-weighted market index) is subtracted from the loan or bond daily return respectively. The Z statistics of ACARs (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, 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

Event window	Loan ACAR (%) (1)	Bond ACAR (%) (2)	Difference in ACAR (%) (3) = (1) - (2)
[-1,+1]	-4.18	-21.52	17.34
	(-4.80)^a	(-9.39)^a	(8.13)^a
[-5,+5]	-9.10	-38.62	29.52
	(-5.46)^a	(-8.80)^a	(6.57)^a
[-10,+10]	-18.24	-47.50	29.26
	(-7.92)^a	(-7.83)^a	(4.53)^a
Obs	74	74	

Panel B: Bond default dates

Event window	Loan ACAR (%) (4)	Bond ACAR (%) (5)	Difference in ACAR (%) (6) = (4) - (5)
[-1,+1]	-3.49	-5.58	2.09
	(-3.73)^a	(-2.17)^b	(0.83)
[-5,+5]	-12.19	-29.05	16.86
	(-6.80)^a	(-5.91)^a	(2.99)^a
[-10,+10]	-18.61	-34.07	15.46
	(-7.51)^a	(-5.02)^a	(1.79)^c
Obs	69	69	

Appendix 6

Unadjusted returns of matched loan-bond pairs with the same loan and bond default days (matched by borrower name)

This table presents the average cumulative abnormal return (ACAR) of matched loan-bond pairs (based on the name of the borrower) with the same loan and bond default days (i.e., within 2 days of each other), surrounding a default date (day 0), namely a loan default date or a bond default date of the same company. This table includes matched loan-bond pairs where we are able to compute the unadjusted cumulative returns for the [-10,+10] event window. That is, the unadjusted loan or bond daily return respectively. The Z statistics of ACARs (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, 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: Unadjusted returns

Event window	Loan ACAR (%) (1)	Bond ACAR (%) (2)	Difference in ACAR (%) (3) = (1) - (2)
[-1,+1]	-3.04	-2.56	-0.48
	(-1.28)	(-0.42)	(-0.17)
[-5,+5]	-20.51	-69.87	49.36
	(-4.50)^a	(-6.03)^a	(4.32)^a
[-10,+10]	-51.25	-82.90	31.65
	(-8.15)^a	(-5.17)^a	(1.81)^c
Obs	26	26	

Appendix 7
Average cumulative abnormal returns of matched loan-bond pairs with the same loan and bond default days (matched by borrower name)

This table presents the average cumulative abnormal return (ACAR) of matched loan-bond pairs (based on the name of the borrower) with the same loan and bond default days (i.e., within 2 days of each other) surrounding a default date (day 0), namely a loan default date or a bond default date 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 (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, 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.

Event window	Loan ACAR (%) (1)	Bond ACAR (%) (2)	Difference in ACAR (%) (3) = (1) - (2)
[-1,+1]	-0.01	-0.00	-0.01
	(-0.57)	(-0.06)	(-0.34)
[-5,+5]	-14.66	-60.66	46.00
	(-3.30)[a]	(-5.22)[a]	(4.06)[a]
[-10,+10]	-41.89	-64.96	23.07
	(-6.82)[a]	(-4.04)[a]	(1.31)
Obs	26	26	

Appendix 8
Linear regression of negative cumulative abnormal return of loan-bond pairs with the same loan and bond default days

This table presents OLS estimates of regression specifications determining the cumulative abnormal return (CAR) performance of matched loan-bond pairs (based on the name of the borrower) with the same loan and bond default days (i.e., within 2 days of each other) surrounding the default date. This table includes loans, and bonds where we are able to compute the CAR based on the market-model adjusted method for the [-10,+10] event window. The dependent variable NEGATIVE CUMULATIVE ABNORMAL RETURN, NCAR[-10,+10] equals -CAR[-10,+10], where day [0] refers to a default date, namely the loan default date or the bond default date 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: LOAN DUMMY takes a value of one if it is a loan, and zero otherwise. LN(MATURITY) stands for natural log of one plus remaining maturity (in years) as on a default date. LN(AMOUNT) stands for natural log of one plus amount of the loan or bond issue (in $ millions). SENIOR SECURED, SENIOR UNSECURED, and SENIOR SUBORDINATED each take a value of one if a loan or bond is classified like-wise and zero otherwise. The t ratios are shown in parentheses (a, b, and c stand for significance at the 1%, 5%, and 10% levels using a two-tailed test).

Dependent Variable: -CAR[-10,+10], Market-model adjusted (%)

Variable	Model 1	Model 2	Model 3	Model 4
INTERCEPT	64.96	82.42	167.49	211.88
	(4.52)^a	(0.49)	(14.61)^a	(2.48)^b
LOAN DUMMY	-23.07	-4.72	-127.31	-124.23
	(-1.14)	(-0.19)	$(-11.76)^a$	(-8.67)^a
LN(MATURITY)		114.10		14.26
		(2.89)^a		(0.73)
LN(AMOUNT)		-39.42		-11.54
		(-1.97)^b		(-1.05)
SENIOR SECURED			-180.60	-176.48
			(-13.13)^a	(-12.31)^a
SENIOR UNSECURED			-54.04	-63.07
			(-2.91)^a	(-3.04)^a
SENIOR SUBORDINATED			13.87	7.28
			(1.34)	(0.63)
Observations	52	52	52	52
Adjusted R^2	0.01	0.22	0.83	0.84

Appendix 9
Recovery rates by debt type and seniority

This table compares three measures of recovery rates, namely trading prices just after default, and 30 days after default, and at ultimate recovery for the 1988-2Q 2003. The sources are: Altman-NYU Salomon Center Default database, prices from numerous broker dealers in distressed debt. Bank Loan data from 1996-2002 (for the first two measures), and Standard & Poor's LossStatsTM database from 1988-2Q-2003 for the third measure (ultimate recoveries discounted at each instrument's pre-default interest rate). Note that the Sub. Discounted Bonds category includes zero coupon and discounted bonds of all seniorities.

Debt Type/Seniority	Price at Default		Price 30 Days After Default		Ultimate recovery			
						Nominal	Discounted	Annual
	#obs.	Mean %	#obs.	Mean %	#obs.	Mean %	Mean %	IRR %
Bank Loans	262	69.2	750	58.0	750	88.9	78.8	20.0
Senior Secured Bonds	152	51.6	222	48.8	222	76.5	65.1	20.5
Senior Unsecured Bonds	752	32.4	419	30.3	419	54.9	46.4	23.0
Senior Subordinated Bonds	346	28.8	350	28.4	350	38.2	31.6	7.7
Subordinated Bonds	180	29.0	293	28.9	343	36.3	29.4	8.9
Sub. Discounted Bonds	130	20.4	–	–	43	–	22.0	–

Figure 1
Secondary Market for Loans