

Credit ratings and the cross-section of stock returns

Doron Avramov^a, Tarun Chordia^b, Gergana Jostova^c,
Alexander Philipov^{d,*}

^a*Robert H. Smith School of Business, University of Maryland, USA*

^b*Goizueta Business School, Emory University, USA*

^c*School of Business, George Washington University, USA*

^d*School of Management, George Mason University, Enterprise Hall 232, MSN 5F5, 4400 University Dr., Fairfax, VA 22030, USA*

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Abstract

Low credit risk firms realize higher returns than high credit risk firms. This is puzzling because investors seem to pay a premium for bearing credit risk. The credit risk effect manifests itself due to the poor performance of low-rated stocks (which account for 4.2% of total market capitalization) during periods of financial distress. Around rating downgrades, low-rated firms experience considerable negative returns amid strong institutional selling, whereas returns do not differ across credit risk groups in stable or improving credit conditions. The evidence for the credit risk effect points towards mispricing generated by retail investors and sustained by illiquidity and short sell constraints.

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0. Introduction

It is a fundamental principle of financial economics that higher-risk assets should command higher expected returns. This risk–return tradeoff underlies the conceptual

*Corresponding author. Tel.: +1 703 993 9762.

E-mail addresses: davramov@rhsmith.umd.edu (D. Avramov), Tarun_Chordia@bus.emory.edu (T. Chordia), jostova@gwu.edu (G. Jostova), aphilipo@gmu.edu (A. Philipov).

framework of asset pricing and investment decisions in efficient markets. Empirically, however, Dichev (1998), Griffin and Lemmon (2002), and Campbell et al. (2008), among others, demonstrate a *negative* cross-sectional correlation between credit risk and future stock returns. This negative credit risk–return relation seems to be an anomalous pattern in the cross-section of stock returns because it suggests that investors pay a premium for bearing credit risk.¹ In this paper, we identify the conditions that give rise to the negative relation between credit risk and returns. This new evidence helps us to distinguish between the potential explanations of the puzzle.

We first confirm the significance of the credit risk effect over the period from October 1985 to December 2007 using a sample of 4,953 NYSE, AMEX, and NASDAQ firms rated by Standard & Poor's. Specifically, the return differential between the highest- and lowest-rated decile portfolio is 1.09% (3.33%) over a 1-month (year) period after the portfolio formation date. The negative relation between credit risk and returns is also confirmed in Fama and MacBeth (1973) cross-sectional regressions of monthly individual stock returns on credit rating. We use the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965), the Fama and French (1993) three-factor model and the Fama and French (1993) three-factor model augmented by a momentum factor, as well as the characteristic-based model of Daniel et al. (1997) to demonstrate that the credit risk effect is robust to adjustments for risk factors, as well as firm characteristics.

Analyzing the credit risk puzzle, recent research by Campbell et al. (2008) shows evidence that the “distress effect” is stronger among small, illiquid stocks. Moreover, Dichev and Piotroski (2001) show that low credit quality firms perform poorly after downgrades, which they attribute to market underreaction. Griffin and Lemmon (2002) find that poorly performing high credit risk firms also have low book-to-market ratios, suggesting that they may be mispriced. Garlappi et al. (2008), on the other hand, do not find the negative credit risk–return relation anomalous. They argue that, due to violations of the absolute priority rule for claimants at bankruptcy, distressed stocks have lower betas and, therefore, command lower returns.

The contribution of this paper is to show that the credit risk effect is concentrated in the worst-rated stocks around downgrades. That is, we isolate the effect much further, and identify a narrow set of circumstances that drive the credit risk effect. In particular, the significant negative credit risk–return relation prevails only 3 months before and after credit rating downgrades and is attributable to the lowest-rated firms in financial distress. Around downgrades, low-rated firms experience sharply deteriorating firm fundamentals, as well as surprisingly poor price performance associated with the selling pressure by institutions who reduce their holdings by a third.

In contrast, the credit risk effect is statistically and economically non-existent during periods of stable or improving credit conditions, which capture more than 90% of the overall sample observations. From an economic perspective, trading strategies that are long low credit risk and short high credit risk stocks during non-downgrade periods provide economically small and statistically insignificant payoffs. Moreover, the credit rating is statistically and economically insignificant in cross-sectional regressions during non-downgrade periods.

¹We do not make an a priori assumption that credit risk should be priced. If it is systematic risk, investors should demand a positive premium for holding high credit risk stocks. If it is non-systematic, then there should be no return differential due to credit risk. In either case the negative credit risk–return relation is a puzzle.

This new evidence contributes to the debate about the cause of the credit risk effect. We find no evidence that the effect has a systematic component or is dependent on the business cycle. Except for rating downgrade periods and except for a small fraction of firms, there is no differential return across high- and low-rated firms. In addition, even though there are more downgrades that lead to the poor price performance of high credit risk stocks during recessions, there is no convincing evidence that the credit risk effect is concentrated in particular stages of the business cycle. The effect is strong and significant in both up and down markets, as well as expansions and recessions. Furthermore, there is no strong evidence that downgrades are clustered, occurring all at the same time for similarly rated firms. Given this evidence, it is unlikely that there is a priced distress factor in the cross-section of stock returns.

It is also unlikely that the credit risk effect is caused by underreaction to downgrades, since the precipitous price decline of high credit risk stocks precedes the downgrade event. Moreover, even if the impact of downgrades happened instantaneously and all prices adjusted immediately, the credit risk effect will still obtain. Neither is the credit risk effect a consequence of delisting. The negative credit risk–return relation is still there after removing delisting returns or stocks that delist subsequent to downgrades.

All our evidence suggests that the credit risk effect is caused by mispricing among the lowest-rated stocks, and reveals another puzzle. Specifically, given (1) the poor price performance of low-rated stocks around downgrades, (2) the strong institutional selling pressures for these stocks, (3) the increased magnitude and frequency of downgrades among them, as well as their increased probability of getting delisted, the puzzling question remains: Why don't prices of low-rated stocks reflect the possibility of large losses around downgrades? In other words, why is there an apparently large and persistent mispricing amongst low-rated stocks as they consistently underperform otherwise similar stocks? Our evidence suggests that these stocks are bought predominantly by individual investors. However, these stocks are also highly illiquid, followed by few analysts, and difficult to short sell. The insufficient analyst coverage and the simple tools and strategies employed by most individual investors may not alert them to how highly overpriced these stocks are, while illiquidity and short-sale constraints may prevent arbitrageurs from fully exploiting this mispricing.

The rest of the paper is organized as follows. The next section discusses the data. Section 2 presents the results and discusses the viability of potential explanations of the credit risk effect. Section 3 concludes.

1. Data

Our sample contains all firms listed on NYSE, AMEX, and NASDAQ with monthly returns in CRSP and with S&P Long-Term Domestic Issuer Credit Rating available in either Compustat or Standard & Poor's new S&P Credit Ratings (also called *Ratings Xpress*) on WRDS. Combining the S&P company rating in Compustat and Rating Xpress provides the maximum coverage each month over the sample period. We start with 1,232 rated firms in October 1985, we have a maximum of 2,497 firms per month in April 2000, and 2,196 in December 2007. The total number of rated firms in our sample is 4,953 with an average of 1,931 per month.

The definition of the company's credit rating is identical in both Compustat and Rating Xpress and is provided by Standard & Poor's directly in both databases. As defined by

S&P, prior to 1998, this issuer rating is based on the firm's senior publicly traded debt. After 1998, the rating is based on the overall quality of the firm's outstanding debt, either public or private.² *Standard & Poor's Rating Definitions* specifies S&P's issuer credit rating as "a current opinion of an obligor's overall financial capacity (its creditworthiness) to pay its financial obligations. This opinion focuses on the obligor's capacity and willingness to meet its financial commitments as they come due. It does not apply to any specific financial obligation, as it does not take into account the nature of and provisions of the obligation, its standing in bankruptcy or liquidation, statutory preferences, or the legality and enforceability of the obligation. In addition, it does not take into account the creditworthiness of the guarantors, insurers, or other forms of credit enhancement on the obligation".

We eliminate penny stocks from the sample by requiring that the beginning-of-month stock price be at least \$1. While this is done to ensure that the empirical findings are not driven by low-priced and extremely illiquid stocks, we find that our results are robust to the inclusion of stocks with price below \$1. Throughout the paper, we use delisting returns whenever a stock is delisted. This is important because a number of stocks delist due to financial distress.

In the empirical analysis that follows, we transform the S&P ratings into conventional numerical scores. Specifically, 1 represents a *AAA* rating and 22 reflects a *D* rating.³ Hence, a higher numerical score reflects higher credit risk. Numerical ratings of 10 or below (*BBB*– or better) are considered investment-grade, and ratings of 11 or higher (*BB*+ or worse) are labeled high-yield or non-investment grade.

To get some perspective about the firms with different credit ratings, we report in Panel A of Table 1 average values of various firm-level characteristics. Each month all stocks rated by S&P are divided into decile portfolios based on their credit rating at time t . For each rating decile, we compute the cross-sectional median characteristic for month $t + 1$. The reported characteristics are computed as the time-series mean of the median cross-sectional characteristic.

Perhaps not surprisingly, the average firm size (as measured by market capitalization) decreases monotonically with worsening credit rating. The highest-rated stocks have an average market capitalization of \$6.44 billion, while the lowest-rated stocks have an average capitalization of \$0.21 billion. The book-to-market ratio increases with credit risk, from 0.46 in C_1 to 0.72 in C_{10} . The average stock price also decreases monotonically with increasing credit risk from \$45.12 for the highest-rated stocks to \$7.55 for the lowest-rated stocks. Notice also that institutions hold far fewer shares of low-rated stocks. Institutional holding amounts to over 54% of shares outstanding for high-rated stocks and less than 34% for low-rated stocks.

High-rated firms are much more liquid than low-rated firms. The average monthly dollar trading volume decreases from \$452 million (\$147 million) for the highest-rated NYSE/AMEX (NASDAQ) stocks to \$25 million (\$25 million) for the lowest-rated stocks. Moreover, Amihud's (2002) illiquidity measure is 0.01 (0.39) for NYSE/AMEX

²We have checked that the results are essentially similar before and after 1998. The change in the long-term issuer ratings definition does not impact the results.

³The entire spectrum of ratings is as follows: *AAA* = 1, *AA*+ = 2, *AA* = 3, *AA*– = 4, *A*+ = 5, *A* = 6, *A*– = 7, *BBB*+ = 8, *BBB* = 9, *BBB*– = 10, *BB*+ = 11, *BB* = 12, *BB*– = 13, *B*+ = 14, *B* = 15, *B*– = 16, *CCC*+ = 17, *CCC* = 18, *CCC*– = 19, *CC* = 20, *C* = 21, *D* = 22.

Table 1
Stock characteristics, alphas, and betas by credit rating decile.

Characteristics	Rating decile (C_1 = lowest, C_{10} = highest risk)										
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	
<i>Panel A: Stock characteristics</i>											
Size (\$billions)	6.44	4.21	2.90	1.99	1.53	1.20	0.68	0.41	0.29	0.21	
Book-to-market ratio	0.46	0.48	0.53	0.57	0.61	0.64	0.63	0.63	0.65	0.72	
Price (\$)	45.12	38.79	35.32	31.94	28.84	25.51	19.62	14.76	11.60	7.55	
Volume—NYSE/AMEX	452.40	343.88	244.01	182.30	147.93	127.42	87.25	58.76	37.44	25.18	
Volume—Nasdaq	146.74	58.08	64.49	68.85	93.26	140.72	59.56	39.46	32.83	25.29	
Illiquidity—NYSE/Amex	0.01	0.02	0.02	0.03	0.04	0.06	0.15	0.34	0.53	1.09	
Illiquidity—Nasdaq	0.39	0.46	0.48	0.14	0.22	0.29	0.42	0.61	0.86	1.54	
Institutional share (%)	54.73	55.75	56.52	57.99	59.28	57.93	55.04	50.62	43.93	33.67	
Number of analysts	17.19	15.13	12.88	11.13	10.06	9.38	7.34	5.52	4.70	3.89	
Analyst revisions (%)	0.00	−0.01	−0.02	−0.04	−0.07	−0.15	−0.14	−0.08	−0.07	−0.16	
LT debt/equity	0.42	0.53	0.59	0.65	0.73	0.83	1.03	1.29	1.53	1.68	
<i>Panel B: Portfolio alphas and betas</i>											
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	$C_1 - C_{10}$
CAPM alpha	0.33 (3.08)*	0.31 (2.92)*	0.35 (3.01)*	0.29 (2.51)*	0.24 (1.91)	0.31 (2.25)*	0.08 (0.45)	−0.11 (−0.53)	−0.10 (−0.44)	−1.24 (−3.91)*	1.57 (4.16)*
CAPM beta	0.74 (30.26)*	0.78 (32.47)*	0.82 (30.79)*	0.86 (32.11)*	0.84 (29.51)*	0.90 (28.56)*	1.11 (28.56)*	1.20 (26.00)*	1.26 (23.83)*	1.46 (20.15)*	−0.72 (−8.33)*
FF93 alpha	0.17 (2.05)*	0.09 (1.20)	0.10 (1.23)	0.02 (0.24)	−0.06 (−0.67)	0.00 (0.02)	−0.26 (−2.28)*	−0.36 (−2.57)*	−0.40 (−2.53)*	−1.33 (−5.70)*	1.50 (5.55)*
Mkt beta	0.87 (40.99)*	0.93 (48.36)*	0.99 (46.00)*	1.02 (47.72)*	1.01 (47.00)*	1.07 (44.69)*	1.27 (43.85)*	1.28 (36.11)*	1.29 (31.26)*	1.40 (23.43)*	−0.53 (−7.67)*
SMB beta	−0.18	−0.07	−0.02	0.12	0.23	0.32	0.52	0.74	0.81	1.13	−1.31

Table 1 (continued)

<i>Panel B: Portfolio alphas and betas</i>											
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	$C_1 - C_{10}$
	(−6.88)*	(−2.92)*	(−0.58)	(4.68)*	(8.81)*	(11.08)*	(14.70)*	(17.14)*	(16.45)*	(15.48)*	(−15.46)*
HML beta	0.28	0.40	0.47	0.52	0.59	0.63	0.71	0.58	0.46	0.33	−0.05
	(8.81)*	(13.96)*	(14.75)*	(16.33)*	(18.39)*	(17.66)*	(16.35)*	(10.92)*	(7.67)*	(3.71)*	(−0.51)

Each month, all stocks rated by Standard & Poor's are divided into decile portfolios based on their credit rating at time t . Stocks priced below \$1 at the beginning of the month are removed. For each rating decile, we compute the cross-sectional median characteristic for month $t + 1$. Panel A reports the average of these monthly means. The sample period is October 1985–December 2007. The numeric S&P rating is ascending in credit risk (i.e., 1 = AAA, 2 = AA+, 3 = AA, ..., 21 = C, 22 = D). Volume is the monthly dollar trading volume (in \$ million). Illiquidity is computed, as in Amihud (2002), as the absolute daily return divided by the total dollar trading volume for the day, averaged across all trading days of the month (multiplied by 10^7). Institutional share is the percentage of shares outstanding owned by institutions. Number of analysts represents the number of analysts following the firm. Analyst revisions are computed as the change in mean EPS forecast since the previous month divided by the absolute value of the previous month mean EPS forecast. In Panel B, CAPM (Fama and French, 1993) alphas and betas are calculated by running time-series regressions of the credit risk decile portfolio excess stock returns on the excess return of the market (Mkt, SMB, and HML factors). The reported alphas are in percentages per month. The t -statistics are in parentheses. * Indicates significance at 5%.

(NASDAQ) highest-quality stocks and 1.09 (1.54) for the lowest-quality stocks.⁴ This measure is computed as the absolute price change per dollar of daily trading volume

$$ILLIQ_{it} = \frac{1}{D_{it}} \sum_{t=1}^{D_{it}} \frac{|R_{itd}|}{DVOL_{itd}} * 10^6, \quad (1)$$

where R_{itd} is the daily return and $DVOL_{itd}$ is the dollar trading volume of stock i on day d in month t , and D_{it} is the number of days in month t for which data are available for stock i (a minimum of 10 trading days is required).

We next analyze several variables that proxy for uncertainty about the firm's fundamentals. In particular, the average number of analysts following a firm decreases monotonically with credit risk from about 17 for the highest to four for the lowest-rated stocks. In addition, analyst revisions are negative and much larger in absolute value for the low- versus high-rated stocks. Finally, leverage, computed as the book value of long-term debt to market capitalization, increases monotonically from 0.42 for the highest-rated stocks to 1.68 for the lowest-rated stocks.

In Panel B of Table 1, we present the risk-adjusted returns for the credit rating-sorted decile portfolios. The CAPM alpha for the $C_1 - C_{10}$ long-short portfolio is 157 basis points per month, the alpha from the Fama–French three-factor model is 150 basis points and the alpha from the Fama–French model augmented by a factor for momentum as in Carhart (1997) amounts to 105 basis points per month (results not reported). The market and size betas (CAPM and three-factor model alphas) increase (decrease) with credit risk. Notice that low-rated stocks have higher beta and, at the same time, they realize lower risk-adjusted returns. If the market beta is a good measure of systematic risk, low-rated stocks should earn higher returns. The realized lower return is, thus, puzzling.

Overall, we have found that low-rated stocks are smaller and lower priced, and have higher market betas, lower dollar trading volumes, higher leverage, lower institutional holding, and higher uncertainty about their fundamentals and future profitability, as compared to high-rated stocks.

2. Results

To confirm the credit risk–return puzzle for our sample of rated firms, we will examine (i) raw and characteristic-adjusted portfolio returns and (ii) cross-sectional regressions of individual (risk-adjusted) stock returns on firm characteristics including ratings. First, we present in Panel A of Table 2 returns for decile portfolios sorted monthly on credit ratings. Portfolio returns are computed first by equally weighting individual stock returns realized in the month subsequent to portfolio formation and then averaging through the mean cross-sectional monthly returns. The average monthly return for the highest (lowest) credit rating portfolio C_1 (C_{10}) is 1.20% (0.12%) per month. The difference in mean returns between the highest and lowest rated portfolio, $C_1 - C_{10}$, is a statistically and economically significant 1.09% per month.

Further, the negative credit rating–return relation persists over several months. Specifically, the $C_1 - C_{10}$ cumulative return over the 6 (12) [24] months subsequent to

⁴Hasbrouck (2009) compares effective and price-impact measures estimated from daily data to those from high-frequency data and finds that Amihud's (2002) measure is the most highly correlated with trade-based measures.

Table 2
Raw and characteristics-adjusted returns by credit rating decile.

	Rating decile (C_1 = lowest, C_{10} = highest risk)										
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	$C_1 - C_{10}$
Panel A: Raw returns											
Average	AA	A+	A	A−	BBB+	BBB−	BB+	BB−	B+	B−	
Rating	2.53	4.62	5.94	7.10	8.25	9.59	11.22	12.67	13.72	16.33	
Overall	1.20	1.20	1.27	1.19	1.17	1.29	1.19	1.07	0.99	0.12	1.09
	(5.38)*	(5.22)*	(5.09)*	(4.60)*	(4.65)*	(4.71)*	(3.55)*	(2.87)*	(2.48)*	(0.23)	(2.61)*
Non-Jan.	1.24	1.19	1.26	1.15	1.14	1.20	1.07	0.88	0.72	−0.43	1.67
	(5.35)*	(4.97)*	(4.84)*	(4.24)*	(4.30)*	(4.22)*	(3.03)*	(2.29)*	(1.76)	(−0.87)	(4.28)*
Jan.	0.80	1.33	1.39	1.66	1.60	2.21	2.55	3.18	4.10	6.12	−5.32
	(0.95)	(1.56)	(1.55)	(1.89)	(1.82)	(2.34)*	(2.45)*	(2.24)*	(2.62)*	(2.76)*	(−2.38)*
Exp.	1.23	1.23	1.28	1.20	1.18	1.29	1.24	1.08	1.05	0.22	1.01
	(5.47)*	(5.31)*	(5.12)*	(4.74)*	(4.69)*	(4.74)*	(3.73)*	(2.98)*	(2.70)*	(0.44)	(2.39)*
Rec.	0.79	0.73	1.08	0.92	1.10	1.21	0.54	0.97	0.17	−1.45	2.25
	(0.63)	(0.58)	(0.78)	(0.56)	(0.72)	(0.75)	(0.25)	(0.37)	(0.06)	(−0.48)	(1.08)
$r_{t+1:t+6}$	6.93	6.86	7.34	7.20	6.84	7.36	6.84	6.34	6.34	3.81	3.12
	(9.94)*	(9.77)*	(9.29)*	(8.51)*	(8.19)*	(7.98)*	(6.01)*	(4.75)*	(4.57)*	(2.12)*	(2.13)*
$r_{t+1:t+12}$	13.99	13.83	14.84	14.87	14.10	14.88	13.75	14.14	13.48	10.66	3.33
	(13.21)*	(13.43)*	(13.66)*	(12.42)*	(11.58)*	(11.99)*	(9.05)*	(7.67)*	(6.65)*	(4.18)*	(1.96)*
$r_{t+1:t+24}$	28.51	28.72	30.11	31.62	29.51	29.39	27.88	30.28	27.58	23.55	4.96
	(17.57)*	(17.98)*	(19.06)*	(17.96)*	(16.14)*	(18.91)*	(13.71)*	(12.17)*	(10.12)*	(7.33)*	(1.99)*
Panel B: Size, book-to-market, and momentum adjusted returns											
Overall	0.06	0.02	0.11	0.04	−0.05	0.00	−0.08	−0.20	−0.32	−0.88	0.93
	(0.76)	(0.31)	(1.73)	(0.70)	(−0.92)	(0.07)	(−1.08)	(−2.29)*	(−3.66)*	(−6.24)*	(4.98)*
Non-Jan.	0.13	0.09	0.17	0.08	−0.02	0.01	−0.07	−0.20	−0.35	−1.02	1.15

	(1.83)	(1.31)	(2.53)*	(1.25)	(−0.29)	(0.17)	(−0.98)	(−2.14)*	(−3.93)*	(−7.39)*	(6.38)*
Jan.	−0.82	−0.73	−0.51	−0.35	−0.42	−0.07	−0.12	−0.26	0.00	0.70	−1.52
	(−2.85)*	(−2.46)*	(−2.01)*	(−1.45)	(−2.33)*	(−0.46)	(−0.47)	(−0.80)	(0.01)	(1.04)	(−1.65)
Exp.	0.05	0.01	0.09	0.04	−0.06	0.00	−0.06	−0.20	−0.28	−0.78	0.82
	(0.63)	(0.19)	(1.36)	(0.60)	(−1.10)	(0.06)	(−0.84)	(−2.27)*	(−3.18)*	(−5.39)*	(4.24)*
Rec.	0.18	0.14	0.43	0.12	0.13	0.01	−0.32	−0.25	−0.84	−2.45	2.62
	(0.60)	(0.44)	(1.65)	(0.44)	(0.61)	(0.02)	(−1.04)	(−0.45)	(−2.18)*	(−4.94)*	(4.69)*
$r_{t+1:t+6}$	0.15	−0.20	0.39	0.01	−0.43	−0.32	−0.80	−1.35	−1.97	−2.88	3.03
	(0.64)	(−0.89)	(1.38)	(0.05)	(−2.21)*	(−1.40)	(−2.45)*	(−3.49)*	(−5.58)*	(−4.32)*	(3.67)*
$r_{t+1:t+12}$	0.05	−0.48	0.62	0.11	−0.73	−0.66	−1.59	−1.68	−2.94	−4.06	4.11
	(0.23)	(−1.81)	(1.82)	(0.37)	(−2.79)*	(−2.23)*	(−3.97)*	(−3.57)*	(−5.95)*	(−5.41)*	(4.47)*
$r_{t+1:t+24}$	−0.06	−0.55	1.35	0.62	−0.92	−1.44	−2.46	−2.00	−5.10	−6.43	6.37
	(−0.25)	(−1.96)*	(4.12)*	(2.17)*	(−3.50)*	(−4.59)*	(−6.30)*	(−3.95)*	(−10.89)*	(−8.89)*	(7.10)*

Each month, all stocks rated by Standard & Poor's are divided into decile portfolios based on their credit rating at time t . Stocks priced below \$1 at the beginning of the month are removed. For each credit rating decile, we compute the cross-sectional mean return for month $t + 1$. Panel A reports the average of these monthly means. Panel B reports the average of the size, book-to-market, and momentum adjusted returns as in Daniel et al. (1997). The last column reports the difference between the return of the best rated versus the worst-rated portfolios. All numbers are in percentages. The t -statistics for cumulative returns (last three rows) are (Newey and West, 1987) adjusted heteroscedastic-serial consistent t -statistics. The sample period is October 1985 to December 2007. The numeric S&P rating is ascending in credit risk, i.e. 1 = AAA, 2 = AA+, 3 = AA, ..., 21 = C, 22 = D. * Indicates significance at 5%.

portfolio formation is 3.12% (3.33%) [4.96%].⁵ The C_1-C_{10} returns are higher, on average, in non-January months (1.67% per month) and negative in January (–5.32% per month). The average C_1-C_{10} return is 1.01% per month during expansions and 2.25% (albeit statistically insignificant) during recessions.⁶

The documented relation between credit ratings and returns represents an anomalous pattern in the cross-section of returns because, if credit risk has a systematic component, investors are expected to demand higher-risk premiums and thus higher expected returns for purchasing stocks with higher credit risk. It is possible that credit ratings measure unsystematic risk that can be diversified away. If so, high- and low-rated stocks should realize statistically and economically indistinguishable average returns. However, the empirical evidence is to the contrary: firms in the highest credit rating decile earn on average a significant 1.09% per month more than firms in the lowest credit rating decile.

It should be noted that a large fraction of the C_1-C_{10} payoff is generated by the lowest-rated stock portfolio C_{10} . In particular, while the overall C_1-C_{10} return is 1.09% per month, the payoff to the portfolio C_1-C_9 is only 0.21% per month and is statistically insignificant at the 5% level. Moreover, the cumulative 6 (12) [24] months return for the C_1-C_9 portfolio is 0.59% (0.51%) [0.93%] compared to 3.12% (3.33%) [4.96%] for the C_1-C_{10} portfolio. Similarly, the return in the non-January months for C_1-C_9 is only 0.52% per month as compared to 1.67% for the C_1-C_{10} portfolio. Of course, the payoff for the C_1-C_9 portfolio, even though smaller, is still anomalous.

Next, we explore whether the return differential between the high- and low-rated stocks can be explained by the size, value, and momentum characteristics following the approach in Daniel et al. (1997). In particular, we form $5 \times 5 \times 5$ size, book-to-market, and past-12-months return sorted portfolios. We then subtract the monthly return of the portfolio to which a stock belongs from the individual monthly stock return to obtain the stock's characteristic-adjusted return. The mean characteristic-adjusted returns are summarized in Panel B of Table 2.

Adjusting for size, value, and momentum leaves the credit rating–return relation unchanged. In particular, the C_1-C_{10} portfolio realizes a characteristic-adjusted monthly payoff of 0.93% that is statistically significant, only slightly lower than the 1.09% raw return. The characteristic-adjusted payoff earned by the C_1-C_9 portfolio is 0.38% per month, even higher than the 0.21% unadjusted payoff. The monthly C_1-C_{10} characteristic-adjusted return is 0.82% during expansions, 2.62% during recessions, and 1.15% in non-January months, all statistically significant at the 5% level. Moreover, the cumulative characteristic-adjusted return generated by the C_1-C_{10} portfolio over 6 (12) [24] months subsequent to the portfolio formation date is 3.03% (4.11%) [6.37%]. Overall, the credit risk effect in the cross-section of returns is an independent anomaly unrelated to the well-documented size, book-to-market, and past return effects.

Thus far, we have studied the credit risk effect based on portfolios. A natural next step is to examine the credit risk effect in cross-sectional regressions. In particular, we run Fama and MacBeth (1973) regressions of individual stock returns on credit rating, controlling for

⁵Cumulative returns are computed using overlapping monthly returns. Hence, throughout the paper, we compute *t*-statistics for cumulative returns using Newey–West standard errors.

⁶Business cycle expansions and recessions are defined by NBER (see www.nber.org/cycles.html). There are 16 recessionary months in our sample, which could explain why the credit risk effect is statistically insignificant although economically large during recessions.

additional firm characteristics

$$R_{jt} = a_t + b_t \text{RATING}_{jt-1} + \sum_{m=1}^M c_{mt} C_{mjt-2} + e_{jt}, \quad (2)$$

where *RATING* represents the numerical score associated with the firm's rating (a higher numerical rating score corresponds to higher credit risk), C_{mjt} is the value of characteristic m for security j at time t , and M is the total number of characteristics.

The firm characteristics included are (i) Log(Size): firm size measured as the market value of equity, (ii) Log(BM): ratio of book value of equity to market value of equity calculated following the procedure in Fama and French (1992), (iii) $r_{(t-7:t-2)}$: cumulative return over the last 6 months, (iv) Log(Turnover): measured as the ratio of monthly share trading volume to the number of shares outstanding, and (v) SUE: standardized unexpected earnings.⁷ Except for SUE, the above characteristics have been shown to be priced in the cross-section by Brennan et al. (1998). We include SUE because Chordia and Shivakumar (2006) show that it is also priced in the cross-section. Following Brennan et al. (1998), these characteristics are lagged by 2 months relative to the month in which the dependent variable is measured. Also, turnover is measured separately for NYSE/AMEX and NASDAQ stocks.

Panel A of Table 3 reports the time-series averages of the slope coefficients $\hat{b}_t$ and $\hat{c}_{mt}$. The t -statistics are obtained using the Fama–Macbeth standard errors. The evidence shows that the coefficient of the lagged credit rating variable is -0.07 (t -stat = -2.38), which means that a one point higher numerical credit score (one point worse credit rating) is followed by seven basis point lower future monthly return. The second regression in Panel A excludes the credit rating and retains the lagged characteristics as independent variables. Of all characteristics, only the past 6 months return and SUE have a significant impact on the cross-section of future returns. The third regression nests credit rating and firm characteristics. The negative credit risk–return relation is still significant and is actually higher at -0.08 when the firm characteristics are included as control variables. In sum, the statistical evidence based on cross-sectional regressions supports the negative credit risk–return relation.

Whereas the credit rating summarizes the risk that creditors may not get repaid, the credit rating effect in the cross-section of returns could be related to a firm's systematic risk. This is what we examine next. In particular, we make sure that risk-based asset pricing models do not capture the negative credit risk–return relation. We risk-adjust raw returns in time-series regressions using the Capital Asset Pricing Model of Sharpe (1964) and Lintner (1965), as well as the Fama and French (1993) three-factor model. Recall, we have already shown that the CAPM and the Fama and French (1993) model, both produce larger alphas and smaller market betas for high-quality firms.

Our risk adjustment is based on cross-sectional asset pricing tests applied to individual stocks. Similar to Brennan et al. (1998), we first run time-series regressions of individual stock returns on the risk factors prescribed by the CAPM and Fama–French model, augmented with the momentum factor of Carhart (1997). We then run cross-sectional regressions of risk-adjusted returns on credit rating, as well the size, book-to-market,

⁷SUE is computed as the difference between actual earnings and earnings four quarters ago, normalized by the standard deviation of these earnings changes over the past eight quarters.

Table 3
Cross-sectional regressions of raw and risk-adjusted returns on firm characteristics.

	Rating _{<i>t</i>-1}	Log(Size _{<i>t</i>-2})	Log(BM _{<i>t</i>-2})	<i>r</i> _(<i>t</i>-7;<i>t</i>-2)	Log(Turnover _{<i>t</i>-2})		<i>SUE</i> _{<i>t</i>-2}
					NYSE/AMEX	Nasdaq	
<i>Panel A: Raw returns</i>							
1	-0.07 (-2.38)*						
2		-0.07 (-1.32)	0.07 (1.10)	1.34 (4.09)*	0.02 (0.17)	-0.00 (-0.03)	0.06 (3.81)*
3	-0.08 (-2.80)*	-0.08 (-1.87)	0.15 (2.30)*	1.20 (3.36)*	0.01 (0.12)	0.04 (0.57)	0.05 (3.34)*
<i>Panel B: Returns risk-adjusted by Fama and French (1993) and momentum factors</i>							
1	-0.07 (-5.26)*						
2		-0.05 (-2.27)*	-0.01 (-0.31)	1.33 (5.45)*	0.03 (0.69)	-0.02 (-0.39)	0.04 (3.54)*
3	-0.07 (-4.00)*	-0.06 (-2.02)*	0.06 (1.09)	1.19 (4.38)*	0.02 (0.46)	0.01 (0.17)	0.04 (2.82)*

We run monthly cross-sectional regressions of returns, *r_{it}*, on the firm’s lagged credit rating and other firm characteristics, *C_{i,t-2}* (BM is lagged as in Fama and French (1992))

$$R_{it} = a_t + b_t RATING_{i,t-1} + c_t C_{i,t-2} + u_{it}.$$

We remove stocks priced below \$1. The table presents the average slope coefficients, *b_t* and *c_t*, multiplied by 100. The sample *t*-statistics of these estimated coefficients are in parentheses (* indicates significance at 5%). Panel A presents results from regressions of raw returns. For Panel B, we first run time-series regressions of each stock return on market factors

$$R_{it} = \alpha_i + \beta_i F_t + e_{it},$$

where *F_t* are the Fama and French (1993) factors augmented with the momentum factor of Carhart (1997). The risk-adjusted return is the intercept and error term from these time-series regressions: *r_{it}^{*}* = *α_i* + *e_{it}*, which we use as the dependent variable in the cross-sectional regressions. The sample period is October 1985–December 2007.

turnover, SUE, and past returns characteristics. Under the null hypothesis of exact pricing, credit rating as well as equity characteristics should be statistically insignificant in the cross-sectional regressions

$$R_{jt} - R_{ft} - \sum_{k=1}^K \hat{\beta}_{jk} F_{kt} = a_t + b_t RATING_{jt-1} + \sum_{m=1}^M c_{mt} C_{mjt-2} + e_{jt}, \tag{3}$$

where *β_{jk}* is estimated by a first-pass time-series regression of the stock’s excess return on the asset pricing factors over the entire sample period with non-missing returns data.⁸

Panel B of Table 3 risk adjusts raw returns using the Fama–French factors augmented by a factor for momentum as in Carhart (1997).⁹ The first regression specification, which does not include any of the characteristic except for credit rating, shows that the coefficient

⁸While this entails the use of future data in calculating the factor loadings, Fama and French (1992) show that this forward looking does not impact the results. See also Avramov and Chordia (2006).
⁹We have also checked (unreported results), that our findings are unchanged when adjusting with the Fama and French (1993) factors or only the excess market return.

of RATING is a statistically significant -0.07 , suggesting that a one point higher numerical credit score is followed by seven basis points lower risk-adjusted return. The credit rating effect is still -0.07 when controlling for firm characteristics and is thus robust to controlling for size, book-to-market, SUE, past returns, and turnover.

Note that in Table 2 the difference in rating between the highest rating decile portfolio, *AA* (numeric rating of 2.53), and the lowest rating decile portfolio, *B-* (16.33), is about 14 rating points. This difference should result in a return differential of 0.98% (14×0.07), which is comparable to the 1.09% reported in Panel A of Table 2.

In sum, results based on (i) raw and risk-adjusted portfolio returns, (ii) characteristic-adjusted portfolio returns, (iii) individual stock returns, and (iv) individual stock returns risk-adjusted by asset pricing models, do conclusively suggest that higher-rated stocks realize higher raw, risk-adjusted, as well as characteristics-adjusted returns than lower-rated stocks.

The negative relation between credit risk and returns is not a new finding. It has been documented by Dichev (1998) based on Altman's *Z*-score and Ohlson's *O*-score, by Garlappi et al. (2008) based on Moody's KMV default measure, and by Campbell et al. (2008) based on a hazard model.¹⁰ Only Vassalou and Xing (2004), who calculate the distance to default based on the Merton (1974) model, find a positive relation between distress risk and returns.

We also note that while the credit risk effect is strong and robust, most of the return differential between high and low credit risk stocks comes from the worst-rated decile. To further pinpoint the segment of the market driving the credit risk effect, we document in Table 4 the credit risk effect for various credit rating sub-samples as we sequentially exclude the worst-rated stocks. We start with all firms in the sample where the return differential across the highest and lowest rating decile stocks is 1.09% per month, as already shown. Upon eliminating all stocks rated *D* from the sample, the return differential across the highest- and lowest-rated stocks drops to 0.89% per month. Excluding all stocks rated *CCC* and below, the return differential across the lowest- and highest-rated stocks is no longer statistically significant at the 5% level. Excluding stocks rated *BB-* and below results in economically small return differential of one basis point per month. Stocks rated *BB-* and below comprise only 4.18% of the sample by market capitalization and 27% by the number of firms. Consistent with Campbell et al. (2008), who show that the “distress effect” is stronger among small and illiquid stocks, we find that this effect is even more limited in the cross-section and is driven by a small segment of the worst-rated stocks.

2.1. The impact of downgrades

Our analysis thus far has focused on the credit rating level. Credit rating downgrade events may offer deeper insights into the economics of the credit risk–return relation. Studying downgrades is motivated by previous work, which demonstrates an asymmetric response of future bond (Hand et al., 1992) and stock (Dichev and Piotroski, 2001) returns to credit rating changes. In particular, both papers document considerable abnormal bond

¹⁰Since our sample is necessarily restricted to rated firms only, we need to provide comfort to the reader that our results are more general. So, we have also used Altman's *Z*-score to sort stocks to examine the return differential between the highest and lowest *Z*-score stocks. The results while weaker are qualitatively similar to those documented here.

Table 4

Credit risk strategy payoffs when sequentially excluding worst-rated stocks.

Stock sample	Credit risk effect	Percentage of market cap	Percentage of firms
AAA–D (all firms)	1.09 (2.61)*	100.00	100.00
AAA–C	0.89 (2.16)*	99.96	99.58
AAA–CC	0.89 (2.16)*	99.96	99.58
AAA–CCC–	0.90 (2.28)*	99.95	99.45
AAA–CCC	0.84 (2.16)*	99.95	99.29
AAA–CCC+	0.66 (1.84)	99.91	98.81
AAA–B–	0.48 (1.38)	99.85	97.99
AAA–B	0.40 (1.22)	99.55	95.72
AAA–B+	0.33 (1.11)	98.85	91.36
AAA–BB–	0.13 (0.49)	97.60	81.82
AAA–BB	0.01 (0.05)	95.82	72.89
AAA–BB+	0.02 (0.08)	93.82	65.86
AAA–BBB–	–0.00 (–0.01)	91.29	60.34
AAA–BBB	–0.09 (–0.56)	86.77	51.97
AAA–BBB+	–0.06 (–0.42)	79.30	41.42
AAA–A–	–0.12 (–0.75)	71.48	32.83

Each month, all stocks rated by Standard & Poor's are divided into decile portfolios based on their credit rating at time t . Stocks priced below \$1 at the beginning of the month are removed. The credit risk effect is computed as the return of the best rated decile portfolio minus the return of the worst-rated decile portfolio. Each subsequent row in the table represents a monotonically decreasing sample of stocks obtained by sequentially excluding firms with the worst credit rating. The second column of the table reports the credit risk effect for each subsamples of firms. t -Statistics are in parentheses. The third column shows the market capitalization of the given subsample as a percentage of the overall sample of S&P rated firms. The third column provides the percentage of firms represented by each subsample. The sample period is October 1985–December 2007. *Indicates significance at 5%.

and stock price declines following rating downgrades but no particular price advances following upgrades. We extend their analysis by looking at the differential response of high- and low credit risk stocks to rating downgrades.

Table 5 provides a comprehensive summary of credit rating downgrades both by credit risk (Panel A) and by frequency of downgrades (Panel B). Panel A presents the number and size of credit rating downgrades, as well as returns around downgrades for the credit risk-sorted decile portfolios. Note that the number of downgrades in the highest-rated

Table 5
Downgrade characteristics, delistings, and returns by credit rating groups.

	Rating decile (C_1 = lowest, C_{10} = highest risk)									
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
<i>Panel A: By credit rating portfolio</i>										
Number of downgrades	793	661	646	685	652	674	809	625	799	1,579
Downgrades/month	2.97	2.48	2.42	2.57	2.44	2.52	3.03	2.34	2.99	5.91
Size of downgrades	1.87	1.54	1.65	1.60	1.62	1.85	1.75	1.79	1.76	2.60
r_{t-1}	0.24	-0.63	-0.44	-1.79	-2.85	-0.85	-3.53	-8.66	-8.66	-16.77
r_t	0.66	1.47	0.04	1.79	-0.14	-0.70	2.09	-2.30	-1.88	-9.71
r_{t+1}	0.77	0.13	0.61	0.87	-1.38	-1.49	-1.39	-1.09	-3.47	-8.76
$r_{t-6:t-1}$	2.16	2.43	2.95	0.15	-4.87	-7.66	-11.82	-19.58	-24.14	-44.19
$r_{t+1:t+6}$	5.43	7.59	8.57	8.43	1.82	3.52	-2.93	-3.19	-6.73	-14.22
$r_{t-12:t-1}$	7.38	6.53	5.61	5.62	-3.70	-9.77	-13.91	-28.36	-30.29	-52.79
$r_{t+1:t+12}$	8.69	15.51	15.11	16.30	7.92	6.24	-0.62	4.86	6.39	-7.16
Delisted over ($t + 1 : t + 6$)	8	12	20	17	23	28	35	41	69	227
Delisted over ($t + 1 : t + 12$)	13	20	32	32	38	50	67	72	114	330
Delisted over ($t + 1 : t + 24$)	23	39	51	66	73	89	121	121	176	437
Downgrades/month ($r_{mt} > 0$)	2.75	2.55	2.12	2.63	2.66	2.65	3.05	2.31	2.83	5.62
Size of downgrades ($r_{mt} > 0$)	1.58	1.52	1.66	1.58	1.62	1.89	1.71	1.81	1.81	2.62
r_{t-1} ($r_{mt} > 0$)	1.66	-1.27	0.08	-0.70	-2.47	-0.47	-3.14	-9.45	-8.82	-16.84
r_t ($r_{mt} > 0$)	2.95	4.24	2.18	4.46	2.04	3.26	3.75	1.45	1.25	-5.31
r_{t+1} ($r_{mt} > 0$)	1.34	0.11	0.46	1.61	-0.70	-0.62	-0.79	0.26	-2.93	-8.72

Table 5 (continued)

	Rating decile (C_1 = lowest, C_{10} = highest risk)									
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
Downgrades/month ($r_{mt} < 0$)	3.37	2.34	2.96	2.44	2.04	2.31	2.99	2.39	3.29	6.45
Size of downgrades ($r_{mt} < 0$)	2.32	1.58	1.64	1.62	1.62	1.76	1.83	1.75	1.68	2.55
r_{t-1} ($r_{mt} < 0$)	−2.31	0.35	−1.42	−4.23	−3.65	−1.65	−4.29	−7.06	−8.36	−16.65
r_t ($r_{mt} < 0$)	−3.59	−2.74	−4.06	−4.16	−4.81	−9.12	−1.45	−9.79	−7.92	−19.02
r_{t+1} ($r_{mt} < 0$)	−0.31	0.14	0.91	−0.75	−2.88	−3.48	−2.76	−3.86	−4.55	−8.84
Downgrades/month (expansions)	2.78	2.48	2.19	2.48	2.32	2.49	2.91	2.21	2.59	5.60
Size of downgrades (expansions)	1.79	1.56	1.68	1.59	1.61	1.83	1.75	1.72	1.73	2.58
r_{t-1} (expansions)	0.75	−0.15	−0.37	−1.55	−2.82	−0.23	−3.53	−8.87	−7.23	−16.46
r_t (expansions)	0.91	0.68	−0.16	1.22	−0.30	0.15	2.09	−2.64	−1.62	−9.67
r_{t+1} (expansions)	1.03	0.38	0.81	1.03	−0.93	−1.08	−1.03	−1.43	−2.87	−8.06
Downgrades/month (recessions)	5.88	2.31	5.56	3.19	3.69	2.75	4.88	4.19	8.19	10.00
Size of downgrades (recessions)	3.20	1.35	1.26	1.77	1.89	2.25	1.81	2.56	2.22	2.88
r_{t-1} (recessions)	−5.71	−6.19	−1.21	−4.57	−3.18	−7.33	−3.43	−6.36	−24.45	−20.95
r_t (recessions)	−2.16	10.67	2.57	8.31	2.17	−9.61	2.08	1.32	−5.06	−10.24
r_{t+1} (recessions)	−2.67	−2.78	−1.93	−0.95	−7.82	−6.30	−6.97	2.58	−10.82	−18.27
Downgrade correlation (%)	2.53	2.53	2.74	3.25	3.79	5.04	4.75	6.26	8.02	9.90

Panel B: By frequency of downgrades

# of downgr. per firm	Firms with N downgr.		Size of each downgr.		Months between downgr.		Returns around each downgrade							
	IG	NIG	IG	NIG	IG	NIG	$r_{t-3:t-1}$		$r_{t:t+3}$		$r_{t-6:t-1}$		$r_{t:t+6}$	
							IG	NIG	IG	NIG	IG	NIG	IG	NIG
$N = 1$	565	598	1.91	2.21			0.19	−19.64	1.78	−6.25	1.00	−28.09	6.26	−3.66
$N = 2$	319	339	1.73	1.98	45.13	19.82	−1.29	−18.97	4.87	−9.95	−2.69	−28.00	9.84	−10.93

$N = 3$	201	168	1.50	1.72	38.55	19.64	−1.72	−17.21	2.05	−12.65	−1.88	−26.95	5.39	−13.41
$N = 4$	122	69	1.38	1.50	34.22	20.15	−3.11	−12.94	3.62	−12.82	−3.21	−19.54	7.05	−14.20
$N = 5$	45	24	1.37	1.60	32.89	17.18	−4.32	−12.84	3.26	−10.07	−6.66	−25.85	7.75	−12.34
$N = 6$	17	5	1.37	1.33	30.24	17.52	−0.80	−18.37	1.83	−1.70	−2.49	−26.24	4.43	−7.82
$N = 7$	6	1	1.14	2.14	24.58	31.00	−1.63	−8.29	4.52	−10.35	−3.37	−1.26	5.09	−2.47
$N = 8$	2	1	1.50	1.00	30.64	34.29	5.57	6.27	9.90	13.78	2.96	−1.16	20.72	17.52
$N = 9$	1		1.33		27.75		−11.98		16.92		−22.33		15.90	
$N = 10$	1		2.20		13.89		4.07		7.97		3.14		10.25	
Obs.							8,060	6,836	10,542	8,268	16,097	13,789	18,052	13,567

The table focuses on stocks with at least one rating downgrade. Panel A analyzes downgrades by credit rating decile portfolios, sorted on their rating at the end of the previous month, $t - 1$. For each decile, we compute the number of downgrades per month, the average size of downgrades, and the average returns (in percentages) around downgrades. Panel A also reports these downgrade statistics for up/down markets (when the excess market return is positive/negative), as well as for expansions and recessions as defined by NBER. The downgrade correlation is the average pairwise time-series correlation between any two stocks with downgrades in this rating decile. This correlation is computed based on an index for each stock which takes the value of 0/1 during months when there is no/a downgrade. We also report the total number of delisted stocks following downgrades. Panel B divides firms by number of downgrades and within each downgrade frequency group, analyzes investment-grade (IG) and non-investment-grade (NIG) firms. The sample period is October 1985–December 2007.

decile is 793 (2.97 per month), while the number in the lowest-rated decile is much larger at 1,579 (5.91 per month). The downgrade magnitude is also much larger for non-investment-grade firms. Specifically, the average size of a downgrade amongst the lowest-rated stocks is 2.60 points (moving from *B–* to *CCC–*), whereas the average downgrade amongst the highest-rated stocks is 1.87 points (moving from *AA* to *A+*).

The stock price change around downgrades is considerably larger for low-rated stocks than for high-rated stocks. For instance, in the month before (after) the downgrade, the return on the lowest-rated stocks averages -16.77% (-8.76%). The average monthly return on the highest-rated stocks before (after) the downgrade is positive at 0.24% (0.77%). A similar return pattern prevails 6 months, 1 year, and 2 years around downgrades. In the year before (after) the downgrade, the return for the lowest-rated stocks is -52.79% (-7.16%), while the corresponding number for the highest-quality stocks is 7.38% (8.69%).

Panel A of Table 5 also documents the number of firms that are delisted across the various rating deciles. Over a 6 (12) [24] months period after a downgrade, the number of delistings amongst the highest-rated stocks are 8 (13) [23] and are 227 (330) [437] amongst the lowest-rated stocks. Overall, the number of delistings are distinctly higher amongst the non-investment-grade firms, suggesting that many delistings are a consequence of financial distress.

We also examine the impact of downgrades in more detail in Table 5. We study downgrades in up and down markets (i.e., when the value weighted market excess returns in the month of the downgrade are positive and when they are negative). Panel A of Table 5 shows that the average number of downgrades in an up (down) market month for a C_{10} firm is 5.62 (6.45); a C_1 firm experiences on average 2.75 (3.37) downgrades in up (down) markets. The major difference in the impact of downgrades during up and down markets is the impact on returns. During the month of the downgrade, the average return in the lowest-rated stocks is -19.02% (-5.31%) when the market excess returns are negative (positive). The difference between the highest- and the lowest-rated firms is bigger for downgrades during down markets (-3.59% versus -19.02%) than during up markets (2.95% versus -5.31%). The probability of delisting of a downgraded firm over 6 months following a downgrade is 18% (108 delistings out of 613 downgrades) during down markets while the probability is 12% (119 delistings out of 966 downgrades) during up markets (results not reported).

We also examine downgrades during expansions and recessions as defined by NBER. While we have only 16 months of recessions in our sample, the low-rated firms have an average of 10 downgrades per month during recessions and only 5.6 during expansions. However, the returns of low-rated stocks just for the month of downgrade are similar in recessions and expansions: -10.24% and -9.67% , respectively. Overall, it does not seem that downgrades and their impact on returns can be solely attributed to a particular state of the economy.

There is also no evidence of significant clustering of downgrades in particular time periods. The downgrade correlation is the average pairwise correlation between any two stocks with downgrades in a particular rating decile. This correlation is computed based on an index for each stock, which takes a value of one (zero) during months where there is a (no) downgrade. As the last row of Panel A of Table 5 reports, while the time-series correlation of downgrades is higher in C_{10} firms (9.9%) than in C_1 firms (2.53%), these correlations are too low to suggest that downgrades tend to happen all at the same time. It appears that downgrades are dispersed idiosyncratic events.

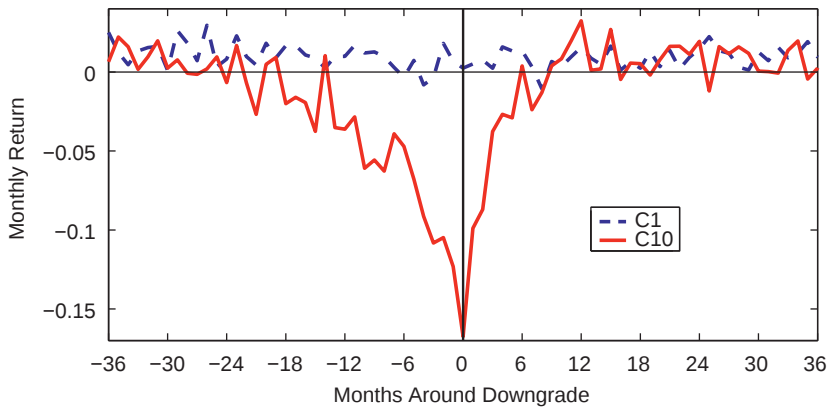


Fig. 1. Returns around downgrades. The figure presents monthly returns of the best (C_1) and worst (C_{10}) rated decile portfolio around periods of rating downgrades. Month 0 is the month of downgrade.

Panel B of Table 5 looks at the frequency of downgrades among investment-grade and non-investment-grade firms. In the investment (non-investment) grade group, there are a couple of firms that experience as many as 10 (eight) downgrades over the sample period, October 1985–December 2007. For each category of overall number of downgrades, the average size per downgrade is much larger and the average time between downgrades is shorter among non-investment-grade firms. This means that high credit risk firms tend to have larger and more frequent downgrades than low credit risk firms. Also, for each particular number of downgrades, non-investment-grade firms experience much larger negative returns, both 3 and 6 months before and after the downgrade, than investment-grade firms. Note also that the non-investment-grade firms experience a series of negative returns with each downgrade. For instance, in the 3 months before (after) the downgrade, the cumulative returns for the non-investment-grade stocks amount to an average of -60% (-43%) by the sixth downgrade. On the other hand, for the investment-grade stocks, the cumulative returns average -11% (19%) in 3 months before (after) the downgrade. We have also examined (results available upon request) the cumulative returns during expansions and recessions and during periods when the market excess returns are positive and negative. Not surprisingly, the cumulative returns for non-investment-grade stocks are far more negative during recessions and during periods of negative market excess returns, especially in the periods after the downgrade.

Overall, the lowest-rated stocks experience significant negative returns around downgrades, whereas, unconditionally, the highest-quality stocks realize positive returns.¹¹ This differential response is further illustrated in Fig. 1. Clearly, during periods of rating downgrades, the low credit rating portfolio, C_{10} , experiences returns that are uniformly lower than those of portfolio C_1 . Moreover, the low-rated stocks earn negative returns over 10 months after the downgrade. Could these major cross-sectional differences in

¹¹The downgrades in the highest-quality firms could arise from an increase in leverage that takes advantage of the interest tax deductibility. This interest tax subsidy along with an amelioration of agency problems due to the reduction in the free cash flows might be the source of the positive returns in the high-quality firms around downgrades.

returns around credit rating downgrades drive the relation between returns and credit risk? We show below that the answer is indeed “Yes.”

In particular, Table 6 repeats the analysis performed in Table 2 after excluding, for each downgraded stock, 3 months of returns before and after a rating downgrade. Note that this requires eliminating a period of 7 months: 3 months before, 3 months after, and the month of the downgrade. Of course, our analysis here does not constitute a real-time trading strategy because we are looking ahead when discarding returns 3 months prior to a downgrade. However, our objective here is merely to examine the pattern of returns across the different credit risk portfolios around credit rating downgrades.¹²

Panel A of Table 6 shows that the highest-rated decile portfolio, C_1 , averages a payoff of 1.22%, whereas the return to the lowest-rated decile portfolio, C_{10} , is 1.17%. The return differential is economically small and statistically insignificant. This reduction in the payoff differential is primarily attributable to the lowest-rated decile portfolio. In Table 2, the C_{10} portfolio averages a raw return of 0.12% per month, whereas the average return is 1.17% per month in non-downgrade periods.

Upon excluding returns around ratings downgrades, the C_1 – C_{10} strategy yields a statistically insignificant 0.56% monthly payoff in non-January months and an insignificant 0.10% during expansions. The cumulative 6 month return for the C_1 – C_{10} portfolio is a statistically insignificant –0.71% per month. The cumulative 12 months return is a statistically insignificant –2.37% per month. These results strongly suggest that the low average returns to low-quality firms result from periods of worsening credit conditions.

Excluding 3 months of returns around downgrades amounts to excluding a total of 33,706 month-return observations ($33,706 = 8,060 + 6,836 + 10,542 + 8,268$, see last row of Panel B in Table 5). The total number of month-return observations in our sample is 469,233. The excluded observations thus represent 7.18% of the total month-return observations in our sample. In fact, the fraction of sample observations ultimately generating the credit risk effect is even smaller. In particular, the average return for the C_1 group during the entire sample is 1.20% (see Table 1) and it is slightly higher at 1.22% (see Table 5) during non-downgrade periods. The corresponding returns for the C_{10} group are 0.12% and 1.17%. Thus, the considerable decline in the return spread across the credit risk groups during periods of stable credit conditions is almost exclusively attributable to the C_{10} firms. Hence, the fraction of sample observations essentially generating the credit spread effect is less than 3.22% [$(6,836 + 8,268)/469,233$].

We also examine whether the impact of downgrades is limited to the lowest-rated firms. To do this we eliminate returns over a period of 7 months, from 3 months before to 3 months after a downgrade, for firms rated *BB*– or lower. The results (available upon request) show that the return differential between high- and low-rated stocks is an insignificant 0.08% per month. Thus, it is indeed the downgrades in the worst-rated stocks that drives the credit risk effect. With our focus on the worst-rated stocks during downgrade periods, we take an even more granular look at the bottom of the credit ratings chain. We further split the worst-rated decile into two bins (not reported)—the highest and

¹²Note that often the rating agencies place firms on a credit watch prior to the actual downgrade. Vazza et al. (2005) document that 64% of the firms placed on a negative credit watch subsequently experience a downgrade. This suggests that the downgrade event is largely predictable.

Table 6
Credit rating effect after removing returns around downgrades.

Characteristics	Rating decile (C_1 = lowest, C_{10} = highest risk)										
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	$C_1 - C_{10}$
<i>Panel A: Returns after eliminating 3 months around downgrades</i>											
Overall	1.22 (5.56)* (5.57)*	1.24 (5.46)* (5.20)*	1.32 (5.34)* (5.10)*	1.26 (4.97)* (4.60)*	1.27 (5.19)* (4.81)*	1.39 (5.23)* (4.76)*	1.39 (4.27)* (3.75)*	1.33 (3.63)* (3.04)*	1.29 (3.28)* (2.56)*	1.17 (2.44)* (1.50)	0.06 (0.14) (1.47)
Jan.	0.70 (0.84) (5.64)*	1.37 (1.65) (5.50)*	1.37 (1.55) (5.35)*	1.69 (1.94) (5.05)*	1.69 (1.99)* (5.21)*	2.13 (2.31)* (5.23)*	2.48 (2.55)* (4.39)*	3.29 (2.43)* (3.73)*	4.26 (2.82)* (3.46)*	6.20 (3.00)* (2.45)*	−5.49 (−2.64)* (0.24)
Rec.	0.81 (0.67) (10.16)*	0.88 (0.73) (10.54)*	1.10 (0.83) (10.14)*	1.10 (0.71) (9.50)*	1.13 (0.80) (9.36)*	1.41 (0.90) (9.10)*	0.92 (0.46) (7.27)*	1.38 (0.54) (6.27)*	0.91 (0.34) (6.17)*	1.41 (0.45) (4.69)*	−0.60 (−0.29) (−0.54)
$r_{t+1:t+12}$	13.47 (13.55)*	13.16 (14.65)*	14.23 (14.83)*	14.85 (14.17)*	14.01 (13.20)*	15.43 (13.45)*	14.66 (10.89)*	16.66 (10.24)*	15.50 (9.03)*	15.84 (7.04)*	−2.37 (−1.23)
$r_{t+1:t+24}$	27.50 (18.27)*	27.24 (19.65)*	28.90 (20.84)*	31.73 (20.40)*	29.76 (18.79)*	30.38 (20.62)*	29.70 (16.61)*	34.69 (15.68)*	31.90 (13.93)	30.61 (10.25)*	−3.12 (−1.14)
	Rating $_{t-1}$	Log(Size $_{t-2}$)		Log(BM $_{t-2}$)		$r_{(t-7:t-2)}$	Log(Turnover $_{t-2}$)		SUE_{t-2}		
							NYSE/AMEX	Nasdaq			
<i>Panel B: Cross-sectional regressions of raw returns</i>											
1	−0.00 (−0.13)										
2		−0.12 (−2.45)*		0.11 (1.66)		0.86 (2.76)*	0.09 (1.00)		0.08 (1.00)		0.04 (3.03)*
3	−0.01 (−0.38)	−0.06 (−1.39)		0.19 (3.01)*		0.43 (1.28)	0.02 (0.32)		0.06 (0.84)		0.04 (2.70)*

Table 6 (continued)

	Rating _{<i>t</i>-1}	Log(Size _{<i>t</i>-2})	Log(BM _{<i>t</i>-2})	<i>r</i> _(<i>t</i>-7;<i>t</i>-2)	Log(Turnover _{<i>t</i>-2})		<i>SUE</i> _{<i>t</i>-2}
					NYSE/AMEX	Nasdaq	

Panel C: Cross-sectional regressions of returns risk-adjusted by the Fama and French (1993) and momentum factors

1	-0.00 (-0.38)						
2		-0.11 (-4.68)*	0.02 (0.47)	0.86 (3.70)*	0.09 (1.92)	0.06 (1.13)	0.03 (2.68)*
3	-0.00 (-0.24)	-0.04 (-1.23)	0.10 (1.93)	0.42 (1.68)	0.01 (0.29)	0.02 (0.42)	0.03 (2.12)*

Each month, all stocks rated by Standard & Poor’s are divided into decile portfolios based on their credit rating at time *t*. Stocks priced below \$1 at the beginning of the month are removed. For each credit rating decile, we compute the cross-sectional mean return for month *t* + 1. Panel A reports the average of these monthly means over the entire sample period after eliminating firms 3 months around rating downgrades (*t* − 3 : *t* + 3), where *t* is the month of downgrade. The *t*-statistics for cumulative month returns (last three rows) are (Newey and West, 1987) adjusted heteroscedastic-serial consistent *t*-statistics. Panels B and C repeat the analysis in Table 3 after first removing 3 months of returns around downgrades. The sample period is October 1985–December 2007. *t*-statistics are in parenthesis. * Indicates significance at 5%.

the second-highest 5% quantiles.¹³ The worst-rated quantile is the only rating group that has an overall negative return—an average of -0.66% per month. The second worst quantile has a monthly return of 0.64% . The differential return between the top-rated 10% and the second worst quantile is a statistically insignificant 0.56% per month, while the difference using the worst-rated quantile is a strongly significant 1.87% per month. Removing 3 months around downgrades occurring in this worst-rated quantile eliminates the credit risk effect. In non-downgrade periods, this latter difference of 1.87% becomes seven basis points per month.

Next we ask whether the impact of downgrades of the non-investment grade stocks is relevant only during recessions or only during periods when the market return is negative. In unreported results we find that the return differential between high- and low-rated stocks is 0.91% (t -statistic = 2.20) and 0.62% (t -statistic = 1.56) upon eliminating the returns of stocks rated *BB-* or worse around downgrades that occur during recessions and those that occur in down markets, respectively. In both cases, the credit risk effect remains strong and significant at $1.16\%/1.46\%$ per month in non-January months, suggesting that the effect is not driven by downgrades only in down markets or recessions. Downgrades in all economic conditions contribute to the credit risk effect.

We have also checked whether the credit risk effect arises mostly from low-rated stocks with multiple downgrades. Multiple downgrades may indicate a deterioration of fundamentals, which is worse than in similar firms with a single downgrade. This will imply that the multiple-downgrade firms have a much smaller probability of recovery, reflected in a much stronger price decline. On the other hand, multiple downgrades may indicate a more serious lack of transparency for those firms, which would imply a higher degree of mispricing and subsequent price correction. Our results (unreported) show that removing downgrade periods only for stocks with two or more downgrades within one year does not eliminate the credit risk effect. Therefore, the circumstances of financial distress around each individual downgrade for the worst-rated stocks contribute equally to the credit risk effect.

We now turn to the Fama and MacBeth (1973) individual stock cross-sectional regressions described in Eq. (3) and examine the impact of ratings on the cross-section of stock returns after eliminating the period around downgrades. Panel B of Table 6 focuses on raw returns and Panel C reports returns risk-adjusted by the Fama and French (1993) three-factor model along with a factor for momentum. The *RATING* coefficient is now statistically insignificant for both specifications, suggesting that the puzzling credit risk–return relation is also statistically nonexistent for the non-downgrade periods.

In unreported results, we find that the industry-adjusted operating and financial performance of low-rated stocks is uniformly worse than that of high-rated stocks around rating downgrades. This poor performance is associated with the significant decline in prices of the low-rated stocks. Moreover, rating changes are known to be sluggish. This sluggishness, combined with the drastic price declines, suggests that the market may already anticipate the documented poor operating and financial performance of low-rated stocks. However, this is not true. We also find (results available upon request) that the poor fundamental performance of low-rated stocks is unanticipated. Analyst forecast revisions, forecast errors, and earnings surprises all point to the fact that analysts are

¹³Ideally, we would like to investigate individual credit rating groups in the worst-rated decile. However, due to a limited number of observations, we can only use two separate rating bins in the worst-rated decile.

surprised by the poor operating and financial performance of low-rated stocks around downgrades.

Overall, our results show that the credit risk–return relation derives from financial distress around credit rating downgrades, in which high credit risk firms experience large negative returns, while low credit risk stocks appear to have a negligible reaction. This differential response to credit rating downgrades ultimately generates the credit risk effect in the cross-section of stock returns. Our evidence does not suggest that any systematic factor is causing these downgrades, and does not point to a particular state of the economy that is accountable for the credit risk effect. Downgrades among the lowest-rated stocks appear to be related mainly to idiosyncratic sources, such as the operating and financial performance of these firms.

Given the substantial fundamental deterioration and negative market surprises among downgraded low-rated stocks, we next explore differences in market selling pressures as further potential sources of the differential response of low- and high-rated firms to rating downgrades. For this purpose, we investigate liquidity and institutional ownership around rating downgrades.

Panels A and B of Table 7 present the Amihud (2002) illiquidity measure (defined in Eq. (1) around rating downgrades for firms in the 10 rating-sorted groups. Consider first the illiquidity of NYSE-AMEX stocks in Panel A. Illiquidity generally increases with credit risk. For the lowest-rated stocks, illiquidity is significantly higher after the rating downgrade than before. Moreover, illiquidity is 0.06 for C_1 and 4.42 for C_{10} during the month of downgrade. Observe from Panel B that also for NASDAQ stocks illiquidity is generally higher for the lowest-rated stocks as compared to the highest-rated stocks. This suggests that any institutional selling has a stronger price impact on low-rated stocks than on their high-rated counterparts.

Panel C of Table 7 presents the institutional holdings for credit rating-sorted portfolios around downgrades. At quarter $q - 4$, institutions hold over 51% of high-rated stocks and only 30.75% of low-rated stocks. Just before the rating downgrade in quarter q , institutions hold 53.39% of high-rated stocks and only 23.38% of the low-rated stocks. In the first quarter, $q + 1$, after the downgrade, institutions hold 52.49% (20.96%) and in quarter $q + 3$, institutions hold 53.92% (25.62%) of the high- (low-) rated stocks.

Thus, while institutional holdings of low-rated stocks decline by about a third around rating downgrades, there is hardly any change in their holdings of high-rated stocks. In fact, the decline in institutional holding occurs mainly for stocks rated less than investment-grade (i.e., less than *BBB*–). This selling by institutions is most likely driven by the poor fundamental performance of low-rated stocks and by the fiduciary responsibilities of institutions that prompt them to disinvest their holdings of low-rated stocks. Institutional selling combined with high illiquidity is consistent with the strongly negative returns realized by low-rated stocks around downgrades.

We also examine the impact of the difficulties in short selling on the credit-risk effect. D'Avolio (2002) has suggested the following proxies for short-sale constraints: (i) institutional holdings, (ii) share turnover, and (iii) shares outstanding. Low institutional holdings and a low number of shares outstanding make it difficult to borrow stocks for short selling, while low share turnover could lead to difficulties with the uptick rules when short selling. We sort stocks independently into 10 credit rating portfolios and three portfolios sorted on the above characteristics in order to examine the impact of low, medium, and high institutional holdings, turnover, and shares outstanding on the credit

Table 7
Market characteristics around downgrades by credit rating decile.

Month	Rating decile (C_1 = lowest, C_{10} = highest risk)									
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
<i>Panel A: Illiquidity (NYSE/AMEX)</i>										
–12	0.14	0.30	0.12	0.06	0.07	0.12	0.44	0.72	1.15	2.27
–11	0.09	0.22	0.11	0.05	0.07	0.11	0.31	0.97	1.38	2.55
–10	0.09	0.45	0.13	0.08	0.08	0.13	0.31	1.04	1.31	2.58
–9	0.07	0.21	0.16	0.09	0.12	0.17	0.38	0.88	1.61	3.08
–8	0.09	0.25	0.14	0.12	0.08	0.14	0.61	1.46	1.64	3.33
–7	0.09	0.36	0.26	0.17	0.07	0.15	0.57	1.20	1.71	3.57
–6	0.10	0.32	0.24	0.08	0.09	0.15	0.47	1.30	1.75	4.13
–5	0.07	0.25	0.20	0.12	0.08	0.14	0.67	1.37	1.76	3.63
–4	0.07	0.20	0.15	0.11	0.08	0.15	0.57	1.45	1.86	4.43
–3	0.06	0.22	0.18	0.17	0.08	0.16	0.64	1.54	1.81	4.25
–2	0.06	0.28	0.28	0.16	0.08	0.16	0.74	1.45	2.14	4.49
–1	0.05	0.32	0.25	0.37	0.09	0.19	0.77	1.86	2.35	4.36
0	0.06	0.24	0.19	0.19	0.09	0.23	0.62	1.81	2.60	4.42
1	0.06	0.26	0.27	0.18	0.12	0.40	0.48	1.94	2.58	5.56
2	0.05	0.10	0.15	0.27	0.14	0.48	0.63	2.44	2.85	5.16
3	0.05	0.24	0.16	0.14	0.12	0.40	0.83	2.46	3.12	5.74
4	0.05	0.21	0.16	0.28	0.19	0.75	0.92	2.28	3.17	4.56
5	0.09	0.23	0.18	0.27	0.28	0.51	1.00	2.60	3.28	4.49
6	0.06	0.20	0.10	0.33	0.16	0.52	0.83	2.16	3.35	4.78
7	0.05	0.20	0.17	0.43	0.22	0.49	1.10	2.12	2.66	4.74
8	0.06	0.24	0.17	0.57	0.29	0.78	1.37	2.65	2.77	4.83
9	0.07	0.24	0.19	0.69	0.42	1.01	1.33	2.62	2.44	4.50
10	0.09	0.25	0.21	0.43	0.37	0.54	0.76	2.16	3.08	4.28
11	0.09	0.14	0.14	0.21	0.12	0.68	0.89	2.10	3.24	4.49
12	0.08	0.13	0.15	0.21	0.14	0.37	0.66	2.09	2.97	2.89
<i>Panel B: Illiquidity (NASDAQ)</i>										
–12	3.03	6.21	7.30	4.13	2.70	3.49	1.87	3.19	5.34	4.98
–11	2.25	4.31	4.44	1.91	1.72	1.33	2.00	2.71	3.98	5.25
–10	4.77	3.88	3.90	3.33	2.87	2.93	1.69	3.25	5.44	5.14
–9	1.40	4.44	6.28	3.62	2.29	1.21	1.75	2.99	4.42	5.93
–8	1.45	4.03	6.26	2.90	2.72	1.93	1.60	3.27	5.31	5.22
–7	2.84	5.91	6.90	3.52	3.37	1.62	2.15	4.88	5.49	6.76
–6	1.06	4.38	5.44	3.63	2.83	1.73	3.63	4.91	6.71	8.10
–5	4.79	8.66	6.81	1.84	2.03	1.69	2.33	4.33	5.40	6.40
–4	5.46	9.49	6.23	3.53	2.65	1.00	3.42	4.82	5.19	7.83
–3	2.41	5.23	4.89	2.01	2.20	1.43	3.43	6.13	7.56	7.55
–2	2.68	7.92	7.72	3.66	3.90	3.07	2.80	4.67	4.90	7.14
–1	4.50	10.07	7.87	3.07	2.35	2.01	4.02	5.16	5.41	7.98
0	5.31	6.51	4.89	3.17	4.43	3.42	3.78	5.13	7.22	8.66
1	8.37	8.17	6.85	4.27	3.00	1.71	2.89	4.32	5.92	9.82
2	6.43	8.96	8.05	3.45	2.15	2.05	3.83	6.74	9.06	11.47
3	6.05	6.64	5.97	2.35	1.74	1.54	4.88	6.44	11.18	11.54
4	6.08	7.67	6.93	4.75	2.29	2.42	3.86	4.95	11.52	12.69
5	5.46	7.11	5.17	3.06	4.41	4.25	5.97	8.08	10.88	11.24
6	3.67	8.15	6.13	4.32	3.37	3.47	5.88	6.60	10.74	11.75
7	3.42	7.74	7.43	3.74	2.42	2.94	3.87	8.12	9.52	11.35

Table 7 (continued)

Month	Rating decile (C_1 = lowest, C_{10} = highest risk)									
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
8	4.80	8.43	8.99	4.42	2.12	2.27	6.09	8.24	9.01	11.73
9	2.34	5.20	5.08	3.51	3.10	1.43	7.74	8.93	10.05	10.45
10	2.62	6.16	5.32	3.19	2.50	2.26	5.60	7.41	9.36	7.48
11	3.47	6.06	5.70	4.46	2.53	3.22	7.73	9.60	11.36	8.73
12	4.19	6.07	4.70	3.38	2.59	2.81	6.16	8.25	11.19	6.94
<i>Panel C: Institutional holdings (×100)</i>										
–4	51.01	49.71	51.78	55.41	57.03	55.76	50.06	43.49	38.01	30.75
–3	50.64	50.97	53.08	55.52	56.51	54.79	48.93	42.73	37.56	29.28
–2	52.20	51.36	52.67	55.23	56.44	54.18	47.45	41.25	36.29	27.13
–1	53.39	51.31	51.33	54.44	56.70	53.22	46.02	40.14	34.44	23.38
0	52.49	51.54	53.87	56.12	55.60	51.39	43.41	35.88	31.13	20.96
1	52.48	52.80	54.82	57.21	56.05	51.31	43.33	35.28	30.08	22.73
2	52.45	54.52	56.73	57.30	54.11	48.97	42.85	35.70	29.96	22.97
3	53.92	55.73	56.46	56.71	54.62	50.95	43.25	36.28	31.21	25.62
4	54.19	58.18	56.76	56.48	53.73	50.70	44.28	37.68	33.20	28.32

All numbers represent the time-series mean of the cross-sectional median market characteristics around rating downgrades. Institutional holdings is defined as the number of shares held by institutions divided by the total number of shares outstanding. Illiquidity is computed as in Amihud (2002). The sample period is October 1985–December 2007. $t = 0$ is the month of downgrade.

risk effect. Table 8 reports that the credit risk effect is prominent amongst stocks that have low institutional holdings, low turnover, and fewer shares outstanding. The credit risk effect declines monotonically as institutional ownership, turnover, and shares outstanding increase.

In sum, the strong response of high credit risk stocks to downgrades is driven by their high sensitivity to increases in their default likelihood, the substantial deterioration in their fundamental operating and financial performance, and the fact that such deterioration is not anticipated by the analysts. This process is exacerbated by the stronger selling pressure by institutions, who sell their losing high credit risk stocks that are highly illiquid. In addition to being highly illiquid, high credit risk stocks are also difficult to short sell.

This evidence has the potential to uncover the cause of the puzzling credit risk–return relation. Next we examine a number of risk and non-risk based explanations and how our new evidence helps distinguish between these.

2.2. Summary of results and discussion

Our findings shed new light on the debate about a priced distress risk factor in equity returns. Chan and Chen (1991) and Fama and French (1992) argue that the size and book-to-market effects proxy for a priced distress risk factor. Moreover, Vassalou and Xing (2004) find evidence that the size and book-to-market factors contain some default-related information. Chan et al. (1985) also support the existence of a distress risk factor. Our results are consistent with Dichev (1998) and Campbell et al. (2008), who conclude that distress risk is unlikely to be systematic because high credit risk stocks earn lower (rather

Table 8
Returns by credit rating and proxies of short selling constraints.

		Rating decile (C_1 = lowest, C_{10} = highest risk)										
		C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	$C_1 - C_{10}$
IO												
Low		1.21	1.13	1.08	0.98	1.02	1.21	0.93	0.75	0.65	−0.63	1.85
		(5.82)*	(5.54)*	(5.21)*	(4.51)*	(4.34)*	(4.41)*	(2.64)*	(1.99)*	(1.58)	(−1.25)	(4.03)*
Medium		1.15	1.23	1.27	1.28	1.29	1.27	1.21	1.00	1.02	0.82	0.33
		(4.91)*	(5.08)*	(5.06)*	(5.10)*	(4.82)*	(4.19)*	(3.41)*	(2.53)*	(2.28)*	(1.42)	(0.66)
High		1.26	1.30	1.39	1.33	1.31	1.27	1.35	1.30	1.11	1.28	−0.02
		(4.72)*	(4.72)*	(4.88)*	(4.63)*	(4.47)*	(4.00)*	(3.71)*	(3.13)*	(2.35)*	(2.05)*	(−0.03)
Turnover												
Low		1.13	1.12	1.17	1.13	1.06	1.10	0.86	0.75	0.47	−0.32	1.45
		(5.74)*	(5.55)*	(5.58)*	(5.38)*	(4.73)*	(4.26)*	(2.83)*	(2.29)*	(1.33)	(−0.76)	(3.79)*
Medium		1.23	1.30	1.31	1.23	1.27	1.33	1.16	1.06	1.00	0.33	0.90
		(5.27)*	(5.37)*	(5.20)*	(4.97)*	(5.04)*	(4.73)*	(3.39)*	(2.82)*	(2.45)*	(0.69)	(1.91)
High		1.22	1.25	1.35	1.30	1.32	1.30	1.30	1.12	1.01	0.40	0.82
		(4.42)*	(4.43)*	(4.59)*	(4.32)*	(4.46)*	(4.03)*	(3.46)*	(2.70)*	(2.18)*	(0.70)	(1.60)
Shares												
Low		1.14	1.03	1.09	1.07	1.06	0.95	0.75	0.63	0.51	−0.52	1.66
		(5.19)*	(4.79)*	(4.63)*	(4.61)*	(4.28)*	(3.16)*	(2.23)*	(1.77)	(1.35)	(−1.20)	(4.48)*
Medium		1.20	1.15	1.06	1.03	1.10	1.22	1.21	0.97	0.79	0.41	0.79
		(5.46)*	(5.09)*	(4.46)*	(4.28)*	(4.28)*	(4.08)*	(3.37)*	(2.43)*	(1.76)	(0.72)	(1.63)
High		1.22	1.29	1.38	1.36	1.38	1.45	1.48	1.77	1.76	1.52	−0.30
		(5.05)*	(5.12)*	(5.20)*	(5.03)*	(5.03)	(4.85)*	(3.94)*	(3.93)*	(3.31)*	(2.38)*	(−0.56)

Each month, all stocks rated by Standard & Poor's are divided into portfolios independently sorted based on ten credit rating and three short-sale constraint proxies groups at time t . Each subsection of the table refer to a particular stock characteristic which has been identified in D'Avolio (2002) as leading to high short-sale constraints: low IO (institutional ownership), low share turnover, and low float (shares outstanding). Stocks priced below \$1 at the beginning of the month are removed. For each portfolio, we compute the cross-sectional mean return for month $t + 1$. The table reports the average of these monthly means. The last column reports the difference between the return of the best rated versus the worst-rated portfolios. All numbers are in percentages. The t -statistic is in parentheses. *Indicates if significant at the 5% level. The sample period is October 1985–December 2007.

than higher) returns than low credit risk stocks. Moreover, we show that there are no cross-sectional differences in average stock returns across stocks of different credit rating except for about 4.18% of the stocks by market capitalization represented by the worst-rated firms, and only during 7 months around downgrades. The credit risk effect appears to be present in a very small subset of firms experiencing severe financial distress, suggesting that the credit risk effect is not pervasive.

Even in the absence of a credit risk factor, the cause of the credit risk effect can still be systematic. The circumstances of financial distress that span the narrow period around downgrades among the worst-rated firms can be occurring all at the same time, triggered by some economy-wide shocks. There is previous evidence of correlations breakdown, which suggests that in down markets, return correlations are much higher than in up markets (Longin and Solnik, 2001). Indeed, we find that there are more downgrades during

recession months, but, given that there are only 16 such months in our sample, and that the credit risk effect is strong in expansions, the evidence is not conclusive. If we look more generally at up versus down market periods, there are no significant differences in the number and effect of downgrades. Moreover, the computed pairwise correlations for the downgrade dummy variable across the whole sample is extremely low at -3.95% across all firms.¹⁴ The downgrade correlation is higher for low-rated companies (9.9%), but is still too low to attest to the existence of a systematic driver of the credit risk effect. Moreover, firms with multiple downgrades do not account for the credit risk effect either.

Garlappi et al. (2008) and Garlappi and Yan (2008) suggest another risk-based explanation of the credit risk effect—that the lower returns on high credit risk stocks may be due to lower systematic risk. Specifically, the model in Garlappi and Yan (2008) suggests that while higher credit risk stocks should typically have higher betas, the most extreme distressed firms should be less risky. However, we show that the market betas increase monotonically with credit risk even for the worst-rated firms. Betas around downgrades would need to be negative, not just lower, as in Garlappi and Yan (2008), to justify the negative returns earned by low-rated firms during those periods. Moreover, alphas for the extreme long–short portfolios estimated using the CAPM and the Fama–French three-factor model are even higher than the raw returns.

In summary, our evidence on the timing of downgrades, as well as on the sensitivities of low-rated firms to systematic factors indicates that the circumstances around downgrades causing the credit risk effect appear to be driven predominantly by idiosyncratic forces. Overall, the evidence does not favor the risk-based explanation for the lower returns on highest credit risk stocks.

As noted earlier, Hand et al. (1992) and Dichev and Piotroski (2001) have demonstrated considerable abnormal bond and stock price declines following rating downgrades. Indeed, Dichev and Piotroski (2001) argue that the poor returns following downgrades are attributable to underreaction to downgrade announcements. In the context of our paper, this potential underreaction does not trigger the return differential across the rating deciles. Instead, it is the low returns realized by low-rated stocks around downgrades (both before and after) that give rise to the negative relation between ratings and returns. These low returns could have occurred on the downgrade day with the market reacting fully to rating downgrades. Or the low returns could obtain over a longer period in the presence of potential underreaction. In either case, the credit risk effect would exist. Moreover, removing returns *after* rating downgrades does not eliminate the significance of the credit risk effect. This suggests that the negative credit risk–return relation is not a manifestation of the previously documented underreaction to rating downgrades.

Consistent with an argument for mispricing, Griffin and Lemmon (2002) attribute the low average returns of financially distressed companies to the poor price performance of low book-to-market firms. Their evidence suggests that, when valuing these companies, investors underweight current fundamentals and overweight payoffs from future growth opportunities. Since we bring a dynamic view of the cause of the credit risk effect, we are able to examine what happens to the book-to-market ratio around downgrades, and

¹⁴This correlation is referred to as the phi correlation coefficient for binary variables. If some binary categories are extremely uneven (for proportions of 0.10 or lower, as is the case of downgrades), the phi coefficient can be biased downward. The assumption of linearity cannot be violated within the context of the phi coefficient of correlation.

whether low book-to-market low-rated firms that get downgraded are causing the effect. As we see in Panel A of Table 1, the book-to-market ratio is monotonically increasing across credit rating deciles, reaching an overall ratio of 0.72 for the worst-rated credit rating decile. However, Fig. 2 shows that 6 months prior to a downgrade, for companies in that rating decile, the average book-to-market ratio is 1.7, and increases monotonically, peaking in the month of downgrade to a value of 2.2, after which it decreases to 1.73 after 6 months. It does not appear that investors in companies driving the credit risk effect are overestimating the importance of payoffs from future growth opportunities, as Griffin and Lemmon (2002) maintain, because it is high rather than low book-to-market firms that drive the mispricing.

One final puzzle remains. The evidence suggests that the burden of the credit risk effect is born mostly by retail investors who buy and hold shares of low-rated companies around downgrades, the time when institutions heavily disinvest from them. The explanation for why retail investors hold on to their high credit risk stocks around downgrades may be related to the well-known disposition effect wherein investors tend to hold on to their losers and sell the winners. However, the disposition effect does not explain why retail investors buy additional shares of these low-rated, financially distressed stocks that are sold by institutions around downgrades. It may be the case that these retail investors may not be aware of the extent of mispricing and may not adjust their expectations to fully account for the likelihood of large losses from these stocks during periods of financial distress around downgrades. Indeed, high credit risk stocks are small value stocks that typically provide superior returns. So the about-to-be downgraded high credit risk stocks look like “good buys,” and they have become “especially cheap,” and “good bargains” as their prices plummet prior to the downgrade. Moreover, these stocks are least covered by analysts, and appear least transparent with respect to the condition of their fundamentals. Considering also the less sophisticated valuation tools at their disposal, it may be difficult for retail investors to differentiate these companies from their highly profitable small value low credit risk counterparts. Finally, given these companies’ illiquidity and difficulty to short sell, arbitrageurs do not seem capable of dissipating the mispricing.

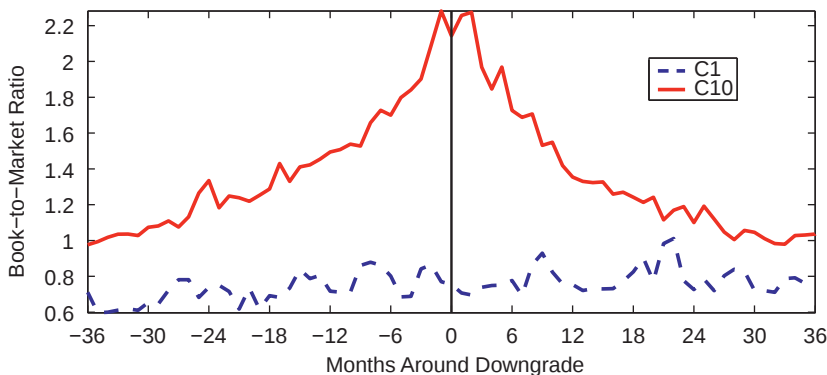


Fig. 2. Book-to-market ratios around downgrades. The figure presents the average book-to-market ratios of the best (C_1) and worst (C_{10}) rated decile portfolio around periods of rating downgrades. Month 0 is the month of downgrade.

3. Conclusion

This paper seeks a resolution to the puzzle that high credit risk stocks realize lower returns than low credit risk stocks. In theory, if distress risk is idiosyncratic, as we find, high credit risk stocks should earn returns similar to low credit risk stocks. Empirically, however, we find that low credit risk stocks earn a return of 1.09% per month higher than that earned by high credit risk stocks. This finding is robust to risk-adjusting returns using the CAPM and the [Fama and French \(1993\)](#) three-factor model and is not an artifact of the known size, book-to-market, and momentum anomalies.

The difference in returns between high- and low-rated stocks derives from financial distress affecting the worst-rated companies in the short period of 3 months before and after credit rating downgrades. There is no return differential between high- and low-rated stocks during periods of stable or improving credit conditions. Around downgrades, low-rated companies experience substantial price declines, sharp deterioration of their fundamentals, and a rush by institutions to divest of their stocks. Still, the prices of low-rated stocks persistently fail to incorporate the possibility of large losses around downgrades. Our evidence points away from a risk-based explanation for this phenomenon and suggests that the apparent mispricing among low-rated stocks is brought about by retail investors and persists due to the inability of arbitrageurs to fully exploit it amidst the high illiquidity and stronger short sale constraints of these low-rated stocks.

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