Journal of Financial Economics 91 (2009) 83–101

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/jfec

Dispersion in analysts' earnings forecasts and credit rating ☆

Doron Avramov [a], Tarun Chordia [b], Gergana Jostova [c,*], Alexander Philipov [d]

[a] Department of Finance, Robert H. Smith School of Business, University of Maryland, College Park, MD 20742, USA
[b] Department of Finance, Goizueta Business School, Emory University, Atlanta, GA 30322, USA
[c] Department of Finance, School of Business, George Washington University, Funger Hall Suite 501, 2201 G Street NW, Washington, DC 20052, USA
[d] Department of Finance, School of Management, George Mason University, Fairfax, VA 22030, USA

ARTICLE INFO

Article history:
Received 23 March 2007
Received in revised form
23 January 2008
Accepted 19 February 2008
Available online 13 November 2008

JEL classification:
G14
G12
G11

Keywords:
Credit rating
Dispersion
Asset pricing anomalies
Financial distress

ABSTRACT

This paper shows that the puzzling negative cross-sectional relation between dispersion in analysts' earnings forecasts and future stock returns may be explained by financial distress, as proxied by credit rating downgrades. Focusing on a sample of firms rated by Standard & Poor's (S&P), we show that the profitability of dispersion-based trading strategies concentrates in a small number of the worst-rated firms and is significant only during periods of deteriorating credit conditions. In such periods, the negative dispersion–return relation emerges as low-rated firms experience substantial price drop along with considerable increase in forecast dispersion. Moreover, even for this small universe of worst-rated firms, the dispersion–return relation is non-existent when either the dispersion measure or return is adjusted by credit risk. The results are robust to previously proposed explanations for the dispersion effect such as short-sale constraints and leverage.

1. Introduction

There is a puzzling negative cross-sectional relation between dispersion in analysts' earnings forecasts and future stock returns. In particular, Diether, Malloy, and Scherbina (2002) (henceforth DMS) show that the trading strategy of buying low dispersion stocks and selling high dispersion stocks yields statistically significant and economically large payoffs over a period of one to three months. Sadka and Scherbina (2007) suggest that the dispersion effect is especially prominent among illiquid stocks, which explains its persistence through time. The dispersion effect is anomalous because, while investors are expected to discount uncertainty about future profitability, they seem to pay a premium for bearing such uncertainty. The cross-sectional dispersion–return relation is unexplained by the standard asset pricing models including the capital asset pricing model (CAPM), the Fama and French (1993) model, and the Fama–French model augmented by a momentum factor.

DMS attribute the negative relation between dispersion and future return to market frictions. Specifically, higher dispersion introduces larger optimistic bias into stock prices as optimistic investors bid prices up, while short-sale constraints prevent pessimistic views from being reflected in stock prices, thus causing high dispersion stocks to become overpriced. The dispersion effect is manifested as the overpricing is corrected over time.

☆ We thank Gurdip Bakshi, Fu Fangjian, Karl Diether, Claudia Moise, Jeffrey Zhang, an anonymous referee, and seminar participants at the 2008 American Finance Association meeting, the 2007 Conference on Financial Economics and Accounting at NYU, the 2007 Financial Management Association, American University, Erasmus University, McGill University, National University of Singapore, Singapore School of Management, Tel Aviv University, and University of Tilburg, for helpful comments. All errors are our own.

* Corresponding author. Tel.: +1 202 994 7478.
E-mail address: jostova@gwu.edu (G. Jostova).

0304-405X/$ - see front matter © 2008 Elsevier B.V. All rights reserved.
doi:10.1016/j.jfineco.2008.02.005

However, our results show that proxies for short-sale costs (including turnover, institutional holdings, and number of shares outstanding) suggested by D'Avolio (2002) do not capture the dispersion effect. Johnson (2004), on the other hand, suggests that the dispersion effect is consistent with a rational asset pricing paradigm. In this paradigm, dispersion is a proxy for unpriced information risk and, in the presence of leverage, expected returns should decrease with idiosyncratic asset risk. Johnson's model predicts that the dispersion effect should strengthen with firm leverage. However, we find that the dispersion effect is indistinguishable across levered and unlevered firms. Liquidity proxies such as turnover, firm size, and the Amihud (2002) illiquidity measure do not capture the dispersion effect either, at least in the sample of rated firms.

This paper shows that the dispersion–return relation may be explained by financial distress as proxied by credit rating downgrades. Indeed, the information in credit risk seems to subsume the information in dispersion in capturing the uncertainty about future earnings. We now examine the theoretical and empirical motivation behind our analysis.

Theoretically, structural models of default risk (e.g., Merton, 1974) view firm equity as a call option on the firm with a strike price equal to the face value of debt. Default occurs when the underlying firm value falls below the strike. Default risk, therefore, captures the uncertainty about future earnings, growth rates, and the cost of equity capital—ingredients used in asset valuation, while the dispersion measure reflects uncertainty about next year's earnings, which is a single component in asset valuation.

Empirically, Dichev (1998) shows that investors pay a premium for bearing default risk. This puzzling finding has recently been confirmed by Griffin and Lemmon (2002), Campbell, Hilscher, and Szilagyi (2008), and Avramov, Chordia, Jostova, and Philipov (2006). Essentially, the negative relation between default risk and stock returns constitutes an anomalous pattern in the cross-section of returns as does the subsequently documented negative relation between stock returns and analysts' forecast dispersion. In the context of the momentum anomaly, Zhang (2006) associates momentum profitability with dispersion, while Avramov, Chordia, Jostova, and Philipov (2007) show that momentum profitability concentrates in high credit risk firms and, moreover, that the credit rating effect subsumes the dispersion effect in capturing momentum profitability.

Motivated by the potential link between credit rating and dispersion in analysts' earnings forecasts, we examine whether the dispersion effect is explained by firm credit conditions. Our experiments are based on a sample of 3,261 firms rated by Standard & Poor's (S&P). More specifically, we use the S&P Long-Term Domestic Issuer Credit Rating, which is available on Compustat on a quarterly basis starting from the second quarter of 1985.

We find that the dispersion effect is a facet of non-investment grade (NIG) firms and is virtually non-existent otherwise. In particular, strategies that buy low dispersion stocks and sell high dispersion stocks yield a statistically insignificant payoff of 31 basis points per month for investment grade (IG) firms (with S&P rating of BBB− or better). In contrast, dispersion strategies are significantly profitable across non-investment grade firms (with S&P rating of BB+ or worse). For such firms, the return differential between the lowest and highest dispersion stocks is a highly significant 101 basis points per month.

Refining the credit rating groups, we demonstrate that the dispersion strategy payoff is insignificant for the subsample of stocks rated AAA–BB+. Strikingly, this subsample accounts for 95.58% of the market capitalization of the rated firms and 73.86% of the total number of the rated firms. In other words, dispersion profitability is derived from a subsample of rated firms that accounts for less than 5% of the total market capitalization of all rated firms or less than 27% of all rated firms. In contrast, implementing dispersion strategies for subsamples of stocks that progressively exclude the smallest stocks leaves dispersion profitability economically and statistically significant even when 72% of the smallest firms are excluded. The impact of credit risk on the dispersion return relation is indeed unique and does not merely reflect the impact of firm size even though low-rated stocks tend to be smaller.

Further, the ability of dispersion to predict future stock returns is attributable to the predictive power of credit rating. First, removing the credit rating component from dispersion yields an adjusted dispersion measure that has no statistical or economic power to predict the cross-section of future returns. Second, implementing dispersion strategies using credit rating-adjusted returns yields investment payoffs that are economically small and statistically insignificant.

Our findings are robust to previously proposed explanations. In particular, we show that firm level leverage, turnover, idiosyncratic volatility, institutional ownership, and size, all of which have been linked to the dispersion–return relation, do not capture the impact of dispersion on returns, whereas credit ratings do capture the dispersion effect. In addition, our results are robust to adjusting returns by common risk factors, equity characteristics, as well as potential industry effects.

To understand the impact of financial distress on the relation between analyst forecast dispersion and returns, we examine credit rating downgrade events. The negative relation between forecast dispersion and future returns prevails only during periods of credit rating downgrades. In such periods, stock prices of the worst-rated firms decline substantially, while the uncertainty about their firm fundamentals rises considerably. There is no significant dispersion–return relation during periods of stable or improving credit conditions for all rated stocks, and there is no significant relation during all periods for the highly rated stocks. The dispersion variable becomes insignificant when we include a dummy variable for credit rating downgrades in Fama and MacBeth (1973) regressions of future returns on dispersion. Moreover, buying low dispersion stocks and selling high dispersion stocks and holding the long and short positions for up to three months provides payoffs that are economically small and statistically insignificant during periods that record no credit rating downgrades.

To summarize, the dispersion effect concentrates in the worst-rated stocks and exists only during periods of financial distress. Even for this small universe of low-rated firms the dispersion effect is non-existent when either dispersion or return is adjusted by credit ratings. The impact of credit ratings is robust and unexplained by short-sale constraints, leverage, size, and illiquidity. Indeed, previous work points out that market anomalies such as the size and book to market effects (Vassalou and Xing, 2004) as well as momentum (Avramov, Chordia, Jostova, and Philipov, 2007) concentrate in high credit risk firms. Here, we show that not only is the dispersion effect concentrated in high credit risk firms but also that it is prevalent only during periods of financial distress.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 presents the results and Section 4 concludes.

2. Data

We extract monthly returns on all NYSE, Amex, and Nasdaq stocks listed in The Center for Research in Security Prices (CRSP) database. We use the I/B/E/S database to obtain the monthly consensus earnings forecasts for fiscal year one and the monthly dispersion in these earnings forecasts. The CRSP and I/B/E/S databases are used in earlier work studying the dispersion effect on future returns. Unique to our analysis is the use the S&P Long-Term Domestic Issuer Credit Rating, which is available from Compustat on a quarterly basis starting from the second quarter of 1985. Prior to 1998, S&P assigns this rating to the firm's most senior publicly traded debt. After 1998, the rating is based on the overall quality of the firm's outstanding debt, both public and private. In the empirical analysis that follows, we transform the S&P ratings into conventional numerical scores. Specifically, one represents an AAA rating and 22 reflects a D rating.[1] Hence, a higher numerical score reflects higher credit risk. Numerical ratings of ten or below (BBB− or better) are considered investment grade, and ratings of 11 or higher (BB+ or worse) are labeled high-yield or NIG.

We exclude stocks priced below \$5 at the beginning of each month to ensure that the empirical findings are not driven by highly illiquid stocks.[2] The intersection of firms with available returns and analyst data consists of 12,312 stocks. From this universe, we focus on stocks rated by S&P, which yields a sample of 3,261 rated stocks over the July 1985–December 2003 period. The beginning of our sample is determined by the first time firm ratings by S&P become available on the Compustat tapes. Notably, although the *total* number of rated firms is substantially smaller than that of unrated firms (there are 3,261 rated firms and 9,051 unrated (UR) firms, a ratio of 1 to 2.78), the *average per month* number of rated and UR firms is considerably closer (1,154 rated firms and 1,794 UR firms, a more appealing ratio of 1 to 1.55).

To examine whether our sample of rated firms is representative, we examine the profitability of dispersion-based trading strategies as well as the dispersion measures for the 3,261 rated firms, 9,051 UR firms, and 12,312 rated and UR firms. Consistent with previous work, dispersion is computed as the standard deviation of earnings per share (EPS) forecasts divided by the absolute value of the mean EPS forecast. In each period t we divide stocks into quintiles based on their dispersion at time $t-1$. Quintile groups for each month are formed using all existing-rated stocks for the month. Portfolio returns are equally weighted across stocks. Dispersion profitability is computed as the return differential between the lowest and highest dispersion quintiles.

Dispersion profitability is presented in Panel A of Table 1. Starting with the entire universe of stocks, we demonstrate that buying low dispersion stocks, selling high dispersion stocks, and holding the position for one month (three months) yields a statistically significant payoff of 79 (75) basis points per month. The corresponding payoffs for the rated firms are 76 (69) basis points and for the UR firms the payoffs are 72 (71) basis points per month. Note that the dispersion profitability exists only in non-January months. Dispersion profitability is in general negative, albeit insignificantly so, in January, and is statistically significant during expansions, but not during recessions.

Panel B of Table 1 displays the returns of the five dispersion portfolios with D_1 (D_5) denoting the portfolio with the lowest (highest) dispersion in analysts' earnings forecasts. Dispersion profitability is measured by the return differential between portfolios D_1 and D_5. Observe that for holding periods of both one month ($K=1$) and three months ($K=3$), the dispersion portfolio returns decline monotonically as we move from portfolio D_1 to D_5. This pattern is consistent with previous work and holds for the entire universe of stocks, as well as for the rated and UR firms. While there is a difference in the portfolio returns for the rated and UR firms, the return differential for D_1-D_5 is about the same.

Panel C of Table 1 presents the mean dispersion measures of the five dispersion portfolios for all firms as well as for rated and UR firms. The evidence suggests that mean dispersion measures for rated and UR firms are quite similar. To illustrate, for the lowest dispersion portfolio (D_1) the mean dispersion measures over a one- and three-month holding period based on UR (rated) firms are 1.49 and 1.52 (1.45 and 1.47), respectively. Similarly, for the highest dispersion portfolio (D_5) the mean dispersion measures for UR firms (rated firms) are 42.27 and 26.51 (46.81 and 28.92), respectively.

Overall, the evidence in the three panels of Table 1 suggests that while there are differences across rated and UR firms, the sample of rated firms is representative enough in capturing the dispersion effect in the cross-section of returns. Of course, it is hard to be certain that the UR firms are not different from the rated firms along some other dimensions that could impact our results. Indeed, on one hand we confirm that both rated and UR

[1] The 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.

[2] This filter is consistent with that of Diether, Malloy, and Scherbina (2002). Our results are robust to the inclusion of stocks priced below \$5.

Table 1
Dispersion strategy payoffs for rated and unrated firms

We collect monthly returns from CRSP, monthly analyst data from I/B/E/S, and quarterly Standard & Poor's company rating data from Compustat. Dispersion is computed as the standard deviation across analysts' EPS forecasts for fiscal year one divided by the absolute value of the mean EPS forecast. Observations are excluded when only one analyst EPS forecast is available in a particular month or when the mean EPS forecast is zero. We also exclude stocks priced below \$5 at the beginning of the month. Each month, stocks are sorted into five portfolios based on dispersion. Dispersion profitability is generated by buying the lowest and selling the highest dispersion portfolio, and holding the position for $K = 1$ or $K = 3$ months. Portfolio returns are equally weighted across all stocks in a portfolio. The monthly returns in month $t + 1$ for the three-month holding period strategy are computed as the equally weighted average of the returns from strategies t, $t - 1$, and $t - 2$. Panel A in the table reports the time-series average of the monthly dispersion profits (in percentages per month). t-statistics are presented in parentheses (bold if indicating 5% significance). Panels B and C report each dispersion portfolio's average return and dispersion (in %). Panel D provides, for each dispersion quintile, the time-series average of the cross-sectional mean characteristics. The sample period is July 1985–December 2003.

Panel A: Dispersion strategy profits (%)

Sample	All firms		Unrated firms		Rated firms	
Number of firms	12,312		9,051		3,261	
K	1	3	1	3	1	3
Overall	0.79	0.75	0.72	0.71	0.76	0.69
	(**5.16**)	(**4.56**)	(**7.02**)	(**6.15**)	(**3.35**)	(**3.06**)
Non-January	0.89	0.87	0.78	0.79	0.92	0.85
	(**5.52**)	(**4.98**)	(**7.30**)	(**6.49**)	(**3.88**)	(**3.62**)
January	−0.30	−0.51	0.06	−0.15	−1.02	−1.07
	(−0.73)	(−1.23)	(0.17)	(−0.49)	(−1.51)	(−1.52)
Expansion	0.74	0.68	0.70	0.68	0.68	0.60
	(**4.83**)	(**4.19**)	(**6.86**)	(**6.10**)	(**2.96**)	(**2.63**)
Recession	1.46	1.59	0.94	1.03	1.75	1.82
	(1.82)	(1.78)	(1.73)	(1.49)	(1.65)	(1.72)

Panel B: Dispersion portfolio returns (%) by dispersion quintiles (D_1 = lowest dispersion, D_5 = highest dispersion)

Sample	All firms		Unrated firms		Rated firms	
K	1	3	1	3	1	3
D_1	1.51	1.44	1.64	1.60	1.31	1.23
D_2	1.28	1.23	1.48	1.42	1.08	1.06
D_3	1.21	1.13	1.35	1.28	1.10	1.06
D_4	1.08	1.01	1.28	1.21	0.90	0.85
D_5	0.72	0.69	0.92	0.89	0.55	0.54
D_1–D_5	0.79	0.75	0.72	0.71	0.76	0.69
	(**5.16**)	(**4.56**)	(**7.02**)	(**6.15**)	(**3.35**)	(**3.06**)

Panel C: Average dispersion (×100) by dispersion quintile (D_1 = lowest dispersion, D_5 = highest dispersion)

Sample	All firms		Unrated firms		Rated firms	
K	1	3	1	3	1	3
D_1	1.48	1.51	1.49	1.52	1.45	1.47
D_2	2.91	2.89	2.92	2.89	2.85	2.82
D_3	5.02	4.94	5.02	4.94	4.96	4.86
D_4	9.67	9.31	9.66	9.29	9.79	9.41
D_5	43.24	26.88	42.27	26.51	46.81	28.92

Panel D: Firm characteristics by dispersion quintiles in rated and unrated firms (D_1 = lowest dispersion, D_5 = highest dispersion)

Sample	Unrated firms					Rated firms				
Dispersion group	D_1	D_2	D_3	D_4	D_5	D_1	D_2	D_3	D_4	D_5
Size (\$ billions)	0.50	0.60	0.47	0.36	0.26	3.87	3.40	2.73	2.24	1.49
Book-to-market (%)	47.94	49.28	55.11	63.08	74.05	42.58	48.82	54.81	63.01	74.41
Price	22.37	22.33	19.25	15.42	10.84	36.24	34.11	31.21	27.43	21.32
Volatility (%)	2.33	2.39	2.84	3.43	4.65	1.06	1.04	1.22	1.42	1.77
Turnover (%)	9.49	10.48	11.13	10.98	10.75	8.04	8.03	9.29	10.10	10.73
Amihud's illiquidity	0.58	0.40	0.51	0.77	1.40	1.17	1.01	1.13	1.49	1.80
Leverage (%)	19.57	19.41	20.27	22.02	24.84	26.86	29.90	32.87	37.24	43.05
Institutional ownership (%)	37.19	39.07	36.78	33.22	28.53	49.43	49.38	48.33	45.18	40.88

firms are similarly represented in the 20 industries of Moskowitz and Grinblatt (1999). On the other hand, Panel D presents equity characteristics of rated and UR firms and shows that size, price, volatility, liquidity, leverage, and institutional holdings are different across the samples. While we believe that the sample of rated firms is representative along many important dimensions, one should bear in mind the data limitations of our analysis.

Finally, we measure the cross-sectional correlation between dispersion and numerical credit rating for each month in the sample. The Spearman rank cross-sectional correlation averages 0.39, suggesting that dispersion and credit rating could proxy for the same underlying economic fundamental. We argue that this economic fundamental is financial distress. At the same time, credit rating is not merely a statistical proxy for dispersion, as we will show below. It is a different economic measure that captures both the dispersion effect in the cross-section of returns as well as the impact of size, turnover, leverage, and other firm-level characteristics on the relation between dispersion and returns.

3. Results

3.1. Credit rating and dispersion in analysts' earnings forecasts

To establish the first link between credit risk and the profitability of trading strategies based on dispersion in earnings forecasts, we examine the credit rating profile of the five dispersion portfolios. The results are exhibited in Table 2. The lowest dispersion portfolio (D_1) is heavily tilted towards the best quality firms. The average credit rating for this portfolio is 7.20, corresponding to an A− rating. On the other hand, the dispersion portfolio D_5 is populated with the highest credit risk stocks and has an average credit rating of 10.88, corresponding to a BB+ rating, which is a below IG rating. In general, higher dispersion portfolios contain lower quality stocks as the numerical value of credit rating increases monotonically with dispersion.

Table 2 also displays the proportion of UR, IG, and NIG firms within each of the five dispersion portfolios. IG corresponds to an S&P rating of BBB− or better. Note that rated firms populate all examined portfolios with fractions ranging between 34.88% and 40.96%. Moreover, portfolios D_1, D_2, D_3, and D_4 consist mostly of higher quality firms. The highest dispersion portfolio, D_5, is the only one tilted towards NIG stocks.

Observe from Table 2 that dispersion profitability is a facet of NIG firms and is virtually non-existent otherwise. In particular, implementing dispersion trading strategies of buying low dispersion stocks and selling high dispersion stocks ($D_1 - D_5$), yields a statistically insignificant payoff of 31 basis points per month among IG firms. In contrast, implementing dispersion strategies among NIG firms yields a highly significant payoff of 101 basis points per month.

In addition, note that for each dispersion group, higher credit quality firms realize higher returns than lower quality firms. For the lowest dispersion portfolio, IG stocks yield a monthly payoff of 1.32% per month, whereas the corresponding return for NIG stocks is 1.20%. Indeed, as noted earlier, prior research shows that higher default risk stocks earn, on average, lower returns. Our sample of rated firms clearly captures this apparent anomalous pattern.

Table 2

Composition of dispersion portfolios

Dispersion portfolios are constructed as explained in Table 1. The first three columns show, for each dispersion portfolio, the percentage of stocks that are unrated, rated investment grade, or rated non-investment grade. The next four columns exhibit the equally weighted average returns. The last column reports the average numerical S&P credit rating. The numeric S&P rating is ascending in credit risk, i.e., 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. The sample consists of 12,312 companies over the period of July 1985–December 2003. The t-statistics are presented in parentheses, bold indicating 5% significance.

Notation: UR = "unrated"; IG = "investment grade", S&P rating BBB− or better; NIG = "non-investment grade", S&P rating BB+ or worse. D_1–D_5 are dispersion quintiles where D_1 = lowest dispersion, D_5 = highest dispersion.

	Percentage of stocks			Returns (% per month)				Rating
Portfolio	UR	IG	NIG	UR	IG	NIG	All	
D_1	65.12	27.42	7.46	1.64	1.32	1.20	1.51	7.20
D_2	59.10	32.79	8.10	1.48	1.23	0.45	1.28	7.43
D_3	60.18	29.71	10.11	1.35	1.25	0.71	1.21	8.14
D_4	60.82	25.50	13.68	1.28	1.19	0.47	1.08	9.05
D_5	59.04	17.96	23.00	0.92	1.01	0.19	0.72	10.88
D_1–D_5				0.72	0.31	1.01	0.79	
				(**7.02**)	(1.41)	(**3.64**)	(**5.16**)	

To get a better sense of the source of dispersion profitability, we consider 25 credit risk-dispersion portfolios. In particular, we form portfolios as the intersection of five credit rating and five dispersion groups.[3] Credit risk-dispersion groups are formed sequentially, first sorting on credit rating and then on dispersion.[4] The five credit risk groups, C_1–C_5, are formed each month by sorting the sample of firms in that month into quintiles based on their credit ratings. Each of the resulting credit rating groups is then divided into five dispersion portfolios, D_1–D_5.

Table 3 presents average monthly raw and risk-adjusted returns for the 25 credit risk-dispersion portfolios, as well as the dispersion profitability ($D_1 - D_5$) across credit rating quintiles, and the credit rating profitability ($C_1 - C_5$) across the dispersion quintiles. Monthly payoffs are presented for holding periods of one month (Panels A1 and B1) as well as three months (Panels A2 and B2). Panels A1 and A2 present raw returns and Panels B1 and B2 present risk-adjusted excess returns (or time-series alphas) based on the Fama and French (1993) factors augmented by the momentum factor of Carhart (1997).[5]

We observe that dispersion profitability strongly depends upon credit rating. Focusing on the one-month investment horizon (findings for the three-month horizon are similar), for the C_1, C_2, and C_3 credit rating quintiles,

[3] We have also experimented (results are available upon request) with 5 × 3, 3 × 5, as well as 3 × 3 credit rating-dispersion portfolios and have confirmed that the empirical evidence is unchanged.

[4] We have checked that the sequential sorting procedure is not driving the results. The payoffs with independent sorts are similar.

[5] Results are similar if the risk-adjustment is based on the CAPM or the Fama and French (1993) factors.

Table 3

Returns by sequentially sorted rating and dispersion groups

For each month t, all stocks rated by Standard & Poor's are divided into 25 groups based on a sequential sort by five credit rating and five dispersion groups. Portfolios are held for $K = 1$ month (Panel A1) and $K = 3$ months (Panel A2). For the one-month holding period strategy, for each rating/dispersion group, we compute the cross-sectional mean return for month $t+1$. For the three-month holding period strategy, the monthly returns for each month $t+1$ are computed as the equally weighted average of the returns of portfolios sorted in months t, $t-1$, and $t-2$. All returns are in percentages per month. t-statistics are presented in parentheses (bold indicating 5% significance). For Panel B, we regress the monthly portfolio returns obtained above (in excess of the risk free rate, except for the zero-investment portfolios, C_1-C_5 and D_1-D_5) on a constant and the Fama and French (1993) factors augmented with the momentum factor of Carhart (1997). Panel B reports the time-series alphas (intercepts in these regressions) and their t-statistics in parentheses. The sample consists of 3,261 companies over the period of July 1985–December 2003.

Panel A: Raw returns

A1: $K = 1$ month holding period

	Dispersion quintile (D_1 = lowest dispersion, D_5 = highest dispersion)					
	D_1	D_2	D_3	D_4	D_5	D_1–D_5
C_1	1.40	1.26	1.30	1.27	1.28	0.11
	(**4.60**)	(**4.21**)	(**4.53**)	(**4.32**)	(**3.89**)	(0.55)
C_2	1.37	1.18	1.29	1.30	1.21	0.15
	(**4.57**)	(**3.97**)	(**4.06**)	(**4.00**)	(**3.51**)	(0.77)
C_3	1.23	1.18	1.17	1.24	0.93	0.30
	(**4.05**)	(**3.70**)	(**3.69**)	(**3.74**)	(**2.56**)	(1.45)
C_4	1.24	1.10	0.95	0.89	0.62	0.62
	(**3.42**)	(**3.09**)	(**2.48**)	(**2.34**)	(1.49)	(**2.71**)
C_5	0.82	0.48	0.23	0.08	−0.03	0.85
	(**1.97**)	(1.10)	(0.47)	(0.18)	(−0.06)	(**2.88**)
C_1–C_5	0.57	0.77	1.07	1.19	1.31	
	(1.87)	(**2.44**)	(**3.10**)	(**3.78**)	(**4.17**)	

A2: $K = 3$ month holding period

	Dispersion quintile (D_1 = lowest dispersion, D_5 = highest dispersion)					
	D_1	D_2	D_3	D_4	D_5	D_1–D_5
C_1	1.35	1.20	1.25	1.24	1.13	0.22
	(**4.48**)	(**4.12**)	(**4.38**)	(**4.25**)	(**3.51**)	(1.11)
C_2	1.33	1.21	1.16	1.25	1.11	0.21
	(**4.51**)	(**4.09**)	(**3.78**)	(**3.90**)	(**3.25**)	(1.14)
C_3	1.20	1.12	1.19	1.18	0.96	0.23
	(**3.95**)	(**3.62**)	(**3.81**)	(**3.58**)	(**2.66**)	(1.18)
C_4	1.13	1.00	0.98	0.76	0.69	0.44
	(**3.14**)	(**2.79**)	(**2.60**)	(**2.06**)	(1.68)	(**1.96**)
C_5	0.74	0.40	0.30	0.10	−0.06	0.80
	(1.77)	(0.90)	(0.64)	(0.22)	(−0.13)	(**2.81**)
C_1–C_5	0.61	0.80	0.95	1.14	1.20	
	(**1.99**)	(**2.55**)	(**2.96**)	(**3.75**)	(**3.96**)	

Panel B: Risk-adjusted excess returns

B1: $K = 1$ month holding period

	Dispersion quintile (D_1 = lowest dispersion, D_5 = highest dispersion)					
	D_1	D_2	D_3	D_4	D_5	D_1–D_5
C_1	0.23	0.06	0.15	0.11	0.17	0.07
	(1.48)	(0.49)	(1.23)	(0.97)	(1.26)	(0.35)
C_2	0.12	−0.01	0.04	0.07	0.05	0.07
	(0.83)	(−0.12)	(0.26)	(0.56)	(0.37)	(0.38)
C_3	−0.02	−0.10	−0.08	−0.08	−0.27	0.25
	(−0.15)	(−0.69)	(−0.55)	(−0.60)	(−1.79)	(1.27)
C_4	−0.14	−0.22	−0.36	−0.44	−0.69	0.55
	(−0.77)	(−1.33)	(−**2.29**)	(−**2.61**)	(−**4.32**)	(**2.55**)
C_5	−0.55	−0.73	−1.08	−1.13	−1.29	0.74
	(−**2.56**)	(−**3.57**)	(−**5.54**)	(−**6.40**)	(−**6.20**)	(**2.52**)
C_1–C_5	0.78	0.79	1.23	1.24	1.45	
	(**3.64**)	(**3.68**)	(**5.56**)	(**5.76**)	(**5.92**)	

Table 3 (*continued*)

B2: $K = 3$ month holding period

	Dispersion quintile (D_1 = lowest dispersion, D_5 = highest dispersion)					
	D_1	D_2	D_3	D_4	D_5	D_1–D_5
C_1	0.22	0.07	0.14	0.11	0.06	0.15
	(1.45)	(0.58)	(1.18)	(1.07)	(0.54)	(0.90)
C_2	0.14	0.03	−0.01	0.06	−0.04	0.18
	(1.00)	(0.22)	(−0.10)	(0.48)	(−0.34)	(1.06)
C_3	−0.03	−0.10	0.01	−0.12	−0.24	0.21
	(−0.21)	(−0.87)	(0.05)	(−0.97)	(−1.62)	(1.11)
C_4	−0.18	−0.28	−0.28	−0.53	−0.59	0.41
	(−0.99)	(−1.91)	(−**1.98**)	(−**3.85**)	(−**3.77**)	(1.94)
C_5	−0.59	−0.78	−0.98	−1.07	−1.27	0.68
	(−**2.86**)	(−**4.14**)	(−**5.63**)	(−**6.67**)	(−**6.25**)	(**2.42**)
C_1–C_5	0.80	0.85	1.12	1.19	1.33	
	(**4.10**)	(**4.33**)	(**5.89**)	(**6.11**)	(**5.84**)	

dispersion profitability, D_1-D_5, is 11, 15, and 30 basis points per month, respectively, and is insignificant at conventional levels. The payoff is statistically and economically significant at 0.62% per month for the fourth quintile and 0.85% per month for the highest credit risk quintile. Note that the dispersion profitability increases monotonically with credit risk. Profitability across credit risk quintiles, C_1-C_5, also increases monotonically with dispersion from 0.57% for the lowest dispersion quintile to 1.31% per month for the highest dispersion quintile. The C_1-C_5 payoffs are significant in all dispersion groups.

Panels B1 and B2 of Table 3 present alphas from time-series regressions of the 25 credit rating-dispersion sorted portfolio excess returns and of the zero-cost portfolio returns (D_1-D_5 and C_1-C_5) on the Fama and French (1993) factors augmented by the momentum factor of Carhart (1997). Alphas of the D_1-D_5 portfolios increase with credit risk and are statistically and economically significant only for the two highest credit risk quintiles given by 55 (C_4) and 74 (C_5) basis points per month. Profitability across credit risk quintiles, C_1-C_5, continues to increases monotonically with dispersion from 0.78% (80%) for the lowest dispersion quintile to 1.45% (1.33%) per month for the highest dispersion quintile in the one-month (three-months) holding strategy. These payoffs are all significant at the 5% level in all dispersion groups.

Indeed, one could argue that just as much as credit conditions could capture the dispersion effect, the dispersion effect could also capture the credit risk effect. There is a clear interaction between dispersion and credit risk but it is unclear, at this stage, which measure, if any, governs this interaction. Below, we show that the impact of credit risk is more prominent possibly because credit ratings are a better proxy for financial distress than analysts' earnings forecast dispersion.

Table 3 presents the means and the statistical significance of dispersion-based trading strategies. To get some perspective about the dynamics of dispersion profitability, we plot in Fig. 1 the wealth accumulated by taking long (short) positions in stocks with low (high) dispersion in analysts' forecasts starting from October 1985. Investing $1 in dispersion strategies implemented among the highest quality stocks (C_1) realizes a payoff of $1.28 in December 2003. The corresponding payoff is much larger at $4.82 when the investment universe is comprised of the lowest quality stocks (C_5). Moreover, it is evident that the payoff differential between C_1 and C_5 firms is quite steady throughout the entire sample as it does not concentrate in one particular period.

3.2. *Dispersion profitability among subsamples of rated firms*

The analysis thus far has examined the relation between dispersion profitability and credit risk using portfolio strategies based on double sorting, first by credit quality and then by dispersion. We now attempt to track more closely the subsample of firms that drives the significant dispersion payoffs. We implement the traditional dispersion strategies based only on dispersion in earnings forecasts, but for different investment subsamples. In particular, we start with the entire sample of rated firms and then sequentially exclude firms with the highest credit risk.

The dispersion profitability is reported in Table 4. Also provided is the percentage of market capitalization represented by each rating subsample, as well as the percentage of the total number of firms included in each subsample. These two measures are computed each month, and we report the time-series average. In Panel A of Table 4 the dispersion portfolio cutoffs are recomputed for each rating subsample to maintain a (roughly) equal number of firms across the five dispersion portfolios. We have also implemented the same analysis using fixed cutoffs based upon the entire universe of rated firms. Results (available upon request) are virtually identical.

It is apparent that the dispersion strategy payoff is insignificant at the 5% level for subsamples that contain stocks in the rating range AAA–BB+. Strikingly, this subsample accounts for 95.58% of the market capitalization of rated firms and 73.86% of the total number of rated

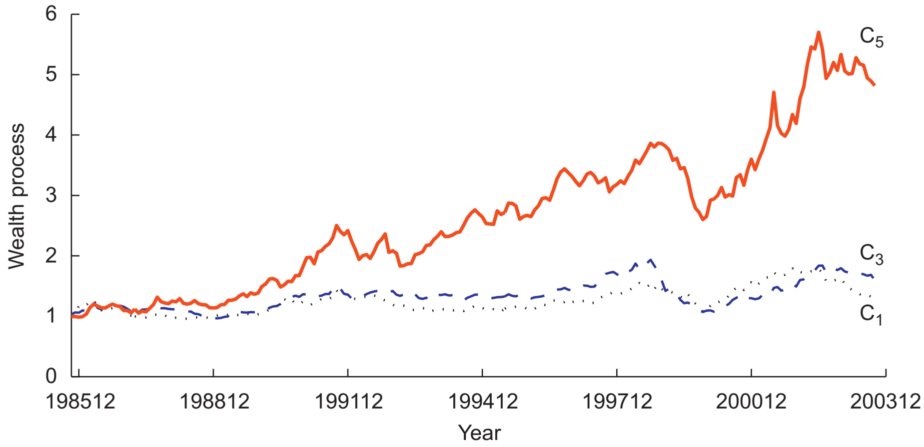

Fig. 1. Wealth process of dispersion strategy. Each month t, all stocks rated by Standard & Poor's are divided into quintiles based on credit rating. For each credit rating quintile, we further sort stocks into quintiles based on dispersion and assume we are \$1 long in the lowest dispersion quintile (D_1) and \$1 short in the highest dispersion quintile (D_5) and hold these positions for one month. This dispersion strategy is followed from October 31, 1985 until December 31, 2003, and includes a total of 3,261 rated stocks. The plot illustrates the wealth processes for rating quintiles C_1 (highest-rated), C_5 (lowest-rated), and the middle quintile C_3.

firms. In other words, the documented dispersion profitability is derived from a sample of rated firms that accounts for less than 5% of the total market capitalization of all rated firms or less than 27% of all rated firms.

Indeed, the profitability of dispersion-based trading strategies exists among firms that constitute a minor fraction of the overall market capitalization of rated firms. Nevertheless, we show in Panel B of Table 4 that the credit risk effect on the dispersion–return relation is not merely a size effect. Specifically, we implement dispersion strategies for all firms, then exclude the 4% smallest firms, then another 4% smallest firms, and so on, until we consider only 20% of the biggest firms. Strikingly, an economically and statistically significant payoff obtains even when 72% of the smallest firms are excluded.[6] The evidence is thus conclusive that the credit risk effect is unique and it does not merely reflect the size effect even when lower rated stocks tend to be smaller.

3.3. *Existing explanations for the dispersion effect*

Here, we check whether the presence of the dispersion effect among high credit risk stocks is already captured by explanations previously suggested in the literature.

We examine dispersion-based trading strategy profits controlling for a number of firm characteristics. In particular, previous work shows that dispersion profitability is related to leverage and idiosyncratic volatility[7] (Johnson, 2004) as well as short-sale constraints (Diether, Malloy, and Scherbina, 2002). D'Avolio (2002) suggests that stock turnover, institutional holdings, and the number of shares outstanding can be used as proxies for short-selling costs. An essential question that arises is whether the relation between dispersion and credit ratings is already captured by such firm characteristics.

Panel A of Table 5 reports results from monthly cross-sectional Fama and MacBeth (1973) regressions of future return on dispersion and other control variables. We use the standard firm characteristics—size, book-to-market ratio, and lagged six-month returns—that have been shown to impact the cross-section of returns. In addition, we also use leverage, dispersion interacted with leverage, illiquidity, dispersion interacted with illiquidity, idiosyncratic volatility, institutional ownership, and firm credit rating. All firm characteristics are lagged one month relative to returns.[8] Given the skewness in the dispersion measure, we use the natural logarithm of dispersion.[9]

In the first specification in Panel A, returns are regressed on lagged dispersion. The coefficient on lagged dispersion is a negative -0.14 and significant (t-ratio $= -2.07$) suggesting that the one-month-ahead returns decrease with dispersion, as expected. Adding credit rating as an explanatory variable, however, renders the dispersion effect statistically insignificant at the 5% level. The slope drops to -0.05 and the t-ratio is -0.84. In contrast, credit rating is significantly negative. Its average slope marginally drops from -0.11 (t-ratio $= -3.74$) when it is the single regressor to -0.09 (t-ratio $= -3.28$) when included with dispersion.

Indeed, this is the first compelling evidence that credit rating subsumes dispersion in explaining the cross-section of future stock returns. In other words, not only is the dispersion effect concentrated in high credit risk firms, but also the negative association between dispersion

[6] As an additional robustness check, we sort firms independently by two credit rating and two size groups and compute dispersion profitability within each group. We find significant dispersion profits in both small and large high credit risk firms, while dispersion profits are absent in both small and large low credit risk firms.

[7] Idiosyncratic volatility might proxy for the idiosyncratic asset risk in Johnson (2004).

[8] The results are qualitatively the same when all the firm characteristics are lagged two months.

[9] The results are similar if we use the level of dispersion and truncate outliers outside the 1st and 99th percentile.

Table 4
Dispersion strategy payoffs over diminishing subsamples

Dispersion portfolios are constructed as explained in Table 1. Each subsequent row in Panel A (Panel B) represents a monotonically decreasing sample of stocks obtained by sequentially excluding firms with the worst credit rating (smallest market capitalization). The first column characterizes each subsample. The second column presents the raw monthly profits from the dispersion strategy for each subsample of firms (t-statistics are in parentheses, bold if indicating 5% significance). The third column shows the market capitalization of the given subsample as a percentage of the overall market capitalization of S&P rated firms. The fourth (fifth) column provides the average number (percentage) of firms per month in each subsample. The sample contains 3,261 companies over the period of July 1985–December 2003.

Panel A: Dispersion profits by sequentially removing worst-rated stocks

Stock sample	Dispersion profits	Percent of total market cap	Number of firms	Percentage of firms
All firms	0.76 (**3.35**)	100.00	1,154.00	100.00
AAA−C	0.75 (**3.33**)	99.99	1,153.52	99.96
AAA−CC	0.75 (**3.33**)	99.99	1,153.52	99.96
AAA−CCC−	0.76 (**3.35**)	99.98	1,153.19	99.93
AAA−CCC	0.76 (**3.34**)	99.98	1,152.91	99.91
AAA−CCC+	0.73 (**3.25**)	99.97	1,151.61	99.79
AAA−B−	0.71 (**3.18**)	99.93	1,148.21	99.50
AAA−B	0.68 (**3.07**)	99.70	1,135.56	98.40
AAA−B+	0.61 (**2.81**)	99.20	1,109.11	96.11
AAA−BB−	0.53 (**2.57**)	98.30	1,023.83	88.72
AAA−BB	0.40 (**1.98**)	97.05	931.90	80.75
AAA−BB+	0.32 (1.58)	95.58	852.36	73.86
AAA−BBB−	0.26 (1.35)	93.73	784.52	67.98
AAA−BBB	0.22 (1.13)	90.07	687.38	59.56
AAA−BBB+	0.18 (0.92)	84.03	560.71	48.59

Panel B: Dispersion profits by sequentially removing smallest stocks

Stock sample	Dispersion profits	Percent of total market cap	Number of firms	Percentage of firms
All firms	0.76 (**3.35**)	100.00	1,154.00	100.00
Biggest 96%	0.67 (**2.91**)	99.96	1,107.84	96.00
Biggest 92%	0.66 (**2.86**)	99.86	1,061.70	92.00
Biggest 88%	0.67 (**2.86**)	99.71	1,015.57	88.00
Biggest 84%	0.60 (**2.56**)	99.51	969.35	84.00
Biggest 80%	0.61 (**2.56**)	99.27	923.21	80.00
Biggest 76%	0.54 (**2.26**)	98.97	877.07	76.00
Biggest 72%	0.53 (**2.23**)	98.61	830.86	72.00
Biggest 68%	0.51 (**2.11**)	98.17	784.75	68.00
Biggest 64%	0.51 (**2.11**)	97.65	738.60	64.00
Biggest 60%	0.49 (**1.96**)	97.05	692.42	60.00
Biggest 56%	0.48 (1.93)	96.34	646.24	56.00
Biggest 52%	0.46 (1.84)	95.52	600.08	52.00

Table 4 (*continued*)

Panel B: Dispersion profits by sequentially removing smallest stocks

Stock sample	Dispersion profits	Percent of total market cap	Number of firms	Percentage of firms
Biggest 48%	0.51	94.54	553.97	48.00
	(**1.99**)			
Biggest 44%	0.51	93.40	507.81	44.00
	(**1.98**)			
Biggest 40%	0.48	92.06	461.63	40.00
	(1.84)			
Biggest 36%	0.44	90.48	415.46	36.00
	(1.66)			
Biggest 32%	0.44	88.58	369.30	32.00
	(1.66)			
Biggest 28%	0.55	86.27	323.19	28.01
	(**2.01**)			
Biggest 24%	0.50	83.47	276.98	24.00
	(1.81)			
Biggest 20%	0.48	79.96	230.85	20.00
	(1.64)			

and future returns is non-existent when credit rating is used as a control variable. In contrast, including the standard firm characteristics of size, book-to-market ratio, and lagged six-month returns does not render the impact of dispersion on returns insignificant.

Next, as suggested by Johnson (2004), we include firm leverage and the interaction of leverage and dispersion. Leverage is measured as the most recent book value of debt divided by the sum of the book value of debt and the market value of equity. The evidence shows that neither of these measures has an impact on the significance of the dispersion coefficient but the credit rating does. Indeed, this apparently contradicts the relevance of leverage in Johnson (2004) and could be due to the different samples used, as we focus on firms rated by S&P. However, Sadka and Scherbina (2007) also find a negative but statistically insignificant coefficient on leverage and leverage interacted with dispersion in their sample of all NYSE-listed firms with December fiscal year end.

We also examine the impact of Amihud's (2002) illiquidity measure, idiosyncratic volatility, and institutional ownership on the dispersion–return relation. While the coefficient on illiquidity is significantly negative, it does not explain away the significance of dispersion.[10] The coefficient of idiosyncratic volatility is also significantly negative but it does not capture the dispersion–return relation. Finally, institutional ownership is not significant and does not call into question the dispersion effect in our sample. Indeed, the relation between analyst forecast dispersion and future returns among rated firms is robust to the inclusion of all variables except for credit ratings.

More importantly, variables that proxy for short-selling costs such as illiquidity, institutional holdings, and firm size are all statistically insignificant and do not impact the relation between dispersion and returns.[11] This is important because Diether, Malloy, and Scherbina (2002) argue that short-sale constraints play an important role in generating the dispersion–return relation. The idea is that in stocks with high dispersion (which proxies for differences in agent beliefs) optimistic investors bid prices up and short-sale constraints prevent pessimistic views from being reflected into the stock price, thus, causing the high dispersion stocks to become temporarily overpriced. The dispersion effect emerges as this overpricing is corrected over time. However, the results show that the standard proxies for short-sale costs are insufficient in explaining the dispersion effect.

Moreover, our results suggest that, while illiquidity can explain the persistence of the dispersion effect, as shown by Sadka and Scherbina (2007), illiquidity does not explain why the dispersion effect exists in the first place. While low-rated stocks are in general illiquid, it is the credit rating and not illiquidity that drives the impact of forecast dispersion on returns.

As noted earlier, Johnson (2004) argues that analyst forecast dispersion is a proxy for unpriced information risk and, for levered firms, expected returns should decrease with idiosyncratic asset risk. Thus, the dispersion effect obtains even when there is no cross-sectional relation between dispersion of beliefs and fundamental risk. One prediction of the Johnson (2004) model is that the dispersion effect should be stronger as firm leverage increases. In Panel B of Table 5 we examine the dispersion

[10] We bear in mind that our results may be different from Sadka and Scherbina (2007) because they include all NYSE firms with December fiscal year end and a different measure of illiquidity—a dummy for the top 20% of price impact (PI)—in their cross-sectional regressions to explain the persistence of the dispersion effect through time.

[11] We also used turnover instead of illiquidity in the regressions and the results were similar. Moreover, we have considered all interactions among the short-sale constraint variables to account for non-linear short-sale effects. The dispersion effect remains significant in their presence.

Table 5

Determinants of the dispersion effect

For Panel A, we run Fama and MacBeth (1973) type cross-sectional regressions of returns at time t on dispersion and characteristics at time $t-1$. Panel A presents the time-series average and t-statistic of the estimated coefficients. Panel B presents dispersion profits for all firms (both rated and unrated), with available data on debt in Compustat to compute leverage, firms with zero debt, and firms with positive debt. For Panel C, in each month t, we adjust dispersion by credit risk by regressing cross-sectionally dispersion on the stock's S&P credit rating: $D_{it} = a_t + b_t CR_{it} + e_{it}$. We define $D^*_{it} = a_t + e_{it}$ as the credit-risk adjusted dispersion. Then in each month t, stocks are sorted into 25 portfolios based on a sequential sort by five credit rating and five D^* groups. For each rating-dispersion portfolio, we compute the cross-sectional mean return for month $t+1$. All returns are in percentages per month. t-statistics are presented in parentheses (bold if indicating 5% significance). We exclude stocks priced below $5 at the beginning of the month. The sample consists of 3,261 companies over the period of July 1985–December 2003.

Panel A: Regressions of returns on lagged characteristics

	1	2	3	4	5	6	7	8	9	10	11	12
$Log(D_{t-1})$	−0.14		−0.05	−0.14	−0.13	−0.03	−0.13	−0.14	−0.09	−0.03	−0.13	−0.04
	(−**2.07**)		(−0.84)	(−**2.41**)	(−**1.98**)	(−0.41)	(−**1.97**)	(−**2.01**)	(−1.95)	(−0.44)	(−**1.96**)	(−0.76)
CR_{t-1}		−0.11	−0.09			−0.11				−0.05		−0.07
		(−**3.74**)	(−**3.28**)			(−**3.43**)				(−**2.08**)		(−**2.47**)
$Size_{t-1}$				0.00								−0.00
				(0.14)								(−1.30)
BM_{t-1}				0.30								0.41
				(**2.11**)								(**2.58**)
$r_{(t-6:t-1)}$				0.80								0.64
				(**2.06**)								(1.71)
$Leverage_{t-1}$					−0.01	−0.00						0.04
					(−0.57)	(−0.15)						(1.24)
$Log(D_{t-1}) * leverage_{t-1}$					−0.01	−0.00						0.01
					(−1.14)	(−0.40)						(0.89)
$Illiquidity_{t-1}$							−0.02	−0.00				−0.04
							(−**2.88**)	(−0.14)				(−0.60)
$Log(D_{t-1}) * illiquidity_{t-1}$								0.01				0.00
								(0.86)				(0.18)
$Idiosyncratic\ volatility_{t-1}$									−18.47	−27.16		−26.37
									(−**4.15**)	(−**5.84**)		(−**5.37**)
$Institutional\ ownership_{t-1}$											0.29	0.12
											(1.15)	(0.39)

Panel B: Dispersion profitability in firms with and without leverage (including all firms: rated and unrated)

Firms	All	With data on debt	Zero debt	Positive debt
Ave. number of firms/month	2,948	2,455	208	2,247
Dispersion profits (D_1–D_5)	0.79	0.76	0.74	0.75
	(**5.16**)	(**4.74**)	(**4.06**)	(**4.45**)

Panel C: Returns by sequentially sorted rating and D^* groups

	D^* Quintile (D^*_1 = lowest, D^*_5 = highest adjusted-dispersion)					
	D^*_1	D^*_2	D^*_3	D^*_4	D^*_5	D^*_1–D^*_5
C_1	1.33	1.35	1.24	1.27	1.35	−0.02
	(**4.48**)	(**4.39**)	(**4.29**)	(**4.21**)	(**4.39**)	(−0.14)
C_2	1.30	1.13	1.30	1.30	1.29	0.02
	(**4.41**)	(**3.64**)	(**4.22**)	(**4.24**)	(**3.70**)	(0.09)
C_3	1.24	1.21	1.13	1.19	0.98	0.15
	(**3.85**)	(**3.80**)	(**3.70**)	(**3.67**)	(**2.73**)	(0.96)
C_4	0.97	1.14	0.99	1.05	0.62	0.25
	(**2.45**)	(**3.11**)	(**2.78**)	(**2.88**)	(1.51)	(1.19)
C_5	0.38	0.57	0.36	0.25	−0.07	0.35
	(0.83)	(1.29)	(0.79)	(0.54)	(−0.15)	(1.35)
C_1–C_5	0.95	0.78	0.88	1.02	1.22	
	(**2.70**)	(**2.64**)	(**2.78**)	(**3.32**)	(**4.19**)	

strategy payoffs to all firms (both rated and UR), to all firms with data on debt available in Compustat, to firms with zero debt, and to firms with non-zero debt. The dispersion strategy payoffs are 0.79%, 0.76%, 0.74%, and 0.75% per month, respectively.

Thus, levered and unlevered firms provide indistinguishable payoffs to dispersion strategies. In contrast, we have shown that the dispersion payoffs in low and high credit risk firms are quite different. Hence, financial leverage and credit risk have a very different impact on the dispersion–return relation. Indeed, while credit rating is affected by financial leverage, we find that the time-series average cross-sectional correlation between credit rating and financial leverage is 0.19 and ranges between −0.01 and 0.38 over the sample months. Indeed, a bad credit rating may be the result of high operating leverage, high uncertainty about future profitability and growth, and/or volatility, even when financial leverage is low. Hence, our finding that financial leverage has little impact on dispersion profitability motivates our search for an alternative explanation for the dispersion effect.

Panel A of Table 5 shows that the dispersion–return relation becomes insignificant when controlling for credit rating. The multiple cross-sectional regression of future returns on the explanatory variables dispersion and credit rating is equivalent to the univariate regression of future returns on a credit rating-adjusted dispersion measure, where the adjusted-dispersion measure is computed as the sum of intercept and residual from the cross-sectional regression of dispersion on credit rating. By construction, the cross-sectional correlation between the rating-adjusted dispersion measure and credit rating is zero. Thus, to map the statistical evidence into an economic one, we construct monthly credit rating-adjusted dispersion measures as monthly residuals in cross-sectional regressions of dispersion on credit rating (of course, the intercept is constant across stocks for any given month). We then compute average payoffs for 25 portfolios constructed as the intersection of five credit rating groups and five adjusted-dispersion groups, sorted first on credit rating. Panel C of Table 5 reports these average returns as well as payoffs to implementing trading strategies based on the adjusted-dispersion measure. We denote the portfolio with the lowest (highest) adjusted-dispersion measure by D_1^* (D_5^*).

The evidence indicates that implementing investment strategies based on credit rating-adjusted dispersion generates payoffs that are not statistically significant or economically large for any of the credit rating groups. Specifically, the payoff differential between low and high adjusted-dispersion portfolios ($D_1^* - D_5^*$) across the credit rating quintiles ranges from −2 basis points to 35 basis points per month, all of which are insignificant. In other words, excluding the credit rating information from dispersion yields an adjusted measure that has no power to generate profitable trading strategies.

Panel A of Table 6 presents supporting evidence that credit risk is more prominent than existing explanations for the dispersion effect. Whereas in Panel C of Table 5 dispersion was adjusted by credit rating, here we adjust returns by credit rating. Credit rating-adjusted returns are obtained by subtracting from each stock return the corresponding return of the credit rating decile to which the stock belongs. The traditional dispersion measure produces insignificant dispersion profits among all credit risk groups once the credit risk effect is removed from stock returns. Focusing on Panel A, the credit risk-adjusted payoffs to the dispersion strategy for the credit rating quintiles are all less than 27 basis points per month, all of which are insignificant. The significance of the dispersion effect also disappears in the overall sample of rated firms (last line).

For robustness, in Panels B–E we compute dispersion profits based on returns adjusted for equity characteristics suggested by alternative explanations for the dispersion effect. In particular, returns are adjusted for the following characteristics: market capitalization, turnover, institutional ownership, and number of shares outstanding.[12] As before, characteristic-adjusted returns are computed by subtracting from each stock return the corresponding return of the characteristic decile to which the stock belongs. The dispersion strategy payoffs are still significant for the low-rated stocks (and for all rated stocks) even after adjusting for the above characteristics. Thus, the dispersion strategy payoffs are insignificant only when adjusting for credit ratings (Panel A).

Finally, we check that the credit risk effect on the dispersion–return relation is not captured by potential industry effects in the cross-section of returns. That is, we implement dispersion strategies based on industry-adjusted returns following the industry groups examined by Moskowitz and Grinblatt (1999). Our findings (available upon request) show that dispersion profitability is statistically and economically significant only for the worst credit quality firms.

In sum, the ability of dispersion to predict future returns is attributable to the predictive power of credit ratings. The dispersion–return relation is significantly weaker when either the dispersion measure or return is adjusted by credit risk. Since credit risk is negatively associated with the cross-section of future stock returns, it is not surprising that dispersion has also been negatively related to future returns.

3.4. The dispersion–return relation during periods of worsening credit conditions

Thus far we have shown that the credit rating level has a large impact on the dispersion effect. Next, we show that it is indeed financial distress that is an important driver of the dispersion effect. We examine financial distress in the context of credit rating downgrades. Our focus on downgrades follows previous work that demonstrates an asymmetric response of future returns to credit rating changes. In particular, both Hand, Holthausen, and Leftwich (1992) and Dichev and Piotroski (2001) find considerable abnormal price declines following rating downgrades but no price advances following upgrades.

In our context, rating downgrades possibly trigger higher uncertainty about firm fundamentals as well as worsening fundamentals (potentially enhanced by suppliers, customers, and creditors abandoning the firm). For financial distress to be the source of the dispersion effect, we have to show that analyst forecast dispersion increases

[12] We have also ensured that the results for other characteristics such as idiosyncratic volatility and leverage are similar to those presented.

around downgrades and that the dispersion effect is not present outside of the downgrade periods. This is precisely what we find in Tables 7 and 8.

Table 7 reports average values of return and the firm-level characteristics: dispersion, revision in analysts' forecasts, earnings surprises, the number of analysts

Table 6

Dispersion strategy payoffs based on characteristic-adjusted returns

The table presents dispersion profits based on credit-rating- (Panel A) or characteristic-adjusted returns (Panels B–E). Returns are adjusted by subtracting from each stock monthly return the monthly return of the characteristic decile to which the stock belongs. We assume a one-month holding period. All returns are in percentages per month. *t*-statistics are presented in parentheses (bold indicating 5% significance). The sample contains 3,261 companies over the period of July 1985–December 2003.

Panel A: Credit-rating-adjusted returns

	Dispersion quintile (D_1 = lowest, D_5 = highest dispersion)					
	D_1	D_2	D_3	D_4	D_5	D_1–D_5
C_1	0.14	−0.06	0.00	0.06	−0.05	0.20
	(1.24)	(−0.64)	(0.00)	(0.71)	(−0.56)	(1.07)
C_2	0.15	−0.04	−0.02	0.06	−0.01	0.16
	(1.49)	(−0.46)	(−0.28)	(0.75)	(−0.05)	(0.87)
C_3	0.12	0.00	0.07	0.07	0.01	0.11
	(1.14)	(0.03)	(0.74)	(0.79)	(0.10)	(0.63)
C_4	0.02	0.27	0.03	0.09	−0.05	0.07
	(1.45)	(**2.34**)	(0.30)	(0.82)	(−0.37)	(0.83)
C_5	0.30	0.10	−0.00	−0.32	0.03	0.27
	(1.76)	(1.38)	(−0.25)	(−0.15)	(0.90)	(0.96)
All rated	0.27	0.03	0.16	0.17	0.15	0.12
	(**2.99**)	(0.56)	(**2.69**)	(**2.42**)	(1.52)	(0.73)

Panel B: Size-adjusted returns

	Dispersion quintile (D_1 = lowest, D_5 = highest dispersion)					
	D_1	D_2	D_3	D_4	D_5	D_1–D_5
C_1	0.31	0.35	0.17	0.38	0.20	0.11
	(**2.09**)	(**2.57**)	(1.31)	(**3.16**)	(1.43)	(0.56)
C_2	0.25	0.10	0.14	0.27	0.27	−0.02
	(1.85)	(0.81)	(1.28)	(**2.09**)	(1.76)	(−0.10)
C_3	0.14	0.23	0.07	0.09	−0.07	0.21
	(1.15)	(1.75)	(0.58)	(0.69)	(−0.45)	(0.97)
C_4	0.25	0.07	−0.16	−0.29	−0.42	0.67
	(1.73)	(0.49)	(−1.17)	(−**2.17**)	(−**2.43**)	(**2.85**)
C_5	−0.20	−0.45	−0.64	−0.88	−1.02	0.83
	(−1.11)	(−**2.39**)	(−**2.76**)	(−**4.10**)	(−**3.95**)	(**2.71**)
All rated	0.23	0.09	0.01	−0.12	−0.46	0.69
	(**2.45**)	(1.18)	(0.14)	(−1.52)	(−**3.49**)	(**3.39**)

Panel C: Turnover-adjusted returns

	Dispersion quintile (D_1 = lowest, D_5 = highest dispersion)					
	D_1	D_2	D_3	D_4	D_5	D_1–D_5
C_1	0.45	0.28	0.29	0.38	0.29	0.17
	(**2.42**)	(1.78)	(**1.97**)	(**2.74**)	(**2.09**)	(0.89)
C_2	0.43	0.28	0.24	0.41	0.27	0.16
	(**2.81**)	(**2.12**)	(**2.02**)	(**3.50**)	(**2.00**)	(0.82)
C_3	0.38	0.27	0.25	0.32	0.16	0.22
	(**2.81**)	(**2.28**)	(**2.26**)	(**2.74**)	(1.14)	(1.10)
C_4	0.42	0.36	0.15	0.03	−0.09	0.51
	(**3.12**)	(**2.92**)	(1.16)	(0.20)	(−0.55)	(**2.21**)
C_5	0.16	−0.20	−0.53	−0.58	−0.75	0.92
	(0.92)	(−1.18)	(−**3.03**)	(−**3.30**)	(−**3.23**)	(**3.15**)
All rated	0.44	0.21	0.21	0.07	−0.30	0.74
	(**3.69**)	(**2.39**)	(**2.89**)	(0.94)	(−**2.52**)	(**3.50**)

Table 6 (*continued*)

Panel D: Institutional-ownership-adjusted returns

	Dispersion quintile (D_1 = lowest, D_5 = highest dispersion)					
	D_1	D_2	D_3	D_4	D_5	D_1–D_5
C_1	0.29	0.21	0.17	0.32	0.39	−0.11
	(1.43)	(1.20)	(1.09)	(**2.21**)	(**2.82**)	(−0.55)
C_2	0.31	0.19	0.11	0.37	0.30	0.01
	(1.87)	(1.35)	(0.86)	(**3.03**)	(**2.15**)	(0.06)
C_3	0.16	0.21	0.08	0.30	0.06	0.10
	(1.13)	(1.76)	(0.79)	(**2.36**)	(0.43)	(0.47)
C_4	0.18	0.13	−0.19	−0.12	−0.32	0.50
	(1.36)	(1.02)	(−1.56)	(−0.89)	(−1.92)	(**2.15**)
C_5	−0.20	−0.62	−0.63	−0.77	−1.09	0.90
	(−1.05)	(−**2.85**)	(−**2.67**)	(−**3.25**)	(−**4.24**)	(**2.95**)
All rated	0.26	0.04	0.07	−0.02	−0.37	0.63
	(**2.18**)	(0.50)	(1.04)	(−0.30)	(−**2.84**)	(**2.75**)

Panel E: Share-outstanding-adjusted returns

	Dispersion quintile (D_1 = lowest, D_5 = highest dispersion)					
	D_1	D_2	D_3	D_4	D_5	D_1–D_5
C_1	0.25	0.14	0.15	0.29	0.27	−0.03
	(1.48)	(0.90)	(1.03)	(**2.07**)	(1.85)	(−0.13)
C_2	0.27	0.14	0.17	0.19	0.24	0.03
	(1.84)	(1.06)	(1.39)	(1.46)	(1.68)	(0.15)
C_3	0.23	0.29	0.18	0.22	0.07	0.16
	(1.73)	(**2.18**)	(1.45)	(1.72)	(0.44)	(0.73)
C_4	0.39	0.12	−0.01	−0.20	−0.24	0.63
	(**2.83**)	(0.89)	(−0.06)	(−1.44)	(−1.41)	(**2.85**)
C_5	−0.13	−0.42	−0.57	−0.86	−0.93	0.80
	(−0.74)	(−**2.15**)	(−**2.46**)	(−**3.86**)	(−**3.45**)	(**2.60**)
All rated	0.20	0.10	0.05	−0.05	−0.34	0.54
	(1.93)	(1.16)	(0.72)	(−0.67)	(−**2.64**)	(**2.59**)

covering a firm, institutional holdings, leverage, turnover, market capitalization, and volatility for the credit rating quintiles. The columns in Table 7 are as follows: the first five columns summarize values for all rated firms. The next 10 columns narrow down the focus to firms that experience at least one credit rating downgrade. In particular, columns 6–10 report the average values of return and the above-noted characteristics for the entire sample period, and columns 11–15 exhibit averages for three-months-around downgrades.

Rating data are available from Compustat on a quarterly basis. We assume that the rating change occurs at the beginning of the quarter. The downgrade interval contains three months before the downgrade, the downgrade month, and three months after the downgrade. Hence, the last five columns pertain to a seven-month period around a credit rating downgrade.

Observe from Table 7 that the lowest quality firms experience the largest magnitude of rating downgrades. Specifically, the C_1 stocks experience downgrades with average numerical size of 1.53. The corresponding downgrade size for the C_5 stocks is 2.37. The difference in downgrade size across credit risk groups is more pronounced during recessionary periods, as determined by the National Bureau of Economic Research (NBER). During recessions, the average numerical downgrade size for C_1 (C_5) is 1.47 (2.94). Also note that the overall number of downgrades is larger for the C_5 relative to the C_1 firms, given by 712 versus 619. Of course, the sample contains many more expansionary periods, hence, the overall number of downgrades is larger during expansions.

It is evident from Table 7 that downgraded firms realize returns during the downgrade interval that are substantially lower than those realized during the entire sample period. While this is to be expected, it is striking that the return differential between downgrade and no-downgrade periods *crucially* depends on the credit risk level. For the highest quality firms, the return differential is 0.72% per month [1.18 − 0.46], whereas the worst-rated firms record a much larger difference of 9.35% per month [−0.41 − (−9.76)].

Comparing the first 5 with the next 5 columns, we note that firms that do not experience downgrades and those that do, have similar firm characteristics. To illustrate, the dispersion measure ranges from 5.59 to 27.38 using the overall sample, as displayed in the first five columns. The corresponding figures for the sample of firms that experience at least one rating downgrade, reported in the

Table 7

Analysis overall and around rating downgrades

Each month $t-1$, all S&P rated stocks within a given subsample are divided into quintiles based on their credit rating. We exclude stocks priced below \$5 at the end of month $t-1$. Each set of five columns reports, for various subsamples of firms, the time-series average of the cross-sectional mean characteristic at time t for each credit rating quintile. The cut-off points for the rating quintiles, C_1 (best-rated quintile), C_2, C_3, C_4, and C_5 (worst-rated quintile), are held constant in all subsamples. The "3 months around downgrade" set of columns reports the average of the characteristic over months $t-3:t+3$. Since rating data is available on a quarterly basis, the downgrade is assumed to happen during the first month of the quarter, t. All numbers are in percentages unless noted otherwise. Dispersion is computed as the standard deviation of EPS forecasts divided by the absolute value of the mean EPS forecast. Observations for dispersion are excluded when only one analyst EPS forecast is available or when the mean EPS forecast is zero. Revisions are computed as the change from last month in mean analysts' forecast for the next fiscal year, standardized by the absolute value of last month's mean EPS forecast. Earning surprise is defined as the actual EPS as of the report date minus last month's forecasted EPS standardized by the absolute value of the actual EPS. Analyst coverage is the number of analysts following the firm. Institutional holdings is the percentage of shares outstanding held by institutions. Leverage is computed as the book value of debt for the most recent quarter, divided by the sum of the same book value of debt and the market value of equity at the end of the previous month. Turnover is the percentage of shares outstanding traded in a particular month. Volatility is the standard deviation of daily returns. The sample of all firms contains 12,312 companies over the period of July 1985–December 2003. The sample of firms with downgrades contains 3,261 companies over the same period.

	All firms					Firms with downgrades									
						Overall					3 months around downgrade				
Ratingquintile	C_1	C_2	C_3	C_4	C_5	C_1	C_2	C_3	C_4	C_5	C_1	C_2	C_3	C_4	C_5
Month-return obs.															
Overall	41,426	53,082	52,980	55,231	52,315	30,799	38,549	37,273	35,004	31,303	2,965	4,013	4,010	4,204	3,485
Expansions	38,412	48,670	49,873	50,573	48,863	28,636	35,445	35,071	32,059	29,322	2,687	3,468	3,641	3,729	3,172
Recessions	3,014	4,412	3,107	4,658	3,452	2,163	3,104	2,202	2,945	1,981	278	545	369	475	313
Number of downgrades															
Overall						619	730	669	698	712					
Expansions						566	623	612	626	628					
Recessions						53	107	57	72	84					
Size of downgrades															
Overall						1.53	1.60	1.69	1.65	2.37					
Expansions						1.54	1.61	1.66	1.65	2.32					
Recessions						1.47	1.44	2.16	1.62	2.94					
Return	1.27	1.15	1.07	0.65	0.04	1.18	1.03	0.90	0.25	−0.41	0.46	−0.22	−1.92	−5.32	−9.76
Dispersion	5.59	8.32	12.97	19.89	27.38	6.04	9.09	14.35	23.09	32.17	11.69	20.28	27.34	40.73	47.54
Revision	−0.68	−1.25	−2.14	−3.33	−4.00	−0.83	−1.47	−2.60	−4.15	−4.82	−3.01	−4.89	−7.95	−10.71	−9.05
Earning surprise	−4.78	−8.60	−13.57	−17.13	−20.70	−5.95	−9.30	−13.31	−21.37	−22.56	−12.07	−23.22	−37.85	−40.36	−33.56
Analyst coverage	17.56	13.74	11.39	8.33	6.71	17.40	14.51	12.01	8.79	6.80	16.20	13.94	11.42	8.27	6.09
Institutional holdings	46.21	47.58	48.52	44.81	37.09	46.43	48.98	49.90	45.75	35.32	45.29	48.27	46.39	39.58	27.02
Leverage	22.24	27.42	33.06	40.08	43.96	23.29	28.28	34.14	42.89	47.73	29.94	34.12	43.27	54.62	59.86
Turnover	6.11	6.81	7.84	10.16	12.05	6.09	6.92	8.05	10.27	11.70	7.63	8.78	9.90	12.49	13.72
Size (\$ billions)	6.66	3.60	2.12	0.97	0.60	6.71	3.92	2.35	1.06	0.59	5.33	2.96	1.55	0.57	0.34
Volatility	0.69	0.79	0.97	1.64	2.35	0.69	0.79	1.00	1.70	2.46	0.91	1.19	1.74	2.97	4.37

next five columns, differ relatively mildly and vary from 6.04 to 32.17. However, the reported measures are substantially larger during periods of downgrades. In such periods, dispersion ranges from 11.69 to 47.54, almost twice as much relative to the averages for the overall period. Similarly, volatility for all firms with (without) downgrades ranges from 0.69 to 2.46 (0.69 to 2.35). During downgrade intervals, volatility is higher and varies from 0.91 to 4.37. Perhaps not surprisingly, institutional investors diminish their holdings of firms that experience downgrades, especially of the worst-rated firms.

In sum, periods of credit rating downgrades are characterized by declining returns as well as much higher uncertainty about firm fundamentals, as indicated by dispersion, forecast revision, and earnings surprises. This finding motivates a formal investigation of the role of credit rating downgrades in explaining the relation between dispersion and future returns, which we conduct below.

Panel A of Table 8 reports slope coefficients and t-ratios in monthly cross-sectional regressions of future return on the natural logarithm of dispersion as well as a dummy variable that takes the value one around credit rating downgrades. We note that the cross-sectional regressions use the dummy variable for downgrades up to three months prior to the downgrade event. However, our attempt here is not to form a real-time trading strategy. Instead, we only assess the impact of financial distress on the cross-sectional relation of dispersion and future return. Our examinations here are similar to those based on the NBER dummy variable for expansions and recessions which is constructed based on future realizations of economic quantities.

Table 8

Dispersion strategy payoffs excluding three-months-around downgrades (months $t-3:t+3$)

For Panel A, we run monthly cross-sectional regressions of returns, r_{it}, on a constant, the natural logarithm of dispersion D_{t-1}, a downgrade dummy, and credit rating CR_{t-1}:

$$r_{it} = a_t + b_{t-1} Characteristics_{i,t-1} + u_{it}.$$

The downgrade dummy takes the value of one three-months-around rating downgrades (i.e., from $t-3$ to $t+3$). Panel A presents the average slope coefficients, b_{t-1}, in the cross-sectional regressions, averaged across all months in the sample, and multiplied by 100. The t-statistics are the sample t-statistics of these estimated coefficients. For Panel B, we first remove firms three-months-around rating downgrades (i.e., from $t-3$ to $t+3$). Then for each month t, all stocks rated by Standard & Poor's are divided into 25 groups based on a sequential sort by five credit rating and five dispersion groups. For each rating/dispersion group, we compute the cross-sectional mean return for month $t+1$. All returns are in percentages per month. t-statistics are presented in parentheses (bold if indicating 5% significance). The sample consists of 3,261 companies over the period of July 1985–December 2003.

Panel A: Cross-sectional regressions of returns on dispersion and a downgrade dummy

	$Log(D_{t-1})$	$dummy_{t-3:t+3}$	CR_{t-1}
1	−0.14		
	(−**2.07**)		
2	−0.09	−1.47	
	(−1.37)	(−**11.49**)	
3	0.03	−1.50	−0.10
	(0.56)	(−**11.59**)	(−**3.59**)

Panel B: Returns by sequentially sorted rating and dispersion groups

	Dispersion quintile (D_1 = lowest dispersion, D_5 = highest dispersion)					
	D_1	D_2	D_3	D_4	D_5	D_1–D_5
C_1	1.46	1.29	1.34	1.36	1.40	0.06
	(**4.81**)	(**4.34**)	(**4.67**)	(**4.60**)	(**4.39**)	(0.29)
C_2	1.41	1.25	1.40	1.39	1.36	0.05
	(**4.68**)	(**4.22**)	(**4.56**)	(**4.46**)	(**3.96**)	(0.24)
C_3	1.31	1.26	1.30	1.42	1.23	0.08
	(**4.32**)	(**4.03**)	(**4.05**)	(**4.35**)	(**3.64**)	(0.41)
C_4	1.32	1.17	1.17	1.13	1.14	0.18
	(**3.67**)	(**3.20**)	(**3.11**)	(**3.05**)	(**2.87**)	(0.79)
C_5	0.86	0.56	0.48	0.58	0.50	0.36
	(**2.06**)	(1.29)	(0.98)	(1.26)	(1.03)	(1.17)
All rated	1.36	1.15	1.27	1.08	0.96	0.40
	(**4.56**)	(**3.75**)	(**3.95**)	(**3.12**)	(**2.46**)	(1.34)

Observe from Table 7 that the seven-month period around credit rating downgrades consists of only 18,677 $[2,965+4,013+4,010+4,204+3,485]$ observations from the overall 255,034 $[41,426+53,082+52,980+55,231+52,315]$ observations in our sample, apparently a small fraction of only 7.32% of the sample observations.

Remarkably, this small fraction generates the dispersion effect in the cross-section of future return. To illustrate, the dispersion measure loses its statistical significance when the downgrade dummy is added to the cross-sectional regressions. The dispersion slope is equal to −0.09 with a t-ratio of −1.37. In contrast, the downgrade dummy is statistically and economically significant with a t-ratio of −11.49. When credit rating is added as an additional explanatory variable the dispersion coefficient becomes 0.03 and the t-ratio 0.56. Thus, in the presence of a downgrade dummy and the level of the credit rating, the dispersion effect in the cross-section of return is virtually non-existent. The downgrade dummy and credit rating are strongly significant with t-ratios given by −11.59 and −3.59, respectively. The cross-sectional impact of forecast dispersion on future returns is captured by credit rating level and by credit rating downgrades.

Next, we compute payoffs to dispersion strategies during no-downgrade periods using the 236,357 $[255,034-18,677]$ observations. Panel B of Table 8 reports dispersion profitability based on five credit rating and five dispersion groups. Strikingly, implementing dispersion strategies during no-downgrade periods generates profits that are statistically insignificant across all credit rating groups. The dispersion payoffs range from 6 to 36 basis points per month, all of which are insignificant.

To get an additional perspective about the impact of rating downgrades on dispersion profitability we plot in Fig. 2 the wealth accumulated by taking long (short) positions in stocks with low (high) dispersion in analysts' earnings forecasts starting from October 1985 but excluding from the analysis periods around downgrades. Investing $1 in dispersion strategies implemented among the highest quality stocks (C_1) yields a payoff of $1.14 in December 2003. The corresponding payoff is $1.62 when the investment universe is composed of low quality stocks

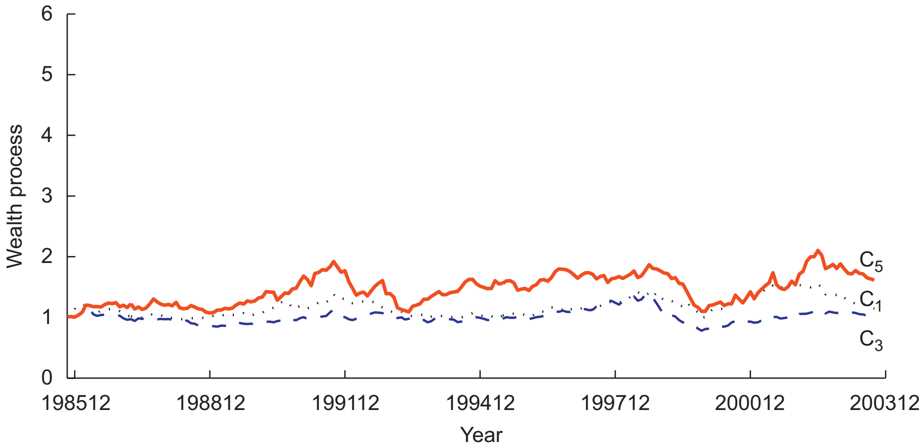

Fig. 2. Wealth process of dispersion strategy in non-downgrade periods. We repeat the strategy outlined in Fig. 1, after excluding return observations of stocks three-months-around rating downgrades ($t-3:t+3$). Each month t, all stocks rated by Standard & Poor's that do not have downgrades in the preceding three months or the subsequent three months are divided into quintiles based on credit rating. For each credit rating quintile, we further sort stocks into quintiles based on dispersion and assume we are \$1 long in the lowest dispersion quintile (D_1) and \$1 short in the highest dispersion quintile (D_5) and hold these positions for one month. This dispersion strategy is followed from October 31, 1985 until December 31, 2003, and includes a total of 3,261 rated stocks. The plot illustrates the wealth processes for rating quintiles C_1 (highest-rated), C_5 (lowest-rated), and the middle quintile C_3.

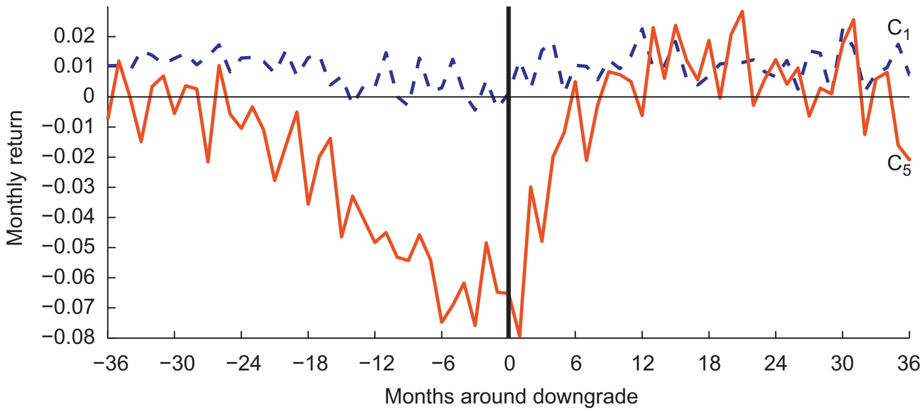

Fig. 3. Returns around rating downgrades. Each month t, stocks with available S&P ratings in Compustat are divided into rating quintiles. Within each quintile, we find stocks that have been downgraded that month and compute their equally weighted average returns over each month from $t-36$ to $t+36$. We repeat this every month. The figure presents these average monthly portfolio returns for the best (C_1) and worst (C_5) rated quintile portfolios around periods of rating downgrades. Month 0 is the month of downgrade. Since S&P ratings are available in Compustat on a quarterly basis, we assume the downgrade happens in the first month of the quarter, $t=0$. The sample consists of 3,261 companies over the period of July 1985–December 2003.

(C_5). Recall from Fig. 1 that the corresponding payoffs are \$1.28 and \$4.82, respectively, when periods of downgrades are included.

Whereas Fig. 2 undertakes the calendar-time perspective, it is also useful to examine the downgrade effect from an event-time perspective. Fig. 3 plots monthly returns around credit rating downgrades. The overall evidence shows that returns on high quality stocks (C_1) display virtually no sensitivity to deteriorating credit conditions. In contrast, prices of low quality stocks (C_5) decrease substantially during periods of worsening credit conditions. At the same time, Fig. 4 displays that analyst dispersion of C_5 stocks rises drastically, while that of C_1 stocks is almost unaffected by the downgrade. This price drop accompanied by an increasing forecast dispersion in high credit risk stocks around downgrades ultimately generates the dispersion effect in the cross-section of returns.

As shown throughout, credit rating downgrade periods are characterized by substantial price drops among low-rated stocks. An essential question remains: are worsening credit conditions merely proxying for negative past returns? To make sure that credit rating changes are economically meaningful, we implement dispersion strategies for different subsamples similar to Table 4, but progressively eliminate loser stocks (rather than low-rated stocks) from the analysis.

Table 9 reports the results. Eliminating the 4–52% of the largest negative past return stocks yields an investment universe with statistically and economically

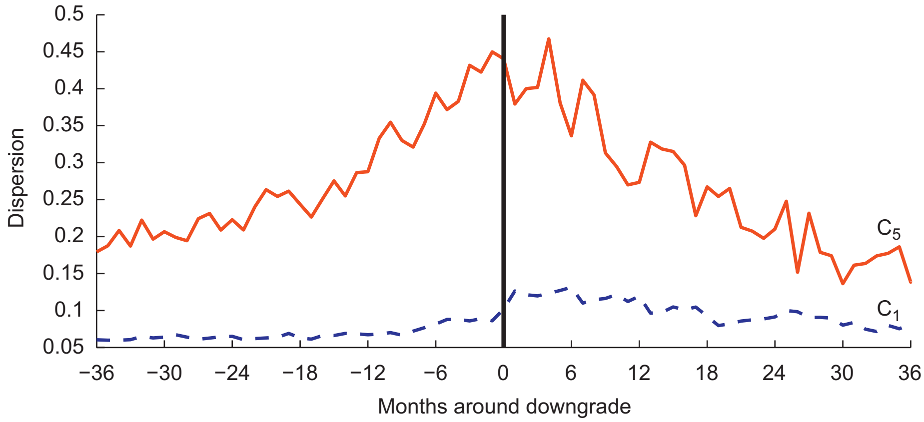

Fig. 4. Dispersion around rating downgrades. Each month t, stocks with available S&P ratings in Compustat are divided into rating quintiles. Within each quintile, we find stocks that have been downgraded that month and compute their average dispersion over each month from $t-36$ to $t+36$. We repeat this every month. The figure presents these average monthly portfolio dispersion averages for the best (C_1) and worst (C_5) rated quintile portfolios around periods of rating downgrades. Month zero is the month of downgrade. Since S&P ratings are available in Compustat on a quarterly basis, we assume the downgrade happens in the first month of the quarter, $t=0$. The sample consists of 3,261 companies over the period of July 1985–December 2003.

Table 9
Dispersion strategy payoffs over diminishing subsamples based on cumulative past returns

We implement the dispersion strategy over diminishing subsamples of firms as in Table 4, but each month we sequentially remove increments of 4% of the worst performing stocks, i.e., the stocks whose cumulative returns are the worst over the past six months. t-statistics are shown in parentheses with bold indicating 5% significance. The sample consists of 3,261 companies over the period of July 1985–December 2003.

Stock sample	Dispersion profits	Percent of total market cap	Number of firms	Percentage of firms
All Firms	0.76 (**3.35**)	100.00	1,154.00	100.00
Top 96%	0.50 (**2.28**)	100.00	1,127.70	97.72
Top 92%	0.48 (**2.21**)	99.05	1,080.73	93.65
Top 88%	0.44 (**2.11**)	96.20	1,033.83	89.59
Top 84%	0.43 (**2.06**)	93.19	986.83	85.51
Top 80%	0.45 (**2.16**)	89.66	939.88	81.45
Top 76%	0.43 (**2.09**)	86.01	892.96	77.38
Top 72%	0.46 (**2.17**)	82.19	845.97	73.31
Top 68%	0.47 (**2.23**)	78.21	799.03	69.24
Top 64%	0.46 (**2.18**)	73.87	752.13	65.18
Top 60%	0.42 (**1.98**)	69.51	705.11	61.10
Top 56%	0.45 (**2.07**)	65.25	658.19	57.04
Top 52%	0.46 (**2.10**)	60.89	611.19	52.96
Top 48%	0.45 (**2.03**)	55.98	564.31	48.90
Top 44%	0.42 (1.85)	51.40	517.31	44.83
Top 40%	0.44 (1.94)	46.99	470.38	40.76

significant dispersion profitability greater than 40 basis points per month. Altogether, the evidence from Table 9 shows that the event of worsening credit conditions carries meaningful information about the cross-section of stock returns and is not merely a facet of poor past returns.

4. Conclusion

This paper establishes a link between credit rating and the profitability of trading strategies that are based on dispersion in analysts' earnings forecasts. The empirical findings are based on a sample of 3,261 NYSE, Amex, and Nasdaq firms rated by S&P over the July 1985–December 2003 period. The selected sample is representative in capturing the negative relation between dispersion and future returns as well as the negative relation between credit risk and future returns, both of which have been perceived to establish anomalous patterns in the cross-section of returns.

Our analysis shows that the documented profitability of dispersion strategies is driven by the worst-rated firms, which account for less than 5% of the overall market capitalization of rated firms. In contrast, dispersion profitability is non-existent among higher quality firms. Even within the small universe of low-rated firms, an adjusted dispersion measure that excludes the credit risk component has no statistical power to predict the cross-section of future returns. Moreover, implementing dispersion strategies using credit rating-adjusted returns yields payoffs that are economically small and statistically insignificant. Firm size, leverage, volatility, past returns, institutional ownership, and turnover, all of which have been proposed by previous work to explain the dispersion–return relation, do not capture the impact of credit rating on dispersion profitability.

Financial distress drives the dispersion effect. In particular, the negative cross-sectional relation between dispersion in analysts' earnings forecasts and future stock returns prevails only during periods of credit rating downgrades. In such periods, prices of low-rated stocks decline substantially and the uncertainty about firm fundamentals (measured by analyst forecast dispersion, forecast revisions, or earnings surprises) rises considerably. In the remaining periods, which consist of about 92.68% of the overall observations in our sample, the dispersion–return relation is insignificant.

References

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time series effects. Journal of Financial Markets 5, 31–56.
Avramov, D., Chordia, T., Jostova, G., Philipov, A., 2006. Credit ratings and the cross-section of stock returns. Working Paper, University of Maryland.
Avramov, D., Chordia, T., Jostova, G., Philipov, A., 2007. Momentum and credit rating. Journal of Finance 62, 2503–2520.
Campbell, J.Y., Hilscher, J., Szilagyi, J., 2008. In search of distress risk. Journal of Finance 63, 2899–2939.
Carhart, M.M., 1997. On persistence in mutual fund performance. Journal of Finance 52, 57–82.
D'Avolio, G., 2002. The market for borrowing stock. Journal of Financial Economics 66, 271–306.
Dichev, I.D., 1998. Is the risk of bankruptcy a systematic risk? Journal of Finance 53, 1131–1147.
Dichev, I.D., Piotroski, J.D., 2001. The long-run stock returns following bond rating changes. Journal of Finance 56, 55–84.
Diether, K.B., Malloy, C.J., Scherbina, A., 2002. Difference of opinion and the cross-section of stock returns. Journal of Finance 57, 2113–2141.
Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.
Fama, E.F., MacBeth, J.D., 1973. Risk, return, and equilibrium: empirical tests. Journal of Political Economy 81, 607–636.
Griffin, J.M., Lemmon, M.L., 2002. Book-to-market equity, distress risk, and stock returns. Journal of Finance 57, 2317–2336.
Hand, J.R.M., Holthausen, R.W., Leftwich, R.W., 1992. The effect of bond rating agency announcements on bond and stock prices. Journal of Finance 47, 733–752.
Johnson, T.C., 2004. Forecast dispersion and the cross-section of expected returns. Journal of Finance 59, 1957–1978.
Merton, R.C., 1974. On the pricing of corporate debt: the risk structure of interest rates. Journal of Finance 29, 449–470.
Moskowitz, T.J., Grinblatt, M., 1999. Do industries explain momentum? Journal of Finance 54, 1249–1289.
Sadka, R., Scherbina, A., 2007. Analyst disagreement, mispricing, and liquidity. Journal of Finance 62, 2367–2403.
Vassalou, M., Xing, Y., 2004. Default risk in equity returns. Journal of Finance 59, 831–868.
Zhang, X.F., 2006. Information uncertainty and stock returns. Journal of Finance 61, 105–136.