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Momentum and Credit Rating

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ABSTRACT

This paper establishes a robust link between momentum and credit rating. Momentum profitability is large and significant among low-grade firms, but it is nonexistent among high-grade firms. The momentum payoffs documented in the literature are generated by low-grade firms that account for less than 4% of the overall market capitalization of rated firms. The momentum payoff differential across credit rating groups is unexplained by firm size, firm age, analyst forecast dispersion, leverage, return volatility, and cash flow volatility.

JEGADEESH AND TITMAN (1993) DOCUMENT that the momentum-based trading strategy of buying past winners and selling past losers provides statistically significant and economically large payoffs. The empirical evidence on stock return momentum is intriguing because it points to a violation of weak-form market efficiency. In particular, Fama and French (1996) show that momentum profitability is the only CAPM-related anomaly unexplained by the Fama and French (1993) three-factor model. Moreover, Schwert (2003) demonstrates that market anomalies related to profit opportunities, including the size and value effects in the cross-section of average returns as well as time-series predictability of returns by the dividend yield, typically disappear, reverse, or attenuate following their discovery. In contrast, Jegadeesh and Titman (2001, 2002) document the profitability of momentum strategies after their initial discovery. The robustness of momentum profitability has generated a variety of explanations, both behavioral and risk based.[1]

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[1] See, for example, Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), Hong, Lim, and Stein (2000), Chordia and Shivakumar (2002), Grinblatt and Han (2005), and Avramov and Chordia (2006a), among others.

It has also been shown that momentum profitability is related to business conditions. Specifically, Chordia and Shivakumar (2002) document that momentum payoffs are large during expansions and nonexistent during recessions. Avramov and Chordia (2006a) demonstrate that the impact of past returns on future returns cannot be captured by conditional and unconditional risk-based asset pricing models. However, they show that the momentum payoffs are related to the component of model mispricing that varies with business cycle variables such as the Treasury bill yield, the term spread, and the default spread. Moreover, Avramov and Chordia (2006b) show that an optimizing investor who uses these business cycle variables is able to successfully load on the momentum strategy during different phases of the economy. Since credit risk varies over the business cycle, it is natural to ask whether the momentum payoffs are related to the credit risk of firms. In this paper, we provide a new and unexplored dimension in understanding the profitability of momentum strategies. We show that momentum profits are restricted to high credit risk firms and are nonexistent for firms of high credit quality.

Specifically, based on a sample of 3578 NYSE, AMEX, and NASDAQ firms rated by S&P over the July 1985 to December 2003 period,[2] we show that over formation periods of three, 6, 9, and 12 months, the extreme loser and winner portfolios of Jegadeesh and Titman (1993) consist of stocks with the lowest and the next-lowest credit rating, respectively. The average rating of the entire sample of rated firms is BBB. The extreme loser (winner) portfolio has an average rating of BB– (BB+). The extreme losers and winners are the only noninvestment grade portfolios in the sample of rated firms.

Trading strategies that condition on three credit rating and 10 prior 6-month return groups yield momentum payoffs that increase monotonically with credit risk—they increase from an insignificant 0.27% per month for the best quality debt tercile to a significant 2.35% for the worst. Similarly, based on 10 credit rating and 3 past return portfolios, momentum payoffs increase from an insignificant 0.07% per month for the highest credit quality decile to a significant 2.04% for the worst. Among the low-rated firms, loser stocks are the dominant source of return continuation and the profitability of momentum strategies. Based on 10 credit risk and 3 past return groups, the return differential between the lowest and highest credit risk loser firms averages 1.60% per month, whereas the return differential for the winner firms is, on average, only 0.37%.

We also implement momentum strategies based on the prior 6-month return for different samples of rated firms, as we sequentially exclude the lowest-rated firms. Strikingly, the significant profits to momentum strategies are derived from a sample of firms that accounts for less than 4% of the market capitalization of all rated firms and for about 22% of the total number of rated firms. When we exclude firms with an overall S&P rating of D, C, CC, CCC–, CCC, CCC+, B–, B, B+, and BB–, the momentum strategy payoffs from the remaining firms,

[2] We use the S&P Long-Term Domestic Issuer Credit Rating. Data on this variable are available on Compustat on a quarterly basis starting from the second quarter of 1985.

which account for 96.6% of the overall market capitalization of rated firms, become statistically insignificant.

Recent work demonstrates the significance of momentum for certain subsamples of stocks. For instance, Jiang, Lee, and Zhang (2005) and Zhang (2006) find evidence of higher momentum payoffs among firms with higher information uncertainty. Information uncertainty is proxied by firm size, firm age, return volatility, cash flow volatility, and analyst forecast dispersion. However, our findings suggest that the credit rating effect on momentum is both independent of and much stronger than the effect of all these information uncertainty variables. In particular, the information uncertainty variables do not capture the momentum profits across credit rating groups whereas credit rating does capture the momentum profits across the uncertainty variables. Specifically, momentum payoffs exist among large-capitalization firms that are low rated, but are absent in highly rated small-capitalization firms. Thus, while momentum profitability does not arise exclusively in small stocks, it is found exclusively among low-rated stocks.

The rest of the paper is organized as follows. Section I presents the data. Section II presents the results and Section III presents robustness checks. Section IV concludes.

I. Data

We extract monthly returns on all NYSE, AMEX, and NASDAQ stocks listed in the CRSP database, subject to several selection criteria. First, stocks must have at least six consecutive monthly return observations. In addition, as in Jegadeesh and Titman (2001), we exclude stocks that, at the beginning of the holding period, are priced below \$5 or have market capitalization that would place them in the bottom NYSE decile. This is done to ensure that the empirical findings are not driven by low-priced and extremely illiquid stocks. However, we find that our results are robust to the inclusion of stocks below \$5 and those that belong to the smallest decile. The filtering procedure delivers a universe of 13,018 stocks. From this universe, we choose those stocks that are rated by Standard & Poor's, leaving us with 3,578 rated stocks over the July 1985 through December 2003 period. The beginning of our sample is determined by the first date for which firm ratings by Standard & Poor's are available on the COMPUSTAT tapes.

The S&P issuer rating used in this paper is an essential component of our analysis. Standard & Poor's assigns this rating to a firm, not an individual bond. As defined by S&P, prior to 1998, this issuer rating is based on the firm's most senior publicly traded debt. After 1998, this rating is based on the overall quality of the firm's outstanding debt, either public or private. The pre-1998 issuer rating therefore represents a select subsample of company bonds, while after 1998 it represents all company debt. We transform the S&P ratings into conventional numerical scores, where 1 represents a AAA rating and 22 reflects a D rating.[3] Thus, a higher numerical score corresponds to a lower credit rating or 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 noninvestment grade. The equally weighted average rating of the 3,578 firms in our sample is 8.83 (approximately BBB, the investment-grade threshold) and the median is 9 (BBB).

To ensure that our sample of stocks is representative, in Table I we compare rated and unrated firms. It is important to note that although the total number of rated firms is much smaller than that of unrated firms (3,578 rated firms and 9,440 unrated firms, for a ratio of 1 to 2.6), the average per month number of rated and unrated firms is considerably closer (1,639 rated firms and 2,246 unrated firms, for a more appealing ratio of 1 to 1.4).

Panel A of Table I presents monthly returns for the loser portfolio (P1), the winner portfolio (P10), and the momentum strategy of buying the winner portfolio and selling the loser portfolio (P10−P1). Momentum portfolios are constructed as in Jegadeesh and Titman (1993). At the beginning of each month t, we rank all eligible stocks on the basis of their cumulative return over the formation period (months $t-6$ to $t-1$) and assign them to 1 of 10 portfolios based on their prior 6-month return. These portfolios are then held for K months. We skip a month between the formation and holding periods (months $t+1$ to $t+K$). Each portfolio return is calculated as the equally weighted average return of the corresponding stocks. The monthly momentum strategy return for a K-month holding period is based on an equally weighted average of the portfolio returns from strategies implemented in the current month and the previous $K-1$ months.[4]

The evidence in Panel A suggests similar momentum profitability among rated and unrated stocks. In particular, the momentum strategy (P10–P1) averages a profit of 1.29% (t-stat $= 3.15$) per month for rated firms and 1.43% (t-stat $= 3.41$) for unrated firms. For both rated and unrated firms, momentum profits are prominent over expansionary periods, as well as in non-January months; consistent with Jegadeesh and Titman (1993), momentum profits are negative in January. We also examine the industry distribution of our sample of 3,578 S&P rated firms relative to the overall sample of 13,018 NYSE, AMEX, and NASDAQ firms listed on CRSP. The 20 industries considered are those analyzed by Moskowitz and Grinblatt (1999). The evidence shows (results are available upon request) that the industry distributions of rated and unrated firms are similar, ruling out concerns that rated firms are concentrated in particular industries.

[3] 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, and D = 22.

[4] A number of stocks delist from our sample over the holding period. Loser stocks are likely to delist due to low prices or bankruptcy while winner stocks may delist due to an acquisition. This could potentially lead to biased results. To ensure that there are no delisting biases, throughout the paper we use the delisting return whenever a stock disappears from our sample.

Table I

Descriptive Statistics

Panel A presents raw momentum in rated and unrated firms. For each month t, all NYSE, AMEX, and NASDAQ stocks on the monthly CRSP tape with returns for months $t - 6$ through $t - 1$ are ranked into decile portfolios according to their cumulative return during that period. We exclude stocks that, at the end of month $t - 1$, are priced below \$5 or are smaller than the smallest NYSE size decile. Decile portfolios are formed monthly and their returns are computed by weighting equally all firms in that decile ranking. The momentum strategy involves buying the winner portfolio (P10) and selling the loser portfolio (P1). The positions are held for the following 6 months ($t + 1$ through $t + 6$). There is a 1-month lag between the formation and the holding periods. Monthly returns represent the equally weighted average return from this month's momentum strategy and all strategies from up to 5 months ago. The table shows the average raw monthly profits during the holding period of the winner and loser portfolios as well as the momentum strategy returns. t-statistics are in parentheses, with * denoting significance at the 5% level. The sample period is July 1985 to December 2003. Panel B presents descriptive statistics of monthly returns for stocks rated by Standard & Poor's and for all stocks listed on CRSP. Returns are computed as the time-series mean of the cross-sectional average return for each month (in % per month). Standard deviation, skewness, kurtosis, alpha (% per month), and beta are computed for each stock and then averaged across all stocks. Alphas and betas are based on stocks with at least 25 return observations during the sample period. Size is computed as the time-series mean of the cross-sectional mean of all market capitalizations in each month (in \$billions).

Panel A: Raw Momentum in Rated and Unrated Firms				
		All Firms	Rated Firms	Unrated Firms
# of Firms		13,018	3,578	9,440
Overall	P10–P1	1.49	1.29	1.43
		(3.48)*	(3.15)*	(3.41)*
	P1	0.17	0.25	–0.05
		(0.29)	(0.45)	(–0.07)
	P10	1.66	1.54	1.39
		(3.15)*	(3.74)*	(2.46)*
Non-January	P10–P1	1.82	1.54	1.81
		(4.55)*	(3.96)*	(4.70)*
	P1	–0.32	–0.07	–0.60
		(–0.55)	(–0.13)	(–0.99)
	P10	1.51	1.47	1.21
		(2.69)*	(3.37)*	(2.02)*
January	P10–P1	–2.36	–1.58	–2.86
		(–0.92)	(–0.65)	(–1.08)
	P1	5.72	3.97	6.21
		(1.90)	(1.53)	(1.91)
	P10	3.37	2.39	3.34
		(2.59)*	(1.91)	(2.49)*
Expansion	P10–P1	1.49	1.27	1.43
		(3.39)*	(3.03)*	(3.31)*
	P1	0.12	0.30	–0.14
		(0.20)	(0.55)	(–0.23)
	P10	1.61	1.57	1.29
		(2.95)*	(3.72)*	(2.21)*
Recession	P10–P1	1.42	1.48	1.46
		(0.80)	(0.83)	(0.81)
	P1	0.83	–0.29	1.14
		(0.24)	(–0.09)	(0.32)
	P10	2.25	1.18	2.60
		(1.09)	(0.65)	(1.18)

(*continued*)

Table I—*Continued*

Panel B: Return and Size Characteristics of Sample Firms		
	Firms Rated by S&P	All Firms
Return – equally weighted mean	1.35	1.24
Return – value weighted mean	1.11	1.09
Return – standard deviation	12.39	13.50
Return – skewness	0.25	0.34
Return – kurtosis	5.00	5.13
CAPM alpha – mean	0.16	0.05
CAPM beta – mean	1.04	1.06
FF alpha – mean	–0.01	0.02
FF mkt beta – mean	1.14	1.04
Size – mean	3.06	0.98

Panel B of Table I provides descriptive statistics for the distribution of raw monthly returns in the sample of rated and unrated firms. The moments of the stock return distribution, as well as the average alphas and market betas, are similar across the two categories. For instance, the mean monthly stock return is 1.35% among rated firms and 1.24% among all firms during the period July 1985 to December 2003. The mean CAPM alpha (beta) of rated firms is 0.16% (1.04), and 0.05% (1.06) among all firms. The mean Fama-French alpha is −0.01% (0.02%) per month for rated (all) firms. It is also evident from Panel B that rated firms have substantially larger market capitalization than unrated firms.

Overall, Table I confirms that our sample of rated firms is representative. Both rated and unrated firms produce similar momentum profits, they share similar industry distributions, and they have similar stock return distributions.

II. Results

A. Momentum and Firm Credit Rating over the Formation Period

To establish the first link between momentum trading strategies and credit risk, we examine the average numerical credit rating for each of the 10 momentum portfolios over formation periods of 3, 6, 9, and 12 months. The results are presented in Table II. The extreme loser portfolio (P1) is heavily tilted towards firms with the lowest quality debt. For example, focusing on a 6-month formation period, the average numerical rating of the loser portfolio is 13.06 (BB–), which is much higher than the average rating of 8.83 (BBB). The extreme winner portfolio (P10) also consists of high credit risk stocks, recording an average credit rating of 11.19 (BB+). The middle portfolio (P6) has the best credit rating of 7.64 (BBB+). Indeed, the average credit rating forms a U-shape across the various momentum portfolios. This suggests that the momentum strategy of

Table II

Credit Rating Profile of Momentum Portfolios over Formation Period

For each month t, all stocks rated by Standard & Poor's with returns for months $t - J$ through $t - 1$ (formation period) available on CRSP are ranked into decile portfolios according to their return during the formation period. We exclude stocks that, at the end of month $t - 1$, are priced below \$5 or are smaller than the smallest NYSE size decile. The table shows for each decile portfolio the median numeric S&P rating during formation periods of $J = 3$, 6, 9, and 12 months. This S&P rating is assigned by Standard & Poor's to a firm (not a bond) based on the overall quality of the firm's outstanding debt, either public or private. The rating is available from COMPUSTAT on a quarterly basis starting in 1985. We transform the S&P ratings into conventional numeric scores. The numeric rating corresponds to: 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, and D = 22. The sample period is July 1985 to December 2003.

	$J = 3$	$J = 6$	$J = 9$	$J = 12$
P1	12.85	13.06	13.18	13.22
P2	9.84	10.12	10.29	10.30
P3	8.66	8.64	8.69	8.62
P4	8.06	8.07	8.00	7.93
P5	7.77	7.75	7.64	7.58
P6	7.72	7.64	7.61	7.49
P7	7.81	7.69	7.60	7.53
P8	8.08	7.89	7.70	7.66
P9	8.91	8.59	8.34	8.22
P10	11.44	11.19	11.01	10.91

buying previous losers and selling previous winners essentially takes long and short positions in firms with the highest credit risk.

Table III presents the composition of unrated, investment grade, and noninvestment grade firms in decile portfolios sorted on past 6-month returns. There are more unrated firms in the extreme winner and loser portfolios. Also, there are significantly fewer firms with investment grade rating and more firms with noninvestment grade rating in the extreme portfolios. Finally, the return differential between the winner and loser portfolios is a statistically insignificant (significant) 0.77% (2.12%) per month for the investment (noninvestment) grade firms and is 1.48% for the unrated firms. Overall, the evidence supports our claim that firms with a low credit rating, or firms that would be low rated if they had a rating, drive the momentum phenomenon.

B. Momentum Profitability and Credit Rating

We implement momentum strategies by conditioning on both credit rating and cumulative 6-month formation period returns. We first consider 3 credit rating groups and 10 formation period return portfolios. We then study 10 credit rating groups and 3 past 6-month return portfolios. Credit risk-past return groups are formed on a sequential basis, sorting first on credit rating and then

Table III

Composition of Momentum Portfolios

For each month t, all stocks rated by Standard & Poor's with returns for months $t-6$ through $t-1$ (formation period) available on CRSP are ranked into decile portfolios according to their return during the formation period. We exclude stocks that, at the end of month $t-1$, are priced below $5 or are smaller than the smallest NYSE size decile. The first three columns in the table show for each decile portfolio the percentage of stocks with no rating and the percentage of stocks that are investment grade (IG) and noninvestment grade (NIG). The last three columns show the equally weighted average return of the three groups in each portfolio. IG represents an S&P rating of BBB– or better and NIG represents an S&P rating of BB+ or worse. The sample period is July 1985 to December 2003. The * denotes significance at the 5% level.

	Composition (% of Stocks)			Returns (% per month)		
Portfolio	No Rating	IG	NIG	No Rating	IG	NIG
P1	75.24	9.32	15.44	0.17	0.97	–0.32
P2	70.92	17.63	11.44	0.57	1.08	0.22
P3	69.80	21.20	9.00	0.81	1.09	0.52
P4	70.52	22.01	7.47	0.93	1.11	0.81
P5	70.68	22.63	6.69	0.99	1.12	0.81
P6	69.70	23.70	6.60	1.03	1.13	0.77
P7	69.31	23.55	7.15	1.14	1.12	0.78
P8	70.04	21.47	8.50	1.19	1.17	1.01
P9	73.08	16.81	10.11	1.35	1.30	1.11
P10	81.58	7.13	11.29	1.65	1.74	1.80
P10−P1				1.48	0.77	2.12
				(3.70)*	(1.77)	(4.29)*

on past returns.[5] For each month t, the low(high) credit risk group (group 1 (group 3)) contains the 30% best(worst)-rated stocks based on their S&P rating for this particular month. The stocks in each group are then divided into 10 momentum portfolios based on their return over months $t-6$ to $t-1$. The 10 credit risk groups are formed each month by dividing the sample of firms in that month into deciles based on the credit ratings. Each of the resulting credit rating groups is then divided into three momentum portfolios (P1, P2, and P3) containing the worst 30%, middle 40%, and top 30% performers based on their past 6-month returns. The two sequential rankings generate 30 credit risk-momentum portfolios.

Panel A of Table IV presents the momentum profits corresponding to the 3 credit risk and 10 momentum groups. Payoffs to momentum strategies strongly depend upon credit rating. Focusing on the low (stocks with an average rating of 4.97 ≈ A+) and medium (average rating of 8.5 ≈ BBB+) credit risk groups, the average payoff to the P10−P1 strategy is 0.27% (t-stat = 0.88) and 0.75% (t-stat = 2.12) per month, respectively. The payoff is much larger as

[5] We verify that our results hold for independent sorts as well.

Table IV

Momentum by Credit Risk Group

For each month t, all stocks rated by Standard & Poor's with available return data for months $t-6$ through $t-1$ are divided into three groups, top 30%, middle 40%, and bottom 30% (Panel A), as well as deciles (Panel B), based on their credit rating. We exclude stocks that, at the end of month $t-1$, are priced below \$5 or are smaller than the smallest NYSE size decile. For each credit rating group, we compute the return of the loser portfolio P1 as the equally weighted average return over the holding period of the worst performing 10% (Panel A, 30% Panel B) and the winner portfolio P10 (P3 in Panel B) of the best-performing 10% (Panel A, 30% Panel B) of the stocks based on their returns over the formation period. There is a 1-month lag between the formation and the holding periods. The momentum strategy involves buying the winner portfolio and selling the loser portfolio and holding the position for 6 months. Since the momentum strategy is implemented each month, the monthly returns represent the equally weighted average return from this month's momentum strategy and all strategies from up to 5 months ago. For each credit rating group, the table shows the average returns of the momentum strategy, as well as the average return of the loser and winner portfolios. The sample period is July 1985 to December 2003. The numeric S&P rating is presented in ascending order by credit risk, that is, 1 = AAA, 2 = AA+, 3 = AA, . . . , 21 = C, and 22 = D. The * denotes significance at the 5% level.

Panel A: 10 Momentum and 3 Credit Rating Groups

		Rating Group (1 = Lowest Risk, 3 = Highest Risk)		
		1	2	3
Average Rating		A+ 4.97	BBB+ 8.50	BB 13.02
Overall	P10−P1	0.27	0.75	2.35
		(0.88)	(2.12)*	(4.21)*
	P1	1.12	0.81	–0.43
		(2.81)*	(1.68)	(–0.59)
	P10	1.40	1.56	1.92
		(4.13)*	(4.26)*	(3.77)*
Non-January	P10−P1	0.43	0.95	2.70
		(1.38)	(2.69)*	(5.21)*
	P1	0.98	0.61	–0.92
		(2.36)*	(1.21)	(–1.28)
	P10	1.41	1.56	1.78
		(4.03)*	(4.05)*	(3.31)*
January	P10−P1	–1.54	–1.55	–1.59
		(–1.10)	(–0.93)	(–0.45)
	P1	2.76	3.10	5.08
		(1.87)	(1.80)	(1.29)
	P10	1.22	1.55	3.48
		(0.94)	(1.31)	(2.36)*
Expansion	P10−P1	0.30	0.78	2.30
		(0.94)	(2.12)*	(4.02)*
	P1	1.14	0.85	–0.39
		(2.95)*	(1.78)	(–0.55)
	P10	1.44	1.63	1.91
		(4.11)*	(4.32)*	(3.69)*
Recession	P10−P1	–0.06	0.38	3.01
		(–0.04)	(0.29)	(1.23)
	P1	0.89	0.34	–0.94
		(0.38)	(0.13)	(–0.21)
	P10	0.84	0.72	2.07
		(0.65)	(0.47)	(0.86)

(*continued*)

Table IV—*Continued*

Panel B: 3 Momentum and 10 Credit Rating Groups											
Rating Decile (1 = Lowest Risk, 10 = Highest Risk)											
Average		AA	A+	A	A–	BBB+	BBB	BBB–	BB	BB–	B
Rating		3.17	4.98	6.13	7.09	8.04	9.03	10.13	11.82	13.19	14.52
Overall	P3−P1	0.07	0.07	0.15	0.20	0.21	0.32	0.55	0.73	1.12	2.04
		(0.32)	(0.36)	(0.73)	(0.94)	(1.01)	(1.52)	(2.18)*	(2.46)*	(3.46)*	(4.63)*
	P1	1.13	1.11	1.14	1.08	0.95	0.95	0.85	0.56	0.17	–0.47
		(3.67)*	(3.36)*	(3.20)*	(2.98)*	(2.63)*	(2.55)*	(1.98)*	(1.14)	(0.31)	(–0.69)
	P3	1.19	1.19	1.28	1.28	1.17	1.27	1.40	1.29	1.29	1.56
		(3.96)*	(3.94)*	(4.17)*	(4.11)*	(3.74)*	(3.93)*	(4.00)*	(3.14)*	(2.88)*	(3.04)*
Non-January	P3−P1	0.22	0.17	0.25	0.30	0.30	0.42	0.70	0.96	1.34	2.28
		(1.05)	(0.84)	(1.25)	(1.43)	(1.46)	(2.03)*	(2.81)*	(3.34)*	(4.35)*	(5.52)*
	P1	1.03	1.04	1.03	0.98	0.86	0.82	0.67	0.27	–0.20	–0.93
		(3.25)*	(3.02)*	(2.81)*	(2.61)*	(2.30)*	(2.13)*	(1.51)	(0.53)	(–0.36)	(–1.40)
	P3	1.26	1.21	1.28	1.27	1.17	1.24	1.38	1.23	1.15	1.36
		(4.06)*	(3.89)*	(4.01)*	(3.91)*	(3.57)*	(3.67)*	(3.75)*	(2.85)*	(2.42)*	(2.52)*
January	P3−P1	–1.68	–1.07	–1.05	–0.94	–0.84	–0.87	–1.23	–1.98	–1.43	–0.77
		(–1.80)	(–1.24)	(–1.10)	(–0.88)	(–0.80)	(–0.86)	(–1.06)	(–1.33)	(–0.77)	(–0.29)
	P1	2.16	1.95	2.31	2.27	2.00	2.46	2.83	3.88	4.40	4.68
		(1.86)	(1.58)	(1.72)	(1.59)	(1.40)	(1.72)	(1.92)	(2.26)*	(1.68)	(1.28)
	P3	0.48	0.87	1.26	1.33	1.16	1.59	1.60	1.90	2.96	3.91
		(0.38)	(0.75)	(1.11)	(1.23)	(1.10)	(1.41)	(1.43)	(1.50)	(2.20)*	(2.39)*
Expansion	P3−P1	0.10	0.11	0.17	0.21	0.25	0.37	0.60	0.78	1.06	1.92
		(0.43)	(0.51)	(0.82)	(0.96)	(1.17)	(1.71)	(2.34)*	(2.55)*	(3.21)*	(4.30)*
	P1	1.12	1.11	1.14	1.11	0.96	0.94	0.85	0.56	0.19	–0.40
		(3.70)*	(3.40)*	(3.29)*	(3.12)*	(2.68)*	(2.54)*	(2.01)*	(1.16)	(0.35)	(–0.61)
	P3	1.22	1.22	1.31	1.32	1.21	1.30	1.45	1.33	1.25	1.51
		(3.90)*	(3.91)*	(4.13)*	(4.13)*	(3.76)*	(3.92)*	(4.01)*	(3.18)*	(2.79)*	(2.92)*
Recession	P3−P1	–0.26	–0.35	–0.10	0.07	–0.26	–0.28	–0.10	0.12	1.80	3.49
		(–0.37)	(–0.42)	(–0.11)	(0.08)	(–0.28)	(–0.32)	(–0.09)	(0.10)	(1.28)	(1.68)
	P1	1.14	1.13	1.04	0.72	0.92	1.14	0.85	0.59	–0.00	–1.33
		(0.68)	(0.61)	(0.51)	(0.35)	(0.45)	(0.56)	(0.36)	(0.20)	(–0.00)	(–0.33)
	P3	0.87	0.78	0.94	0.79	0.66	0.86	0.75	0.71	1.80	2.16
		(0.76)	(0.66)	(0.74)	(0.59)	(0.51)	(0.64)	(0.54)	(0.39)	(0.77)	(0.87)

well as statistically and economically significant at 2.35% (t-stat = 4.21) for the highest credit risk group (rating of 13.02 ≈ BB–). Momentum profits are highest in firms with the poorest quality of outstanding debt, as rated by S&P. This is a new finding that sheds light on the source of profitability of momentum strategies.

Momentum strategy payoffs in the non-January months are also insignificant for the lowest risk tercile. For the medium risk stocks the momentum payoffs are a significant 0.95% per month and for the high risk stocks the payoffs are 2.70% per month. The payoffs in January are negative albeit statistically insignificant. During recessions, the momentum strategy payoffs increase monotonically with credit risk but are statistically insignificant.[6] On the other hand, during expansions, not only do the payoffs increase monotonically with

[6] Recessionary and expansionary months are identified by NBER.

credit risk, but they are a statistically and economically significant 2.30% per month for the poorest credit quality firms.

Panel B of Table IV presents the results for 10 credit risk and 3 momentum portfolios. Again, the evidence shows that momentum profits strongly depend on credit risk. Focusing on the lowest risk group (an average rating of 3.17 ≈ AA), the monthly momentum profit (P3−P1) is an insignificant 0.07%. Payoffs to momentum strategies increase monotonically across the credit rating groups. The highest momentum payoff of 2.04% (t-stat = 4.63) per month is recorded for the highest credit risk group (an average rating of 14.52 ≈ B). Consistent with the results in Table III, momentum profits become statistically significant only when credit quality deteriorates to a rating of BBB– or below (BBB or below for the non-January months). Further, during economic expansions, it is once again only stocks rated BBB– or lower that exhibit significant momentum profits. Panel B of Table IV documents that the difference in momentum profits across credit risk groups is driven primarily by loser stocks. The return differential between the loser portfolios (P1) for the lowest and highest credit risk firms averages 1.60% per month [1.13 − (−0.47)], whereas the winner portfolio (P3) for the highest credit risk firms earns, on average, only 0.37% more than its lowest credit counterpart [1.56–1.19].

Thus far, we have examined the relation between momentum profitability and credit risk using portfolio strategies based on double sorting, first by credit risk then by prior 6-month return. We now turn to implementing the traditional momentum strategies, that is, those based only on the prior 6-month return, but we consider different investment subsamples. In particular, we start with the entire sample of rated firms and then sequentially exclude firms with the highest credit risk (worst credit rating). This analysis reveals the subsample of firms that drive momentum profits.

Table V reports the average payoffs from momentum strategies in each subsample as we progressively drop the worst-rated firms. It also provides the percentage of market capitalization represented by each 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. The payoffs to momentum strategies are insignificant at the 5% level when the investment sample contains stocks in the rating range AAA through BB. Remarkably, this sample accounts for 96.62% of the market capitalization of the rated firms and it contains 78.84% of the total number of the rated firms. In other words, the momentum profits are derived from a sample of firms that accounts for less than 4% of the total market capitalization of all rated firms or less than 22% of all rated firms.

As we progressively drop the best-rated firms (results available upon request), the momentum profits increase monotonically as only the worst-rated firms remain in the sample. For a sample of stocks rated B or lower, the momentum profit amounts to 3.74% per month. More remarkably, there are only about 70 firms on average per month that are rated B or lower. These 70 firms comprise only 0.77% of the sample by market capitalization and 4.22% of the

Table V

Unconditional Momentum over Different Rating Subsamples

For each month t, all NYSE, AMEX, and NASDAQ stocks rated by S&P and available on CRSP with returns for months $t-6$ through $t-1$ are ranked into decile portfolios based on their return during that period. We exclude stocks that, at the end of month $t-1$, are priced below \$5 or are smaller than the smallest NYSE size decile. Portfolio returns are computed monthly by weighting equally all firms in that decile ranking. The momentum strategy involves buying the winner and selling the loser portfolio and holding the position for 6 months (from $t+1$ to $t+6$). The monthly returns represent the equally weighted average return from this month's momentum strategy and all strategies from up to 5 months ago. Each subsequent row in the table represents a monotonically decreasing sample of stocks obtained by sequentially excluding firms with the lowest credit rating. The first column shows the raw monthly profits from the momentum strategy for each subsample of firms. t-statistics are in parentheses. The second column shows the market capitalization of the given subsample as a percentage of the overall sample of S&P rated firms. The third (forth) column provides the average number (percentage) of firms per month in each subsample. Sample: July 1985 to December 2003. The * denotes significance at the 5% level.

Stock Sample	Momentum Profits	Percent of Total Market Cap	Number of Firms	Percentage of Firms
All firms	1.29	100.00	1,639.00	100.00
	(3.15)*			
AAA-D	1.28	100.00	1,638.79	99.99
	(3.13)*			
AAA-C	1.23	99.98	1,637.69	99.92
	(2.98)*			
AAA-CC	1.23	99.98	1,637.69	99.92
	(2.98)*			
AAA-CCC	1.21	99.97	1,636.91	99.87
	(2.96)*			
AAA-CCC	1.18	99.97	1,635.83	99.81
	(2.89)*			
AAA-CCC+	1.13	99.95	1,632.70	99.62
	(2.79)*			
AAA-B	1.12	99.90	1,625.35	99.17
	(2.81)*			
AAA-B	1.00	99.65	1,603.33	97.82
	(2.62)*			
AAA-B+	0.84	99.12	1,559.48	95.15
	(2.33)*			
AAA-BB	0.68	98.12	1,426.10	87.01
	(2.02)*			
AAA-BB	0.56	96.62	1,292.14	78.84
	(1.73)			
AAA-BB+	0.43	95.03	1,181.43	72.08
	(1.38)			
AAA-BBB	0.39	92.96	1,085.80	66.25
	(1.26)			
AAA-BBB	0.31	89.06	943.73	57.58
	(1.02)			
AAA-BBB+	0.26	82.96	762.56	46.53
	(0.84)			
AAA-A	0.23	75.65	612.67	37.38
	(0.75)			
AAA-A	0.21	68.02	467.64	28.53
	(0.69)			
AAA-A+	0.13	51.97	287.00	17.51
	(0.42)			
AAA-AA	0.33	38.94	176.44	10.76
	(1.12)			

total number of firms. In other words, the momentum phenomenon occurs in a small fraction of the worst-rated stocks.

III. Robustness Checks

In this section we conduct numerous checks to ensure that the impact of credit rating on momentum is robust to various alternative explanations.

A. Could Credit Ratings Proxy for Systematic Risk?

Thus far, we have examined raw momentum strategy payoffs. A natural exercise would be to risk-adjust the raw payoffs to ensure that the profitability of momentum strategies among high credit risk firms does not merely compensate for exposure to common sources of risk. We regress the momentum payoffs for the three credit risk groups on the three Fama and French (1993) factors as well on the excess market return. Focusing on the Fama-French factors (available upon request), we find that the monthly alphas are 0.41% (t-stat = 1.28), 1.02% (t-stat = 2.85), and 2.53% (t-stat = 4.47) for the low, middle, and high credit risk groups, respectively. If anything, the alphas are higher than the raw momentum payoffs reported in Table IV, suggesting that loser stocks are riskier than winner stocks and that the momentum strategy does not have positive exposure to systematic risk factors. The evidence strongly suggests that momentum profitability across high credit risk firms does not represent compensation for systematic risk, at least based on the CAPM and the Fama-French three-factor model.

B. Momentum Profits in Various Subsamples

Recent work argues that momentum is stronger in stocks that have high information uncertainty. Information uncertainty is the degree of ambiguity about firm fundamentals. High information uncertainty firms can be associated with higher information acquisition costs and less reliable estimates of their value. Specifically, Jiang, Lee, and Zhang (2005) and Zhang (2006) argue that price drift is larger in stocks with greater information uncertainty, which is proxied by firm size, firm age, analyst coverage, dispersion in analyst forecasts, return volatility, and cash flow volatility.[7]

An essential question that arises is whether the impact of credit ratings on momentum profitability is subsumed by information uncertainty. To address this question, we assess the robustness of momentum profitability across the credit rating dimension based on 3×3 portfolios sorted independently on credit rating and variables that proxy for information uncertainty.

Panel A of Table VI presents results for sorts by credit rating and firm size. Momentum returns increase with credit risk across all size groups. For instance, for the small (large) firms, momentum returns increase monotonically

[7] Jiang, Lee, and Zhang (2005) also show that high information uncertainty stocks have lower future returns.

Table VI

Independent Sorts by Credit Risk and Alternative Firm Characteristics

For each month t, all stocks rated by Standard & Poor's with available return data for months $t-6$ through $t-1$ (formation period) are divided into nine groups based, alternatively, on their size, volatility, leverage, cash flow volatility, age, analyst following, dispersion (bottom 30%, average 40%, and top 30%), and S&P rating (best 30%, average 40%, and worst 30%). We exclude stocks that, at the end of month $t-1$, are priced below \$5 or are smaller than the smallest NYSE size decile. For each group, the table shows the average returns of the momentum strategy, which involves buying the winner portfolio P10 of the best performing 10% of the stocks based on their returns over the formation period and selling the loser portfolio P1 and holding the position for 6 months ($t+1$ through $t+6$). Cash Flow Volatility (CVOL) is computed as in Zhang (2006) as the standard deviation of cash flow from operations in the past 5 years (with a minimum of 3 years). The Age variable represents the number of months since the firm's IPO. If the IPO date is not available in Compustat, then the Age variables represents the number of months since CRSP first reported return data for this firm. Analyst coverage is computed as the average number of analysts following a firm. Analyst dispersion is measured as the standard deviation in analyst EPS forecasts for the next quarter, extracted from I/B/E/S. The * denotes significance at the 5% level.

	Rating Tercile		
	Low Risk	Average Risk	High Risk
Panel A: Independent Sort by Credit Risk and Size			
Small	0.31	0.75	2.66
	(0.64)	(1.70)	(4.94)*
Average	0.34	0.58	2.04
	(1.05)	(1.67)	(3.23)*
Big	0.28	0.94	1.79
	(0.84)	(2.10)*	(2.25)*
Panel B: Independent Sort by Credit Risk and Volatility			
Low volatility	0.11	0.43	1.18
	(0.53)	(1.95)	(3.36)*
Average volatility	0.40	0.79	1.69
	(1.29)	(2.49)*	(4.59)*
High volatility	–0.07	1.30	2.68
	(–0.14)	(2.59)*	(4.17)*
Panel C: Independent Sort by Credit Risk and Leverage (BV(Debt)/MV(Equity))			
Low Leverage	–0.08	0.96	2.76
	(–0.21)	(2.24)*	(2.87)*
Average Leverage	–0.20	0.14	1.29
	(–0.56)	(0.40)	(2.57)*
High Leverage	0.79	0.51	2.80
	(1.50)	(1.12)	(4.10)*
Panel D: Independent Sort by Credit Risk and Age of Firm			
Young	0.45	1.02	2.75
	(0.99)	(2.31)*	(4.26)*
Average	0.23	0.65	1.82
	(0.80)	(1.96)*	(3.63)*
Old	0.17	0.51	1.50
	(0.59)	(1.59)	(3.14)*

(*continued*)

Table VI—*Continued*

	Rating Tercile		
	Low Risk	Average Risk	High Risk
Panel E: Independent Sort by Credit Risk and Cash Flow Volatility			
Low CVOL	0.20	0.38	1.21
	(0.69)	(1.03)	(1.96)*
Average CVOL	0.51	0.77	2.51
	(1.21)	(1.79)	(3.59)*
High CVOL	0.27	0.68	2.49
	(0.46)	(1.10)	(3.25)*
Panel F: Independent Sort by Credit Risk and Dispersion in Analyst Forecasts			
Low dispersion	0.28	0.76	1.57
	(0.90)	(2.01)*	(2.84)*
Average dispersion	0.07	0.37	2.04
	(0.24)	(0.98)	(3.77)*
High dispersion	0.28	0.59	2.11
	(0.74)	(1.40)	(2.81)*

from 0.31% (0.28%) to 2.66% (1.79%) per month moving from low risk to high risk firms. While the momentum profits decrease with size for the high risk firms, there is no size impact in the low risk firms. There is some interaction between firm size and credit risk as the highest momentum return exists in the small, high risk firms (2.66%) and the lowest exists in the large, low risk firms (0.28%). Overall, the evidence suggests that it is credit risk and not firm size that provides the divergent momentum returns.

Panels B and C show similar results for firm volatility and leverage.[8] For instance, when sorting independently on credit risk and volatility, the monthly momentum returns to low credit risk, high(low) volatility stocks are a statistically insignificant –0.07% (0.11%). In other words, there is no differential momentum return across volatility for the low credit risk stocks. When sorting on credit risk and leverage, the monthly momentum payoffs to the high risk, low(high) leverage stocks are 2.76% (2.80%). Once again, there is no differential momentum return across leverage amongst the high-risk stocks.

Panel D presents the results for sorts on credit rating and age.[9] Momentum returns increase monotonically with credit risk across all age groups. Also, the momentum strategy profits decrease with firm age but the effect is absent amongst the low risk firms. Importantly, the differential impact of firm age on momentum profits is far smaller that that of credit risk. Similar results obtain for sorts on credit rating and cash flow volatility (CVOL)[10]

[8] Monthly volatility for a stock is the sum of the square of the daily returns within the month and leverage is defined as the ratio of book value of debt to the market value of equity.

[9] Firm age is measured as the number of months since the firm's IPO.

[10] Cash flow volatility is computed as in Zhang (2006).

in Panel E and for sorts on credit rating and analyst forecast dispersion in Panel F. While momentum returns increase monotonically with credit risk across all CVOL and analyst forecast dispersion groups, the reverse is not true. More importantly, the differential impact of credit risk on momentum profits is far larger than the impact of CVOL or that of analyst forecast dispersion.

In sum, sorting on credit rating provides a payoff differential in momentum strategies, but the same does not necessarily hold for sorts on size, return volatility, leverage, cash flow volatility, firm age, and analyst forecast dispersion.[11] These proxies for information uncertainty seem to provide differential momentum payoffs only in the case of high credit risk stocks, whereas credit risk provides differential momentum payoffs across different values of the information uncertainty variables. The evidence strongly suggests that credit risk has an independent effect not captured by variables that proxy for information uncertainty.

C. The Impact of Distress

Table II shows that, over the formation period, the extreme loser and winner portfolios contain a disproportionately large number of high credit risk firms. Moreover, the average credit rating of the loser stocks (BB–) is lower than that of the winner stocks (BB+). We also find that the difference in returns between the highest and the lowest decile rating group is 0.61% per month and the difference between the highest and the second-to-last rating decile portfolio is 0.18% per month, suggesting that distressed stocks experience lower average returns. To summarize, we have the following three observations: (i) The momentum strategy goes long (short) the winner (loser) stocks, (ii) loser stocks have, on average, lower ratings than winner stocks, and (iii) lower-rated stocks earn lower returns. These three observations together suggest that the impact of distress should result in higher returns for momentum portfolios that are long winners and short losers.

Thus, an essential question that arises is whether the impact of credit ratings on momentum profitability is entirely explained by distressed stocks that realize lower returns. We rule this possibility out for several reasons. First, the maximum return differential across decile rating portfolios is only 61 basis points per month (results not reported), whereas, as noted earlier, the return differential across winner and loser low-rated stocks is over 2% per month. Moreover, we implement momentum strategies on credit rating–adjusted returns by subtracting the matched-decile credit rating portfolio holding period return from the individual stock holding period return. The rating-momentum relation is robust to such an adjustment (results available upon request). Finally, observe from Panel C of Table VI that the impact of leverage on momentum strategy profits is far smaller than that of credit rating. Since leverage can be thought

[11] We do not present results for analyst following because firm size and analyst following are highly correlated.

of as a proxy for distress, this suggests that it is not distress but credit ratings that drive our results.

D. Other Robustness Checks

Moskowitz and Grinblatt (1999) document that industry momentum accounts for much of the individual stock return momentum. Hence, stronger momentum in lower-rated stocks could be attributed to such stocks being concentrated in one particular industry that consistently exhibits higher momentum. However, we confirm that our findings are not driven by industry momentum. In particular, following Moskowitz and Grinblatt (1999), we compute industry-adjusted stock returns by subtracting from each stock return over the holding period the return of the corresponding industry over the same period. The credit risk effect on momentum profitability is robust to such an industry adjustment (results are unreported but available upon request).

In a similar manner, we implement further robustness checks, controlling for size, volatility, trading volume, illiquidity, analyst coverage, and analyst forecast dispersion. Indeed, low-rated stocks are smaller, have higher volatility, lower liquidity, lower analyst coverage, and higher forecast dispersion than high-rated stocks. We subtract the decile portfolio return corresponding to the above characteristics from the holding period returns of the individual stocks in the winner and the loser portfolios. The results (available upon request) show that the link between momentum and credit risk remains strong and significant even after controlling for the above potentially relevant momentum determinants.

IV. Conclusion

This paper establishes a strong link between momentum profitability and firm credit rating. The empirical findings are based on a sample of 3,578 NYSE, AMEX, and NASDAQ firms rated by S&P over the July 1985 to December 2003 period. The selected sample is representative, as rated and nonrated firms share similar characteristics in terms of (i) their stock return distribution, (ii) the momentum profits they generate, and (iii) their industry distribution among the 20 industries studied by Moskowitz and Grinblatt (1999).

The extreme winner and loser portfolios are comprised mainly of high credit risk stocks. Momentum profitability is statistically significant and economically large among low-rated firms, but it is nonexistent among high-grade firms. The results are robust and cannot be explained by information uncertainty as proxied by firm size, firm age, analyst forecast dispersion, leverage, return volatility, and cash flow volatility. Excluding from the analysis the highest credit risk firms, which altogether account for less than 4% of the market capitalization of rated firms, renders the momentum profitability statistically insignificant.

Indeed, our cross-sectional analysis explicitly shows that momentum trading strategies are profitable only among the highest credit risk firms. This may suggest that aggregate momentum payoffs are higher during recessionary periods when credit risk is a major concern. However, as noted earlier, the time-series analysis demonstrates that momentum profitability does vary with the business cycle, but apparently in the wrong direction, that is, momentum payoffs are economically and statistically significant only during expansions when there are fewer defaults. This disagreement between the cross-sectional and time-series findings is a puzzle that future work should address.

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