The Cross-Section of Expected Returns in the Secondary Corporate Loan Market

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Corporate loans increasingly have become an important part of portfolio management with the advent of a liquid and transparent secondary market. This paper examines the pricing of characteristics and betas in the cross-section of expected loan returns. Expected loan returns decrease with default beta. Default beta contains information not captured by rating or spread-to-maturity. Among loan characteristics, a 3-month formation momentum strategy earns a monthly premium of 122 bps. Momentum is prominent in loans issued by the lowest-rated borrowers. (*JEL* G10, G12, G20)

Introduction

The secondary corporate loan market has exponentially grown over the past two decades. In the United States, loan trading volume has increased from $7 billion in 1991 to $517 billion in 2013. This translates into an increase from 2% of the notional value of corporate loans outstanding in 1991 to 38% in 2013 (Figure 1). The development of a transparent market has transformed the market for corporate loans from the private domain of banks into a well-established alternative asset class for a broad range of nonbank investors, such as mutual funds, hedge funds, finance institutions, insurance companies, and securitization pools.[1]

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[1] A number of factors have contributed to this growth: the leveraged buyout boom of the mid-1980s created enormous demand for bank credit and therefore caused banks to seek out new ways to finance deals by engaging with nonbank capital providers; the increasing demand by institutional investors and portfolio managers largely has been driven by the flexibility of the contract terms and the high yields, but with lower riskiness of loans relative to other similar products; the introduction of Rule 144a of the Securities Act in 1993 facilitated loan-trading activities; and the inception of the Loan Trading and Syndication Association (LSTA) in 1995 acted as a nonprofit organization and provided standardized forms and market practices for corporate loans. For more details on the structure of the loan-sale market, see Standard & Poor's "A Guide to The Loan Market", published in September 2011, Leverage Commentary & Data's "A Guide to the U.S. Loan Market", published in September 2013, and Taylor and Sansone (2006).

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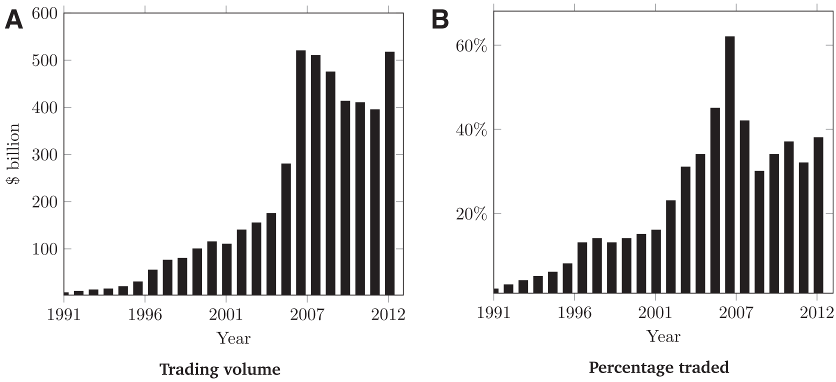

Figure 1
Trading volume in the secondary corporate loan market between 1991 and 2013
This figure demonstrates the total dollar value of loans traded in the secondary corporate loan market from 1991 to 2013 in the United States *(A)* and the percentage of outstanding loans traded in the secondary market each year between 1991 and 2013 *(B)*. *Source*: Shared National Credits Program 2013 Review available at www.federalreserve.gov and the LSTA Trade Data Study avaiable at www.lsta.org.

Corporate loans have several characteristics that offer distinct features compared with other debt instruments. Loans mainly are secured and senior to other types of debt on the issuer's capital structure. As a result, loans generally have higher recovery rates in the event of issuers' default. Unlike corporate bonds (which pay fixed-rate coupons), loans are floating-rate investments with interest payments that periodically adjust based on a predetermined benchmark rate, such as LIBOR. This means that, unlike bonds, loans have the potential to benefit from a rise in interest rates. For most traded loans, the principal is partially paid (amortized) over the loan's lifetime with the remaining balance being paid at maturity, and for most bonds, the entire principal is paid on the maturity date.[2] These properties reduce the duration and volatility of loans compared with corporate bonds with similar maturity and rating. Figure 2 presents the time series of cumulative returns for two markets populated by speculative-grade borrowers. Consistent with differentiating features of loans, the figure shows that returns on loans are less volatile than the returns on speculative grade bonds.

The loan sale market has been reviewed in the literature of corporate finance and banking. Güner (2006), Drucker and Puri (2009), Berndt and Gupta (2009), and Gande and Saunders (2012) studied the consequences of lenders' activities in the secondary market on borrowers' short-term and long-term performance and also on borrowers' debt liquidity and cost of borrowing. Pennacchi (1988), Wittenberg-Moerman (2008), Parlour and Plantin

[2] Most traded loans are term B loans, also known as "institutional" term loans. Most term B loans pay 1% amortization per year.

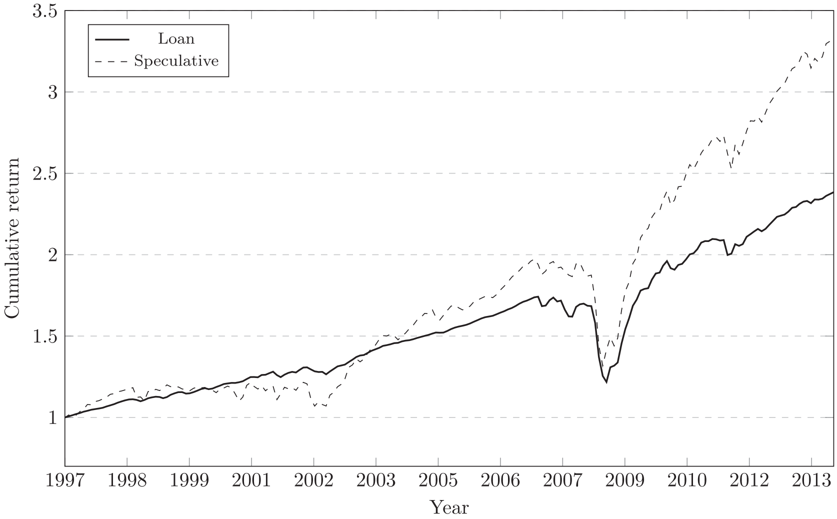

Figure 2
Cumulative returns on loans and speculative bonds between 1997 and 2013
This graph displays the cumulative returns on a dollar invested in the secondary loan market and B of A Merrill Lynch US High Yield Master II Total Return Index for the period of January-1997 to December-2013

(2008), and Parlour and Winton (2013) considered the benefits of the secondary loan market for lenders in terms of efficient risk sharing and balance-sheet management. Altman, Gande, and Saunders (2010) examined whether banks have an informational advantage relative to public bondholders prior to a loan default. Despite the tremendous growth in the secondary market trading and the emergence of syndicated loans as an important asset class among institutional investors, this market is largely unexplored in the context of empirical asset pricing literature.

In this paper, we provide a comprehensive empirical analysis of the cross-section of expected corporate loan returns using an extensive database of secondary market dealer quotes. We examine the pricing effects of eight loan characteristics, including spread-to-maturity (STM), price, rating, momentum, market value, idiosyncratic volatility, number of dealer quotes, and bid-ask spread. Of all the characteristics considered, momentum is significantly related to future returns. Momentum is stronger among loans subject to more dealer quotes and issued by low-rated borrowers. Momentum profits are driven by capital gains as the interest returns on momentum-sorted portfolios are similar. The effect is concentrated in a sample of nonstale loan quotes, among which the premium of the strategy is 121 basis points per month. Loan momentum crashes when equity momentum crashes, but the magnitude of the decline is smaller. Our results complement studies that document anomalous returns related to momentum strategies.[3]

Next, we examine linear factor models wherein risk premiums are associated with the conditional covariances between asset returns and variation in state variables. Specifically, since this market is also known as the "Leveraged Loan Market" because of the high leverage of the issuing firms and since highly leveraged companies are more at risk of default, aggregate default risk is a natural candidate for a priced factor.[4] We estimate a monthly premium of about -20 basis points per unit of default beta, supporting the conjecture that default risk is a state variable and, therefore, loans whose returns covary positively with systematic default risk command lower returns. Default beta is related to proxies of default risk, such as rating and STM, but its effect remains significant after adjusting for those characteristics. Gebhardt, Hvidkjaer, and Swaminathan (2005) documented similar results regarding the features of default beta in the cross-section of corporate bond returns.

An equal- (value-) weighted default-mimicking factor that purchases the top quintile and shorts the first quintile of loans ranked on default beta generates a monthly premium of −0.38% (−0.43%). Time-series regressions suggest that the mimicking factor covaries with measures of liquidity in the loan market and the economy. Consistent with this finding, the tradable liquidity factor of Pástor and Stambaugh (2003) explains a part of the default beta premium. Finally, we estimate the price of risk for common risk factors using the two-stage Fama and MacBeth (1973) procedure at the issue and portfolio levels. Various cross-sectional tests further confirm that among the candidate risk factors, default risk is consistently priced.

One caveat of our analysis is that our sample of secondary market dealer quotes does not cover more recent data (year 2010 and after). Therefore, we are confronted with the problem of the potential lack of external validity as a result of the sample coverage.

1. Data and Empirical Measures

Our primary data set includes all loans to U.S. firms in the Reuters Loan Pricing Corporation's DealScan data set (henceforth DealScan) prior to 2014. DealScan is the main source of data used in studies on corporate loans and provides detailed information on the majority of loans originating in the

[3] Momentum is documented in stocks (Jegadeesh 1990; Jegadeesh and Titman 1993; Carhart 1997), mutual funds (Hendricks, Patel, and Zeckhauser 1993; Brown and Goetzmann 1995; Grinblatt, Titman, and Wermers 1995), hedge funds (Baquero, Ter Horst, and Verbeek 2005; Boyson 2008; Jagannathan, Malakhov, and Novikov 2010), stock, currency, and bond futures (Bhojraj and Swaminathan 2006; Asness, Moskowitz, and Pedersen 2013; Moskowitz, Ooi, and Pedersen 2012), corporate bonds (Jostova et al. 2013), commodity futures (Miffre and Rallis 2007; Szakmary, Shen, and Sharma 2010), currencies (Menkhoff et al. 2012; Asness, Moskowitz, and Pedersen 2013), and credit default swaps (Lee, Naranjo, and Sirmans 2014).

[4] Following previous studies, we proxy aggregate default risk by the return spread between AA and BBB corporate bonds.

United States.[5] The database contains borrower identity, loan type (term versus revolver), original amount, currency, country of origination, initiation and ending dates, seniority condition, whether or not the loan is secured, loan base rate (LIBOR, Prime, etc.), spread, and payment schedule. The secondary loan pricing data come from the Loan Syndication and Trading Association (LSTA) and the LPC mark-to-market pricing service. The LSTA data set available to us is from May 22, 1998 to December 7, 2009, and provides bid and ask quotes averaged across all dealers, mean of average bid and average ask quotes, number of quotes, date, type of facility, loan identification number, and borrower name and ID on a daily basis (total of 8,811,210 loan-day observations). We merge the LSTA with the DealScan data set using loan identification numbers (LINs) and/or facility IDs. Primary loan data for 7,047,713 loan-day observations are successfully located.

To reduce the effect of outliers and to ensure that only loans with reliable quotes enter the sample, we employ the following filters: We limit the sample to term loans because unlike revolvers these loans are fully funded at the origination.[6] This leads to 5,199,015, or 74% of the total observations. We exclude loans that are not USD based, do not originate in the United States (3,516,391 observations after this step), or have less than 90 days to maturity (3,296,168 observations after this step). Following Standard & Poor's loan market indices, we restrict the sample to secured and senior loans (3,223,532 observations). We also exclude loans with missing data on any of these items: loan spreads, base rate, initiation date, or ending date, leading to 3,189,569 observations. Moreover, loans for which the original facility amount does not match the sum of the total scheduled principal payments are removed from the sample because the principal payment is an important component of returns in loans. Duplicate quotes or quotes on nonbusiness dates as well as those with a bid price greater or equal to the ask price are discarded. At the end of the screening process, we have 1,446,499 loan-day observations. We omit quotes prior to June 1999 because quotes are not reported on a daily basis during the first year of the sample. These data are used for estimating rolling betas, end of month characteristics, and monthly returns.[7]

We use the DealScan-Compustat Link Data provided on Michael Robert's Web site (Chava and Roberts 2008) to obtain borrower gvkeys. We then use gvkeys to match loans with issuers' credit ratings assigned by Standard & Poor's from Wharton Research Data Services (WRDS). Issuer rating is not available for approximately half of the loans in our final sample. We also use the DealScan-Compustat Link to identify borrowers in the CRSP and

[5] Following the literature on corporate loans, we use "loan", "facility", and "loan facility" interchangeably throughout the paper.

[6] For the same reason, S&P/LSTA only includes the term loans in computing the U.S. Leveraged Loan 100 Index.

[7] In the Internet Appendix, we use the data omitted during the screening process to run out-of-sample tests for robustness checks.

Compustat data sets to obtain stock returns and characteristics. We obtain data on base interest rates (Prime and LIBOR rates), the short-term treasury (risk-free) rate, and aggregate index values of Bank of America Merrill Lynch 10-year US Treasury, AA, BBB, and High Yield Master II from the Federal Reserve Economic Data (FRED) provided by the Federal Reserve Bank of St. Louis. Data on aggregate monthly loan returns are drawn from S&P Captial IQ LCD.[8]

1.1 Loan market returns

Table 1 provides descriptive statistics on excess returns for the U.S. loan market, the U.S. stock market (CRSP universe), and four bond market indices between 1999 and 2009. Average risk premium for the loan index is 0.17% per month, which is lower than average risk premium (0.31%) for the speculative-grade index. This is expected because, all else equal, loans might have smaller expected returns than high-yield corporate bonds given that they carry a smaller premium for interest rate risk. The column labeled "Corr." indicates that the loan market has the largest time-series correlations with the speculative and BBB bond markets. The most compelling common source of risk among these assets is credit risk. Nevertheless, loan returns are not strongly correlated with returns on other high-yield products, and offer significant diversification benefits.[9]

The relationship between the loan market index and the default risk factor is displayed in the last row, where the default risk factor is defined as the difference between the return on a portfolio of AA and a portfolio of BBB bonds, as is standard in the literature. Among all portfolios considered in Table 1, loan returns have the highest exposure to the default factor.[10]

An interesting observation is the positive, significant, and slowly decaying autocorrelation in the time series of loan index monthly returns. The first two lags of the series are statistically significant, with the first lag alone explaining 35% of variations in index returns. A closer look reveals that the autocorrelation in loan returns originates from the high autocorrelation of short-term rates. Given that loan prices are not highly sensitive to fluctuations in interest rates, the main source of return volatility is shifts in systematic default risk. In absence of such shifts, prices remain stable and therefore returns will only be driven by principal repayment and accrued interest, which itself depends on

8 These data are available at https://www.lcdcomps.com/lcd/f/indexreturns.html

9 We perform two mean-variance optimizations using the 1997-2014 data to test whether loan returns contribute to mean-variance efficiency of the optimal risky portfolio. When the risk-free rate is assumed to be the one-month Treasury rate, the optimal risky portfolio consists of 63% AA bonds, 30% loans, and 7% stocks, but when the risk-free rate is equal to the three-month Treasury rate, optimal weights become 43% AA bonds, 43% BBB bonds, and 15% stocks.

10 Given the large correlation between loans and high-yield bonds, we examined whether an alternative proxy of default risk, defined as the difference between the return on a portfolio of AA and the return on a portfolio speculative bonds, could provide better insights regarding the credit risk in the loan market. The correlation between the loan index and the alternative measure of credit risk is −0.53, which is smaller than −0.80. In the rest of the paper, we proceed with the standard definition of default risk.

Table 1
Summary statistics for excess returns of assets classes and the default factor

	Mean (%)	SD (%)	Min. (%)	Max. (%)	Skew.	Kurt.	Corr.	Autocorrelation Lag 1	Lag 2	Lag 3
Loan	0.17	2.27	−13.49	8.97	−1.44	17.02	1.00	**0.59**	**0.23**	0.09
Treasury	0.29	2.37	−7.36	9.61	0.11	4.79	**−0.37**	0.01	**−0.27**	0.07
AA	0.28	1.41	−5.55	4.95	−0.43	5.46	**0.34**	**0.20**	**−0.26**	−0.01
BBB	0.33	1.94	−10.63	4.95	−1.32	10.52	**0.50**	**0.26**	−0.04	0.04
Junk	0.31	3.27	−15.58	12.12	−0.79	8.62	**0.66**	**0.37**	−0.07	0.09
MKT	0.00	4.83	−17.23	10.19	−0.60	3.54	**0.46**	**0.19**	−0.05	0.08
$r_{AA} - r_{BBB}$	−0.06	1.11	4.62	7.44	1.69	20.01	**−0.80**	**0.26**	0.16	0.00

This table reports the summary statistics for monthly excess returns on five fixed-income indexes, the market portfolio, and a default factor. Treasury is the return on Merrill Lynch 10-year US Treasury Futures Total Return Index, less the risk-free rate. AA, BBB, Junk, and MKT represent the excess return on the Merrill Lynch AA, BBB, High Yield, and market portfolio, respectively. $r_{AA} - r_{BBB}$ is the difference between the return on the AA index and the return on the BBB index. All statistics are for monthly returns between September 1999 and December 2009. "Corr." presents the pairwise correlation coefficient between each factor and the aggregate loan market return. The last three columns present the autocorrelation up to the third lag for each series. Significant coefficients at the 5% level are bold.

the benchmark rate. Principal payment is known ex ante and the short-term interest rate normally does not change dramatically, making future cash flows and returns on a diversified index less random.

1.2 Individual loan returns

We compute daily and monthly returns for individual loans based on the procedure described in S&P/LSTA U.S. Leveraged Loan 100 Index Methodology.[11] This index is value-weighted and is constructed to reflect the performance of the 100 largest facilities in the leveraged loan market. On day t, the total return on each loan consists of price, principal repayment, and interest returns:

$$r_t = \frac{Par_t \cdot (P_t - P_{t-1}) + (Par_t - Par_{t-1}) \cdot (1 - P_{t-1}) + (AI_t - AI_{t-1}) + C}{Par_{t-1} \cdot P_{t-1} + AI_{t-1}} \quad (1)$$

where Par is the par value (remaining balance) of the loan, adjusted for any principal payments. P is the average market bid and ask quotes. A price of one means that loan is trading at par. $(Par_t - Par_{t-1})$ is the principal repayment (if any) on day t and is assumed to be made at par. AI_t is the income accrued as of time t based on a 360-day basis. Accrued income is reduced to zero after each coupon payment. C is the coupon payment (if any) paid on quarterly anniversaries of the loan's origination date. The principal repayment return, reflected in the second term, enters the equation because the date and amount of each payment are agreed on at origination, although the loan may not be priced at par on the repayment dates. In our final sample, 85.59%

[11] For more details, visit http://us.spindices.com/indices/fixed-income/sp-lsta-us-leveraged-loan-100-index.

of the facilities prepay the principal on a quarterly basis while the remaining pay the principal on a semiannually (5.30%), annually (7.54%), or biannually (0.30%) basis. Only 1.27% of observations belong to "Bullet" loans that do not prepay any principal before expiration.

For portfolio analysis in the following sections, it is assumed that the hypothetical investor sells a facility whenever its price lies outside the 50%-102.5% range. This means that if the price of a loan falls out of the indicated range in month m, we maintain month m return but exclude the loan from future analysis. The agent buys the loan again if the price reappears in the indicated range. This procedure removes less than 1% of all monthly quotes but is necessary since the lower bound filters distressed loans for which returns might not be accurate, and the upper bound filters loans that are at risk of being called.[12]

The screening criteria described above mostly filters small and illiquid loans, so the sample is tilted towards larger loans that are generally more accessible and more easily tracked. An aggregate value-weighted index of all the loans in our sample has an average monthly return of 0.380% compared to 0.384% for the S&P Syndicated Total Return Index. The two indices have a time-series correlation of 0.989, indicating that our sample represents the broad loan market accurately. The 0.38% average monthly return for the loan series consists of 0.53% interest return, 0.01% principal repayment return, and −0.16% price return.

1.3 Individual loan characteristics

In our empirical analysis, we employ a range of loan characteristics to examine possible factors that affect the discount rates and consequently drive returns in the corporate loan market. These characteristics can be classified into three categories.

The first set of variables pertains to loan risk characteristics and includes spread-to-maturity (STM), issuer rating, and price. STM is initial spread over the base rate, adjusted for any deviation in loan price from par value, over the life of the loan.[13] More than half of the issuers in our sample have ratings in the S&P's credit portal. We use issuer debt rating as a proxy for issue rating. Since all loans in our sample are senior and secured, issuer rating can be a good proxy for loan rating. We map each credit rating to a numeric scale between 1 (for D) and 22 (for AAA). The average and median credit rating in

[12] For example, for a loan that is not paying interest and is in default, a small change in the bid or ask quotes may change the implied price from \$1 to \$2, thereby resulting in a 100% return. Whether this return is because of higher demand or a bounce in the bid or ask quotes is unclear.

[13] Given that loans pay a floating interest and benchmark interest rates are stochastic, the amount of future coupon payments is not certain. Hence, instead of YTM, the practitioners in this market use STM. To calculate STM, we solve for STM in $P = \sum_{i=t}^{T} \frac{Prin._i}{(1+STM)^i} + \sum_{j=\tau}^{T'} \frac{Spread_j}{(1+STM)^j}$, where P, *Prin.*, and *Spread* are the price, principal, and spread payments, respectively. i is the ratio of remaining days to a principal repayment to 360 and j is the ratio of remaining days to a spread payments to 360. The STM in this equation can be interpreted as the return on the loan if the benchmark rate is equal to zero over the loan's lifetime.

the sample are 9.37 and 9, respectively (equivalent to a B+ rating), revealing the considerable presence of non-investment-grade issuers in this market. The last variable in this set, loan market price, is the average of bid and ask market quotes, expressed as a percentage. A market price of 100 means that the loan is trading at par. This variable is sometimes used as a measure of distress (Taylor and Sansone 2006; Berndt and Gupta 2009).

The second set of variables includes momentum, size, and volatility. The benchmark momentum is the loan's cumulative return over the past three months. Size is the market value of the loan, the product of the outstanding balance and market price, plus the accrued income. Volatility is the annualized standard deviation of residuals in a regression with daily excess loan returns as the dependent variable, and the market, term, and default factors as the independent variables.

The third set of variables is related to liquidity. The first measure is bid-ask spread and is computed by the ratio of the difference between bid and ask quotes to their average. Further, loans trade over-the-counter. As a result, loans that are associated with a larger number of dealer quotes are more readily available for trade. Hence, the second measure of liquidity is the number of bid and ask dealer quotes. This number is between 1 and 18, with 85% of observations falling in the 1 to 5 range. We do not restrict the sample to loans with more than one quote but we show in robustness checks that results become stronger if we do so.

Table 2 provides an overview of the sample. A considerable number of loans satisfy the filter criteria. The number of loans is 490 in 1999, rises to 867 by 2002, and reaches its minimum of 422 in 2009. Although the number of loans fluctuates over time, the size of the average loan steadily increases. The average market value of a loan in 2009 is more than three times larger than the average market value of a loan in 1999. Prices of corporate loans do not typically rise beyond par because unlike many corporate bonds that are noncallable for a certain period, loans are callable at any time. The ability of the borrower of a loan to repay the principal prior to maturity places a cap on the investment's upside potential. Table 2 shows that although loans usually trade close to par, the average price still correlates with the status of the economy; it reaches its maximum in 2005-2006 and drops significantly during the financial crisis. By construction, spread-to-maturity is closely related to loan price. Average spread-to-maturity is smallest in the 2005-2007 period, when average loan was trading at par, and peaks during the financial crisis. Among the aggregate statistics of Table 2, liquidity displays wider swings over time. There has been a sevenfold increase in the bid-ask spread between 2007 and 2009, with the average difference between the bid and ask quotes being 4.5% of the loan price in 2009.

Panel (b) presents the frequency of observations by credit rating. Only 3% of issuers are investment grade. The majority of issuers either are noninvestment grade with B, B+, BB-, and BB ratings, or do not have a rating.

Table 2
Descriptive statistics of the sample

Panel (A): Summary statistics

Year	n_{total}	n_{loans}	Days (%)	Price (%)	STM (%)	MV ($bil)	Ret (%)	B–A (%)
1999	2,019	490	93.49	96.90	6.33	0.19	0.38	1.36
2000	6,691	738	99.53	96.17	6.83	0.20	0.51	1.35
2001	8,017	831	99.07	94.25	7.76	0.20	0.29	1.76
2002	7,778	867	99.97	93.57	8.12	0.20	0.12	1.90
2003	7,257	824	99.89	95.60	7.55	0.21	0.83	1.63
2004	5,702	770	99.91	99.32	6.23	0.23	0.44	0.83
2005	4,331	587	99.89	100.43	5.45	0.28	0.45	0.67
2006	4,003	479	99.91	100.30	4.92	0.36	0.58	0.60
2007	4,385	552	99.83	98.76	4.93	0.55	0.26	0.68
2008	4,503	458	99.64	90.01	8.19	0.69	−1.97	1.25
2009	3,922	422	99.93	85.29	10.71	0.63	2.61	4.51

Panel (B): Observations by rating

Rating	< B-	B-	B	B +	BB-	BB	BB +	>BB+	Not available
n	2,146	1,946	4,691	8,808	7,821	4,629	2,153	1,780	24,634
Percent	3.66	3.32	8.00	15.03	13.34	7.90	3.67	3.04	42.03

This table reports the coverage and descriptive statistics for our sample. The first and second columns show the total number of observations (n_{total}) and the number of loans included in the sample (n_{loans}). In the third column (Days), every month, we average the number of daily quotes across all loans, we divide this number by the total business days in that month. We then average the monthly means every year to proxy for the overall percentage of business days with quotes in each year. The fourth and fifth columns show the average of bid and ask quotes across all dealers (Price) and the average spread-to-maturity (STM). The column "MV" shows the average market value in billions of dollars. The last two columns show the average loans returns (Ret) and the difference between bid and ask prices divided by the mid price (B–A). Panel (b) reports the number and percentage of observations by rating.

2. Cross-Sectional Properties of Loan Portfolios

Our focus in this section is on examining the relation between loan characteristics and subsequent returns. As an initial step, we utilize univariate sorts to explore how each characteristic is related to other characteristics and expected returns. We then perform bivariate sorts and cross-sectional regressions.

2.1 Univariate portfolio sorts

At the end of month m, loans are sorted into five portfolios based on one of the eight characteristics outlined in section 1.3. We then compute equal- and value-weighted returns for each portfolio over month $m + 1$ and report the time-series average returns with the corresponding Newey and West (1987) adjusted t-statistics. The weights used in value-weighted results are the market value of loans at the end of month m. For each variable, we also compute the average value of other characteristics to investigate the univariate relationships between possible pricing characteristics. Table 3 reports the results.

The first four rows report the relationship between STM and expected returns. Similar to yield-to-maturity, STM can act as a collection of observed or unobserved sources of risk. We find that, on average, high-STM loans have higher returns, although the return on a portfolio with a long position in high-STM loans and a short position in low-STM loans is not statistically different from zero. STM is positively associated with price because high-STM loans are cheaper when evaluated as a percentage of the par value. Loans with higher STM are mostly among the recent underperformers, measured by the facility's momentum. The results related to other risk and liquidity characteristics imply a higher level of riskiness for high-STM loans. They have lower ratings, are smaller, and are less liquid. The bid-ask spread of these loans is more than three times larger than the bid-ask spreads of the loans in the first quintile.

The second variable is market price. Loans in the first quintile have the lowest price. In terms of relation with other factors, because STM and price are related by construction, sorting on price produces the opposite results to those of STM. The two variables have an average cross-sectional Pearson correlation coefficient of −0.78. Therefore, like high-STM loans, loans with low prices are more volatile and are among the recent losers. Price is weakly associated with size, but negatively correlated with liquidity.

The third variable is issuers' rating. Our sample with rating has 33,974 observations compared to the original sample of 58,608 observations. While the sample includes a large range of ratings, the majority of the borrowers have a credit rating between B and BB (high credit quality in the non-investment-grade group). Loans with lower ratings appear riskier because they have smaller prices, higher STMs, higher volatilities, and wider bid-ask spreads. However, there is no significant difference between the expected returns of these loans and those with good credit ratings.

The fourth characteristic is momentum. There is a positive and significant relationship between momentum and expected returns for both equal- and value-weighted portfolios. Recent winners outperform losers by 0.94% (0.87%) if portfolios are equal- (value-) weighted and the difference is statistically significant at the 1% level. However, there is no consistent relationship between momentum and other possible risk measures. For example, loans in the the second and third quintiles have the smallest volatility, bid-ask spread, and yield. They also have the highest rating. There seems to be no significant difference in riskiness between the loans in the first and fifth quintiles. Although the average price is higher for top quintile loans, STM is lower for first quintile loans. Loans in the first quintile are issued by firms with better ratings but are also more volatile. Momentum appears to be a strong predictor of loan returns although it is orthogonal to other proxies of loan risk. We investigate the momentum effect in detail in the following sections.

The next panel reports results when loans are sorted according to their market value. There exists a large variation in loan sizes in the cross-section, with the average size of the loans in the fifth quintile ($1 billion) being more than sixteen times larger than the average size of the loans in the first quintile ($60 million). Most risk measures indicate that larger loans are less risky than

Table 3
Expected returns and characteristics of loan portfolios sorted on eight characteristics

	1	2	3	4	5	5–1		1	2	3	4	5	5–1
Panel A. STM							*Panel B. Price*						
$E[R_{EW}]$	0.31***	0.33**	0.35*	0.41	0.51	0.21	$E[R_{EW}]$	0.47	0.39	0.33*	0.35***	0.36***	−0.11
	(3.22)	(2.50)	(1.74)	(1.50)	(1.18)	(0.57)		(1.02)	(1.42)	(1.91)	(2.66)	(4.12)	(−0.28)
$E[R_{VW}]$	0.33***	0.36***	0.34*	0.42	0.52	0.19	$E[R_{VW}]$	0.40	0.41	0.39**	0.34**	0.37***	−0.03
	(3.68)	(2.85)	(1.70)	(1.42)	(1.05)	(0.44)		(0.82)	(1.39)	(2.22)	(2.61)	(5.09)	(−0.07)
Price	99.18	98.56	97.67	95.59	85.89		Price	84.85	95.38	97.83	98.99	100.17	
STM	3.75	5.00	5.97	7.39	13.05		STM	11.79	6.79	5.68	5.34	5.38	
Volatility	1.47	1.82	2.54	3.90	8.95		Volatility	9.24	3.89	2.33	1.69	1.34	
Momentum	1.46	1.56	1.64	1.85	1.46		Momentum	1.27	1.68	1.63	1.61	1.78	
Rating	10.79	9.77	9.30	8.79	7.41		Rating	7.80	9.22	9.71	9.94	9.87	
MV	0.45	0.36	0.34	0.33	0.26		MV	0.32	0.34	0.36	0.35	0.38	
Quotes	3.42	3.54	3.19	2.88	2.67		Quotes	3.09	2.83	2.98	3.12	3.73	
BA	0.78	0.90	1.14	1.44	3.48		BA	3.84	1.43	0.97	0.81	0.69	
Panel C. Rating							*Panel D. Momentum*						
$E[R_{EW}]$	0.43	0.46*	0.44**	0.35**	0.39***	−0.04	$E[R_{EW}]$	−0.11	0.28	0.40**	0.51***	0.83***	0.94***
	(1.18)	(1.75)	(2.37)	(2.60)	(3.75)	(−0.14)		(−0.31)	(1.28)	(2.36)	(2.80)	(3.38)	(3.92)
$E[R_{VW}]$	0.32	0.40	0.40**	0.35***	0.37***	0.05	$E[R_{VW}]$	−0.06	0.31	0.43**	0.51***	0.80***	0.87***
	(0.80)	(1.52)	(2.24)	(2.42)	(4.27)	(0.15)		(−0.18)	(1.46)	(2.36)	(3.06)	(3.36)	(2.95)
Price	91.78	96.49	97.88	98.67	98.38		Price	91.78	97.32	97.93	97.18	92.74	
STM	9.06	6.43	5.41	5.08	4.66		STM	8.19	5.63	5.74	6.54	9.00	
Volatility	6.10	3.24	2.28	1.60	2.57		Volatility	7.64	2.15	1.85	2.10	4.88	
Momentum	1.93	1.61	1.55	1.43	1.32		Momentum	-3.56	0.49	1.39	2.49	7.22	
Rating	6.93	8.92	9.94	10.95	12.77		Rating	9.22	9.95	9.80	9.42	8.29	
MV	0.36	0.44	0.37	0.43	0.50		MV	0.37	0.39	0.35	0.32	0.31	
Quotes	3.49	3.56	3.49	4.05	3.39		Quotes	3.22	3.29	3.21	3.07	2.91	
BA	2.38	1.04	0.91	0.72	0.85		BA	2.58	1.12	0.92	1.05	1.79	
Panel E. MV							*Panel F. Volatility*						
$E[R_{EW}]$	0.39*	0.39*	0.41*	0.40*	0.33	−0.06	$E[R_{EW}]$	0.36***	0.36	0.36	0.46	0.35	−0.00
	(1.77)	(1.86)	(1.75)	(1.71)	(1.48)	(−0.58)		(2.83)	(1.57)	(1.56)	(1.64)	(1.01)	(−0.01)
$E[R_{VW}]$	0.35	0.40*	0.41*	0.40*	0.34	−0.01	$E[R_{VW}]$	0.38***	0.35*	0.34	0.43	0.31	−0.07
	(1.59)	(1.89)	(1.74)	(1.69)	(1.53)	(−0.12)		(4.46)	(1.78)	(1.44)	(1.55)	(0.84)	(−0.23)

(continued)

Table 3
Continued

	1	2	3	4	5	5–1		1	2	3	4	5	5–1
Price	93.29	95.26	95.75	96.13	96.53		Price	96.66	98.10	97.99	95.93	89.23	
STM	8.65	7.22	6.78	6.50	5.95		STM	6.75	5.31	5.64	6.58	9.91	
Volatility	4.34	3.80	3.73	3.78	2.97		Volatility	0.12	1.18	1.60	3.12	13.10	
Momentum	1.53	1.55	1.61	1.78	1.50		Momentum	1.58	1.46	1.65	1.80	1.35	
Rating	8.69	9.01	9.45	9.54	9.88		Rating	9.76	10.02	9.82	9.25	8.23	
MV	0.06	0.13	0.21	0.35	1.00		MV	0.20	0.47	0.47	0.46	0.32	
Quotes	1.55	2.02	2.65	3.62	5.89		Quotes	1.64	4.73	4.73	3.84	3.03	
BA	2.87	1.48	1.26	1.21	0.99		BA	2.02	0.89	0.91	1.18	2.65	
Panel F. Quotes							*Panel G. BA*						
$E[R_{EW}]$	0.36**	0.41**	0.42	0.36	0.39	0.03	$E[R_{EW}]$	0.37***	0.38**	0.40*	0.46*	0.30	−0.06
	(2.27)	(2.01)	(1.60)	(1.24)	(1.55)	(0.22)		(3.05)	(2.16)	(1.73)	(1.71)	(0.86)	(−0.23)
$E[R_{VW}]$	0.36**	0.40**	0.37	0.31	0.38	0.02	$E[R_{VW}]$	0.37***	0.40**	0.40	0.44	0.30	−0.07
	(2.53)	(2.07)	(1.56)	(1.11)	(1.60)	(0.15)		(2.63)	(2.07)	(1.49)	(1.36)	(0.71)	(−0.22)
Price	95.62	95.62	94.97	94.86	95.66		Price	99.17	98.51	97.43	95.19	86.53	
STM	7.28	7.00	7.12	6.99	6.47		STM	5.22	5.43	6.02	6.99	11.50	
Volatility	3.30	5.39	5.66	3.97	3.15		Volatility	1.23	1.90	2.34	3.95	9.28	
Momentum	1.54	1.50	1.66	1.68	1.49		Momentum	1.79	1.73	1.74	1.94	0.76	
Rating	9.46	9.37	9.31	9.38	9.37		Rating	10.04	9.89	9.64	9.03	7.76	
MV	0.16	0.23	0.29	0.39	0.81		MV	0.50	0.41	0.34	0.30	0.19	
Quotes	1.00	1.87	2.71	4.11	7.76		Quotes	3.63	3.74	3.16	2.82	2.35	
BA	1.62	1.40	1.32	1.29	1.02		BA	0.51	0.70	0.91	1.39	3.93	

This table reports the average monthly expected returns and characteristics sorted by loan characteristics. At the end of month t, we sort loans into quintile portfolios based on one character. The table reports the average characteristics of each portfolio at the end of month t, as well as the returns at month $t+1$. All portfolios are rebalanced monthly. $E[R_{EW}]$ and $E[R_{VW}]$ are the average expected returns (in percentage) on equal-weighted and value-weighted portfolios. STM is the loan's spread-to-maturity, the initial loan spread over the base rate, adjusted for loan price and repayments, over the life of the loan. Price is the average of the bid and ask quotes as a percentage of the loan's remaining balance (par value). Rating is the borrower's credit rating with one being the lowest, and twenty-two the highest, rating. Momentum is the loan's cumulative return from the beginning of month $t-2$ to the end of month t. MV is the market capitalization of the loan, the product of the outstanding balance and market price, plus accrued income. Volatility is the annualized standard deviation of the residuals of a regression with daily loan excess returns as the dependent, and (excess) returns on market, term spread, and default spread factors as the independent variables over the time period $t-2$ to t. Number of quotes is the number of bid and ask dealer quotes. B–A is the bid-ask spread, the average of the bid and ask quotes, divided by the mid-price. Our benchmark sample has 58,608 observations; all values are estimated using this sample, except for that of the rating. Estimations involving with rating utilize a sample that has 33,974 observations. The sample period covers September 1999 to December 2009. Newey and West (1987) adjusted t-statistics with twelve lags are reported in parantheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

smaller loans but there is no association between loan size and future returns. The next part reports the characteristics of portfolios sorted on volatility. The average annualized standard deviation of loans in the top volatility quintile is substantially larger than that of loans in the first quintile. Volatile loans are also more risky according to measures such as price, yield, rating, and liquidity. The average momentum across volatility quintiles shows a negative contemporaneous relationship between volatility and return. Loans with a high idiosyncratic volatility over the last three months are outperformed by less volatile loans.

Next, we rank loans based on the number of dealer quotes. Loans in the fifth quintile can be interpreted as popular and liquid because they are subject to more dealer quotes. These loans are larger ($810 million compared to $160 million) and have smaller STM. Loans with few quotes exhibit patterns similar to loans with higher bid-ask spreads. Sort results associated with both measures of liquidity suggest a positive relationship between liquidity and other risk characteristics, but neither bid-ask spread nor the number of quotes are significantly related to subsequent returns.

2.2 Momentum effect

The univariate sort results suggest that variables that measure loan riskiness are correlated with each other, but not with subsequent returns. Nevertheless, there exists a short-term momentum effect that, in spite of not being related to risk measures, is strongly related to future returns.

To investigate the momentum effect in more detail, at the end of each month, we sort loans into decile portfolios based on their momentum. The first decile (portfolio 1) includes loans with the worst recent performance (losers) and the tenth decile (portfolio 10) contains the winners. We then compute the excess return for equal- and value-weighted decile portfolios over the next month.

Table 4 reports average excess returns and other return characteristics for each portfolio as well as a zero-cost portfolio that is long portfolio 10 and short portfolio 1. Several conclusions emerge from this table. For both equal- and value-weighted portfolios, average returns increase monotonically from portfolio 1 to portfolio 10. Portfolios 1 and 2 underperform the risk-free rate while equal- (value-) weighted portfolio 10 has a monthly excess return of 69 (67) basis points. As a result, the zero-cost portfolio ($10 - 1$) has an average return of 112 (115) basis points per month. The second column reports the standard deviation of the monthly excess returns. Standard deviation declines from portfolio 1 to portfolio 7 and then increases for the last three portfolios, displaying an assymetric U-shaped curve if plotted against portfolio ranking.

The next three columns report the 25th, 50th, and 75th percentile returns of each portfolio. Similar to our previous finding, there is an assymetric U-shaped relationship between extreme returns and portfolio ranking.

Table 4
Excess return characteristics of portfolios sorted on momentum

	Equally weighted								
Decile	Mean	SD	25th	50th	75th	Skew.	Kurt.	Sharpe	A.S.
1	−0.43	3.29	−1.57	0.06	0.85	−0.71	9.92	–	–
2	−0.26	2.42	−0.27	0.18	0.35	−3.38	21.81	–	–
3	0.02	1.99	0.01	0.23	0.32	−2.09	27.12	0.04	0.880
4	0.06	1.67	0.13	0.24	0.33	−4.33	33.12	0.13	0.243
5	0.15	1.47	0.13	0.22	0.36	−1.27	20.07	0.36	0.080
6	0.18	1.38	0.10	0.23	0.37	−2.90	30.48	0.44	0.071
7	0.23	1.29	0.11	0.25	0.40	−3.06	30.55	0.63	0.053
8	0.31	1.55	0.08	0.28	0.43	−0.54	20.41	0.69	0.049
9	0.49	1.57	0.09	0.31	0.58	1.81	10.32	1.09	0.021
10	0.69	1.93	−0.04	0.49	1.15	1.03	7.91	1.24	0.026
10 − 1	1.12	2.46	−0.14	0.72	2.25	0.03	8.72	1.58	0.032
Monotonicity test (10,000 bootstraps):									
		H0: Decreasing					*H0*: Increasing		
		p-value = 0.00					*p*-value = 0.99		
				Value weighted					
Decile	Mean	SD	25th	50th	75th	Skew.	Kurt.	Sharpe	A.S.
1	−0.48	3.73	−1.60	0.20	0.78	−0.88	9.95	–	–
2	−0.18	2.39	−0.14	0.18	0.33	−2.35	17.66	–	–
3	0.06	1.90	0.04	0.21	0.33	−1.03	21.94	0.10	0.322
4	0.09	1.63	0.08	0.23	0.33	−2.11	20.40	0.19	0.162
5	0.17	1.63	0.08	0.23	0.35	−0.05	20.18	0.35	0.085
6	0.24	1.54	0.08	0.23	0.35	−0.84	21.67	0.53	0.061
7	0.25	1.28	0.12	0.26	0.39	−0.60	15.98	0.68	0.040
8	0.31	1.41	0.07	0.27	0.45	0.13	13.01	0.76	0.037
9	0.46	1.55	0.02	0.30	0.52	1.74	9.52	1.02	0.022
10	0.67	2.08	−0.07	0.43	1.20	0.87	7.57	1.11	0.032
10 − 1	1.15	2.84	−0.31	0.55	2.40	1.07	7.91	1.40	0.034
Monotonicity test (10,000 bootstraps):									
		H0: Decreasing					*H0*: Increasing		
		p-value = 0.01					*p*-value = 0.97		

This table reports the descriptive statistics for monthly excess returns on portfolios sorted based on momentum. At the end of every month, we sort loans into deciles based on the momentum. We then compute the equal- and value-weighted excess returns over the next month. The table reports the distribution characteristics for each portfolio and a zero-cost portfolio that buys portfolio 10 and shorts portfolio 1. The last row of each panel reports the *p*-values from Patton and Timmermann (2010) time-series block-bootstrapping monotonicity tests. "H0: Increasing" and "H0: Decreasing" report the *p*-values for the hypothesis that expected returns are monotonically increasing and decreasing across deciles, respectively.

For equal-weighted results, portfolio 1 experiences an excess return of −1.57% in the bottom 25% of observations and an excess return of 0.85% in the top 25%. These figures are −0.04% and 1.15% for portfolio 10. The difference between the returns of the 25th and 75th percentile observations drops for middle portfolio deciles, consistent with their lower volatility. The trend in skewness reverts a few times. High-ranked portfolios are the most preferred as they have the largest positive skewness. Kurtosis, on the other hand, is a reverse U-shaped function of portfolio ranking, with the return distribution of portfolios 1 and 10 being the least heavy tailed. Consistent with the trends observed in average excess returns and standard deviations, the Sharpe ratio increases monotonically with the ranking of the portfolio.

The last column displays the values for Aumann and Serrano's (2008) index of riskiness (hereafter A.S.). To estimate A.S., we compute R for each portfolio by solving the expectation $E[e^{-r_t/R}] = 1$ using numerical iterations. This measure provides better insight with respect to the riskiness of the asset, since it incorporates all moments of the payoff distribution to generate a single index of risk. In line with our findings regarding mean and higher moments of portfolio returns, the estimated A.S. indices of the low-ranked portfolios are substantially larger than the high-ranked portfolios.

The row labeled "$10 - 1$" reports the characteristics for the zero-cost portfolio. The return distribution of this portfolio is desirable from a risk-averse agent perspective. The zero-cost portfolio has a large Sharpe ratio of 1.58 (or 1.40 for value weighted) and is positively skewed with a moderate kurtosis.

The final rows display the nonparametric monotonicty tests of Patton and Timmermann (2010). For all decile portfolios, we test two null hypothesis: there is a monotonically increasing or decreasing relation among portfolio returns. *p*-values determine whether we can reject the null hypothesis and are obtained from the time-series block-bootstrapping of Patton and Timmermann (2010). For both equal- and value-weighted portfolios, the null hypothesis of the monotonic increasing trend among portfolio returns cannot be rejected while the null of decreasing is rejected at the 1% level.

Figure 3 plots cumulative and monthly returns for the zero-cost momentum porfolios (*FMom*) over the sample period. The returns on the factor illustrate the positive average return of the momentum strategy. Irrespective of the weighting scheme, the average premium of the strategy is positive in all years except for 2005 and 2007. The zero-cost equal- (value-) weighted portfolio has positive returns in 89 (84) out of 124 months, and, except for 2005, there are at least 6 months of positive returns in all years.

2.3 Cross-sectional regressions

We conduct empirical tests at the issue level by employing cross-sectional regressions to examine the relationship between momentum and expected returns by controlling for a range of control variables jointly. Specifically, every month, we conduct Fama and MacBeth (1973) cross-sectional regressions of individual loan returns that take the following form:

$$r_{i,t+1} = \alpha_{t+1} + \gamma_{Mom,t+1} Mom_{i,t} + \sum_{c=1}^{n} \gamma_{c,t+1} X_{c,i,t} + \epsilon_{i,t+1}, \tag{2}$$

where $r_{i,t+1}$ is the month $t+1$ return on loan i, $Mom_{i,t}$ is the momentum of loan i in month t, $\gamma_{Mom,t+1}$ is the slope coefficient corresponding to momentum, $X_{c,i,t}$ is loan i's characteristic c at month t, and $\gamma_{c,t+1}$ is the corresponding slope coefficient. We then test the time-series averages of the estimated slope coefficients from the first step and adjust the standard errors for autocorrelation and heteroscedasticity using the Newey and West (1987) procedure. The average slopes and their t-stats determine whether a characteristic has a nonzero premium over the sample period.

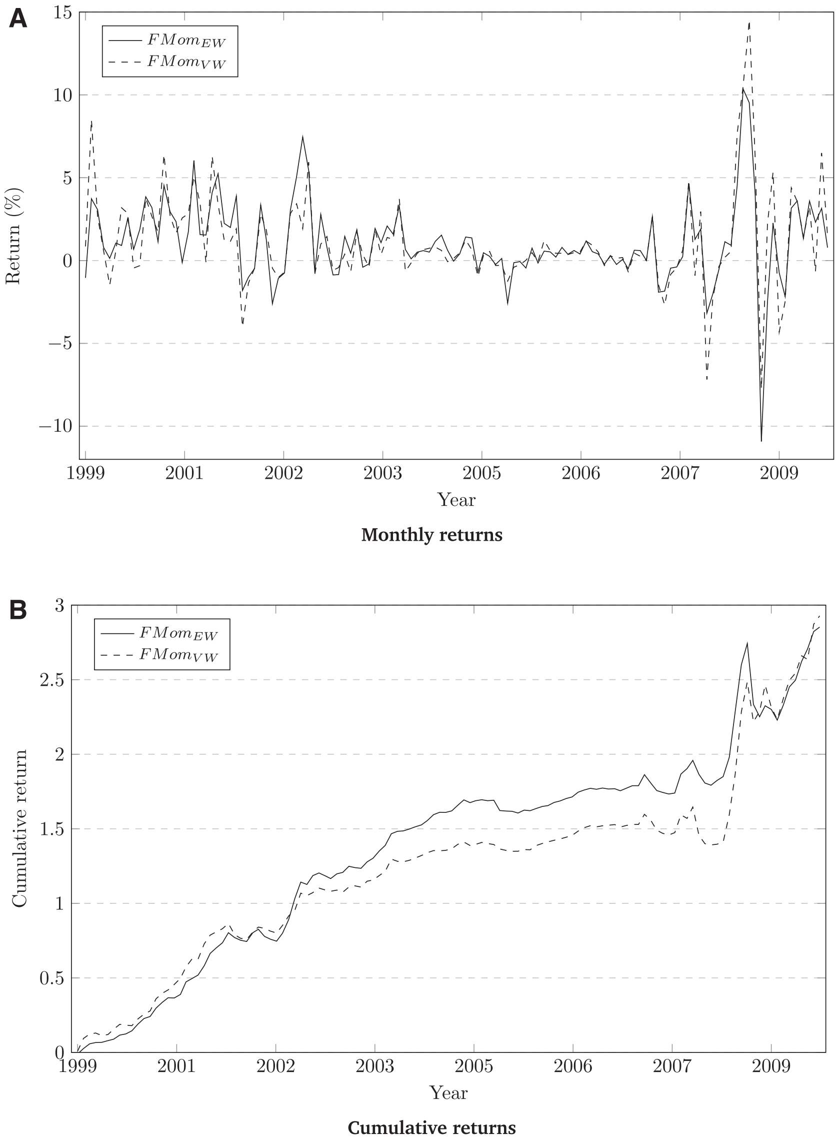

Figure 3
Cumulative and monthly returns of the momentum factor
The figure displays the monthly returns of the equal- and value-weighted portfolios that buy portfolio 10 and shorts portfolio 1 *(A)*. Portfolios are rebalanced every month. The figure also shows the time series for cumulative returns for the momentum factor *(B)*. The sample period runs from September 1999 to December 2009.

Table 5 reports the results from regressions of next-month excess return on momentum with and without control variables. The univariate test in the first column indicates a positive relation between momentum and future loan returns. The average coefficient is 6.32 with a t-stat of 3.42. This implies that a one-standard-deviation increase in momentum (7.72%) is associated with 0.49% higher returns over the following month.

The following specifications employ different sets of explanatory variables when included jointly with momentum. In Columns (2) to (4), we add one variable to the first specification. The effect of STM on momentum is minimal with the coefficient and t-stat close to those of the benchmark. When we control for price, the coefficient drops to 4.83 with a t-stat of 2.61. The fourth specification uses rating and therefore employs a sample of loans issued by public firms. Controlling for rating does not affect the size and statistical significance of the momentum variable. Previous studies find that the momentum effect is concentrated in securities issued by companies with a low credit rating. Avramov et al. (2007) showed that equity momentum is generated by high credit risk firms, and Jostova et al. (2013) documented the absence of momentum strategies in investment grade bonds. In Column (5), we test for this hypothesis by including an interaction term between momentum and credit rating. The coefficient for the interaction term is −0.39, supporting the conjecture that momentum is stronger in loans issued by low-rated firms.[14]

In Column (6), we control for STM and rating. We do not control for price jointly with STM because of their high collinearity. The momentum coefficient becomes 5.75 and statistically significant at the 1% level. The coefficient of STM becomes larger in this specification, although still statistically insignificant. We conclude that yield and rating characteristics do not explain the momentum effect.

Columns (7) to (9) control for size (the natural logarithm of market value), volatility, and number of quotes. The size and statistical significance of the momentum coefficients remain consistent with earlier models. Between 25% and 30% of observations have only one average dealer quote. That is, one bid and one ask is posted for the trading date. If the momentum effect is limited to loans with few quotes, we may be picking a measurement error instead of a pricing characteristic. In Column (10), we include the interaction term between momentum and number of quotes to test for this conjecture. The positive coefficient on the interaction term suggests that the momentum effect is stronger among loans with many quotes. We control for the bid-ask spread in model (11) and for volatility, size, and liquidity variables jointly in Column (12).

In Columns (13) and (14), we run two general regressions. In the first model, to maintain all observations, we include all variables except for rating and obtain a coefficient of 5.38 with a t-stat of 2.84. In the final

[14] In the Internet Appendix, we perform bivariate sorts on rating and momentum. The results show that momentum profits are 0.94% per month among firms with a low credit rating. The premium is positive (0.26% per month), but weaker among better-rated loans.

Table 5

Fama and MacBeth (1973) regressions of loan expected returns on loan momentum and characteristics

	Yield and rating characteristics						Volatility, size, and liquidity characteristics						All characteristics	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Mom	6.32***	5.44***	4.83**	7.26***	10.18*	5.75***	6.26***	6.40***	6.32***	5.55**	5.52***	6.12***	5.38***	4.07**
	(3.42)	(3.04)	(2.61)	(3.40)	(1.94)	(2.89)	(3.42)	(3.14)	(3.47)	(2.43)	(2.94)	(3.12)	(2.84)	(2.18)
STM		0.87				4.69							2.17	5.13*
		(0.40)				(1.57)							(0.81)	(1.66)
Price			0.01											
			(0.36)											
Rating				−0.01	−0.01	0.03								0.03**
				(−0.26)	(−0.19)	(1.44)								(1.98)
Mom×Rating					−0.39									
					(−0.57)									
Size							0.00					−0.03	−0.01	−0.04
							(0.06)					(−1.28)	(−0.45)	(−1.38)
Vol								−0.59				−0.30	−1.08	−0.32
								(−0.53)				(−0.29)	(−1.13)	(−0.27)
Quote									0.01	0.01		0.02	0.02	0.02*
									(0.75)	(0.44)		(1.39)	(1.20)	(1.91)
Mom×Quote										0.48				
										(0.72)				
BA											−1.51	−2.01	-4.45	3.92
											(−0.45)	(−0.59)	(−1.17)	(0.70)
Constant	0.07	−0.08	−0.64	0.14	0.10	−0.55**	0.02	0.04	0.04	0.04	0.08	0.72	0.10	0.21
	(0.38)	(−0.77)	(−0.38)	(0.31)	(0.31)	(−2.22)	(0.02)	(0.26)	(0.23)	(0.34)	(0.49)	(1.13)	(0.16)	(0.31)
n	58,608	58,608	58,608	33,974	33,974	33,974	58,608	58,608	58,608	58,608	58,608	58,608	58,608	33,974
Adj. R^2	0.08	0.13	0.15	0.13	0.19	0.21	0.09	0.12	0.09	0.12	0.10	0.16	0.19	0.30

We run monthly cross-sectional regressions of loan expected excess returns (in percentage) on momentum and other loan characteristics: $r_{i,t+1} - r_{f,t+1} = \alpha_{t+1} + \gamma_{Mom,t+1} Mom_{i,t} + \sum_{c=1}^{n} \gamma_{c,t+1} X_{c,i,t} + \epsilon_{i,t+1}$, where $X_{c,i,t}$ is the loan i's characteristic c at time t. We then test the time series of estimated slopes. The table reports the average slopes with Newey and West (1987) adjusted t-statistics. The sample period is from September 1999 to December 2009. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

specification, we include rating and the coefficient on momentum becomes 4.07 and statistically significant with a t-stat of 2.18. Cross-sectional regressions provide strong evidence for a positive and significant relationship between momentum and expected loan returns.

3. Risk Premiums in the Cross-Section of Loan Returns

The covariance structure of returns reveals that loan risks are likely multidimensional. The objective of this section is to provide a comprehensive empirical investigation of the pricing of common risk factors in the cross-section of expected loan returns. Multifactor models can be justified by the intertemporal capital asset pricing model of Merton (1973) or the arbitrage pricing theory of Ross (1976), where risk premiums are associated with the conditional covariances between asset returns and variation in state variables. In the ICAPM framework, factor loadings with respect to the factors that are candidates to proxy for the variation of investment opportunities are appropriate measures of systematic risk. Expected returns of risky assets are affected by their covariance with state variables such that investors require lower expected returns on assets that hedge them against bad news. ICAPM allows us to develop a prior for the price of different factors that reflect changes in the opportunity set. If an increase in default risk is an unfavorable shift in future investment opportunities, an asset that covaries positively with default risk is desirable and commands a lower expected return. Indeed, a large strand of literature finds evidence on the relation between credit spread and basic price dynamics. For example, Campbell et al. (2013) found that credit spread is a strong predictor of long-run volatility up to 10 years. As a result, shocks to default spread may signal shocks to expected volatility and future investment opportunities.

Motivated by the multifactor models, we empirically examine the pricing of common risk factors such as term, default, the loan market index, value-weighted stock market index, equal-weighted stock market index, the size and value factors, and a volatility factor in the cross-section of loan expected returns. Our empirical design to finding risk premiums follows previous studies that employ linear factor models in which excess returns are explained by their exposure to risk factors:

$$\begin{aligned} r_t^i - r_t^f = a_i &+ \sum_{F=1}^{n}\beta_{F,0}^i F_t + \sum_{F=1}^{n}\beta_{f,-1}^i F_{t-1} + \sum_{F=1}^{n}\beta_{F,-2}^i F_{t-2} + \sum_{F=1}^{n}\beta_{F,-3}^i F_{t-3} \\ &+ \sum_{F=1}^{n}\beta_{F,-4}^i F_{t-4} + \sum_{F=1}^{n}\beta_{F,-5}^i F_{t-5} + \epsilon_t^i \end{aligned} \tag{3}$$

where r_t^i and F_t are the return on security i and factor n on day t, respectively. We include five Dimson (1979) lags (one week) to control for the effect of nonsynchronous trading in obtaining coefficients. The sum of estimated coefficients, $\beta^i_{F,0}+\beta^i_{F,-1}+\ldots+\beta^i_{F,-5}$, is the measure of loan i's exposure to factor n at time t.[15] For each multifactor model considered, the coefficients are estimated at the security level and every month (m), using twelve months (from $m-11$ to m) of daily excess returns. In two-stage regressions, we also consider three- and six-month estimation windows. We do not directly control for all risk factors at this stage since estimations are at the loan level and doing so may add noise. We perform tests at the issue level in Section 3.1 and at the portfolio level in Section 3.2.[16]

3.1 Portfolios sorted on exposure to risk factors

Every month, we sort loans into quintiles based on the realized factor loading to create portfolios that are sufficiently different in exposure to one risk factor. Then, for each portfolio, we compute the next month return by equal and value weighting loans. The procedure generates a time series of pre-ranking coefficients and post-ranking monthly returns. We then test the time series of monthly excess returns for each portfolio and a zero-cost portfolio that is long the top and short the bottom portfolio. The cross-sectional performance of portfolios determines the price of risk associated with each factor. If a factor is priced in the cross-section, we would see an increasing or decreasing pattern across average returns of portfolio sorted on that factor's beta. We find that the loan market index and factors related to the stock market are not significantly priced in the cross-section over our sample period. We do not present the results for these factors in interest of brevity.

Following Fama and French (1993) and Gebhardt, Hvidkjaer, and Swaminathan (2005), we employ a model with term and default factors as the most notable sources of risks for fixed-income products. Table 6 reports the corresponding results. In panel (a), loans are ranked based on default beta. Expected returns exhibit a decreasing pattern in β_D. Note that we defined the systematic default risk factor as $r_{AA}-r_{BBB}$; therefore, the decreasing pattern is consistent with riskier loans having higher returns. For the equal-weighted portfolio, the difference between portfolios 5 and 1 is -0.38% per month with a significant t-stat of -2.11. This premium, with a

[15] Unlike monthly returns (see Table 1), daily factor returns do not exhibit serial correlation, and adjusting for autocorrelation does not change the estimated exposures.

[16] Chen, Ferson, and Peters (2010) showed that if the extent of stale pricing is related to a common factor (systematic stale pricing), estimates of the covariance between returns and common factors will be biased. Chen, Ferson, and Peters (2010) assumed that the measured return in time t is a function of true returns in times t and $t-1$ ($r^*_t=\theta_t r_{t-1}+(1-\theta_t)r_t$). As the degree of staleness (θ_t) drops, measured return at time t converges to the true return of time t. Systematic stale pricing biases moments of measured return, namely mean and covariance with common factors. Since $0\leq\theta_t\leq 1$, we proxy θ at the aggregate level by computing the ratio of loans with stale quotes to all loans to be consistent with the definition in Chen, Ferson, and Peters (2010). We then estimate a linear regression of systematic stale pricing on common factor returns. We find no significant relationship between factor returns and systematic staleness, but the absolute value of returns on the market and on the default factor are weakly associated with systematic staleness (t-stats of -1.74 and -1.81, respectively).

pre-ranking default beta spread of 1.82, implies a price of −0.20% per each unit of default beta.[17] The estimated price of default beta is in line with Gebhardt, Hvidkjaer, and Swaminathan (2005) monthly estimate of 0.17% to 0.24% per each unit of default beta in the cross-section of corporate bond returns. The value-weighted portfolios generate similar patterns. The negative price of default risk is consistent with an ICAPM story whereby loans that covary positively with credit spread hedge investors against unfavorable shifts in aggregate default risk and, therefore, are desirable and command a lower expected return.[18]

Panel (b) shows the results of ranking loans based on term beta. We expect the term factor to command a positive risk premium because loans whose returns covary positively with the return on long-term bonds are most likely associated with higher duration. Empirically, Gebhardt, Hvidkjaer, and Swaminathan (2005) found that term beta is positively related with expected bond returns in the cross-section of investment grade corporate bonds. We find similar results although the relation is not statistically significant. This finding is consistent with loans' "floating" feature, which makes them less sensitive to changes in the term structure of interest rates.

If the estimated pre-ranking betas are good estimates of post-ranking betas, post-ranking betas should exhibit the same monotonic patten across rankings, and as a result, the default-mimicking factor that buys 5 and shorts 1 should track the returns on the rating-based factor closely. We obtain this result as shown in Figure 4. However, as panel (a) of Table 6 shows, the post-ranking beta is not strictly monotone in portfolio ranking. The post-ranking beta increases from portfolio 1 to 4 but decreases from 4 to 5. Panel (c) shows that the average rating and STM for default sorted portfolios exhibit the same asymmetric pattern. Loans with the smallest default beta (highest default risk - quintile 1) have the lowest rating and largest yield. Rating increases with portfolio ranking up to portfolio 4, but then drops from 4 to 5. This pattern suggests that loans in the highest quintile experience a decrease in rating or an increase in default risk in the subsequent month. Panel (d) shows the changes in credit rating across portfolio ranking. We identify 914 rating changes in this sample. On average, rating has been deteriorating over time across all quintiles, but loans in quintile 5 face the worst decline. These loans also experience the largest increase in yield. This evidence suggests that the

[17] Gilbert et al. (2014) argued that the effect of systematic news is revealed with a delay in price of "opaque" (or complex) firms. This dampens the betas of opaque firms, making them smaller at high frequencies. Extending this argument to our results, if the loans in higher ranked portfolios covary less with default risk because of opacity, we expect the difference in betas between high and low portfolios to be overestimated. Therefore, any adjustment in the framework of Gilbert et al. (2014) should reduce the difference between betas and, therefore, increase the size (in absolute terms) and statistical significance of our estimates for the price of risk.

[18] We also examined the robustness of default beta when controlling for STM and rating in a bivariate sort setting. We find that the premium on the long-short default-beta portfolio remains intact after controlling for STM and rating individually.

Table 6
Portfolios sorted on exposure to the default ($r_{AA} - r_{BBB}$) and term ($r_T - r_f$) factors

	Quintile portfolios						
	1	2	3	4	5	5 − 1	
Panel A. Sorting on β_D							
Ave. pre-ranking β_D	−1.47	−0.45	−0.26	−0.12	0.35	1.82	
$E[R_{EW}]$	0.35	0.24	0.17	0.14	−0.02	−0.38	
	(1.33)	(1.20)	(1.18)	(1.12)	(−0.15)	(−2.11)	
Post-ranking β_D	−1.80	−1.33	−0.96	−0.78	−1.03	0.77	
$E[R_{VW}]$	0.39	0.21	0.10	0.10	−0.04	−0.43	
	(1.38)	(0.99)	(0.66)	(0.71)	(−0.23)	(−2.29)	
Post-ranking β_D	−1.96	−1.47	−0.94	−0.90	−1.07	0.89	
Panel B. Sorting on β_T							
Ave. pre-ranking β_T	−0.38	−0.13	−0.07	−0.02	0.15	0.54	
$E[R_{EW}]$	0.10	0.19	0.18	0.15	0.26	0.16	
	(0.37)	(0.98)	(1.23)	(1.26)	(1.83)	(0.90)	
Post-ranking β_T	−0.30	−0.12	−0.08	−0.06	−0.11	0.18	
$E[R_{VW}]$	0.15	0.21	0.15	0.16	0.21	0.06	
	(0.53)	(1.16)	(1.12)	(1.29)	(1.43)	(0.33)	
Post-ranking β_T	−0.26	−0.12	−0.05	−0.04	−0.10	0.15	
Panel C. Characteristics of portfolios sorted on β_D							
	1	2	3	4	5	5 − 1	t-stat (5 − 1)
STM	9.40	6.55	6.10	6.07	7.84	−1.55	(−8.76)
Rating	8.03	9.28	9.81	9.94	9.32	1.29	(15.05)
Panel D. Change of rating and STM across default beta sorted portfolios							
	1	2	3	4	5		
ΔRating	−0.88	−0.81	−0.67	−0.36	−1.01		
ΔSTM	0.08%	0.01%	0.04%	0.02%	0.14%		

At the end of each month, we sort loans into five value- (VW) and equal-weighted (EW) portfolios based on their exposure to risk factors. We then record the next-month return for each portfolio. The procedure provides a time series of pre-ranking betas and post-ranking returns. Pre-ranking betas are estimated using 12 months of daily data using five Dimson (1979) lags (1 week). Panels (a) and (b) report the average pre-ranking betas with corresponding post-ranking returns and betas for each portfolio. Panel (c) reports the time-series average for spread-to-maturity and rating for each quintile portfolio sorted on default beta. In panel (d) we present changes in most recent rating and STM across default beta sorted portfolios. t-statistics are reported in parentheses.

non-strictly-monotonic relationship between pre-ranking betas and rating from portfolio 4 to 5 is related to changes in a firm's rating status.

3.2 Exploring the risk premiums

We estimate a negative price for default risk by computing the average monthly return spread among portfolios sorted on default beta. We now estimate the price of risk factors by adopting the two-step procedure of Fama and MacBeth (1973). To create portfolios with sufficiently disperse betas with respect to default and term factors, we sort loans into 25 equal-weighted and 25 value-weighted portfolios based on their exposure to default and term betas. The choice of portfolios ascribe to our cross-section of about 473 loans per month. The 5 × 5 portfolios sorted on term and default betas have the largest spread in their exposure to default and term risks by construction so that the cross-sectional regression tests based on these portfolios yield a good estimate of prices of default and term risks. As in Black, Jensen, and Scholes (1972) and Fama and MacBeth (1973), we follow a grouping

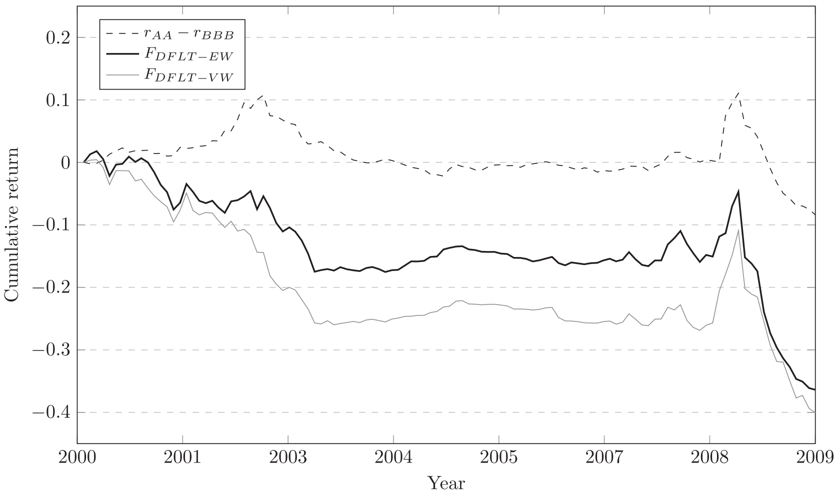

Figure 4
Cumulative returns on the default risk factor and the default-mimicking factors between July 2000 and December 2009
The dashed line plots the cumulative returns on a portfolio with a long position in AA grade bonds and a short position in BBB bonds. The two solid lines plot the cumulative returns for the equal- and value-weighted default-mimicking factors.

procedure (portfolio approach) to create test assets in order to reduce the error-in-variables (EIV) problem (Shanken 1992) in estimating the first-stage betas.

At the end of each month, we identify loans with at least twenty observations of daily returns over the last three months. For each loan, we then estimate term and default betas using a two-factor model with term and default risks. We then construct quintile portfolios based on term beta (lowest in quintile 1). Within each quintile portfolio, we create five more portfolios based on default beta (lowest in quintile 1). Post-ranking portfolio returns are computed for the following month, after which the estimation and formation procedures are repeated until the sample is exhausted. Pre-ranking portfolio daily returns and post-ranking portfolio monthly returns are then linked for all portfolios. The time-series returns of twenty-five sorted portfolios are the test assets used to estimate the risk premiums in the cross-section of loan returns.

As a first step in the analysis, we follow Black, Jensen, and Scholes (1972) to estimate factor betas using a single time-series regression per portfolio. In the first stage, we estimate the exposure of each portfolio to risk factors by running a single time-series regression of the form:

$$r_{p,t} = a_p + \sum_{f=f_1}^{f_n} \beta_{p,f} f_t + \epsilon_{p,t}. \tag{4}$$

In the second stage, we run a single cross-sectional regression of the average portfolio returns on first-stage betas to estimate the price of risk:

$$E[r_p] = \alpha + \sum_{f=f_1}^{f_n} \lambda_f \hat{\beta}_{p,f}. \tag{5}$$

Figure 5 plots two default risk lines according to a conditional estimate based on the rating-based factor ($r_{AA} - r_{BBB}$), and the unconditional cross-sectional regression (CSR) of equation 5. The slope of the conditional line is restricted to be the time-series average of the rating-based factor and its intercept is obtained by minimizing the mean squared pricing errors. Clearly, the unconditional estimate from CSR exceeds (in absolute value) the time-series average of -0.06% for the rating-based default risk. The CSR point estimate (-0.12%) is roughly twice the average return of the original factor, resulting in steeper lines. Panel (a) of Table 7 presents the results for additional models. Regarding the assumption on the form of specifications in estimating betas and then premiums in Equations (4) and (5), we choose these models: (1) loan market excess returns, (2) two bond market factors from Fama and French (1993), (3) loan market index and Fama and French (1993) bond market factors, (4) loan market index and Fama and French (1993) size and value factors, (5) loan market index and Fama and French (1993) factors, (6) loan market index and the volatility factor, and (7) loan, volatility, and two bond market factors.[19] The price of loan market risk is highly significant in all models, suggesting that aggregate loan market index returns is priced. Estimates for SMB, HML, and volatility risk differ considerably across models. The price of term risk is mostly positive but statistically significant in only one case. In line with the evidence in Figure 5, point estimates for default risk premiums always are negative and significant in 6 out of 8 specifications.[20]

The second set of results corresponds to predictive tests and employs rolling estimation windows. In the first stage, we estimate exposure of each portfolio to risk factors by running time-series regressions of 3, 6, and 12 months of

[19] We also test for the pricing of the loan momentum factor discovered in this paper. Exposure to the loan momentum factor is related to returns in contemporaneous tests, but not, in predictive tests. We do not find convincing evidence in support of a priced momentum factor. Models including excess return on a value-weighted stock market index yield insignificant results and are ommitted in the interest of brevity.

[20] The returns on the loan market and default factors are highly correlated. Excluding the loan market returns from the specifications in this table will result in stronger coefficients for default beta.

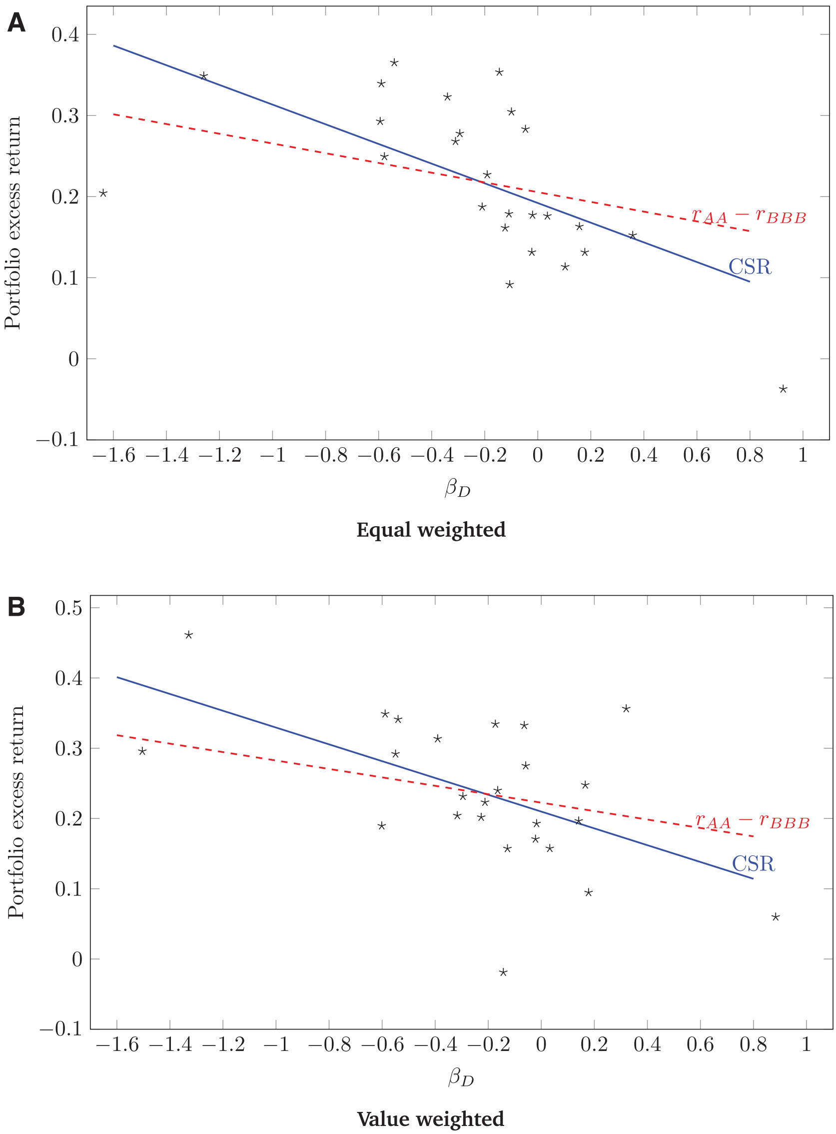

Figure 5
Default risk lines for loan returns
The figures plot the return - default beta line where the slope is restricted to equal the time-series average of the rating-based factor (dashed lines), or is estimated from cross-sectional OLS regressions for equal weighted *(A)* and value-weighted *(B)* loan portfolio excess returns (Table 7). The cross-section contains 25 portfolios sorted on loan level pre-ranking term and default betas. The post-ranking beta for each portfolio is obtained from a single time-series regression of excess daily returns over the sample period.

Table 7
Price of risk

	Equal weighted							Value weighted						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Panel A. Single time series														
λ_L	0.15		0.14	0.16	0.21	0.15	0.14	0.14		0.13	0.14	0.14	0.13	0.13
	(3.47)		(3.05)	(3.26)	(4.42)	(3.41)	(2.92)	(4.31)		(3.96)	(3.89)	(3.75)	(4.05)	(3.57)
λ_T		0.08	−0.06		0.45		−0.08		0.03	−0.08		0.17		−0.10
		(0.67)	(−0.29)		(1.75)		(−0.38)		(0.22)	(−0.44)		(0.49)		(−0.49)
λ_D		−0.13	−0.12		−0.17		−0.10		−0.12	−0.10		−0.13		−0.08
		(−3.67)	(−1.90)		(−2.19)		(−1.15)		(−2.88)	(−1.74)		(−1.85)		(−1.15)
λ_{SMB}				−0.36	−2.05						1.53	−0.99		
				(−0.96)	(−1.12)						(0.73)	(−0.34)		
λ_{HML}				−0.01	3.92						−0.07	3.86		
				(−0.00)	(1.44)						(−0.04)	(0.87)		
λ_{Vol}						−3.37	8.31						−3.44	4.99
						(−0.50)	(0.33)						(−0.55)	(0.24)
R^2	0.70	0.31	0.70	0.72	0.79	0.69	0.68	0.79	0.29	0.79	0.78	0.78	0.79	0.78
Panel B. Three-month beta estimation period														
λ_L	0.02		−0.00	0.02	−0.00	0.02	−0.03	−0.03		−0.10	−0.02	−0.06	−0.03	−0.15
	(0.21)		(−0.02)	(0.15)	(−0.00)	(0.15)	(−0.17)	(−0.35)		(−0.76)	(−0.23)	(−0.49)	(−0.25)	(−1.07)
λ_T		0.66	0.51		0.35		0.48		0.85	0.11		0.48		−0.02
		(2.24)	(1.44)		(0.67)		(2.06)		(1.87)	(0.28)		(1.08)		(−0.05)
λ_D		−0.21	−0.23		−0.25		−0.16		−0.25	−0.18		−0.19		−0.18
		(−2.92)	(−2.50)		(−2.01)		(−1.83)		(−2.64)	(−1.58)		(−1.70)		(−1.69)
λ_{SMB}				−1.36	−2.87						−1.65	−2.35		
				(−0.71)	(−1.81)						(−0.61)	(−0.89)		
λ_{HML}				0.17	1.33						0.62	2.05		
				(0.21)	(0.62)						(0.49)	(0.75)		
λ_{Vol}						-12.64	-19.07						-12.51	−6.24
						(−1.58)	(−1.19)						(−1.20)	(−0.88)
Cons.	0.14	0.15	0.16	0.18	0.17	0.16	0.16	0.10	0.11	0.12	0.13	0.14	0.13	0.16
	(0.70)	(0.70)	(0.82)	(0.96)	(0.99)	(0.85)	(0.94)	(0.50)	(0.56)	(0.65)	(0.76)	(0.82)	(0.69)	(0.91)
R^2	0.23	0.28	0.50	0.46	0.63	0.36	0.58	0.26	0.28	0.51	0.48	0.63	0.37	0.56

(continued)

Table 7
Continued

	Equal weighted							Value weighted						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Panel C. Six-month beta estimation period														
λ_L	0.05		0.07	0.07	0.00	0.04	0.10	−0.02		0.04	0.06	−0.03	−0.02	0.01
	(0.34)		(0.33)	(0.47)	(0.02)	(0.26)	(0.46)	(−0.18)		(0.23)	(0.46)	(−0.23)	(−0.12)	(0.07)
λ_T		0.49	0.41		0.41		0.00		0.57	0.36		0.45		0.13
		(1.48)	(1.18)		(0.76)		(0.01)		(1.68)	(0.87)		(0.98)		(0.30)
λ_D		−0.17	−0.19		−0.25		−0.15		−0.19	−0.16		−0.19		−0.17
		(−1.99)	(−2.45)		(−1.98)		(−1.42)		(−2.52)	(−1.67)		(−1.59)		(−1.62)
λ_{SMB}				−1.48	−3.04						−4.15	−2.19		
				(−0.46)	(−1.85)						(−1.03)	(−0.83)		
λ_{HML}				1.80	1.24						−1.50	2.27		
				(0.87)	(0.57)						(−0.66)	(0.81)		
λ_{Vol}						-11.37	17.00						−1.86	13.25
						(−0.96)	(0.98)						(−0.24)	(1.06)
Cons.	0.15	0.15	0.15	0.18	0.17	0.19	0.16	0.11	0.12	0.11	0.14	0.14	0.13	0.14
	(0.75)	(0.70)	(0.75)	(0.97)	(0.98)	(0.99)	(0.89)	(0.56)	(0.57)	(0.59)	(0.81)	(0.80)	(0.66)	(0.76)
R^2	0.24	0.28	0.50	0.45	0.62	0.53	0.67	0.26	0.27	0.51	0.46	0.62	0.38	0.57
Panel D. Twelve-month beta estimation period														
λ_L	0.12		0.14	0.18	0.05	0.11	0.17	0.05		0.07	0.06	−0.02	0.05	0.11
	(0.70)		(0.64)	(0.73)	(0.27)	(0.56)	(0.75)	(0.30)		(0.38)	(0.33)	(−0.12)	(0.29)	(0.59)
λ_T		0.44	0.25		0.39		0.54		0.56	0.31		0.44		0.43
		(1.65)	(0.76)		(0.69)		(1.20)		(1.59)	(0.85)		(0.92)		(1.19)
λ_D		−0.19	−0.15		−0.26		−0.04		−0.19	−0.14		−0.21		−0.07
		(−2.49)	(−1.85)		(−1.96)		(−0.35)		(−2.37)	(−1.64)		(−1.68)		(−0.77)
λ_{SMB}				−0.86	−2.89						−0.49	−0.49		
				(−0.36)	(−1.74)						(−0.22)	(−0.30)		
λ_{HML}				0.10	1.45						0.89	2.26		
				(0.07)	(0.65)						(0.44)	(0.79)		
λ_{Vol}						-13.41	7.99						2.39	−5.89
						(−1.29)	(0.36)						(0.21)	(−0.25)
Cons.	0.16	0.15	0.14	0.18	0.17	0.18	0.16	0.11	0.12	0.09	0.14	0.14	0.13	0.12
	(0.74)	(0.70)	(0.69)	(0.93)	(0.93)	(0.94)	(0.91)	(0.53)	(0.58)	(0.48)	(0.75)	(0.75)	(0.69)	(0.75)
R^2	0.25	0.27	0.50	0.45	0.67	0.38	0.57	0.14	0.25	0.37	0.41	0.55	0.27	0.47

(continued)

Table 7
Continued

	Equal weighted								Value weighted						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)		(8)	(9)	(10)	(11)	(12)	(13)	(14)
Panel E. Fama and MacBeth regressions using individual loan returns															
		β_D		β_T		STM		Rating		Mom		Contant	n	R^2	
1		−0.29		0.73								0.07	39,509	0.08	
		(−2.24)		(1.99)								(0.70)			
2		−0.28		0.59		−0.71						0.07	39,509	0.13	
		(−2.22)		(1.76)		(−0.37)						(0.56)			
3		−0.37		0.98				0.02				−0.07	25,041	0.15	
		(−2.97)		(2.57)				(0.73)				(−0.25)			
4		−0.23		1.06		4.00		0.04				−0.58	25,041	0.21	
		(−1.99)		(2.99)		(1.69)		(2.21)				(−2.10)			
5		−0.30		0.96		5.45		0.05		4.68		−0.79	25,041	0.29	
		(−2.53)		(2.79)		(2.46)		(2.52)		(2.25)		(−2.84)			

We apply the two-pass regression procedure of Fama and MacBeth (1973) to estimate the prices of risk factors ($\hat{\lambda}$) in seven models. The models are (1) excess returns on the loan market index, (2) two bond market factors from Fama and French (1993), (3) loan index and Fama and French (1993) bond market factors, (4) loan index and the Fama and French (1993) size and value factors, (5) all the factors in the previous four models, (6) loan index and the volatility factor, and (7) loan index, volatility, and two bond market factors. Every month, loans are sorted into 5 × 5 portfolios based on the loan's exposure to term and default factors. The equal- and value-weighted return on each portfolio is calculated every day, and is linked to create a time series of daily contemporaneous and monthly expected returns. The 25 equal- and 25 value-weighted portfolios are the test assets for estimating risk premiums. In panel (a), in the first step, for each of the 25 portfolios, coefficients are estimated using a single time-series regression of daily portfolio excess returns on factor returns: $r_{p,t} = a_p + \sum_{f=f_1}^{f_n} \beta_{p,f} f_t + \epsilon_{p,t}$. In the second stage, we estimate risk premiums ($\hat{\lambda}$) by running a single cross-sectional regression of the average monthly excess returns on the estimated betas from the first step: $\overline{r_p} = \alpha + \sum_{f=f_1}^{f_n} \lambda_f \beta_{p,f}$. Panel (a) reports the point estimates for $\hat{\lambda}$s with t-statistics that are adjusted with Shanken (1992) EIV correction. For panels (b), (c), and (d), at the end of each month, exposures are estimated using rolling time-series regressions of 3, 6, or 12 months of daily portfolio excess returns on factor returns. We repeat this procedure with a step size of 1 month to have a time series of betas for each portfolio. In the second stage, we estimate risk premiums ($\hat{\lambda}$) by running monthly cross-sectional regressions of next month excess returns on the estimated betas from the first step. Then, we perform a test on estimated slopes ($\hat{\lambda}$) and report average $\hat{\lambda}$s and Newey and West (1987) adjusted t-statistics to determine whether a risk factor has a nonzero premium. In panel (e), we run monthly cross-sectional regressions of individual loan expected returns on loan default beta, term beta, and control variables. This panel reports the time-series averages of the estimated slopes over our sample period. β_D and β_T are winsorized at the 5% and 95% levels.

Table 8
Relationship between default beta premium and liquidity

Panel A. Relation to liquidity measures

	H-L (EW)	H-L (VW)
TED	1.51	1.20
	(1.51)	(1.99)
ΔMMMF	0.01	0.00
	(0.90)	(0.42)
ΔLoan issuance	42.30	45.57
	(2.59)	(2.69)
Constant	−0.50	−0.53
	(−2.84)	(−2.90)
R^2	0.12	0.13

Panel B. Time-series regressions on the traded liquidity factor

	Equal weighted					
	1	2	3	4	5	5-1
Liquidity	0.22	0.17	0.12	0.07	0.10	−0.11
	(3.87)	(4.05)	(4.01)	(2.49)	(3.40)	(−2.72)
Intercept	0.09	0.04	0.03	0.06	−0.16	−0.25
	(0.36)	(0.19)	(0.18)	(0.47)	(−1.03)	(−1.39)
	Value weighted					
	1	2	3	4	5	5-1
Liquidity	0.26	0.20	0.14	0.11	0.11	−0.15
	(4.32)	(4.76)	(4.48)	(3.38)	(3.08)	(−3.72)
Intercept	0.09	−0.04	−0.07	−0.02	−0.17	−0.25
	(0.32)	(−0.18)	(−0.46)	(−0.16)	(−1.03)	(−1.37)

Panel (a) of the table reports the results of this regression: $\mathrm{H}-\mathrm{L}_t=\beta_0+\beta_1\Delta\mathrm{MMF}_t+\beta_2\Delta\mathrm{Loan\ Issuance}_t+\beta_3\mathrm{TED}_t+\epsilon_t$. H-L is difference between the returns of portfolios with high and low default betas. ΔMMF is the change in sum of retail money funds and institutional money funds (in billions). ΔLoan Issuance is the monthly change in Commercial and Industrial Loans outstanding on the portfolio of all Commercial Banks (in billions). Funding liquidity (TED) is the spread between the 3-month LIBOR and the 3-month Treasury bill (in %). Panel (b) reports the results of a time-series regression with excess returns on the default beta portfolios as the dependent and the traded liquidity factor of the Pástor and Stambaugh (2003) as the independent variable.

daily excess returns to allow for time-varying betas. Then, every month, we regress the cross-section of the next month excess returns of twenty-five portfolios on their estimated factor betas to estimate the monthly price of risk ($\hat{\lambda}_f$). Finally, we run a test on the time-series of monthly slopes to determine whether a risk factor has a nonzero premium over the sample period. Results are presented in panel (b) to (d) of Table 7. Once again, the estimates for default risk are always negative, and mostly significant. In Column (2) of panel (b), the estimate of default risk premium is −0.21% with *t*-statistics of -2.92. In other cases, the values for default risk premiums range from −0.15% to −0.26%, implying an annual risk premium of 1.80% to 3.15% per each unit of default beta.

In panel (d), we run cross-sectional regressions on individual loan returns to reduce data snooping biases inherent in the portfolio formation approach (Lo and MacKinlay 1990). The coefficients for default and term betas are generally larger in these tests. When included jointly with term and default betas, rating and STM become significantly related to future returns with signs that are consistent with prior studies. As expected, the coefficient for spread-to-maturity is positive, implying that high-yield loans command higher returns. The coefficient for rating is also positive, implying that loans with better rating outperform. This counterintuitive result is consistent with Avramov et al. (2009) who found that high credit rating firms outperform. In summary, our results on the cross-sectional pricing implications of aggregate default risk are consistent with the results in Section 3.1, which suggests that time-varying aggregate default risk has a large effect on expected loan returns.

3.3 Illiquidity and default risk premium

Recent studies show that variables related to credit risk do not fully explain the yield spread of risky bonds over treasuries. Longstaff, Mithal, and Neis (2005) find that while most of the corporate spread is due to default risk, there is a significant nondefault component that is time varying and is related to measures of bond illiquidity. Chen, Lesmond, and Wei (2007) and Bao, Pan, and Wang (2011) find supporting evidence on the relationship between yield spreads and liquidity in bonds. Huang and Huang (2012) find that credit risk accounts for only a small fraction of the corporate yield spreads for investment grade bonds, but a much higher fraction of yield spreads for junk bonds. They do not explore the effect of liquidity, but suggest that their results are consistent with the hypothesis that liquidity premiums account for the remainder of the corporate yield spreads.

To test whether the return spread between loans of low and high default beta is related to illiquidity, we examine the time-series relationship between our default-mimicking factor and liquidity. Table 8 reports the results from monthly regressions of the factor on inter-bank funding liquidity, measured by the TED spread, flows into money market mutual funds, and net dollar amount of loans issued. TED spread (Brunnermeier 2009) is the spread between the 3-month LIBOR based on US dollars and the 3-month Treasury rate. LIBOR and Treasury rates represent the cost of unsecured and secured fundings that banks receive through the inter-bank market. A high TED spread indicates that banks find it more difficult to raise funds in the unsecured inter-bank market. Therefore, an increase in TED is associated with a decrease in liquidity. The coefficient for TED is positive and significant for the value-weighted factor, supporting the view that the spread between low and high default beta loans widens with illiquidity. The coefficient for the dollar amount of new issues is positive and highly significant. The net dollar amount of loans issued is the change in the dollar amounts of total loans outstanding in one period. As new loans are issued, prices of risky loans drop, which is consistent with the interpretation of new issues reducing the liquidity of existing risky issues. These results support the hypothesis that the variation of the spread between high and low default beta loans is related to changes in liquidity in the loan market and the general economy.

To formally test for a liquidity premium in portfolios sorted on default beta, we adopt the approach of Elton et al. (2001), who relate the variation in bond spreads to Fama and French's (1993) equity factors using linear regressions. Because our focus is on liquidity, the dependent variable is the traded liquidity factor of Pástor and Stambaugh (2003). Panel (b) of 8 shows the results of regressing returns on each of the quintile portfolios sorted on default beta on the liquidity factor. The regression coefficient is positive and significant for all five portfolios. This is the sign we would expect because it implies that loan returns covary positively with liquidity. The coefficient declines from portfolio 1 to portfolio 5, suggesting that loans that hedge against increases in aggregate default risk (loans in higher rankings) have smaller exposure to liquidity. If there is a risk premium for sensitivity to liquidity, differences in sensitivities should explain differences in premiums. This is the case, the high-minus-low factor loads significantly on the liquidity factor, and the intercept (the factor premium) becomes statistically insignificant. Our results are consistent with the hypothesis that the premium of the default-mimicking factor includes an important liquidity risk premium, in addition to compensation for credit risk.

4. Conclusion

The secondary corporate loan market has grown by leaps and bounds over the past two decades. In this paper, we examine the cross-sectional determinants of expected corporate loan returns using an extensive loan market data set. We consider loan characteristics, such as momentum, rating, price, market value, spread-to-maturity, idiosyncratic volatility, number of dealer quotes, and bid-ask spread. We also analyze the pricing of common risk factors, including term, default, Fama and French (1993) equity factors, loan market, and volatility. Systematic default risk commands a nontrivial price of around -0.20% per unit of default beta, consistent with the dominant presence of lower-rated borrowers in this market. A default-mimicking factor that buys the top and shorts the bottom quintile of loans ranked on default beta generates a monthly spread of -38 to -43 basis points. This factor covaries with measures of aggregate liquidity and can be partially explained by a tradable liquidity factor. As a result, this suggests that the return spread between portfolios sorted on default beta includes an important liquidity risk premium, in addition to compensation for credit risk. Other candidate risk factors are not consistently priced.

Loan-specific proxies of risk, such as spread-to-maturity, credit rating, volatility, and liquidity, are correlated with each other, but not with expected returns. Instead, a three-month formation momentum that is orthogonal to the above characteristics earns a monthly premium of 112 bps. Loan momentum strategy is most profitable among loans issued by low-rated or unrated firms, as in bond and equity momentum strategies. Despite the robustness of our findings in this paper, given the sample period of 126 months, examining these findings in an extended period covering post-2009 appears to be crucial.

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