Asset-Pricing Anomalies and Financial Distress

Doron Avramov*
Department of Finance
Robert H. Smith School of Business
University of Maryland
davramov@rhsmith.umd.edu

Tarun Chordia
Department of Finance
Goizueta Business School
Emory University
Tarun_ Chordia@bus.emory.edu

Gergana Jostova
Department of Finance
School of Business
George Washington University
jostova@gwu.edu

Alexander Philipov
Department of Finance
School of Management
George Mason University
aphilipo@gmu.edu

First draft: February 5, 2007

This Revision: July 16, 2009

* We are grateful for financial support from the Q-Group and the FDIC Center for Financial Research.

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Abstract

This paper explores commonalities across asset-pricing anomalies in a unified framework. In particular, we assess implications of financial distress for the profitability of anomaly-based trading strategies. Strategies based on price momentum, earnings momentum, credit risk, dispersion, and idiosyncratic volatility derive their profitability from taking short positions in high credit risk firms that experience deteriorating credit conditions. Such distressed firms are highly illiquid and hard to short sell, which could establish nontrivial hurdles for exploiting these anomalies in real time. The value effect emerges from taking long positions in high credit risk firms that survive financial distress and subsequently realize high returns. The accruals anomaly is an exception - it is robust amongst high and low credit risk firms as well as during periods of deteriorating, stable, and improving credit conditions.

Asset pricing theories, such as the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965), prescribe that riskier assets should command higher expected returns. Existing theories, however, leave unexplained a host of empirically documented cross-sectional patterns in average returns, classified as anomalies. Specifically, price momentum, first documented by Jegadeesh and Titman (1993), reflects the strong abnormal performance of past winners relative to past losers. Earnings momentum, documented by Ball and Brown (1968), is a related anomaly[1] that describes the outperformance of firms reporting unexpectedly high earnings relative to those reporting unexpectedly low earnings. The size and book-to-market effects have been documented, among others, by Fama and French (1992). In particular, small stocks, as measured by market capitalization, have historically outperformed big stocks, and high book-to-market (value) stocks have outperformed their low book-to-market (growth) counterparts. Sloan (1996) documents that high accruals stocks underperform low accruals stocks. Dichev (1998), Avramov, Chordia, Jostova, and Philipov (2009), and Campbell, Hilscher, and Szilagyi (2008) demonstrate a negative correlation between credit risk and average returns. Diether, Malloy, and Scherbina (2002) show that buying/selling stocks with low/high dispersion in analysts' earnings forecasts yields statistically significant and economically large payoffs. Finally, Ang, Hodrick, Xing, and Zhang (2006) suggest that stocks with high idiosyncratic volatility realize abnormally low returns.

This paper examines the price momentum, earnings momentum, credit risk, dispersion, idiosyncratic volatility, accruals, and value premium anomalies in a unified framework. We explore commonalities across all anomalies and, in particular, assess potential implications of financial distress, as proxied by credit rating downgrades, for the profitability of anomaly-based trading strategies. It is quite apparent that a downgrade, or even a concern of financial distress, leads to sharp responses in stock and bond prices. Indeed, Hand, Holthausen, and Leftwich (1992) and Dichev and Piotroski (2001) show that bond and stock prices decline considerably following credit rating downgrades. However, understanding the potential dependence of market anomalies on financial distress is an unexplored territory. This paper attempts to fill this gap.

Methodologically, our analysis is based on portfolio sorts and cross-sectional regressions, as in Fama and French (2008). Investment payoffs are value-weighted as well as equally-weighted across stocks. Payoffs based on equally-weighted returns are typically

[1] See Chordia and Shivakumar (2006).

dominated by small stocks which account for a very low fraction of the entire universe of stocks based on market capitalization, while payoffs based on value-weighted returns can be dominated by a few big stocks. Our sorting procedure gets around this potential problem, as investment payoffs are computed separately for micro, small, and big firms, following the size classification of Fama and French (2008). In addition, we implement trading strategies within subsamples based on the intersection of best rated, medium rated, and worst rated firms with micro, small, and large capitalization firms. Credit ratings, for a total of 4,953 firms and an average of 1,931 firms per month, are obtained at the monthly frequency from Compustat North America and S&P Credit Ratings.

The analysis, based on both portfolio sorts and cross-sectional regressions, shows that the profitability of the price momentum, earnings momentum, credit risk, dispersion, and idiosyncratic volatility anomalies is concentrated in the worst-rated stocks. The profitability of these anomalies disappears when firms rated BB or below are excluded from the investment universe. Strikingly, these low-rated firms represent only 6.3% of the market capitalization of the sample of rated firms. Yet, credit risk is not merely a proxy for size. In particular, the above anomalies are reasonably robust among all size groups, including the big low-rated stocks. Moreover, the profitability of these anomalies is generated almost entirely by the short side of the trade. The value effect also appears to be related to credit risk. While it is insignificant in the overall sample of firms, it is significant among low rated stocks, both small and big. The accruals strategy is an exception, as it is robust across all credit risk groups.

Focusing on financial distress, as proxied by credit rating downgrades, we find that the profitability of strategies based on price momentum, earnings momentum, credit risk, dispersion, and idiosyncratic volatility derives exclusively from periods of financial distress. These strategies provide payoffs that are statistically insignificant and economically small when periods around credit rating downgrades (from six months before to six months after a downgrade) are excluded from the sample. None of these strategies produces significant payoffs during stable or improving credit conditions. Accruals is again an exception. It is significant during deteriorating, stable, and improving credit conditions. In contrast, the value anomaly is significant only during stable or improving credit conditions and comes mostly from long positions in low-rated stocks.

The distinct patterns exhibited by the accruals and value strategies suggest that these effects are based on different economic fundamentals. The accruals anomaly is based on managerial discretion about the desired gap between net profit and operating cash flows and this target gap does not seem to depend upon credit conditions. The value strategy is more profitable in stable credit conditions. The value effect seems to emerge from long positions in low-rated firms that survive financial distress and realize relatively high subsequent returns. Thus, while an accruals-based trading strategy is unrelated to financial distress and a value-based trading strategy bets on low-rated firms surviving financial distress, the other five anomalies bet on falling prices of low-rated stocks around periods of financial distress.

A natural questions that emerges is: are market anomalies explained by economy-wide conditions? Our analysis suggests that the answer is no. Firm rating downgrades tend to be idiosyncratic events. In particular, we compute a downgrade correlation as the average pairwise correlation between any two stocks in a particular rating tercile. Each stock is represented by a binary index taking the value one during a month when there is a downgrade and zero otherwise. We find that the downgrade correlations are just too low across the board to indicate that downgrades occur in clusters. In addition, downgrades do not cluster in up or down markets and they do not cluster over the business cycle during recessions or expansions.

Finally, we examine whether there are any frictions that prevent these anomalous returns from being arbitraged away. Indeed, we show that impediments to trading such as short selling and poor liquidity could establish nontrivial hurdles for exploiting market anomalies. In particular, low rated stocks are considerably more difficult to short sell and are substantially more illiquid. Institutional holdings and the number of shares outstanding for low rated stocks are substantially lower and the Amihud (2002) illiquidity measure is significantly higher. Low institutional holdings and a low number of shares outstanding make it difficult to borrow stocks for short selling (see D'Avolio (2002)), and poor liquidity makes the short transaction quite costly to undertake. Exploiting asset pricing anomalies would, thus, be relatively difficult in real time because investment profitability is derived from short positions in low rated stocks that are highly illiquid and hard to short sell. It should also be noted that investors do not perceive distressed stocks to be overvalued. The evidence shows that investors are consistently surprised by the poor performance realized by distressed firms. In particular, analysts covering distressed firms face large negative earnings surprises and make large negative forecast revisions.

The rest of the paper proceeds as follows. The next section describes the data. Section 2 discusses the methodology. Section 3 presents the results and section 4 concludes.

1 Data

The asset-pricing anomalies we study use data on firm return, credit rating, and a variety of equity characteristics (e.g., the book-to-market ratio, quarterly earnings, and idiosyncratic volatility). The full sample consists of the intersection of all US firms listed on NYSE, AMEX, and NASDAQ with available monthly returns in CRSP and monthly Standard & Poor's Long-Term Domestic Issuer Credit Rating available on Compustat North America or S&P Credit Ratings (also called Ratings Xpress) on WRDS. Combining the S&P company rating in Compustat and Rating Xpress provides the maximum coverage each month over the entire sample period. The total number of rated firms with available return observations is 4,953 with an average of 1,931 per month. There are 1,232 (2,196) rated firms in October 1985 (December 2007), when the sample begins (ends). The maximum number of firms, 2,497, is recorded in April 2000.

The momentum, idiosyncratic volatility, and credit-risk-based trading strategies condition on returns and credit ratings. Hence, the analysis of these anomalies makes use of the full sample. For the earnings momentum strategy, we extract quarterly earnings along with their announcement dates from I/B/E/S Detail History Actuals files. The standardized unexpected earnings (SUE) is computed as the difference between current quarterly EPS (earnings per share) and EPS reported four quarters ago, divided by the standard deviation of quarterly EPS changes over the preceding eight quarters. Hence results for the earnings momentum anomaly are based on the subsample of our rated firms with SUE data on I/B/E/S, which consists of 3,442 firms with an average of 1,296 firms per month. We also use the I/B/E/S Summary database to obtain dispersion in analysts' earning forecasts. As in Diether, Malloy, and Scherbina (2002), dispersion is calculated as the standard deviation of analyst earnings forecasts for the upcoming fiscal year end, standardized by the absolute value of the mean (consensus) analyst forecast. Dispersion observations are excluded if there are less than two analysts covering the firm. The analysis of the dispersion anomaly is based on a total of 4,074 firms with an average of 1,429 firms per month. Idiosyncratic volatility is computed as the sum of the stock's squared daily returns from CRSP minus the sum of the corresponding squared daily market returns, following Campbell, Lettau, Malkiel, and Xu (2001). Accruals is computed following Sloan (1996) based on Compustat's Fundamentals Quarterly files.[2] Results for the accruals anomaly are based on a total of 3,493 firms with an average of 1,464 firms per month. For the value anomaly book-to-market ratios for July of year t to June of year $t+1$ are calculated as the book value of equity standardized by the market capitalization from CRSP, both measured as of December of year $t-1$, as in Fama and French (1992). Results for the value anomaly are based on a sample of 2,868 firms with an average of 1,353 per month.

The definition of a company's Long Term Issuer credit rating is identical in both Compustat and Rating Xpress and is provided in both databases directly by Standard & Poor's. As defined by S&P, prior to 1998, this issuer rating is based on the firm's senior publicly traded debt. After 1998, the rating is based on the overall quality of the firm's outstanding debt, either public or private.[3] *Standard & Poor's Rating Definitions* specifies S&P's issuer credit rating as the current opinion of an obligor's overall financial capacity (its creditworthiness) to pay its financial obligations. This opinion focuses on the obligor's capacity and willingness to meet its financial commitments as they come due. It does not apply to any specific financial obligation, as it does not take into account the nature of the obligation, its provisions, its standing in bankruptcy or liquidation, its statutory preferences, or its legality and enforceability. In addition, it does not take into account the creditworthiness of the guarantors, insurers, or other forms of credit enhancement on the obligation.

In the empirical analysis that follows, we transform the S&P ratings into numerical scores. Specifically, 1 represents a AAA rating and 22 reflects a D rating.[4] Hence, a higher numerical score reflects higher credit risk. Numerical ratings of 10 or below ($BBB-$ or better) are considered investment-grade, and ratings of 11 or higher ($BB+$

[2]Accruals=[(dCA-dCash)-(dCL-dSTD-dTP)-Dep]/TA, where dCA=change in Current Assets - Total ['ACTQ'], dCash=change in Cash and Short-Term Investments ['CHEQ'], dCL=change in Current Liabilities - Total ['LCTQ'], dSTD=change in Debt in Current Liabilities ['DLCQ'], dTP=change in Income Taxes Payable ['TXPQ'], Dep=Depreciation and Amortization - Total ['DPQ'], and TA=average of this quarter's and last quarter's Assets - Total ['ATQ']. All variables are from Compustat's Fundamentals Quarterly with their variable names defined in brackets above and all changes are since the prior quarter values.

[3]We have checked that the results are similar before and after 1998. The change in the long-term issuer ratings definition does not impact the results, nor does it impact the individual company ratings.

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

or worse) are labeled high-yield or non-investment grade.

Stocks do get delisted from our sample over the holding period. Some stocks delist due to low prices or bankruptcy while others may delist due to an acquisition or a merger. Throughout the paper, we use the delisting returns from CRSP whenever a stock gets delisted.

Summary statistics are reported in Table 1. Each month all stocks rated by S&P are divided into three portfolios based on their credit rating at time t. For each portfolio, we compute the cross-sectional median characteristic for month $t+1$. The reported characteristics represent the time-series averages of the median cross-sectional characteristic.

Not surprisingly, the average firm size (as measured by market capitalization) decreases monotonically with deteriorating credit rating. The highest-rated stocks have an average market capitalization of $3.37 billion, while the lowest-rated stocks have an average capitalization of $0.33 billion. The book-to-market ratio increases monotonically with credit risk, from 0.51 in C1 (the lowest rated porfolio) to 0.66 in C3 (the highest rated portfolio). The average stock price also decreases monotonically with increasing credit risk from $38.22 for the highest-rated stocks to $12.35 for the lowest-rated stocks. Notice also that institutions hold fewer shares of low-rated stocks. Institutional holding (obtained from Thomson's Financial Database on WRDS) amounts to about 56% of shares outstanding for high-rated stocks and less than 46% for low-rated stocks.

High-rated firms are considerably more liquid than low-rated firms. The average monthly dollar trading volume (obtained from CRSP Monthly Stock Files) decreases from $287 million ($61 million) for the highest-rated NYSE/AMEX (NASDAQ) stocks to $49 million ($32 million) for the lowest-rated stocks. Moreover, the Amihud (2002) illiquidity measure is 0.02 (0.23) for NYSE/AMEX (NASDAQ) highest-quality stocks and 0.48 (0.91) for the lowest-quality stocks.[5] This measure is computed as the absolute price change per dollar of daily trading volume:

$$ILLIQ_{it} = \frac{1}{D_{it}} \sum_{t=1}^{D_{it}} \frac{|R_{itd}|}{DVOL_{itd}} * 10^7, \tag{1}$$

where R_{itd} is the daily return and $DVOL_{itd}$ is the dollar trading volume (both from

[5] Hasbrouck (2005) compares effective and price-impact measures estimated from daily data to those from high-frequency data and finds that Amihud (2002)'s measure is the most highly correlated with trade-based measures.

CRSP Daily Stock Files) of stock i on day d in month t, and D_{it} is the number of days in month t for which data are available for stock i (a minimum of 10 trading days is required).

We next analyze several variables that proxy for uncertainty about firm's future fundamentals. In particular, the average number of analysts following a firm (obtained from I/B/E/S) decreases monotonically with credit risk from about 14 for the highest to five for the lowest-rated stocks. In addition, analyst revisions are negative and much larger in absolute value for the low-versus-high rated stocks. The standardized unexpected earnings (SUE) also decreases monotonically from 0.60 for the highest to 0.13 for the lowest rated stocks. Finally, leverage, computed as the book value of long-term debt to common equity ('DLTTQ' to 'CEQQ' from the Compustat Fundamentals Quarterly Files), increases monotonically from 0.54 for the highest-rated stocks to 1.36 for the lowest-rated stocks. Next, market betas increase monotonically from an average of 0.8 for the highest rated stocks to 1.29 for the lowest rated stocks. Finally, the CAPM alpha decreases from 0.33% for the highest rated stocks to -0.57% for the lowest rated stocks.

Overall, low-rated stocks have smaller market cap, lower price, higher market beta, lower dollar trading volume, higher illiquidity, higher leverage, lower institutional holding, and higher uncertainty about their future fundamentals.

2 Methodology

We examine the price momentum, earnings momentum, credit risk, dispersion, idiosyncratic volatility, accruals, and value anomalies. Our analysis is based on both portfolio sorts and cross-sectional regressions. Focusing on the former, investment payoffs are value weighted as well as equally weighted across stocks. Payoffs based on equally weighted returns can be dominated by tiny (microcaps) stocks which account for a very low fraction of the entire universe of stocks based on market capitalization but a vast majority of the stocks in the extreme anomaly-sorted portfolios. On the other hand, value weighted returns can be dominated by a few big stocks. Separately, either case could result in an unrepresentative picture of the importance of an anomaly.

We run the analysis not only for the entire universe of investable stocks but also for subsets based on market capitalization and credit ratings. In particular, we implement trading strategies across microcap, small cap, and large cap firms following the classifications outlined by Fama and French (2008). Microcap firms are those below the 20^{th} percentile of NYSE stocks, small firms are those between the 20^{th} and 50^{th} percentile of NYSE stocks, and large firms are those with market capitalizations above the median NYSE capitalization. The idea here is to examine the pervasiveness of anomalies across the different market capitalization groups. Similarly, we run the analysis for subsamples based on credit rating. We examine each anomaly within credit risk terciles: C1 (highest quality), C2 (medium quality), and C3 (worst quality). The profitability of each anomaly is also studied for subsamples based on the interaction of the three size and three credit rating groups.

Our portfolio formation methodology for all anomalies is consistent with prior literature. In particular, at the beginning of each month t, we rank all eligible stocks into quintile portfolios[6] on the basis of the strategy-specific conditioning variable (defined below). P1 (P5) denotes the portfolio containing stocks with the lowest (highest) value of the conditioning variable based on an J-month formation period. Each strategy buys one of the extreme quintile portfolios P1 (or P5), sells the opposite extreme quintile portfolio P5 (or P1), and holds both portfolios for the next K months. Each quintile portfolio return is calculated as the equally or value weighted average return of the corresponding stocks. When the holding period is longer than a month ($K > 1$), the monthly return is based on an equally weighted average of portfolio returns from strategies implemented in the prior month and previous $K - 1$ months. While the above-described portfolio formation methodology applies to all strategies studied here, trading strategies use different conditioning variables and may differ with respect to the formation and holding periods as well. Below we describe all trading strategies in detail.

The price momentum strategy is constructed as in Jegadeesh and Titman (1993). Stocks are ranked based on their cumulative return over the formation period (months $t - 6$ to $t - 1$). The momentum strategy buys the winner portfolio (P5), sells the loser portfolio (P1), and holds both portfolios for six months. We skip a month between the formation and holding periods (months $t + 1$ to $t + 6$) to avoid the potential impact of short run reversals.

The earnings momentum strategy conditions on the latest standardized unexpected

[6]Ranking into decile portfolios has delivered similar results. We present results based on quintiles for consistency with Fama and French (2008).

earnings (SUE) reported over the past quarter. The earnings momentum strategy involves buying the portfolio with the highest SUE (P5), selling the portfolio with the lowest SUE (P1), and holding both portfolios for six months.

The credit risk strategy conditions on prior month credit rating. It involves buying the best rated quintile portfolio (P1), selling the worst rated quintile portfolio (P5), and holding both portfolios for one month.

The dispersion-based trading strategy conditions on the prior month standard deviation of analyst earnings forecasts for the upcoming fiscal year end, standardized by the absolute value of the mean (consensus) analyst forecast. The dispersion strategy is formed by buying P1 (the lowest dispersion portfolio), selling P5 (the highest dispersion portfolio), and holding both portfolios for one month.

The idiosyncratic volatility strategy conditions on prior month idiosyncratic volatility, computed as described in the Data section. It involves buying the lowest volatility quintile (P1), selling the highest volatility quintile (P5), and holding both positions for one month.

The accruals anomaly conditions on lagged firm level accruals, calculated as explained in the Data section. There is a four-month lag between formation and holding periods to ensure that all accounting variables used to form firm level accruals are in the investor's information set. The strategy involves buying the lowest accrual portfolio (P1), selling the highest accrual portfolio (P5), and holding both portfolios for the next 12-month.

The value strategy conditions on the book-to-market ratio, which is calculated as in Fama and French (1992) and described in the Data section. The strategy involves buying the highest BM quintile (value stocks: P5), selling the lowest BM quintile (growth stocks: P1), and holding both portfolios for one month.

3 Results

Table 2 presents monthly returns for the extreme portfolios (P1 and P5) and the difference between the two (P5-P1 or P1-P5, as noted at the top of each column) for the price momentum, earnings momentum, credit risk, dispersion, idiosyncratic volatility, accruals, and value strategies. Panel A (B) exhibits the size and book-to-market adjusted equally- (value-) weighted portfolio returns. The size and book-to-market adjustment is made as follows. The monthly return for each stock is measured net of the return on a matching portfolio formed on the basis of a 5×5 independent sort on size and book-to-market.

Let us first examine investment profitability for all rated firms based on equally weighted returns. The price momentum strategy yields a winner-minus-loser return of 1.28% per month with the loser (winner) stocks returning -103 (25) basis points. The earnings momentum strategy yields a 57 basis point monthly return. The credit risk strategy provides a 91 basis point monthly return. The dispersion strategy returns 60 basis points per month and the idiosyncratic volatility strategy yields 106 basis points per month. All of the above investment payoffs are economically and statistically significant. The accruals strategy payoff is a statistically significant 23 basis points per month. The value strategy delivers the lowest return – a statistically insignificant 19 basis points per month. Thus, for the overall sample of rated firms, except for the value effect, all anomaly-based trading strategies are statistically and economically profitable.

Next, we examine trading strategies implemented among microcap, small, and big firms. The evidence shows that both earnings and price momentum strategies provide payoffs that monotonically diminish with market capitalization. The payoff to the earnings (price) momentum strategy is 126 (216) basis points per month for microcap stocks. The corresponding figures are 85 (133) for small stocks and 26 (69) basis points for big stocks. The P1 portfolio (the short side of the transaction) leads to the large differences across the size-sorted portfolios. Focusing on earnings (price) momentum, for example, the P1 portfolio returns -104, -65, and -23 (-162, -114, and -51) basis points per month for microcap, small, and big stock portfolios, respectively. In contrast, the long side of the transaction (P5 portfolio) delivers earnings (price) momentum returns of 22, 20, and 3 (53, 18, and 18) basis points per month for the corresponding size groups.

The credit risk and dispersion strategies deliver returns that do not exhibit particular patterns across the size groups. Both strategies yield the highest (lowest) returns for the small (microcap) firms. The idiosyncratic volatility strategy payoff decreases monotonically with firm size from 122 basis points per month for microcap stocks to 75 basis points per month for big stocks. Once again, the return differential around the short (long) side of the transaction is large (small), amounting to -128, -102, and -78 (-7, 0, and 3) basis points per month for the microcap, small, and big stocks, respectively. The accruals strategy yields 30 (32) [19] basis points per month for the microcap (small) [big] firms. The value strategy provides statically significant payoffs of 60 basis points per month for small stocks only, whereas payoffs based on microcap and big stocks are statistically insignificant at the 5% level. Interestingly, all anomalies, excluding dispersion, provides payoffs that are significant at the 10% level, among big rated firms.

Our objective is to examine the impact of credit risk on prominent asset pricing anomalies. To pursue the analysis, we further partition the sample into high-rated (C1), medium-rated (C2), and low-rated (C3) stocks.[7] The evidence indeed shows that the impact of credit conditions is quite striking. For instance, the price momentum (accruals) strategy delivers overall payoffs of 8, 41, and 253 (15, 25, and 28) basis points per month for the high, medium, and low-rated stocks, respectively. We now analyze, in detail, the impact of credit ratings on the various asset pricing anomalies.

Amongst the high-rated, C1, firms, no strategy (except for the accruals, which provides a statistically significant 0.15% monthly return amongst the big stocks) provides significant payoffs. Amongst the medium-rated, C2, stocks, price momentum is profitable at 52 and 47 basis points per month for small and big firms, respectively. The earnings momentum strategy is profitable only for small firms, realizing a return of 42 basis points per month. The accruals strategy is profitable for small (33 basis points) and big (24 basis points) firms. None of the other trading strategies (credit risk, dispersion, idiosyncratic volatility, or value) displays significant investment payoffs.

Remarkably, all trading strategies are profitable only amongst the low-rated, C3, stocks. Observe from Table 2 that the highest return (3.05% per month) is earned by the price momentum strategy upon conditioning on low-rated, microcap stocks. The next highest investment return (2.35%) per month is also earned by the price momentum strategy but in the intersection of low-rated and small stocks. Even big market cap stocks having low rating deliver a significant price momentum return of 140 basis points per month. The earnings momentum and idiosyncratic volatility strategies are profitable across the board for low-rated microcap, small, and big stocks. The idiosyncratic volatility strategy implemented among low rated stocks yields above 200 basis points per month for all size groups. The credit risk strategy is profitable for microcap and small stocks, while the dispersion strategy is profitable only for small low-rated stocks.

[7] Given our independent sort on firm size and credit rating, there may not be enough stocks belonging to the high-rated, microcap growth (P1) portfolio.

The value strategy provides a significant 69 basis point monthly return for small stocks and 129 basis points for big stocks.

Panel B of Table 2 is the value-weighted counterpart of Panel A. Indeed, the value-weighted payoffs are often considerably lower, suggesting a role for small firms. For instance, the overall unconditional return to the price (earnings) momentum strategy in Panel B is 56 (17) basis points per month, as compared to 128 (57) basis points per month in Panel A. Nevertheless, investment profitability is typically significant at the 5% or 10% levels amongst big low rated firms. Moreover, investment payoffs generally increase with worsening credit rating, and all strategies are profitable for small low rated firms. Only the accruals strategy payoffs are statistically significant across the board for all credit rating categories. Indeed, the accruals strategy displays a return pattern that is markedly different from those generated by all other anomalies studied here.

Quite prominent in the results is the overwhelming impact of the short side of the trading strategies. To illustrate, consider the price momentum strategy. The size-book-to-market value weighted adjusted return for the winner portfolio is 3 basis points per month among C1 stocks and 21 basis points among C3 stocks. This represents a return differential of 18 basis points per month. On the other hand, the return differential across the loser stocks is 152 [158-6] basis points per month. The short side of the transaction is clearly the primary source of momentum profitability. Consider now the earnings momentum strategy. The return differential for the long (short) portfolios across the low and high-rated stocks is 14 (85) basis points per month. The return differential for the long (short) portfolios for the credit risk strategy is 28 (134) basis points; for the dispersion strategy it is 39 (57); for the idiosyncratic volatility strategy it is 17 (196); for the value strategy it is 33 (73) basis points. Only in the case of the accruals strategy are the long and short portfolio return differentials similar, 87 versus 80 basis points per month. This evidence further reinforces the distinctive patterns of the accruals strategy. Indeed, except for the accruals strategy, the short side of the transaction provides the bulk of profitability.

Let us summarize the takeaways from Table 2: (i) The profits generated by the trading strategies typically diminish with improving credit ratings; (ii) Except for the accruals strategy, the short side of the trade is the primary source of investment profitability; (iii) The accruals strategy is robust across the credit rating sorted portfolios; (iv) Most trading strategies (all but value and dispersion) are remarkably robust across the size-sorted portfolios; (v) Focusing on value-weighted portfolios, trading strategies (excluding accruals) are especially profitable among small stocks, though the intersection of big market cap low credit rating stocks still gives rise to significant investment payoffs. Indeed, the overall evidence suggests that credit risk plays an important role in explaining the source of market anomalies.

To further pinpoint the segment of firms driving investment profitability, we document in Table 3 the equally-weighted size and book-to-market adjusted returns for various credit rating subsamples as we sequentially exclude the worst-rated stocks. We display investment payoffs for all stocks belonging to each of the rating categories as well as sub groups of microcap, small, and big stocks.

The starting point pertains to all rating categories (AAA-D). The results here are identical to those exhibited in Panel A of Table 2. Note from the last two columns of the table that whereas microcap stocks consist of 17.81% of the total number of stocks, they account only for 0.43% of the market capitalization; small stocks comprise 27.07% of the total number of stocks and 2.97% of the total market capitalization; big firms comprise 55.12% of the total number of stocks and an overwhelming 96.59% of the total market capitalization. Fama and French (2008) report that the microcap stocks account for 3.07%, small stocks account for 6.45%, and big stocks account for 90.48% of the total market capitalization. Our figures are slightly different because big market cap firms are more likely to have bonds outstanding and, consequently, are more likely to be rated.

Table 3 suggests that investment profitability typically falls as the lowest rated stocks are excluded from the sample. The earnings (price) momentum strategy payoffs monotonically diminish from 0.57% (1.28%) per month in the overall sample to a statistically insignificant 0.21% (0.30%) as firms rated BB or below are eliminated. The accruals strategy is an exception, generating a 23 basis point monthly return for the entire sample. The maximum profitability for the accruals strategy (32 basis points) emerges when stocks rated B and below are excluded. Investment profitability then diminishes to a statistically significant 19 basis points, focusing on investment grade firms. The value strategy also does not display a clear pattern with respect to the stocks included. It delivers an insignificant 19 basis point monthly payoff for the overall sample. The payoff increases to a statistically significant 29 basis points when firms rated CCC and below are excluded. Except for the accruals anomaly, the unconditional profitability of all other anomalies disappears when firms rated BB and below are excluded. Such firms comprise only 6.31% of the sample based on market capitalization.

Conditioning on market capitalization, we show that the earnings momentum, the credit risk, and the dispersion anomalies are altogether unprofitable among big firms for all rating categories. Among big firms, the price momentum anomaly becomes unprofitable as firms rated B+ and below are eliminated from the sample. Those firms account only for 1.73% (96.59%-94.86%) of the market capitalization of firms in our sample. Only the accruals anomaly displays significant profitability as all non-investment grade stocks are excluded.

Moving to small market capitalization firms, the profitability of all anomalies disappears when non-investment grade stocks, comprising 2.07% (2.97%-0.9%) of the sample by market capitalization, are eliminated. Overall, the results suggest that except for the accruals anomaly, a minor fraction of firms, based on market capitalization, drive the trading strategy profits.[8]

We have shown that investment profitability typically rises with worsening credit conditions. Moreover, the short side of the trading generates most of the profits. The overall evidence indicates that credit risk has a major impact on the cross-section of stock returns in general and market anomalies in particular.

Thus far, the analysis has exclusively focused on credit rating levels. Studying the impact of credit rating changes is our next step. Indeed, rating changes have already been analyzed in the context of empirical asset pricing. In particular, Hand, Holthausen, and Leftwich (1992) and Dichev and Piotroski (2001) show that bond and stock prices, respectively, sharply fall following credit rating downgrades, while credit rating upgrades play virtually no role. However, understanding potential implications of credit rating downgrades for market anomalies is virtually an unexplored territory. This paper fills in the gap.

3.1 Credit rating downgrades

Panel A of Table 4 presents the number and size of credit rating downgrades, as well as returns around downgrades for the credit risk-sorted tercile portfolios. Note that

[8] While we have presented the equally-weighted results, the value-weighted results (available upon request) show that an even smaller fraction of the low rated firms drive the anomaly profits.

the number of downgrades in the highest-rated portfolio is 2,276 (8.56 per month on average), while the corresponding figure for the lowest-rated portfolio is much larger at 3,286 (12.35 per month on average). Moreover, the average size of a downgrade amongst the lowest-rated stocks is 2.24 points (moving from B to $CCC+$), whereas the average downgrade amongst the highest-rated stocks is lower at 1.77 points (moving from $AA-$ to A).

The stock price impact around downgrades is considerably larger for low-versus-high rated stocks. For example, the return during the month of downgrade averages -0.34% for the best rated stocks and -15.21% for the worst rated. In the six-month period before (after) the downgrade, the lowest-rated firms deliver average return of -29.38% (-16.73%). The corresponding figure for the highest-rated stocks is 3.64% (7.55%). A similar return pattern prevails over one year and two years around downgrades. In the year before (after) the downgrade, the return for the lowest-rated stocks is -31.95% (-11.72%), while the return for the highest-quality stocks is 7.59% (13.15%).

Panel A of Table 4 also documents the number of firms that are delisted across the various rating deciles. Over a period of 6 (12) [24] months after a downgrade, the number of delistings amongst the highest-rated stocks are 53 (85) [138], while they are 379 (601) [847] amongst the lowest-rated stocks. Overall, the number of delistings are distinctly higher amongst the lowest-rated firms, suggesting that delisting events could be a direct consequence of financial distress, as proxied by rating downgrades.

Next, we examine downgrades during up and down markets (i.e., when the value weighted market excess returns in the month of the downgrade are positive and when they are negative). Panel A of Table 4 shows that the average number of downgrades per month in an up (down) market month for a low-rated firm is 11 (15); a high-rated firm experiences on average 8 (10) downgrades in up (down) markets. This indicates that firm financial distress is most likely a dispersed idiosyncratic event. Moreover, during the month of a credit rating downgrade, the average return in the lowest-rated stocks is -22.24% (-10.80%) when the market excess returns are negative (positive). This considerable fall in equity prices upon downgrades during down markets occurs despite the size of the downgrade being larger during up (2.27 points) than down (2.18 points) markets. Thus, even when the downgrade event itself could be rather idiosyncratic, the stock price fall following a downgrade is linked to the macroeconomic environment. In the month prior to a downgrade, low-rated firms realize return of -12.22% (-11.77%) in up (down) market. The corresponding quantity for high-rated firms is 1.35% (-0.16%) in up (down) market. The probability of delisting of a low-rated firm over 6 months following a downgrade is 13% (187 delistings out of 1,438 downgrades) during down markets while the probability is 11% (192 delistings out of 1,814 downgrades) during up markets (results not reported).

We also examine downgrades during expansions and recessions as defined by NBER. This analysis is merely suggestive as there are only 16 months of recessions in our sample. We find that the low-rated firms have an average of 26 downgrades per month during recessions and 12 during expansions. On the other hand, the returns of low-rated stocks for the month of a downgrade during recessions of -10.30% per month are smaller (in absolute value) than those during expansions, -15.59%.

We find further evidence that downgrades tend to be rather idiosyncratic events. In particular, we compute a downgrade correlation as the average pairwise correlation between any two stocks in a particular rating tercile. This correlation is computed based on three scenarios. In particular, we construct a binary index for each stock taking the value one during (i) a month when there is a downgrade, (ii) the downgrade month plus three months before and after the downgrade, and (iii) the downgrade month plus six months before and after the downgrade. The index takes on the value zero otherwise. The last three rows of Panel A of Table 4 show no evidence of significant clustering of downgrades during particular time periods. For example, under the first scenario, the downgrade correlation is indeed higher in the low-rated firms (7.48%) than in the high-rated firms (2.31%). However, the downgrade correlations are just too low across the board to indicate that downgrades tend to occur in clusters.

Panel B of Table 4 exhibits the frequency of downgrades among investment-grade and non-investment-grade firms. In both groups, several firms experience multiple credit rating downgrades during the sample period, October 1985 to December 2007. The evidence further shows that for each category of number of downgrades (N ranging between one and ten), the average size per downgrade is much larger and the average time between downgrades is considerably shorter among non-investment-grade firms. Indeed, high credit risk firms tend to have larger and more frequent downgrades.

Notice that non-investment grade firms experience a series of negative returns with each downgrade. For instance, in the 3 months before (after) a downgrade, the cumulative 3-month returns for the non-investment grade stocks average -16.64% (-20.78%)

per downgrade by the sixth downgrade (N=6). On the other hand, for the investment grade stocks, the cumulative 3-month returns average -2.56% (-0.24%) per downgrade in the 3 months before (after) a downgrade. For each downgrade frequency, we have also examined (results available upon request) the cumulative returns during periods of expansions and recessions as well as periods when the market excess returns are positive and negative. Not surprisingly, returns for non-investment grade stocks are far more negative during recessions as well as periods of negative market excess returns.

Overall, the lowest-rated stocks experience significant price drops around downgrades, whereas, unconditionally, the highest-quality stocks realize positive returns.[9] This differential response is further illustrated in Figure 1. Clearly, during periods of credit rating downgrades, the low credit rating portfolio realizes returns that are uniformly lower than those of the high-rated portfolio. Moreover, the low-rated stocks deliver negative returns over six months following the downgrade. Could these major cross-sectional differences in returns around credit rating downgrades drive investment profitability for anomalies? We show below that the answer is indeed "Yes."

3.2 Impact of Downgrades on Anomalies

Table 5 repeats the analysis performed in Table 2 but focusing on periods of stable or improving credit conditions. For each downgraded stock, we exclude observations six months before the downgrade, six months after the downgrade, and the month of the downgrade. Of course, our analysis here does not intend to constitute a real-time trading strategy as we look ahead when discarding the six-month period prior to a downgrade. Our objective here is merely to examine the pattern of returns across the different portfolios around periods of improving (or stable) versus deteriorating credit conditions.[10]

Panel A (B) of Table 5 presents the equally-weighted (value-weighted) portfolio returns for the various strategies. Panel A shows that the economic and statistical signifi-

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

[10]Note that rating agencies often place firms on a credit watch prior to the actual downgrade. Vazza, Leung, Alsati, and Katz (2005) document that 64% of the firms placed on a negative credit watch subsequently experience a downgrade. This suggests that the downgrade event is largely predictable.

cance of trading strategies diminishes strongly when only periods of stable or improving conditions are considered. Of the price momentum, earnings momentum, credit risk, dispersion, and idiosyncratic volatility strategies only the price and earnings momentum strategy returns are statistically significant and that too only for the small, low-rated stocks. Both strategies deliver insignificant payoffs for all other credit risk groups. The accruals strategy is robust in periods of improving or stable credit conditions. For instance, when the strategies are not conditioned on credit ratings, the accruals strategy returns 36 basis points per month overall (as opposed to 23 basis points in Table 2). The strategy results in payoffs of 76, 33, and 22 basis points per month for the microcap, small, and big firms, respectively (as compared to 30, 32, and 19 basis points in Table 2). Similarly, the accrual strategy profits become higher for the low-rated small and microcap stocks during periods of stable credit conditions. The overall unconditional value strategy is also more profitable at 43 basis points when the period around downgrades is eliminated as opposed to 19 basis points per month for the entire sample.

Panel B of Table 5 shows that the value-weighted portfolio returns display patterns similar to the equally-weighted returns, exhibited in Panel A. Except for the accruals and value strategies, only the price momentum strategy is profitable and that too only for the small, low rated stocks.

Recall from Table 2 that a large fraction of investment profitability is attributable to the short side of the trades. Here, the short side does not play such a crucial role. To illustrate, the difference in the P1 portfolios (the short side) across the high and low-rated stocks for the price momentum strategy is 34 basis points as compared to 152 basis points in Panel B of Table 2. Moreover, the long side of the trade generates a 28 basis point difference. Similarly, for the earnings momentum strategy the short (long) side of the trade yields 11 (3) basis points per month. The short (long) side of the trade yields 40 (10) basis points for the credit risk anomaly, 23 (21) basis points for the dispersion anomaly, and 76 (2) basis points for the idiosyncratic volatility anomaly. Whereas the 76 basis point payoff seems large, it is far lower than the 196 basis points per month when the downgrade periods are included in the sample. Even for the accruals the value strategies the short side of the trades is less profitable now. The short (long) side of the trades yields 7 (6) basis points per month for the accruals anomaly and 31 (82) basis points per month for the value anomaly. Moreover, a larger fraction of the profits for the value strategy derives from the long side of the trade.

The distinct patterns exhibited by the accruals and value strategies suggest that these effects are based on different economic fundamentals. All other trading strategies are profitable due to the strongly negative returns around financial distress. In particular, a large fraction of investment profitability emerges from the short side of the trades. The strategies are no longer profitable during periods of stable or improving credit conditions. The accruals anomaly profitability is partially based on managerial discretion about the desired gap between net profit and cash flows from operation and that target does not seem to depend upon credit conditions.

The value strategy is profitable only during stable or improving credit conditions. Around financial distress the firm book-to-market ratio rises due to falling market value. This leads to the inclusion of low-rated distressed stocks in the long side of the value-based trading strategy. If such firms get downgraded, they realize abysmally low returns and the strategy could become unprofitable. Instead if the firm rebounds, the strategy succeeds. Indeed, the value effect seems to emerge from long positions in low-rated firms that survive financial distress and subsequently realize relatively high returns.

Figure 1 examines the various anomalies around downgrades. The first panel shows the equally-weighted monthly returns for the high-rated (C1) and the low-rated (C3) portfolio around downgrades. It is clear that the monthly returns are negative for the C3 portfolio from around fifteen months before the downgrade to six months after. The return is as low as -15% in the month of the downgrade. A profitable price momentum strategy would require going short in the C3 stocks. The second panel of Figure 1 shows the equally-weighted standardized unexpected earnings (SUE) for the C1 and C3 stocks around downgrades. The SUE for the C3 stocks becomes increasingly negative from about fifteen months prior to the downgrade, reaching a minimum of -0.8 in the downgrade month, and remains negative until about ten months after the downgrade. A profitable earnings momentum strategy would require going short in the C3 stocks. Analyst forecast dispersion and idiosyncratic volatiltiy increase around the downgrade for the C3 stocks. Thus, forecast dispersion and idiosyncratic volatility for the C3 stocks is high when the returns are low and a profitable dispersion strategy or the idiosyncratic volatility strategy would require going short the high dispersion or high idiosyncratic volatility, C3 stocks.

Given that the acccruals anomaly is a result of managerial discretion, there is no discernible pattern in accruals across the high- or the low-rated stocks. In the case of the value strategy, it is indeed the case that the book-to-market ratio increases around downgrades (reaching a maximum of over 2.2) for the C3 stocks. However, the value strategy involves buying the high book-to-market stocks. Thus, unlike the other strategies which go short the C3 stocks, the value strategy goes long the high book-to-market C3 stocks around downgrades. The bet is that these high book-to-market stocks survive the financial distress and provide high returns subsequently.

3.3 Regression Analysis

In this section, we further scrutinize the asset pricing anomalies using regression analysis. In particular, following Brennan, Chordia, and Subrahmanyam (1998), we consider the following cross-sectional specification

$$R_{it} - R_{ft} - \sum_{k=1}^{K} \hat{\beta}_{ik} F_{kt} = a_t + b_t \, C_{it-1} + e_{it}, \tag{2}$$

where $\hat{\beta}_{ik}$ is beta estimated by a first-pass time-series regression of the firm's excess stock return on the Fama and French (1993) factors over the entire sample period with non-missing returns data,[11] and C_{it-1} is the value of the conditioning variable underlying the trading strategy (e.g., the book-to-market ratio for the value anomaly) for security i at time $t-1$. We report the time-series averages of the slope coefficients, $\hat{b}_t$, and the corresponding t-ratios. The standard errors of the slope estimates are obtained from the time series of monthly estimates.

The firm characteristics on the right hand side of the cross-section regression represent the conditioning variables underlying the trading strategy including price and earnings momentum, credit rating, analyst dispersion, idiosyncratic volatility, size, the book-to-market ratio, and accruals. We also include dummy variables D_{NIG} and D_{IG} to denote the six month period around credit rating downgrades for non-investment and investment grade stocks, respectively. All equity characteristics are lagged one month relative to the month when the dependent variable is measured.

The results are presented in Table 6. Consider Panel A, which exhibits the cross-sectional regression coefficients for all stocks in univariate cross-sectional regressions.

[11] While this entails the use of future data in calculating the factor loadings, Fama and French (1992) show that this forward looking does not impact the results. See also Avramov and Chordia (2006).

The evidence is indeed quite similar to that based on returns from portfolio sorts, as reported in Table 2. In particular, the coefficient estimates for past returns (0.90) and standardized unexpected earnings (0.14) are positive and significant, consistent with the price and earnings momentum anomalies. The coefficient estimates for credit risk (-0.09), analyst dispersion (-0.23), idiosyncratic volatility (-6.03), and accruals (-2.42) are negative and significant, again consistent with prior results. The coefficient estimates for firm size and the book-to-market ratio are both insignificant in the cross-sectional regressions.

Next we introduce dummy variables for the six-month period around downgrades. We start with a dummy for non-investment grade stocks only. The coefficient on the dummy variable is significantly negative across the board, consistent with the negative returns realized around credit rating downgrades. The regression analysis suggests that only the earnings momentum, the accruals, and the value strategies are profitable. Then we consider both dummies for investment grade and noninvestment grade stocks. The coefficient estimates on both dummy variables are significantly negative although for investment grade stocks the coefficient is uniformly smaller in absolute value. With both dummy variables, only the accruals and value strategies result in positive payoffs, whereas none of the other strategies is profitable. Overall, the evidence is consistent with our findings from the portfolio based analysis presented in Table 5. That is, the earnings and price momentum, credit risk, dispersion, and idiosyncratic volatility anomalies are driven by the sharp drop in stock prices around credit ratings downgrades.

Note that the point estimates for the book-to-market ratio actually increase as the dummy variables for periods around downgrades are introduced into the regression. Indeed, the value strategy is profitable during periods of stable or improving credit conditions. This indicates that the value strategy is prominent across firms that survive financial distress. In contrast, during periods of financial distress, as proxied by credit rating downgrades, stock prices fall sharply and the book to market ratio thus rises. This leads to a temporally negative relation between book-to-market and stock returns during the period of financial distress.

Panel B, C, and D of Table 6 presents the regression evidence for microcap, small, and big stocks, respectively.[12] Only the coefficients for earnings momentum and the

[12]Fama and French (2008) have shown that a vast majority of the stocks are classified as microcap. Thus, there is a sufficiently large number of stocks included in the cross-section regressions.

book-to-market ratio are significant for small and microcap stocks in the presence of the downgrade dummy variables. For big stocks, only the accruals trading strategy is profitable in the presence of the downgrade dummy variables.

Overall, conditioning on market capitalization, the results suggest that the accruals and value anomalies are robust across credit rating groups. However, all other anomalies display diminishing coefficient estimates as the dummy variables for the downgrade periods are introduced into the regression. Further, the accruals anomaly is profitable for big stocks, which account for over 96% of the sample by market capitalization. Except for the accruals and value anomalies, profitability of all other anomalies is attributable to negative returns realized on the short side of the trade around credit rating downgrades.

The questions that arise are: (i) Why are these negative returns not arbitraged away? (ii) Are there any frictions that prevent these anomalous returns from being arbitraged away? We now examine such frictions including the lack of liquidity and the difficulties to taking short positions.

3.4 Short Sale Constraints and Illiquidity

Impediments to trading such as short selling and poor liquidity could establish non trivial hurdles for exploiting market anomalies. Hence, we examine how short sell constraints and illiquidity are related to the profitability of investment strategies. Following D'Avolio (2002), we consider the following proxies for short sale constraints: (i) institutional holdings, (ii) share turnover, and (iii) shares outstanding. Low institutional holdings and a low number of shares outstanding make it difficult to borrow stocks for short selling, while low share turnover could lead to difficulties with the uptick rules (starting with July 6, 2007 traders can short all securities on an up, down, or zero tick) when short selling. We examine illiquidity using the Amihud (2002) measure noted earlier.

Table 7 presents the mean and median measures of institutional holdings, turnover, shares outstanding, and illiquidity for portfolios sorted on credit ratings and firm size. Starting with all rated stocks - not surprisingly, big stocks are more liquid and they have more shares outstanding and higher institutional holdings. Turnover does not exhibit a monotonic trend with firm size. Big stocks have a lower turnover than small stocks presumably because they have a much higher number of shares outstanding.

Conditioning on credit ratings, we do show that low rated stocks are substantially more illiquid. For instance, the median Amihud measure increases monotonically from 0.02 (0.23) for the high rated NYSE/AMEX (Nasdaq) stocks to 0.48 (0.92) for the low rated NYSE/AMEX (Nasdaq) stocks. This general pattern is also manifested among size sorted portfolios. Institutional holdings for low rated stocks are also lower than those of high rated stocks although the relation is not monotonic. The number of shares outstanding decreases with deteriorating credit ratings, from a median measure of $85.37 million for the high rated stocks to $25.42 million for the low rated stocks. Each of the above measures suggests that short selling would be more difficult to implement among low-versus-high rated stocks.

Overall, we demonstrate a consistent relationship between investment profitability (reported in Table 2) and illiquidity and short-sale constraints (demonstrated in Table 7). The profitability of asset-pricing anomalies is derived from short positions, which are difficult to implement, and it crucially depends upon highly illiquid stocks facing poor credit conditions. The evidence suggests that it would be difficult to exploit asset pricing anomalies in real-time trading.

4 Conclusions

The empirically documented price momentum, earnings momentum, credit risk, analyst forecast dispersion, idiosyncratic volatility, accruals, and value effects are all unexplained by canonical asset pricing models, such as the capital asset pricing model. Thus they are perceived to be market anomalies. This paper examines all these anomalies in a unified framework. In particular, we explore commonalities across anomalies and assess potential implications of financial distress for the profitability of anomaly-based trading strategies. At the firm level, financial distress is proxied for by credit rating downgrades.

We document that the profitability of the price momentum, earnings momentum, credit risk, dispersion, and idiosyncratic volatility anomalies is concentrated in the worst rated stocks. The profitability of these anomalies completely disappears when firms rated BB or below are excluded from the sample. Remarkably, the eliminated firms represent only 6.3% of the market capitalization of the rated firms. Indeed, the profitability of price momentum, earnings momentum, credit risk, dispersion, and idiosyncratic volatility anomalies is concentrated in a small sample of low-rated stocks facing deteriorating credit conditions. Moreover, we show that a vast majority of the profitability of anomaly-based trading strategies is derived from the short side of the trade. The anomaly-based trading strategy profits are statistically insignificant and economically small when periods around credit rating downgrades are excluded from the sample. None of the above strategies delivers significant payoffs during stable or improving credit conditions.

The anomaly-based trading strategy profits are not arbitraged away possibly due to trading frictions such as short-sale constraints and illiquidity. The low-rated stocks are substantially more illiquid. They are more difficult to short sell as they have fewer shares outstanding and low institutional holdings, which makes it difficult to borrow stocks for short selling. Ultimately, the asset-pricing anomalies studied here would be difficult to exploit in real time due to trading frictions.

The unifying logic of financial distress does not apply to the accruals and value anomalies. The accruals anomaly is based on managerial discretion about the desired gap between net profit and operating cash flows and this target gap does not seem to depend upon credit conditions. The value-based trading strategy is more profitable in stable credit conditions. The value effect seems to emerge from long positions in low-rated firms that survive financial distress and realize relatively high subsequent returns. Thus, the accruals and value anomalies are based on different economic fundamentals and do not emerge during periods of deteriorating credit conditions. Nor are they attributable to the short side of the trading strategy.

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Table 1
Stock Characteristics, Alphas, and Betas by Credit Rating Tercile

Each month, all stocks rated by Standard & Poor's are divided into tercile portfolios based on their credit rating at time t. For each rating group, we compute the cross-sectional median characteristic for month $t+1$. The sample period is October 1985 to December 2007. Panel A reports the time-series average of these monthly medians. Dollar volume is the monthly dollar trading volume (in $ mln). Amihud's illiquidity is computed, as in Amihud (2002) (see eq. (1)), as the the absolute daily return divided by the total dollar trading volume for the day, averaged across all trading days of the month and multiplied by 10^7. Institutional share is the percentage of shares outstanding owned by institutions. Number of analysts represents the number of analysts following the firm. Analyst revisions is computed as the change in mean EPS forecast since last month divided by the absolute value of the mean EPS forecast last month. Standardized Unexpected Earnings [SUE] is the difference between the EPS reported this quarter and the EPS four quarters ago, divided by the standard deviation of these EPS changes over the last eight quarters. Leverage is computed as the book value of long-term debt to common equity. In Panel B, CAPM and Fama and French (1993) alphas and betas are calculated by running time-series regressions of the credit risk tercile portfolio excess stock returns on the factor returns. The reported alphas are in percentages per month. The associated sample t-statistics are in parentheses (bold if significant at the 95% confidence level).

PANEL A: Stock Characteristics

	Rating Tercile (C1=Lowest , C3=Highest Risk)		
Characteristics	C1	C2	C3
Size ($ bln)	3.37	1.24	0.33
Book-to-Market Ratio	0.51	0.61	0.66
Price ($)	38.22	26.46	12.35
Dollar Volume - NYSE/AMEX ($ mln)	287.14	128.70	49.05
Dollar Volume - Nasdaq ($ mln)	61.22	73.38	32.44
Amihud's Illiquidity-NYSE/AMEX	0.02	0.05	0.48
Amihud's Illiquidity - Nasdaq	0.23	0.23	0.91
Institutional Share (%)	55.96	57.56	45.64
Number of Analysts	14.14	9.33	5.05
Analyst Revisions (%)	-0.01	-0.10	-0.13
SUE	0.60	0.34	0.13
LT Debt/Equity Ratio	0.54	0.79	1.36

PANEL B: Portfolio Alphas and Betas

	Rating Tercile (C1=Lowest , C3=Highest Risk)			
	C1	C2	C3	C1-C3
CAPM Alpha (%/month)	0.33	0.23	-0.57	0.90
	(**3.28**)	(1.88)	(**-2.44**)	(**3.50**)
CAPM Beta	0.80	0.91	1.29	-0.49
	(**34.26**)	(**31.99**)	(**24.20**)	(**-8.34**)
FF93 Alpha (%/month)	0.11	-0.06	-0.76	0.88
	(1.62)	(-0.74)	(**-4.79**)	(**5.04**)
Mkt Beta	0.95	1.08	1.32	-0.37
	(**53.78**)	(**51.94**)	(**32.36**)	(**-8.37**)
SMB Beta	-0.06	0.28	0.89	-0.96
	(**-2.98**)	(**11.09**)	(**17.90**)	(**-17.64**)
HML Beta	0.41	0.60	0.50	-0.09
	(**15.55**)	(**19.30**)	(**8.16**)	(-1.32)

Table 2
Profits from Asset-Pricing Anomalies in Rated Firms

Our sample includes all NYSE, AMEX, and NASDAQ stocks with available credit rating data on COMPUSTAT or Standard and Poor's Rating Xpress. Stocks are also sorted into micro, small, and big, based on the 20th and 50th size percentile bounds of all NYSE stocks listed on CRSP, based on size computed at the end of June of the prior year as in Fama and French (2008). Whenever we condition on credit rating, the conditioning is first done by credit rating based on all rated stocks in our sample at the beginning of the month, and then by size (micro, small, big), based on the NYSE cutoffs. Within each subsample, stocks are sorted into quintile portfolios based on various firm-level conditioning variables. For strategies with holding periods longer than a month ($K > 1$), each month's profits are computed by weighting equally all portfolios formed over the preceding K months. The price momentum strategy conditions on the cumulative returns over the past 6 month. The SUE strategy conditions on standardized unexpected earnings (SUE) announced over the past four months ($t-4$ to $t-1$). SUE is computed as the quarterly EPS this quarter minus the EPS four quarters ago, standardized by the standard deviation of these earnings changes over the preceding eight quarters. Credit risk conditions on prior month credit rating. Dispersion conditions on the prior month standard deviation of analyst earnings forecasts for the upcoming fiscal year end, standardized by the absolute value of the mean analyst forecast. Observations of dispersion based on less than two analysts are excluded. Idiosyncratic volatility conditions on prior month sum of the stock's squared daily returns minus prior month squared daily market returns. Accruals is computed as in Sloan (1996) based on quarterly data from Compustat and there's a four month lag between portfolio formation and the holding period to ensure that all accounting variables are know when investing. Book-to-market ratios for July of year t to June of year $t+1$ are calculated as the book value of equity standardized by the market capitalization from CRSP, both measured as of December of year $t-1$, as in Fama and French (1992). The sample period is October 1985 to December 2007. The line 'Strategy' specifies the long and the short position of each strategy, i.e. P5-P1 implies long P5 and short P1. t-statistics are in parentheses (bold if indicating 5% significance). Panel A/B provides the equally/value weighted anomaly profits based on size and book-to-market adjusted returns as in Fama and French (2008). In particular, we form 5×5 size and book-to-market sorted portfolios. We then subtract the monthly return of the portfolio to which a stock belongs from the individual monthly stock return to obtain the stock's characteristic-adjusted return. The 'All Rated' row presents the profits based on all firms having a rating for the month prior to portfolio formation. The 'C1', 'C2', and 'C3' rows present the profits within the highest, average, and lowest rated firm tercile, based on prior month available ratings.

Table 2 (continued)

Panel A: Equally Weighted Size and BM adjusted Returns

Anomaly		Momentum	SUE	Credit Risk	Dispersion	Idio Vol	Accruals	BM
Strategy		P5-P1	P5-P1	P1-P5	P1-P5	P1-P5	P1-P5	P5-P1
All Rated	P1	-1.03	-0.49	0.03	0.09	-0.01	-0.18	-0.35
	P5	0.25	0.07	-0.87	-0.51	-1.08	-0.41	-0.16
	Strategy	1.28	0.57	0.91	0.60	1.06	0.23	0.19
		(**5.42**)	(**4.48**)	(**4.76**)	(**3.14**)	(**3.62**)	(**3.22**)	(1.30)
Micro Rated	P1	-1.62	-1.04	-0.21	-0.65	-0.07	-0.31	-0.72
	P5	0.53	0.22	-0.85	-0.91	-1.28	-0.60	-0.39
	Strategy	2.16	1.26	0.64	0.26	1.22	0.30	0.34
		(**8.86**)	(**3.69**)	(**1.96**)	(1.70)	(**3.64**)	(**2.03**)	(0.64)
Small Rated	P1	-1.14	-0.65	0.00	0.23	0.00	-0.25	-0.73
	P5	0.18	0.20	-0.88	-0.61	-1.02	-0.57	-0.12
	Strategy	1.33	0.85	0.88	0.84	1.02	0.32	0.60
		(**5.16**)	(**4.49**)	(**2.98**)	(**3.66**)	(**3.04**)	(**2.78**)	(**2.62**)
Big Rated	P1	-0.51	-0.23	0.05	0.09	-0.03	-0.05	-0.21
	P5	0.18	0.03	-0.60	-0.19	-0.78	-0.24	0.10
	Strategy	0.69	0.26	0.65	0.28	0.75	0.19	0.30
		(**2.44**)	(1.90)	(1.89)	(1.18)	(**2.01**)	(**2.39**)	(1.78)
C1 All	P1	0.02	-0.02	0.01	0.14	0.00	0.11	0.01
	P5	0.10	0.11	0.10	-0.01	-0.03	-0.04	-0.04
	Strategy	0.08	0.13	-0.09	0.15	0.03	0.15	-0.05
		(0.47)	(1.05)	(-1.05)	(0.96)	(0.14)	(**2.71**)	(-0.29)
C1 Micro	P1	-0.46	-0.35	-0.12	-1.03	0.60	0.27	
	P5	0.13	0.61	-0.06	-0.13	-0.86	-0.34	-0.06
	Strategy	0.74	0.44	-0.07	-0.73	0.87	0.54	
		(1.74)	(0.56)	(-0.20)	(-1.12)	(1.76)	(1.77)	
C1 Small	P1	-0.11	-0.35	-0.07	-0.01	0.03	-0.25	-0.72
	P5	-0.00	0.11	-0.06	-0.14	-0.40	-0.11	-0.00
	Strategy	0.11	0.43	-0.01	0.20	0.48	-0.15	0.89
		(0.39)	(1.18)	(-0.03)	(0.51)	(1.71)	(-0.91)	(0.38)
C1 Big	P1	0.06	0.02	0.02	0.17	-0.03	0.15	0.01
	P5	0.13	0.10	0.12	0.05	0.07	-0.01	-0.07
	Strategy	0.07	0.09	-0.10	0.12	-0.09	0.15	-0.08
		(0.41)	(0.68)	(-1.02)	(0.71)	(-0.42)	(**2.53**)	(-0.46)
C2 All	P1	-0.20	-0.21	0.00	0.08	-0.02	0.02	-0.05
	P5	0.21	0.05	0.01	0.03	-0.10	-0.24	0.02
	Strategy	0.41	0.26	-0.01	0.05	0.07	0.25	0.08
		(**2.22**)	(1.91)	(-0.10)	(0.30)	(0.31)	(**3.05**)	(0.49)
C2 Micro	P1	0.11	-0.57	0.03	-0.14	0.21	-0.07	3.32
	P5	-0.16	0.13	0.11	-0.16	-0.14	-0.26	-0.25
	Strategy	-0.22	0.49	-0.19	-0.40	0.32	0.19	-4.08
		(-0.55)	(0.87)	(-0.55)	(-0.64)	(0.74)	(0.64)	(-1.17)
C2 Small	P1	-0.32	-0.24	-0.32	-0.00	-0.12	0.07	-0.45
	P5	0.20	0.18	-0.03	-0.12	-0.15	-0.26	-0.01
	Strategy	0.52	0.42	-0.30	0.12	0.03	0.33	0.44
		(**2.55**)	(**2.18**)	(-1.79)	(0.51)	(0.12)	(**2.69**)	(0.98)
C2 Big	P1	-0.22	-0.18	0.06	0.10	-0.01	-0.02	-0.05
	P5	0.26	0.02	0.01	0.08	-0.12	-0.26	0.10
	Strategy	0.47	0.20	0.05	0.02	0.12	0.24	0.15
		(**2.24**)	(1.35)	(0.52)	(0.10)	(0.46)	(**2.34**)	(0.85)
C3 All	P1	-2.10	-1.08	-0.12	-0.05	-0.10	-0.52	-0.89
	P5	0.43	0.12	-1.54	-0.80	-2.11	-0.79	-0.26
	Strategy	2.53	1.19	1.42	0.75	2.01	0.28	0.63
		(**7.45**)	(**6.63**)	(**6.59**)	(**3.24**)	(**6.24**)	(**2.09**)	(**2.33**)
C3 Micro	P1	-2.31	-1.35	-0.11	-0.58	0.05	-0.41	-0.72
	P5	0.74	0.08	-1.54	-1.25	-2.03	-0.77	-0.37
	Strategy	3.05	1.43	1.43	0.67	2.08	0.36	0.34
		(**9.34**)	(**4.33**)	(**4.55**)	(1.70)	(**6.06**)	(1.90)	(0.69)
C3 Small	P1	-2.02	-1.01	-0.09	0.19	-0.05	-0.50	-0.88
	P5	0.32	0.32	-1.49	-0.76	-2.18	-0.84	-0.19
	Strategy	2.35	1.33	1.40	0.95	2.13	0.35	0.69
		(**5.85**)	(**5.41**)	(**3.87**)	(**3.13**)	(**4.83**)	(1.95)	(**2.38**)
C3 Big	P1	-1.27	-0.75	-0.20	-0.29	-0.28	-0.50	-0.80
	P5	0.13	-0.08	-0.65	-0.43	-2.41	-0.98	0.50
	Strategy	1.40	0.66	0.45	0.14	2.13	0.48	1.29
		(**3.12**)	(**2.18**)	(1.04)	(0.43)	(**3.52**)	(1.64)	(**2.45**)

Table 2 (continued)

Panel B: Value Weighted Size and BM adjusted Returns

Anomaly		Momentum	SUE	Credit Risk	Dispersion	Idio Vol	Accruals	BM
Strategy		P5-P1	P5-P1	P1-P5	P1-P5	P1-P5	P1-P5	P5-P1
All Rated	P1	-0.44	-0.22	-0.04	-0.03	-0.11	-0.03	-0.16
	P5	0.12	-0.05	-0.91	-0.32	-0.55	-0.30	-0.05
	Strategy	0.56	0.17	0.86	0.29	0.43	0.27	0.11
		(**2.10**)	(0.95)	(**2.65**)	(1.06)	(1.19)	(**2.41**)	(0.59)
Micro Rated	P1	-1.60	-1.06	-0.28	-0.79	-0.07	-0.37	-0.62
	P5	0.35	0.05	-0.98	-1.03	-1.42	-0.57	-0.27
	Strategy	1.95	1.11	0.70	0.21	1.36	0.19	0.37
		(**7.56**)	(**3.35**)	(1.92)	(0.52)	(**3.84**)	(1.33)	(0.64)
Small Rated	P1	-1.21	-0.67	0.02	0.22	-0.00	-0.20	-0.69
	P5	0.21	0.12	-0.98	-0.64	-1.10	-0.58	-0.13
	Strategy	1.42	0.79	1.00	0.87	1.10	0.38	0.56
		(**5.18**)	(**3.99**)	(**3.16**)	(**3.66**)	(**3.07**)	(**3.13**)	(**2.37**)
Big Rated	P1	-0.35	-0.20	-0.04	-0.04	-0.12	-0.02	-0.15
	P5	0.11	-0.05	-0.59	-0.26	-0.41	-0.27	-0.05
	Strategy	0.46	0.14	0.55	0.22	0.29	0.26	0.10
		(1.68)	(0.78)	(1.43)	(0.79)	(0.76)	(**2.26**)	(0.55)
C1 All	P1	-0.06	-0.10	-0.04	0.13	-0.06	0.06	-0.08
	P5	0.03	0.04	-0.05	-0.04	-0.14	-0.16	-0.10
	Strategy	0.09	0.14	0.01	0.17	0.08	0.22	-0.02
		(0.43)	(0.73)	(0.08)	(0.67)	(0.31)	(**2.01**)	(-0.13)
C1 Micro	P1	-0.50	-0.45	0.00	-1.06	0.57	0.27	
	P5	-0.06	0.55	-0.30	0.07	-1.00	-0.37	0.04
	Strategy	0.57	0.62	0.30	-0.81	1.01	0.54	
		(1.37)	(0.77)	(0.73)	(-1.09)	(1.91)	(1.88)	
C1 Small	P1	-0.03	-0.33	-0.02	-0.04	0.03	-0.23	-0.72
	P5	0.01	0.11	-0.04	-0.21	-0.27	-0.11	0.03
	Strategy	0.04	0.41	0.02	0.24	0.36	-0.11	1.22
		(0.15)	(1.12)	(0.11)	(0.59)	(1.22)	(-0.71)	(0.54)
C1 Big	P1	-0.07	-0.09	-0.04	0.13	-0.06	0.06	-0.08
	P5	0.03	0.04	-0.06	-0.04	-0.14	-0.15	-0.11
	Strategy	0.10	0.13	0.01	0.17	0.08	0.22	-0.03
		(0.44)	(0.71)	(0.08)	(0.65)	(0.29)	(**2.00**)	(-0.15)
C2 All	P1	-0.40	-0.40	-0.03	0.07	0.02	-0.10	-0.17
	P5	0.34	-0.20	-0.11	-0.21	-0.30	-0.45	-0.06
	Strategy	0.74	0.20	0.08	0.27	0.32	0.35	0.10
		(**2.82**)	(0.93)	(0.63)	(0.96)	(0.97)	(**2.77**)	(0.44)
C2 Micro	P1	-0.06	-0.64	-0.03	-0.16	0.04	-0.24	3.51
	P5	-0.22	0.14	-0.24	-0.60	-0.33	-0.30	-0.38
	Strategy	-0.10	0.55	0.07	0.11	0.34	0.06	-4.33
		(-0.23)	(0.94)	(0.21)	(0.16)	(0.75)	(0.20)	(-1.25)
C2 Small	P1	-0.33	-0.26	-0.29	0.07	-0.10	0.11	-0.51
	P5	0.20	0.17	-0.07	-0.12	-0.25	-0.23	-0.02
	Strategy	0.53	0.43	-0.22	0.19	0.14	0.33	0.49
		(**2.50**)	(**2.08**)	(-1.32)	(0.76)	(0.54)	(**2.40**)	(1.06)
C2 Big	P1	-0.40	-0.40	-0.03	0.07	0.03	-0.12	-0.16
	P5	0.35	-0.21	-0.10	-0.21	-0.29	-0.46	-0.06
	Strategy	0.75	0.20	0.08	0.27	0.33	0.35	0.10
		(**2.79**)	(0.89)	(0.56)	(0.93)	(0.97)	(**2.63**)	(0.43)
C3 All	P1	-1.58	-0.95	-0.32	-0.26	-0.23	-0.81	-0.81
	P5	0.21	-0.10	-1.39	-0.61	-2.10	-0.96	0.23
	Strategy	1.79	0.85	1.07	0.35	1.87	0.15	1.04
		(**4.28**)	(**3.05**)	(**3.08**)	(1.18)	(**4.04**)	(0.69)	(**2.47**)
C3 Micro	P1	-2.31	-1.38	-0.12	-0.66	0.01	-0.49	-0.93
	P5	0.49	-0.13	-1.65	-1.25	-2.41	-0.72	-0.18
	Strategy	2.80	1.25	1.53	0.59	2.41	0.24	0.75
		(**7.96**)	(**3.79**)	(**4.42**)	(1.37)	(**6.41**)	(1.30)	(1.36)
C3 Small	P1	-2.20	-1.03	-0.09	0.18	-0.10	-0.47	-0.80
	P5	0.35	0.21	-1.62	-0.81	-2.27	-0.93	-0.19
	Strategy	2.55	1.24	1.53	0.99	2.17	0.46	0.61
		(**5.98**)	(**4.57**)	(**3.90**)	(**3.07**)	(**4.54**)	(**2.35**)	(**2.03**)
C3 Big	P1	-1.10	-0.78	-0.32	-0.44	-0.28	-0.74	-0.77
	P5	0.13	-0.16	-0.63	-0.50	-2.25	-0.97	0.29
	Strategy	1.23	0.62	0.30	0.06	1.97	0.23	1.06
		(**2.65**)	(1.79)	(0.65)	(0.17)	(**3.09**)	(0.77)	(1.66)

Table 3
Profits from Asset-Pricing Anomalies in Decreasing Subsamples of Rated Firms

We repeat the analysis in Table 2 sequentially eliminating the worst rated stocks. The results presented here are based on equally weighted size and BM adjusted returns.

Anomaly	Momentum	SUE	Credit Risk	Dispersion	Idio Vol	Accruals	BM	% of Firms	% of MV
All (AAA-D)	1.28	0.57	0.91	0.60	1.06	0.23	0.19	100.00	100.00
	(**5.42**)	(**4.48**)	(**4.76**)	(**3.14**)	(**3.62**)	(**3.22**)	(1.30)		
Micro (AAA-D)	2.16	1.26	0.64	0.26	1.22	0.30	0.34	17.81	0.43
	(**8.86**)	(**3.69**)	(**1.96**)	(1.70)	(**3.64**)	(**2.03**)	(0.64)		
Small (AAA-D)	1.33	0.85	0.88	0.84	1.02	0.32	0.60	27.07	2.97
	(**5.16**)	(**4.49**)	(**2.98**)	(**3.66**)	(**3.04**)	(**2.78**)	(**2.62**)		
Big (AAA-D)	0.69	0.26	0.65	0.28	0.75	0.19	0.30	55.12	96.59
	(**2.44**)	(1.90)	(1.89)	(1.18)	(**2.01**)	(**2.39**)	(1.78)		
All (AAA-C)	1.20	0.55	0.75	0.54	0.91	0.25	0.23	99.10	99.93
	(**5.14**)	(**4.37**)	(**4.02**)	(**2.84**)	(**3.07**)	(**3.54**)	(1.57)		
Micro (AAA-C)	2.01	1.21	0.44	0.20	0.96	0.37	0.45	17.06	0.42
	(**8.34**)	(**3.64**)	(1.26)	(0.54)	(**2.84**)	(**2.59**)	(0.85)		
Small (AAA-C)	1.28	0.84	0.76	0.79	0.91	0.33	0.60	26.97	2.96
	(**5.06**)	(**4.47**)	(**2.70**)	(**3.46**)	(**2.76**)	(**2.92**)	(**2.63**)		
Big (AAA-C)	0.67	0.26	0.56	0.25	0.68	0.18	0.31	55.07	96.54
	(**2.41**)	(1.88)	(1.67)	(1.07)	(1.84)	(**2.24**)	(1.84)		
All (AAA-CC)	1.20	0.55	0.75	0.54	0.90	0.25	0.23	99.09	99.93
	(**5.14**)	(**4.37**)	(**4.01**)	(**2.84**)	(**3.06**)	(**3.54**)	(1.59)		
Micro (AAA-CC)	2.01	1.21	0.43	0.20	0.95	0.37	0.45	17.06	0.42
	(**8.34**)	(**3.64**)	(1.25)	(0.54)	(**2.82**)	(**2.60**)	(0.87)		
Small (AAA-CC)	1.27	0.84	0.76	0.79	0.91	0.33	0.60	26.97	2.96
	(**5.06**)	(**4.47**)	(**2.70**)	(**3.46**)	(**2.75**)	(**2.91**)	(**2.63**)		
Big (AAA-CC)	0.67	0.26	0.56	0.25	0.68	0.18	0.31	55.07	96.54
	(**2.41**)	(1.88)	(1.67)	(1.07)	(1.85)	(**2.24**)	(1.85)		
All (AAA-CCC-)	1.18	0.54	0.71	0.54	0.87	0.26	0.23	98.87	99.91
	(**5.05**)	(**4.26**)	(**3.83**)	(**2.83**)	(**2.94**)	(**3.69**)	(1.62)		
Micro (AAA-CCC-)	1.95	1.20	0.39	0.21	0.89	0.42	0.33	16.89	0.42
	(**8.14**)	(**3.51**)	(1.11)	(0.57)	(**2.64**)	(**2.97**)	(0.61)		
Small (AAA-CCC-)	1.26	0.83	0.73	0.79	0.91	0.33	0.59	26.93	2.96
	(**5.04**)	(**4.41**)	(**2.60**)	(**3.45**)	(**2.74**)	(**2.92**)	(**2.58**)		
Big (AAA-CCC-)	0.66	0.25	0.56	0.26	0.66	0.18	0.31	55.05	96.53
	(**2.40**)	(1.81)	(1.69)	(1.10)	(1.80)	(**2.25**)	(1.86)		
All (AAA-CCC)	1.16	0.54	0.67	0.53	0.84	0.26	0.25	98.62	99.90
	(**4.99**)	(**4.28**)	(**3.63**)	(**2.80**)	(**2.84**)	(**3.75**)	(1.76)		
Micro (AAA-CCC)	1.89	1.24	0.35	0.20	0.84	0.43	0.39	16.70	0.42
	(**7.91**)	(**3.57**)	(1.03)	(0.54)	(**2.50**)	(**3.03**)	(0.71)		
Small (AAA-CCC)	1.26	0.82	0.67	0.79	0.89	0.32	0.59	26.88	2.96
	(**5.06**)	(**4.41**)	(**2.41**)	(**3.44**)	(**2.69**)	(**2.89**)	(**2.59**)		
Big (AAA-CCC)	0.66	0.25	0.52	0.26	0.65	0.18	0.32	55.04	96.52
	(**2.39**)	(1.83)	(1.57)	(1.09)	(1.79)	(**2.24**)	(1.91)		
All (AAA-CCC+)	1.11	0.51	0.60	0.50	0.75	0.27	0.29	98.03	99.86
	(**4.78**)	(**4.05**)	(**3.45**)	(**2.65**)	(**2.58**)	(**3.84**)	(**2.03**)		
Micro (AAA-CCC+)	1.76	1.12	0.27	0.22	0.69	0.45	0.37	16.30	0.41
	(**7.38**)	(**3.22**)	(0.81)	(0.60)	(**2.09**)	(**3.25**)	(0.69)		
Small (AAA-CCC+)	1.24	0.81	0.63	0.74	0.84	0.32	0.60	26.75	2.95
	(**5.03**)	(**4.33**)	(**2.36**)	(**3.22**)	(**2.58**)	(**2.89**)	(**2.59**)		
Big (AAA-CCC+)	0.64	0.24	0.47	0.26	0.63	0.18	0.31	54.98	96.49
	(**2.36**)	(1.73)	(1.46)	(1.10)	(1.74)	(**2.25**)	(1.85)		
All (AAA-B-)	1.03	0.48	0.52	0.45	0.65	0.27	0.26	97.07	99.78
	(**4.52**)	(**3.79**)	(**3.07**)	(**2.39**)	(**2.29**)	(**3.96**)	(1.86)		
Micro (AAA-B-)	1.61	1.03	0.21	0.10	0.61	0.47	0.08	15.67	0.40
	(**6.84**)	(**2.99**)	(0.62)	(0.28)	(1.92)	(**3.49**)	(0.14)		
Small (AAA-B-)	1.16	0.78	0.54	0.67	0.70	0.32	0.59	26.52	2.93
	(**4.79**)	(**4.15**)	(**2.07**)	(**3.00**)	(**2.23**)	(**2.90**)	(**2.52**)		
Big (AAA-B-)	0.62	0.23	0.47	0.24	0.57	0.18	0.29	54.88	96.45
	(**2.32**)	(1.67)	(1.52)	(1.05)	(1.61)	(**2.30**)	(1.76)		

Table 3 (continued)

Anomaly	Momentum	SUE	Credit Risk	Dispersion	Idio Vol	Accruals	BM	% of Firms	% of MV
All (AAA-B)	0.90	0.43	0.45	0.41	0.53	0.29	0.21	94.74	99.44
	(**4.17**)	(**3.50**)	(**2.85**)	(**2.27**)	(1.94)	(**4.33**)	(1.55)		
Micro (AAA-B)	1.40	1.09	0.11	0.16	0.52	0.46	0.15	14.41	0.37
	(**6.38**)	(**3.36**)	(0.35)	(0.45)	(1.68)	(**3.47**)	(0.24)		
Small (AAA-B)	1.03	0.75	0.49	0.62	0.58	0.34	0.49	25.79	2.85
	(**4.51**)	(**3.96**)	(1.91)	(**2.84**)	(1.93)	(**3.09**)	(**2.10**)		
Big (AAA-B)	0.54	0.17	0.39	0.22	0.46	0.22	0.24	54.54	96.21
	(**2.11**)	(1.30)	(1.35)	(0.95)	(1.37)	(**3.01**)	(1.56)		
All (AAA-B+)	0.73	0.38	0.35	0.33	0.37	0.32	0.16	90.34	98.72
	(**3.65**)	(**3.19**)	(**2.42**)	(1.86)	(1.47)	(**4.74**)	(1.21)		
Micro (AAA-B+)	1.18	1.36	0.05	-0.02	0.39	0.55	0.54	12.04	0.32
	(**5.60**)	(**3.81**)	(0.16)	(-0.05)	(1.32)	(**3.98**)	(0.91)		
Small (AAA-B+)	0.84	0.64	0.40	0.50	0.39	0.38	0.39	24.43	2.72
	(**3.98**)	(**3.48**)	(1.63)	(**2.31**)	(1.43)	(**3.53**)	(1.67)		
Big (AAA-B+)	0.47	0.16	0.29	0.20	0.29	0.24	0.17	53.87	95.69
	(**1.97**)	(1.23)	(1.13)	(0.88)	(0.93)	(**3.27**)	(1.15)		
All (AAA-BB-)	0.52	0.27	0.16	0.22	0.19	0.27	0.12	80.93	97.42
	(**2.77**)	(**2.45**)	(1.21)	(1.29)	(0.79)	(**4.48**)	(0.96)		
Micro (AAA-BB-)	0.84	0.96	-0.10	-0.23	0.32	0.34	-0.93	8.00	0.21
	(**3.17**)	(**2.26**)	(-0.29)	(-0.54)	(0.98)	(1.84)	(-1.09)		
Small (AAA-BB-)	0.66	0.49	0.14	0.25	0.26	0.34	0.35	20.55	2.35
	(**3.41**)	(**2.70**)	(0.59)	(1.28)	(1.00)	(**3.32**)	(1.34)		
Big (AAA-BB-)	0.37	0.14	0.26	0.18	0.13	0.23	0.07	52.38	94.86
	(1.73)	(1.16)	(1.36)	(0.87)	(0.49)	(**3.47**)	(0.51)		
All (AAA-BB)	0.40	0.26	0.05	0.19	0.10	0.24	0.10	72.16	95.68
	(**2.22**)	(**2.26**)	(0.40)	(1.14)	(0.42)	(**3.96**)	(0.78)		
Micro (AAA-BB)	0.54	0.84	-0.18	-0.02	0.37	0.27	-1.74	5.57	0.14
	(1.83)	(1.85)	(-0.53)	(-0.04)	(1.06)	(1.12)	(-0.87)		
Small (AAA-BB)	0.53	0.54	0.06	0.17	0.13	0.29	0.11	16.30	1.87
	(**2.82**)	(**2.85**)	(0.27)	(0.89)	(0.54)	(**2.97**)	(0.23)		
Big (AAA-BB)	0.33	0.16	0.09	0.18	0.07	0.22	0.05	50.29	93.67
	(1.67)	(1.30)	(0.60)	(0.90)	(0.27)	(**3.27**)	(0.38)		
All (AAA-BB+)	0.30	0.21	0.05	0.19	0.06	0.19	-0.03	65.24	93.69
	(1.75)	(1.94)	(0.50)	(1.18)	(0.29)	(**3.58**)	(-0.20)		
Micro (AAA-BB+)	0.25	1.35	-0.06	-0.47	0.26	0.09	7.04	4.63	0.11
	(0.82)	(**2.23**)	(-0.17)	(-1.00)	(0.70)	(0.34)	(**2.63**)		
Small (AAA-BB+)	0.40	0.47	0.10	0.13	0.13	0.16	0.10	12.93	1.47
	(**2.21**)	(**2.51**)	(0.51)	(0.66)	(0.58)	(1.65)	(0.17)		
Big (AAA-BB+)	0.29	0.15	0.08	0.20	0.02	0.21	-0.03	47.68	92.11
	(1.57)	(1.28)	(0.67)	(1.07)	(0.08)	(**3.36**)	(-0.21)		
All (AAA-BBB-)	0.23	0.14	0.05	0.14	0.07	0.19	-0.02	59.79	91.20
	(1.36)	(1.30)	(0.56)	(0.91)	(0.33)	(**3.57**)	(-0.16)		
Micro (AAA-BBB-)	0.16	0.69	0.19	-0.15	0.87	-0.09		4.03	0.09
	(0.53)	(1.26)	(0.57)	(-0.29)	(1.39)	(-0.31)			
Small (AAA-BBB-)	0.29	0.39	0.10	0.08	0.15	0.19	0.14	10.97	1.25
	(1.59)	(**2.11**)	(0.55)	(0.38)	(0.67)	(1.70)	(0.22)		
Big (AAA-BBB-)	0.23	0.09	0.04	0.13	-0.01	0.19	-0.06	44.79	89.86
	(1.30)	(0.78)	(0.39)	(0.72)	(-0.03)	(**3.07**)	(-0.42)		
All (AAA-BBB)	0.19	0.15	0.06	0.15	-0.00	0.19	0.01	51.51	86.70
	(1.12)	(1.35)	(0.64)	(0.97)	(-0.01)	(**3.25**)	(0.06)		
Micro (AAA-BBB)	0.16	0.44	-0.06	-0.12	0.50	0.07		3.54	0.08
	(0.50)	(0.83)	(-0.15)	(-0.23)	(1.28)	(0.25)			
Small (AAA-BBB)	0.17	0.28	0.05	-0.21	0.13	0.15	0.13	8.28	0.90
	(0.87)	(1.39)	(0.28)	(-0.91)	(0.56)	(1.18)	(0.14)		
Big (AAA-BBB)	0.20	0.12	0.07	0.17	-0.06	0.18	-0.01	39.70	85.72
	(1.12)	(1.03)	(0.73)	(0.97)	(-0.29)	(**2.84**)	(-0.08)		

Table 4

Downgrade Characteristics, Delistings, and Returns by Credit Rating Groups

The table focuses on stocks with at least one downgrade. Panel A analyzes downgrades by credit rating tercile, sorted on firm rating at the end of month $t-1$. We also report statistics for up/down markets (when the excess value-weighted market return is positive/negative), as well as for expansions and recessions as defined by NBER. The downgrade correlation is the average pairwise time-series correlation between any two stocks in a given rating tercile. This correlation is computed based on an index for each stock which takes the value of 0/1 during months with no/one downgrade. Also reported are downgrade correlations computed based on dummies taking the value of 1 three (six) months before and after downgrades. Panel B divides firms by number of downgrades and for each downgrade frequency, analyzes investment-grade (IG) and non-investment grade (NIG) firms. The sample period is October 1985 to December 2007.

PANEL A: By Credit Rating Portfolio

	Rating Group (C1=Lowest , C3=Highest Risk)		
	C1	C2	C3
Number of Downgrades	2,276	2,363	3,286
Downgrades/month	8.56	8.88	12.35
Size of Downgrades	1.77	1.77	2.24
r_{t-1}	0.75	-3.09	-12.04
r_t	-0.34	-2.23	-15.21
r_{t+1}	0.76	0.42	-3.52
$r_{t-6:t-1}$	3.64	-6.37	-29.38
$r_{t+1:t+6}$	7.55	0.47	-16.73
$r_{t-12:t-1}$	7.59	-3.92	-31.95
$r_{t+1:t+12}$	13.15	4.41	-11.72
$r_{t-24:t-1}$	21.04	0.27	-28.92
$r_{t+1:t+24}$	28.95	19.52	9.49
Delisted over $(t+1:t+6)$	53	105	379
Delisted over $(t+1:t+12)$	85	165	601
Delisted over $(t+1:t+24)$	138	298	847
Downgrades/month ($r_{mt}>0$)	7.64	7.90	10.61
Size of Downgrades	1.71	1.83	2.27
r_{t-1}	1.35	-3.56	-12.22
r_t	1.83	1.71	-10.80
r_{t+1}	1.69	0.91	0.32
Downgrades/month ($r_{mt}<0$)	10.16	10.31	15.30
Size of Downgrades	1.85	1.66	2.18
r_{t-1}	-0.16	-2.42	-11.77
r_t	-3.61	-7.84	-22.24
r_{t+1}	-0.67	-0.29	-9.77
Downgrades/month (Expansions)	8.19	8.61	11.59
Size of Downgrades	1.72	1.76	2.20
r_{t-1}	0.84	-1.96	-11.51
r_t	0.16	-2.01	-15.59
r_{t+1}	0.18	0.64	-3.29
Downgrades/month (Recessions)	13.00	13.93	25.87
Size of Downgrades	1.90	1.68	2.97
r_{t-1}	-0.55	-16.25	-19.13
r_t	-7.45	-4.80	-10.30
r_{t+1}	8.93	-2.10	-6.38
Downgrade Correlation (%)	2.31	4.23	7.48
Downgrade Correlation (±3 months) (%)	1.59	1.87	3.96
Downgrade Correlation (±6 months) (%)	1.87	2.21	4.68

Table 4 (continued)

PANEL B: By Frequency of Downgrades

# of Downgr. per Firm	Firms with N Downgr.		Size of Each Downgr.		Months Between Downgr.		Returns Around Each Downgrade $r_{t-3:t-1}$		$r_{t:t+3}$		$r_{t-6:t-1}$		$r_{t:t+6}$	
	IG	NIG	IG	NIG	IG	NIG	IG	NIG	IG	NIG	IG	NIG	IG	NIG
N=1	577	583	1.99	2.35			-0.04	-14.58	-0.25	-13.59	1.95	-21.96	3.07	-12.34
N=2	318	357	1.72	2.22	45.71	18.48	-0.75	-14.87	0.93	-18.77	-1.42	-24.61	5.70	-20.09
N=3	204	191	1.51	1.91	38.19	18.05	-0.72	-16.41	-0.83	-20.17	-1.02	-26.35	2.59	-22.88
N=4	118	99	1.39	1.70	34.33	18.79	-2.53	-14.58	0.76	-14.21	-2.32	-17.19	5.84	-22.50
N=5	47	30	1.36	1.69	33.84	15.57	-3.56	-17.80	0.19	-10.75	-5.82	-25.75	2.78	-9.90
N=6	17	8	1.37	1.42	30.24	13.20	-2.56	-16.64	-0.24	-20.78	0.03	-29.76	2.72	-21.69
N=7	7	2	1.22	1.79	26.00	22.00	-1.33	-4.11	-0.89	-10.03	-2.67	-14.66	4.26	2.86
N=8	1	1	1.25	1.00	27.86	34.29	4.10	-1.36	20.03	20.74	3.20	-6.95	33.51	27.05
N=9	1		1.33		27.75		-13.98		11.30		-19.36		17.39	
N=10	1		2.20		13.89		1.03		7.15		-0.86		14.40	
Obs.							8,112	7,432	10,605	9,491	16,196	14,824	18,105	15,665

Table 5
Impact of Downgrades on Profits from Asset-Pricing Anomalies

We repeat the analysis described in Table 2 after removing 6-months of returns before and after rating downgrades.

Panel A: Equally Weighted Size and BM adjusted Returns

Anomaly		Momentum	SUE	Credit Risk	Dispersion	Idio Vol	Accruals	BM
Strategy		P5-P1	P5-P1	P1-P5	P1-P5	P1-P5	P1-P5	P5-P1
All Rated	P1	0.09	0.16	0.11	0.16	0.07	0.38	-0.07
	P5	0.37	0.22	0.05	0.28	0.05	0.02	0.36
	Strategy	0.28	0.05	0.06	-0.12	0.02	0.36	0.43
		(1.22)	(0.43)	(0.34)	(-0.64)	(0.07)	(**4.99**)	(**2.79**)
Micro Rated	P1	0.25	0.24	-0.30	-0.40	-0.04	0.92	0.12
	P5	0.69	0.69	0.35	0.37	0.43	0.16	0.48
	Strategy	0.44	0.45	-0.64	-0.77	-0.46	0.76	0.40
		(1.77)	(1.18)	(-1.65)	(-1.57)	(-1.32)	(**4.18**)	(0.73)
Small Rated	P1	-0.02	0.11	0.04	0.31	0.10	0.28	-0.25
	P5	0.36	0.42	-0.05	0.35	0.00	-0.05	0.34
	Strategy	0.38	0.31	0.08	-0.04	0.10	0.33	0.59
		(1.61)	(1.69)	(0.31)	(-0.18)	(0.30)	(**2.75**)	(**2.48**)
Big Rated	P1	0.17	0.17	0.14	0.15	0.06	0.22	-0.01
	P5	0.25	0.13	-0.11	0.21	-0.16	0.00	0.27
	Strategy	0.08	-0.04	0.24	-0.06	0.22	0.22	0.28
		(0.29)	(-0.28)	(0.76)	(-0.27)	(0.60)	(**3.03**)	(1.67)
C1 All	P1	0.18	0.10	0.07	0.17	0.06	0.19	0.07
	P5	0.13	0.15	0.18	0.12	0.14	0.04	0.06
	Strategy	-0.05	0.05	-0.11	0.05	-0.07	0.15	-0.01
		(-0.30)	(0.38)	(-1.27)	(0.28)	(-0.35)	(**2.74**)	(-0.03)
C1 Micro	P1	-0.71	-0.40	-0.28	-1.04	0.47	0.19	
	P5	0.04	0.36	-0.13	-0.45	-0.83	-0.42	0.16
	Strategy	0.91	0.46	-0.17	-0.35	0.69	0.59	
		(1.87)	(0.56)	(-0.41)	(-0.56)	(1.26)	(1.89)	
C1 Small	P1	0.02	-0.20	0.00	-0.02	0.09	-0.21	-0.72
	P5	-0.05	0.23	0.01	-0.03	-0.44	-0.20	0.00
	Strategy	-0.07	0.43	-0.01	0.09	0.53	-0.02	0.69
		(-0.26)	(1.06)	(-0.04)	(0.22)	(1.85)	(-0.12)	(0.29)
C1 Big	P1	0.24	0.15	0.09	0.20	0.04	0.24	0.07
	P5	0.16	0.15	0.22	0.19	0.24	0.09	0.05
	Strategy	-0.07	-0.01	-0.13	0.01	-0.20	0.15	-0.02
		(-0.41)	(-0.04)	(-1.25)	(0.05)	(-0.89)	(**2.43**)	(-0.10)
C2 All	P1	0.31	0.13	0.12	0.16	0.07	0.24	0.12
	P5	0.26	0.17	0.25	0.30	0.26	0.01	0.24
	Strategy	-0.04	0.04	-0.12	-0.14	-0.19	0.23	0.12
		(-0.25)	(0.29)	(-1.54)	(-0.82)	(-0.81)	(**2.72**)	(0.70)
C2 Micro	P1	0.21	-0.61	-0.25	-0.12	0.18	0.19	3.89
	P5	-0.04	-0.12	0.16	0.18	0.01	-0.22	-0.38
	Strategy	-0.21	0.12	-0.45	-0.49	0.10	0.43	-4.71
		(-0.54)	(0.19)	(-1.19)	(-0.67)	(0.20)	(1.47)	(-1.26)
C2 Small	P1	0.29	0.06	-0.17	0.14	-0.03	0.26	-0.23
	P5	0.31	0.30	0.33	0.31	0.30	0.07	0.29
	Strategy	0.02	0.24	-0.50	-0.17	-0.34	0.19	0.52
		(0.10)	(1.31)	(-1.06)	(-0.68)	(-1.31)	(1.45)	(1.15)
C2 Big	P1	0.28	0.21	0.20	0.16	0.11	0.20	0.10
	P5	0.30	0.15	0.21	0.32	0.24	-0.02	0.28
	Strategy	0.02	-0.06	-0.00	-0.16	-0.13	0.23	0.18
		(0.09)	(-0.40)	(-0.05)	(-0.78)	(-0.51)	(**2.18**)	(0.94)
C3 All	P1	-0.02	0.13	0.22	0.09	0.13	0.56	-0.32
	P5	0.62	0.44	0.08	0.48	-0.04	0.02	0.70
	Strategy	0.64	0.30	0.14	-0.39	0.17	0.54	1.03
		(1.81)	(1.60)	(0.67)	(-1.57)	(0.48)	(**3.88**)	(**3.70**)
C3 Micro	P1	0.55	0.17	0.30	-0.44	0.27	0.94	-0.01
	P5	0.93	0.60	0.45	0.62	0.62	0.15	0.75
	Strategy	0.38	0.43	-0.15	-1.07	-0.35	0.80	0.76
		(1.06)	(1.17)	(-0.45)	(-1.15)	(-0.88)	(**3.45**)	(1.42)
C3 Small	P1	-0.42	0.12	0.28	0.31	0.21	0.39	-0.37
	P5	0.51	0.61	0.08	0.53	-0.49	-0.11	0.60
	Strategy	0.93	0.49	0.20	-0.22	0.70	0.50	0.97
		(**2.37**)	(**1.99**)	(0.61)	(-0.73)	(1.55)	(**2.50**)	(**3.16**)
C3 Big	P1	0.05	0.18	0.10	-0.20	-0.10	0.23	-0.38
	P5	0.29	0.14	-0.34	0.45	-1.03	-0.17	0.91
	Strategy	0.23	-0.03	0.44	-0.66	0.96	0.40	1.27
		(0.52)	(-0.11)	(1.08)	(-1.86)	(1.49)	(1.45)	(**2.19**)

Table 5 (continued)

Panel B: Value Weighted Size and BM adjusted Returns

Anomaly		Momentum	SUE	Credit Risk	Dispersion	Idio Vol	Accruals	BM
Strategy		P5-P1	P5-P1	P1-P5	P1-P5	P1-P5	P1-P5	P5-P1
All Rated	P1	0.08	0.14	0.06	0.03	-0.03	0.19	-0.05
	P5	0.16	0.02	-0.16	0.12	-0.01	-0.10	0.14
	Strategy	0.08	-0.13	0.22	-0.08	-0.02	0.28	0.18
		(0.31)	(-0.77)	(0.69)	(-0.32)	(-0.06)	(**2.54**)	(1.06)
Micro Rated	P1	0.19	0.18	-0.19	-0.38	-0.06	0.73	0.04
	P5	0.53	0.39	0.18	0.09	0.28	0.13	0.52
	Strategy	0.34	0.21	-0.37	-0.48	-0.33	0.60	0.52
		(1.28)	(0.59)	(-1.06)	(-1.17)	(-0.89)	(**3.35**)	(0.92)
Small Rated	P1	-0.03	0.12	0.06	0.31	0.09	0.32	-0.17
	P5	0.37	0.35	-0.04	0.37	0.01	-0.07	0.30
	Strategy	0.40	0.23	0.10	-0.06	0.08	0.39	0.47
		(1.62)	(1.23)	(0.36)	(-0.24)	(0.24)	(**3.28**)	(1.90)
Big Rated	P1	0.10	0.14	0.06	0.03	-0.04	0.19	-0.04
	P5	0.15	0.01	-0.03	0.09	0.01	-0.09	0.10
	Strategy	0.05	-0.13	0.09	-0.06	-0.04	0.28	0.14
		(0.18)	(-0.78)	(0.23)	(-0.23)	(-0.11)	(**2.41**)	(0.77)
C1 All	P1	0.19	0.12	0.03	0.15	0.02	0.20	-0.02
	P5	0.07	0.09	0.08	0.13	0.09	-0.05	0.06
	Strategy	-0.11	-0.03	-0.04	0.02	-0.07	0.25	0.08
		(-0.51)	(-0.14)	(-0.25)	(0.09)	(-0.24)	(**2.20**)	(0.41)
C1 Micro	P1	-0.73	-0.51	-0.08	-1.07	0.44	0.20	
	P5	-0.08	0.33	-0.24	-0.25	-0.91	-0.44	0.28
	Strategy	0.79	0.73	0.15	-0.56	0.84	0.62	
		(1.85)	(0.87)	(0.33)	(-0.79)	(1.45)	(**2.05**)	
C1 Small	P1	0.11	-0.21	0.06	-0.06	0.10	-0.20	-0.72
	P5	-0.03	0.22	0.02	-0.07	-0.29	-0.18	0.02
	Strategy	-0.14	0.43	0.04	0.09	0.39	-0.02	1.01
		(-0.50)	(1.08)	(0.20)	(0.21)	(1.30)	(-0.11)	(0.45)
C1 Big	P1	0.18	0.12	0.03	0.15	0.02	0.21	-0.02
	P5	0.08	0.09	0.08	0.13	0.09	-0.04	0.06
	Strategy	-0.11	-0.03	-0.04	0.02	-0.07	0.25	0.08
		(-0.49)	(-0.16)	(-0.25)	(0.09)	(-0.25)	(**2.20**)	(0.39)
C2 All	P1	0.02	0.03	0.10	0.19	0.14	0.06	0.04
	P5	0.37	-0.04	0.16	0.13	0.03	-0.22	0.08
	Strategy	0.35	-0.06	-0.05	0.07	0.11	0.28	0.04
		(1.35)	(-0.33)	(-0.43)	(0.24)	(0.34)	(**2.12**)	(0.17)
C2 Micro	P1	0.14	-0.74	-0.33	-0.13	0.02	-0.00	3.89
	P5	-0.12	-0.10	-0.15	-0.11	0.06	-0.23	-0.50
	Strategy	-0.22	0.27	-0.22	-0.38	-0.13	0.25	-4.70
		(-0.52)	(0.43)	(-0.59)	(-0.46)	(-0.23)	(0.92)	(-1.25)
C2 Small	P1	0.24	0.04	-0.12	0.24	-0.03	0.27	-0.20
	P5	0.29	0.29	0.27	0.31	0.22	0.13	0.25
	Strategy	0.04	0.25	-0.39	-0.07	-0.25	0.15	0.45
		(0.21)	(1.27)	(-1.30)	(-0.26)	(-0.94)	(1.01)	(0.95)
C2 Big	P1	0.01	0.03	0.11	0.19	0.16	0.04	0.04
	P5	0.38	-0.05	0.16	0.12	0.02	-0.24	0.07
	Strategy	0.37	-0.07	-0.05	0.07	0.13	0.28	0.03
		(1.40)	(-0.36)	(-0.37)	(0.24)	(0.39)	(**2.01**)	(0.14)
C3 All	P1	-0.15	0.01	-0.07	-0.06	0.00	0.14	-0.33
	P5	0.35	0.12	-0.32	0.36	-0.67	-0.12	0.88
	Strategy	0.50	0.11	0.25	-0.42	0.67	0.26	1.21
		(1.19)	(0.40)	(0.83)	(-1.35)	(1.41)	(1.29)	(**2.77**)
C3 Micro	P1	0.38	0.10	0.32	-0.40	0.20	0.76	-0.06
	P5	0.71	0.25	0.50	0.25	0.59	0.13	0.93
	Strategy	0.33	0.15	-0.17	-0.65	-0.39	0.63	1.00
		(0.88)	(0.42)	(-0.49)	(-1.31)	(-0.83)	(**2.88**)	(1.70)
C3 Small	P1	-0.45	0.20	0.28	0.31	0.14	0.43	-0.26
	P5	0.54	0.53	0.07	0.55	-0.51	-0.15	0.61
	Strategy	0.99	0.33	0.22	-0.24	0.65	0.58	0.86
		(**2.36**)	(1.29)	(0.63)	(-0.76)	(1.34)	(**2.96**)	(**2.71**)
C3 Big	P1	0.03	0.01	-0.13	-0.28	-0.04	0.09	-0.34
	P5	0.25	0.04	-0.35	0.34	-1.11	-0.15	0.74
	Strategy	0.22	0.03	0.22	-0.62	1.09	0.24	1.04
		(0.47)	(0.08)	(0.52)	(-1.62)	(1.60)	(0.82)	(1.50)

Table 6
Cross-Sectional Regressions

Each month t, we run univariate cross-sectional regressions of monthly risk-adjusted stock returns on a lagged firm characteristic based on each of the anomalies studied using all NYSE, AMEX, and NASDAQ stocks with available credit rating data on COMPUSTAT or Standard and Poor's Rating Xpress:

$$r_{it}^{*} = a_t + b_t C_{it-1} + e_{it}.$$

Each firm characteristic, C_{it-1}, is a conditioning variable described in Table 2. Each column reports the results from a separate univariate regression and shows the time-series average of these cross-sectional regression coefficients, b_t, with their associated sample t-statistics in parentheses (bold if significant at the 95% confidence level). We use risk-adjusted returns as dependent variable, i.e. the constant and error term obtained from time-series regressions of raw excess returns on the Fama and French (1993) factors: $r_{it}^{*} = R_{it} - R_{ft} - \sum_{k=1}^{K} \hat{\beta}_{ik} F_{kt}$. Each panel also provides results where in the regression for each anomaly we include dummies indicating rating downgrades:

$$r_{it}^{*} = a_t + b_t C_{it-1} + d_{t,IG} D_{IG} + d_{t,NIG} D_{NIG} + e_{it},$$

where D_{IG} (D_{NIG}) is a dummy variable which takes the value of 1 from 6 months before to 6 months after rating downgrades from an investment-grade (non-investment-grade) rating. Panel A presents results for all stocks, while Panel B/C/D show results for Micro/Small/Big stocks, respectively.

Panel A: Risk-Adjusted Returns: All Stocks

	Momentum	SUE	Credit Risk	Dispersion	Idio Vol	Accruals	Size	BM
b	0.90	0.14	-0.09	-0.23	-6.03	-2.42	-0.05	0.02
	(**3.30**)	(**5.04**)	(**-5.17**)	(**-3.77**)	(**-2.86**)	(**-2.41**)	(-1.54)	(0.20)
b	0.19	0.05	-0.01	-0.02	-4.87	-3.67	-0.04	0.28
	(0.63)	(**2.12**)	(-0.71)	(-0.31)	(-1.70)	(**-3.27**)	(-1.60)	(**2.69**)
d_{NIG}	-4.07	-3.70	-3.93	-4.29	-3.92	-3.65	-4.04	-3.35
	(**-16.57**)	(**-11.52**)	(**-15.69**)	(**-13.44**)	(**-16.65**)	(**-12.26**)	(**-14.65**)	(**-10.00**)
b	0.09	0.04	-0.02	-0.01	-5.16	-3.69	-0.02	0.32
	(0.31)	(1.53)	(-1.49)	(-0.13)	(-1.81)	(**-3.30**)	(-1.01)	(**3.00**)
d_{IG}	-0.83	-0.87	-0.87	-0.81	-0.86	-0.79	-0.82	-0.82
	(**-9.35**)	(**-9.00**)	(**-8.64**)	(**-7.93**)	(**-9.09**)	(**-6.81**)	(**-8.49**)	(**-8.18**)
d_{NIG}	-4.13	-3.75	-3.90	-4.31	-3.94	-3.67	-4.05	-3.38
	(**-16.77**)	(**-11.64**)	(**-15.68**)	(**-13.49**)	(**-16.69**)	(**-12.31**)	(**-14.66**)	(**-10.05**)

Panel B: Risk-Adjusted Returns: Micro Stocks

	Momentum	SUE	Credit Risk	Dispersion	Idio Vol	Accruals	Size	BM
b	1.36	0.45	-0.18	-0.39	-6.58	-0.73	-0.20	0.06
	(**4.56**)	(**7.17**)	(**-5.44**)	(**-2.92**)	(**-2.88**)	(-0.43)	(**-2.41**)	(0.32)
b	0.29	0.21	-0.05	-0.13	-3.59	-3.30	0.03	1.02
	(0.64)	(**2.27**)	(-1.55)	(-0.72)	(-1.22)	(-1.23)	(0.23)	(**2.54**)
d_{NIG}	-4.75	-4.47	-4.62	-5.78	-4.72	-4.25	-4.77	-4.54
	(**-14.85**)	(**-9.43**)	(**-13.97**)	(**-10.48**)	(**-14.92**)	(**-10.70**)	(**-13.64**)	(**-8.71**)
b	0.26	0.21	-0.06	-0.14	-3.74	-3.42	0.03	1.10
	(0.56)	(**2.23**)	(-1.85)	(-0.81)	(-1.26)	(-1.27)	(0.20)	(**2.70**)
d_{IG}	-0.46	-0.85	-0.80	-0.36	-0.55	-0.24	-0.78	-1.51
	(-1.18)	(-1.62)	(**-2.03**)	(-0.86)	(-1.43)	(-0.38)	(-1.93)	(**-2.75**)
d_{NIG}	-4.80	-4.50	-4.62	-5.81	-4.76	-4.28	-4.82	-4.58
	(**-15.09**)	(**-9.51**)	(**-13.96**)	(**-10.53**)	(**-15.09**)	(**-10.76**)	(**-13.79**)	(**-8.76**)

Table 6 (continued)

Panel C: Risk-Adjusted Returns: Small Stocks

	Momentum	SUE	Credit Risk	Dispersion	Idio Vol	Accruals	Size	BM
b	0.90	0.20	-0.11	-0.27	-7.61	-2.67	-0.17	-0.09
	(**2.93**)	(**5.07**)	(**-4.38**)	(**-2.80**)	(**-2.25**)	(-1.90)	(-1.81)	(-0.68)
b	0.35	0.12	-0.03	-0.04	-10.20	-2.81	-0.24	0.36
	(1.07)	(**2.51**)	(-1.28)	(-0.34)	(-1.83)	(-1.57)	(**-2.15**)	(**1.99**)
d_{NIG}	-3.71	-3.47	-3.59	-3.96	-3.58	-3.44	-3.62	-2.84
	(**-12.93**)	(**-9.35**)	(**-11.76**)	(**-10.70**)	(**-13.63**)	(**-9.57**)	(**-10.78**)	(**-6.68**)
b	0.25	0.10	-0.05	-0.02	-10.69	-2.87	-0.18	0.41
	(0.75)	(**2.17**)	(-1.67)	(-0.18)	(-1.87)	(-1.61)	(-1.66)	(**2.30**)
d_{IG}	-1.16	-1.22	-1.31	-1.22	-1.23	-1.07	-1.19	-1.12
	(**-6.92**)	(**-5.52**)	(**-7.19**)	(**-5.95**)	(**-7.32**)	(**-3.95**)	(**-6.86**)	(**-4.74**)
d_{NIG}	-3.75	-3.48	-3.53	-3.99	-3.57	-3.44	-3.62	-2.83
	(**-13.05**)	(**-9.37**)	(**-11.67**)	(**-10.79**)	(**-13.58**)	(**-9.59**)	(**-10.77**)	(**-6.64**)

Panel D: Risk-Adjusted Returns: Big Stocks

	Momentum	SUE	Credit Risk	Dispersion	Idio Vol	Accruals	Size	BM
b	0.08	0.07	-0.04	-0.20	-5.63	-4.07	0.00	-0.11
	(0.24)	(**2.59**)	(**-2.57**)	(**-2.00**)	(-1.18)	(**-3.32**)	(0.13)	(-0.91)
b	-0.45	0.04	-0.01	-0.07	-7.88	-4.96	-0.01	0.05
	(-1.32)	(1.48)	(-0.38)	(-0.67)	(-1.35)	(**-3.73**)	(-0.26)	(0.38)
d_{NIG}	-3.56	-3.28	-3.28	-3.75	-3.36	-3.15	-3.27	-2.94
	(**-10.10**)	(**-7.36**)	(**-9.30**)	(**-8.49**)	(**-10.54**)	(**-5.84**)	(**-8.31**)	(**-7.05**)
b	-0.63	0.02	-0.01	-0.04	-7.53	-5.00	-0.00	0.11
	(-1.84)	(0.75)	(-0.82)	(-0.40)	(-1.30)	(**-3.76**)	(-0.14)	(0.93)
d_{IG}	-0.77	-0.72	-0.73	-0.69	-0.74	-0.69	-0.71	-0.71
	(**-8.70**)	(**-7.05**)	(**-7.50**)	(**-6.55**)	(**-7.91**)	(**-5.52**)	(**-7.32**)	(**-6.81**)
d_{NIG}	-3.57	-3.26	-3.22	-3.71	-3.33	-3.09	-3.24	-2.92
	(**-10.12**)	(**-7.31**)	(**-9.19**)	(**-8.42**)	(**-10.45**)	(**-5.71**)	(**-8.24**)	(**-7.00**)

Table 7

Asset-Pricing Anomalies and Short-Sale Constraints

The table presents the time-series average of the cross-sectional mean and median characteristic for each size and credit rating sorted portfolio. The sorts are described in Table 2. We examine characteristics, which have been identified by D'Avolio (2002) as leading to high short-sale constraints: low institutional ownership (calculated as shares held by institutions over shares outstanding), low share Turnover (shares traded over shares outstanding), and low level of shares outstanding. Amihud's Illiquidity measure, computed as in eq. (1)) is also presented. Turnover and Illiquidity are presented separately for NYSE/AMEX and Nasdaq stocks.

	Institutional Ownership (%)		Turnover (%) NYSE/AMEX		Turnover (%) Nasdaq		Shares Outstanding (mln)		Illiquidity NYSE/AMEX		Illiquidity Nasdaq	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
All Rated	50.64	53.78	9.47	7.08	14.59	9.75	126.73	45.13	5.34	0.05	21.32	0.46
Micro Rated	36.87	34.94	9.01	5.83	10.98	7.09	15.08	10.30	43.23	2.60	59.60	4.43
Small Rated	48.23	49.65	10.09	7.30	15.00	10.59	31.83	24.58	0.79	0.25	3.20	0.36
Big Rated	56.21	59.46	9.29	7.26	18.80	14.15	211.37	96.65	0.09	0.02	0.66	0.03
C1 All	52.92	55.96	7.89	6.18	9.73	6.49	221.34	85.37	0.29	0.02	4.35	0.23
C1 Micro	41.98	40.33	12.33	6.94	10.49	6.68	5.05	3.37	3.42	1.35	15.32	4.61
C1 Small	41.89	37.68	7.49	4.87	6.63	3.95	22.26	18.95	0.49	0.24	2.50	0.55
C1 Big	55.40	57.76	7.66	6.30	11.20	8.37	280.04	120.61	0.06	0.01	0.12	0.03
C2 All	53.72	57.56	9.89	7.76	13.67	9.48	90.08	45.63	0.79	0.05	3.65	0.23
C2 Micro	39.50	38.42	8.64	5.45	10.84	7.58	9.97	7.88	9.55	1.83	13.00	3.62
C2 Small	50.19	52.33	9.14	7.00	11.61	8.10	28.59	24.09	0.74	0.23	1.73	0.40
C2 Big	57.70	61.90	10.36	8.34	17.23	13.57	134.16	76.68	0.09	0.03	0.84	0.04
C3 All	44.80	45.64	11.60	8.50	16.37	11.23	51.10	25.42	19.34	0.48	34.24	0.92
C3 Micro	36.08	34.52	8.51	5.77	10.96	7.26	18.42	13.28	56.33	3.40	70.28	4.65
C3 Small	49.16	50.72	12.32	9.39	18.58	14.18	38.21	28.37	0.95	0.30	3.94	0.33
C3 Big	53.89	57.56	14.83	11.65	26.99	22.86	139.55	84.74	0.22	0.05	1.31	0.03

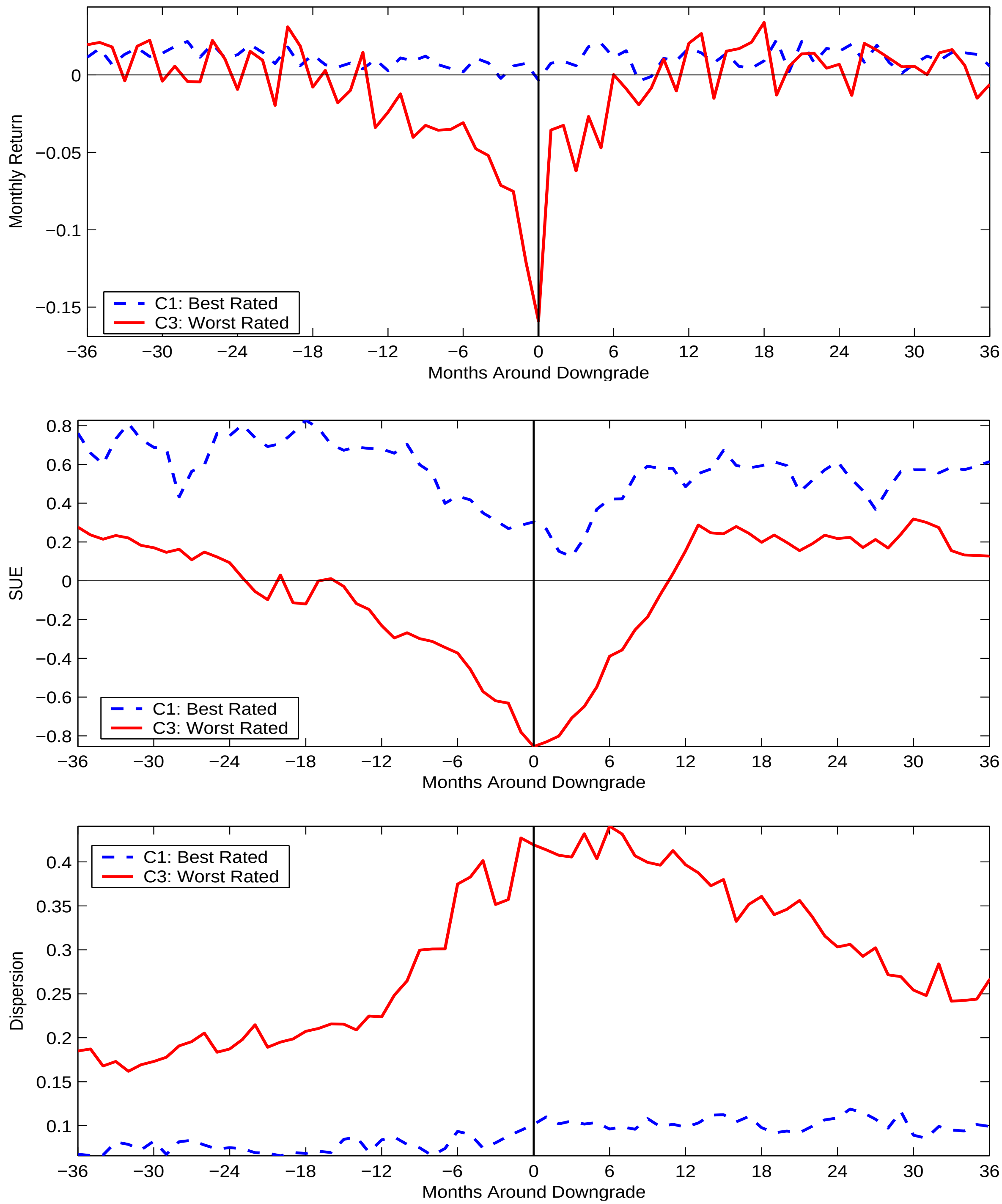

Figure 1. Firm Characteristics around Downgrades. Each month t, all stocks rated by Standard & Poor's with available return data in CRSP are divided into terciles based on credit rating. Within each tercile, we find firms that have been downgraded in month t and compute their equally weighted average firm characteristic over each month from $t-36$ to $t+36$. We repeat this every month. The figure presents these average monthly portfolio characteristics for the best (C1) and worst (C3) rated terciles around rating downgrades. Month 0 is the month of downgrade. The characteristics are described in detail in Table 2. The sample period is October 1985 to December 2007.

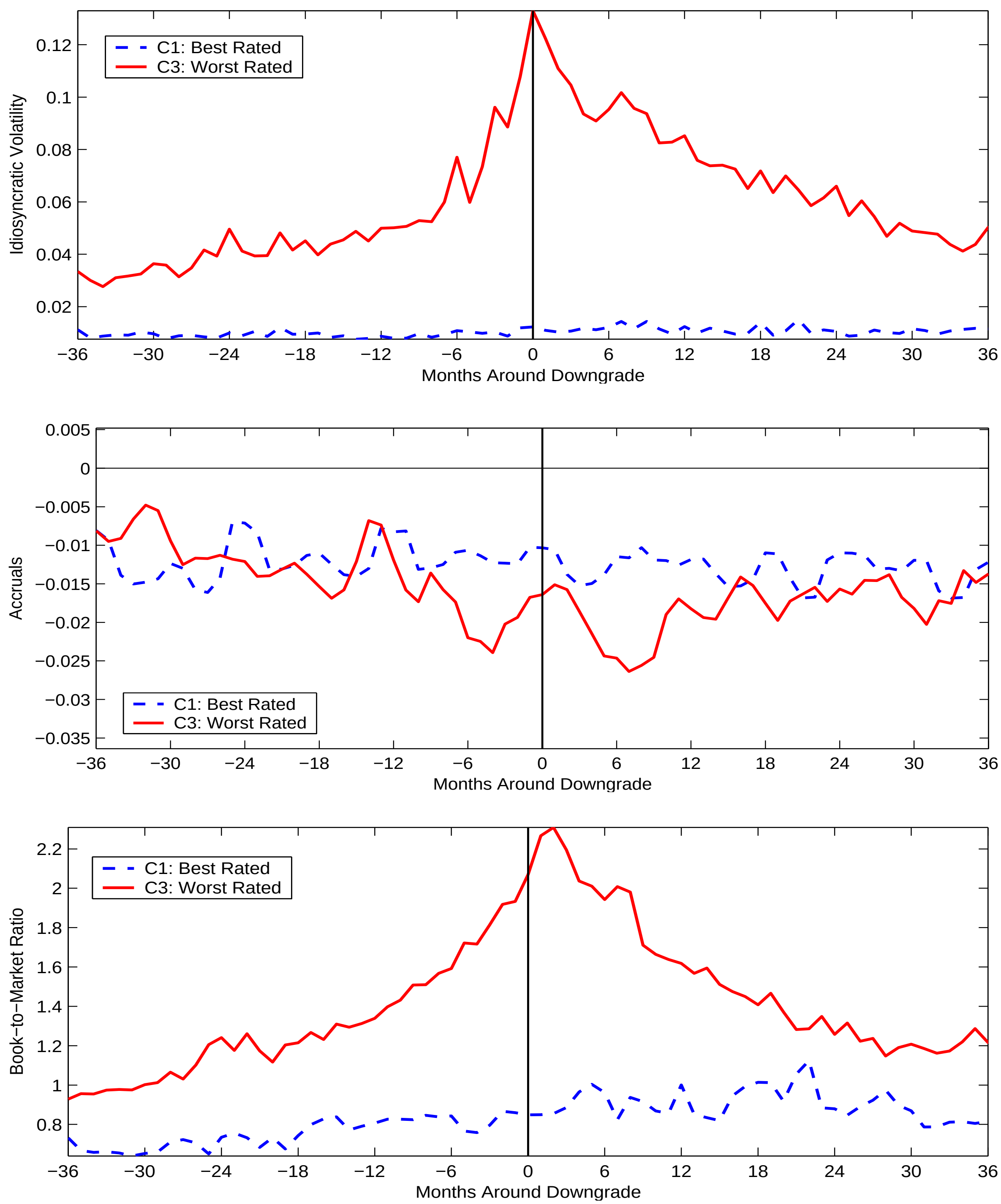

Figure 1(continued). Firm Characteristics around Downgrades.