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Anomalies and Financial Distress

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Anomalies and Financial Distress

Abstract

This paper explores commonalities across asset-pricing anomalies. 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, idiosyncratic volatility, and capital investments 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 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 investment payoffs. Existing theories, however, leave unexplained a host of empirically documented cross-sectional patterns in average stock returns, classified as anomalies. Specifically, price momentum, 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), describes the outperformance of firms reporting unexpectedly high earnings relative to firms reporting unexpectedly low earnings. The size and book-to-market effects have been documented, among others, by Fama and French (1992). In particular, small market cap stocks have historically outperformed big market cap 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), Campbell, Hilscher, and Szilagyi (2008), and Avramov, Chordia, Jostova, and Philipov (2009a) demonstrate a negative credit risk return relation. 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. Titman, Wei, and Xie (2004) document a negative relation between capital investments and returns, and Cooper, Gulen, and Schill (2008) document a negative relation between asset growth and returns. Finally, Ang, Hodrick, Xing, and Zhang (2006) demonstrate that stocks with high idiosyncratic volatility realize abnormally low returns.

This paper examines the price momentum, earnings momentum, credit risk, dispersion, idiosyncratic volatility, asset growth, capital investments, accruals, and value 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 experienced by a low-rated firm, or even a concern of emerging 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 up to one year following credit rating downgrades. Notwithstanding, the potential implications of financial distress for market anomalies have not yet comprehensively been explored. 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 calculated from portfolio sorts are based on size and book-to-market adjusted stock returns whereas stock returns, the dependent variables in the cross-sectional regressions, are risk-adjusted for systematic factors. Investment payoffs are value-weighted as well as equally-weighted across stocks. Payoffs based on equally-weighted returns are typically 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. 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 evidence shows that the profitability of strategies based on price momentum, earnings momentum, credit risk, dispersion, idiosyncratic volatility, asset growth, and capital investments is concentrated in the worst-rated stocks. This profitability disappears when firms rated BB+ or below are excluded from the investment universe. Strikingly, these low-rated firms represent only 9.7% of the market capitalization of the sample of rated firms. Yet, credit risk is not merely a proxy for size, as anomalies are reasonably robust among all size groups. Moreover, credit risk impacts anomaly payoffs already adjusted for firm size. The analysis also suggests that the profitability of price momentum, earnings momentum, credit risk, dispersion, idiosyncratic volatility, asset growth, and capital investments anomalies is generated almost entirely by the short side of the trade among the worst rated firms. The value effect is also related to credit risk. While it is insignificant in the overall sample of firms, it is significant among low-rated stocks. The accruals strategy is an exception, while it is more profitable among higher credit risk firms, it is statistically and economically robust across all credit risk groups.

Focusing on financial distress, as proxied by credit rating downgrades, we find that the profitability of trading strategies based on price momentum, earnings momentum, credit risk, dispersion, idiosyncratic volatility, and capital investments, derives exclusively from periods of financial distress. All 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 investment strategies produces significant payoffs during stable or improving credit conditions. The asset-growth anomaly exhibits similar patterns and derives most of its profitability from high credit risk stocks undergoing financial distress. Its profitability in non-distress periods diminishes and disappears from all subsamples, except for the low-rated microcap and the medium-rated big stocks. Accruals is again an exception. It is profitable during deteriorating, stable, and improving credit conditions. The value anomaly is significant only during stable or improving credit conditions and is mostly attributable to long positions in low-rated stocks.

The distinct patterns exhibited by the accruals and value strategies suggest that these effects emerge from different economic premises. 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 display sensitivity to credit conditions. The value strategy is more profitable in stable credit conditions. The value effect emerges 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, all other anomalies derive their profitability from low-rated firms experiencing falling stock prices around periods of financial distress.

It is important to note that it is financial distress, and not poor past performance reflected through falling stock prices, that impacts anomalies. Indeed, there could be inherent endogeneity of rating downgrades and poor past returns among low-rated stocks. Negative returns leading up to the downgrade, rather than financial distress, could be affecting the profitability of asset pricing anomalies. We address this endogeneity concern in several ways. First, we replicate most results using past-returns-adjusted ratings and rating downgrades, instead of raw ratings and rating downgrades. Past-returns-adjusted ratings are computed as the sum of intercept and residuals from cross-sectional regressions of rating levels on cumulative past-six-month returns. Reexamining anomaly profits among subsamples sorted on past-returns-adjusted ratings, we demonstrate that ratings rather than past returns impact investment profitability.

Similarly, we calculate past-returns-adjusted rating changes as the intercept and residual from regressing rating changes on past six-month returns. A past-returns-adjusted rating change that is larger than two standard deviations above the mean is considered a downgrade. This measure of downgrade, which is independent of past returns, is used to identify the period of financial distress. Removing periods around past-returns-adjusted downgrades eliminates anomaly profits in much the same way as when periods around raw downgrades are removed. Second, it is evident that most negative returns among high credit risk stocks occur during the month of downgrade, suggesting that the downgrade is informative. Third, the Altman's Z-score of high credit risk companies reaches a minimum around downgrades, suggesting that downgrades do capture financial distress. Forth, profit margins, interest coverage, and asset turnover ratios of low-rated stocks around downgrades deteriorate considerably relative to industry benchmarks, implying that these firms are indeed experiencing financial distress. Finally, we find that the rate of covenant violations among low-rated firms reaches its highest level right around downgrades, suggesting that downgrades are associated with real financial problems. In sum, the evidence shows that it is financial distress that is driving investment profitability.

A question that emerges is: are market anomalies explained by common economic determinants? Our analysis suggests that firm credit rating downgrades tend to be rather idiosyncratic events. For one, we measure 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 or during periods of recessions or expansions.

Finally, we examine whether there are trading frictions that prevent anomalous investment payoffs from being arbitraged away. Indeed, we show that trading impediments 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 are hard to short sell. Interestingly, 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. To illustrate, analysts covering distressed firms encounter 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. Section 4 concludes.

1 Data

The asset-pricing anomalies we study require 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 2008), when the sample begins (ends). The maximum number of firms, 2,497, is recorded in April 2000.

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 implementing the earnings momentum strategy, we extract quarterly earnings along with their announcement dates from I/B/E/S Detail History Actuals files. Standardized unexpected earnings (SUE) are 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 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 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 (IV) is computed as the sum of the stock's squared daily returns from CRSP minus the sum of the corresponding squared daily market returns, as in Campbell, Lettau, Malkiel, and Xu (2001). Following Cooper, Gulen, and Schill (2008), asset growth is measured as the percentage change in total assets from the Annual Compustat Files (data item 'AT'). Results for the asset-growth anomaly are based on 3,736 firms or 1,758 firms per month on average. As in Titman, Wei, and Xie (2004), capital investments is measured as the current year's capital expenditures (data item 'CAPX' in Compustat Annual) over the prior year Property, Plant and Equipment (data item 'PPENT' in Compustat Annual). The investments trading strategy is based on a total of 3,426 firms or 1,525 firm per month on average. Accruals is computed following Sloan (1996) using Compustat's Fundamentals Quarterly files.[1] 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 (BM) 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, issuer rating is based on the firm's senior publicly traded debt. After 1998, the rating is based on the overall quality of the firm's outstanding debt, either public or private.[2] *Standard & Poor's Rating Definitions* specifies S&P's issuer credit rating as 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 or its provisions, standing in bankruptcy or liquidation,

[1] 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.

[2] 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.

statutory preferences, or legality and enforceability. In addition, the opinion 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.[3] Hence, a higher numerical score reflects higher credit risk. Numerical ratings of 10 or below ($BBB-$ or better) are considered investment-grade, and ratings of 11 or higher ($BB+$ or worse) are labeled high-yield or non-investment grade.

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. Delisting returns from CRSP are used whenever a stock gets delisted. We have checked that our results are not driven by the delisting returns by setting the delisting return to zero as well as by eliminating the delisted stock-month from the sample. Stocks priced less than a dollar at the beginning of the month are excluded from the analysis.

Summary statistics are reported in Table 1. Each month t, all stocks rated by S&P are divided into three portfolios based on their credit rating. 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. The highest-rated portfolio of stocks (portfolio C1) has an average rating of A+, the medium-rated portfolio (portfolio C2) has an average rating of BBB-, and the lowest-rated portfolio (portfolio C3) – an average rating of B+.

Not surprisingly, the average firm size (as measured by market capitalization) decreases monotonically with credit rating. The highest-rated stocks have an average market capitalization of $3.30 billion, while the lowest-rated stocks have an average capitalization of $0.35 billion. The book-to-market ratio increases monotonically with credit risk, from 0.52 in C1 (the lowest credit risk porfolio) to 0.64 in C3 (the highest credit risk portfolio). The average stock price also decreases monotonically with increasing credit risk from $38.07 for the highest-rated stocks to $12.47 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 59% of shares

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

outstanding for high-rated stocks and 49% 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 \$284 million (\$73 million) for the highest-rated NYSE/AMEX (NASDAQ) stocks to \$53 million (\$40 million) for the lowest-rated stocks. Moreover, the Amihud (2002) illiquidity measure is 0.02 (0.12) for NYSE/AMEX (NASDAQ) highest-quality stocks and 0.44 (0.48) for the lowest-quality stocks.[4] This measure is computed as the absolute price change per dollar of daily trading volume:

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

where R_{itd} is the daily return and $DVOL_{itd}$ is the dollar trading volume (both from 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 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 decrease monotonically from 0.58 for the highest to 0.14 for the lowest rated stocks. Dispersion in analysts EPS forecasts increases from 0.03 in C1 to 0.05 in C2 to 0.11 in C3 firms. 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 1.17 for the lowest-rated stocks. Capital investments average 18% in the highest-rated and over 22% in lowest-rated firms, and total assets grow at an annual rate of 8% in highest-rated and 9.5% in lowest-rated companies. Next, market betas increase monotonically from an average of 0.82 for the highest-rated stocks to 1.31 for the lowest-rated stocks. Thus, the lowest-rated stocks have more market risk than the higher-rated stocks. However, the CAPM (Fama-French) alpha decreases from 0.30% (0.11%) per month for the

[4]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.

highest-rated stocks to -0.60% (-0.80%) for the lowest-rated stocks. The SMB beta also increase from -0.06 for the highest-rated stocks to 0.82 for the lowest-rated stocks. Both the market beta and the SMB beta suggest that the returns should be higher for the low-rated stocks but the low-rated stocks have lower returns than the high rated ones.

Overall, low-rated stocks have smaller market cap, lower price, higher market beta, higher SMB 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, asset growth, capital investments, 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 for the entire universe of investable stocks as well as subsets based on market capitalization and credit ratings. In particular, we implement trading strategies across microcap, small cap, and large cap firms. Following 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. We 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.

Investment payoffs from portfolio sorts are based on size and book-to-market adjusted stock returns, as in Fama and French (2008). The size and book-to-market adjustment is made as follows: the monthly return for each stock is measured net of the value-weighted return on a matching portfolio formed on the basis of a 5×5 independent sort on size and book-to-market using all stocks in CRSP.

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[5] 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 standardized unexpected earnings (SUE) based on the latest quarterly EPS reported over the past four months, $t - 4$ to $t - 1$. 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

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

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. It involves buying the lowest volatility quintile (P1), selling the highest volatility quintile (P5), and holding both positions for one month.

The asset growth based trading strategy conditions on the percentage change in total assets from December of year $t-2$ to December of year $t-1$. The strategy involves buying stocks in the lowest asset growth quintile (P1), selling stocks in the highest growth quintile (P5), and holding both positions from July of year t through June of year $t+1$.

The capital investments based trading strategy conditions on the ratio of capital expenditures for year $t-1$ to the amount of property, plant, and equipment as of December of year $t-2$. The strategy involves buying stocks in the lowest capital investments quintile (P1), selling stocks in the highest capital investments quintile (P5), and holding both positions from July of year t through June of year $t+1$.

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 as of December of year $t-1$, 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 from July of year t to June of year $t+1$.

3 Results

One concern we address upfront is whether the sample of rated firms is representative enough. For each anomaly we compute the percentage of market capitalization captured by our sample of rated firms as compared to the entire CRSP sample. Our sample captures 89.35% of market capitalization of the overall CRSP sample for the price momentum anomaly; 90.72% for the earnings momentum anomaly; 90.44% for the dispersion anomaly; 89.30% for the idiosyncratic volatility anomaly; 88.64% for the asset growth anomaly; 88.60% for the capital investments anomaly; 86.84% for the accruals anomaly; and 88.43% for the value anomaly. On average we capture about 89.04% of the CRSP overall market capitalization, suggesting that our sample of rated firms is reasonably representative. In addition, in unreported results, we have compared the investment payoffs for our sample of rated firms to the investment payoffs generated by all firms in CRSP, as well as those generated by the subsample of unrated firms. In both cases, anomaly payoffs are comparable to the ones based on rated firms, and their significance across micro, small, and big firms is very similar. This paper focuses on rating as a proxy for credit conditions, because the rating provides us with a publicly available, non-model-specific, measure of credit risk and financial distress.

Table 2 presents monthly returns for the extreme portfolios (P1 and P5) as well as return differentials (P5-P1 or P1-P5, as noted at the top of each column) for the price momentum, earnings momentum, credit risk, dispersion, idiosyncratic volatility, asset growth, investments, accruals, and value strategies. Panel A (B) exhibits the size- and BM-adjusted equally- (value-) weighted portfolio returns.

We first examine investment profitability for all rated firms based on equally-weighted returns. The price momentum strategy yields a winner-minus-loser return of 100 basis points [bps] per month with the loser (winner) stocks returning -74 (27) bps. The earnings momentum strategy yields a 44 bps monthly return. The credit risk strategy provides a 71 bps monthly return. The dispersion strategy returns 62 bps per month and the idiosyncratic volatility strategy yields 81 bps per month. The asset growth strategy yields 54 bps and the capital investments strategy yields 45 bps per month. The accruals strategy payoff is 27 basis points per month. All these investment payoffs are economically and statistically significant. The value strategy delivers the lowest return – a statistically insignificant -15 bps 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, based on size- and BM-adjusted stock returns.

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 135 (187) basis points per month for microcap stocks. The corresponding figures are 68 (103) for small stocks and 14 (57) 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 -99, -41, and -4 (-144, -76, and -34) 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 37, 27, and 10 (43, 27, and 23) basis points per month for the corresponding size groups. Thus, a large portion of the anomaly profit derives from the short side of the trades.

Likewise, the credit risk, dispersion, idiosyncratic volatility, asset growth, and capital investments strategies deliver returns that monotonically diminish across the size groups, with the highest (lowest) returns attributable to the microcap (big) stock portfolios. The credit risk and the dispersion strategies earn 68 (58) [43] and 111 (75) [34] basis points per month across the microcap (small) [big] stocks. The idiosyncratic volatility strategy payoff decreases from 82 basis points per month for the microcap stocks to 59 basis points for the big stocks. The asset growth (capital investments) based trading strategies deliver returns that decrease from 118 (75) for the microcap to 41 (24) for the big stocks. Once again, the return differential across microcap and big stocks around the short (long) side of the transaction is large (small). For instance, focusing on the asset growth trading strategy, the return differential across microcap and big stocks is 109 basis points on the short side of the trade and 32 basis points per month on the long side of the trade. The accruals strategy yields 31 (38) [21] basis points per month for the microcap (small) [big] firms. After adjusting returns for size and BM, the value strategy is not profitable in the overall sample. Note that amongst the big stocks only the price momentum, asset growth, and accruals based trading strategies are profitable at the 5% level.

Our objective throughout is to examine the impact of credit risk on market anomalies. To pursue the analysis, we further partition the sample into high-rated (C1), medium-rated (C2), and low-rated (C3) stocks. The evidence indeed shows that the impact of credit conditions is quite striking. For instance, the price momentum (asset growth) strategy delivers overall payoffs of 26, 41, and 193 (15, 26, and 76) basis points per month for the high, medium, and low-rated stocks, respectively.

Amongst the high-rated, C1, firms, no strategy (except for the accruals, which provides a statistically significant 0.14% monthly return overall and amongst the big stocks) provides significant payoffs. Amongst the medium-rated, C2, stocks, only the asset growth and accruals based strategies are profitable, and even these two are not profitable among micro and small stocks. None of the other trading strategies (earnings and price momentum, credit risk, dispersion, idiosyncratic volatility, capital investments, or value) displays significant investment payoffs in the C1 and C2 subsamples.

Remarkably, all trading strategies (except for value) are profitable amongst the low-rated, C3, stocks. Observe from Table 2 that the highest return (2.62% per month) is earned by the price momentum strategy upon conditioning on low-rated, microcap stocks. The next highest investment return (1.84%) 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 ratings deliver a significant (at the 10% level) price momentum return of 81 basis points per month. All the trading strategies are profitable for the low rated microcap and the small stocks. The only exception is the analyst dispersion based strategy for small stocks which is profitable only at the 10% level. Amongst the low-rated, big stocks only the idiosyncratic volatility-, accruals- and value-based strategies are profitable. The value-based trading strategy provides statistically and economically significant returns (103 basis points per month) for only the low-rated big stocks. Thus, even though the returns are adjusted for size and BM, the value strategy is profitable in the low-rated stocks.

Panel B of Table 2 is the value-weighted counterpart of Panel A. Indeed, the value-weighted payoffs are often lower, suggesting a role for small firms. For instance, the overall unconditional return to the price (earnings) momentum strategy in Panel B is 64 (18) basis points per month, as compared to 100 (44) basis points per month in Panel A. Nevertheless, investment profitability is typically significant amongst low-rated firms. Moreover, investment payoffs generally increase with worsening credit rating. Only the idiosyncratic volatility, asset growth, capital investments and the value based trading strategy is profitable amongst the low-rated, big stocks.

Quite prominent in the results is the overwhelming impact of the short side of the trading strategies. To illustrate, consider the small rated stocks. For price momentum the long side of the trade earns 27 basis points per month and the short side 79 basis points per month. For earnings momentum the corresponding long (short) returns are 20 (42) basis points; for credit risk 4 (64); for dispersion 38 (39); for idiosyncratic volatility 9 (72); for asset growth 3 (58); and for capital investments 4 (67). Another way to see the importance of the short side of the trade is to examine the return differential across the lowest- and the highest-rated stocks. Consider the price momentum strategy. The size and book-to-market adjusted value-weighted return for the winner portfolio is 21 basis points per month among C1 stocks and 8 basis points among C3 stocks. This represents a return differential of 13 basis points per month. On the other hand, the return differential across the loser stocks is 108 [114-6] 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 (63) basis points per month. The return differential for the long (short) portfolios for the credit risk strategy is 37 (64) basis points; for the dispersion strategy it is 23 (44); for the idiosyncratic volatility strategy it is 12 (151); for the asset growth strategy it is 16 (73); for the capital investments strategy it is 4 (93); and for the value strategy it is 1 (66) basis points. Only in the case of the accruals strategy are the long and short portfolio return differentials similar, 51 versus 69 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 are remarkably robust for the small and microcap stocks. 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 BM-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 is the full sample with 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 17.78% of the total number of rated stocks, they account only for 0.46% of the market capitalization; small stocks comprise 27.26% of the total number of stocks and 3.03% of the total market capitalization; big firms comprise 54.97% of the total number of stocks and an overwhelming 96.51% 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 capitalization 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 0.44% (1.00%) per month in the overall sample to a statistically insignificant 0.17% (0.36%) as firms rated BB- or below are eliminated. The asset growth strategy is reduced to an insignificant 19 basis points when firms rated BB+ and below are removed from the sample. The accruals strategy is an exception, remaining statistically significant throughout. The maximum profitability for the accruals strategy (29 basis points) emerges when stocks rated CC and below are excluded. The profitability then diminishes to a statistically significant 12 basis points when the sample consists of only the investment grade firms. 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 9.7% of the sample based on market capitalization.

Conditioning on market capitalization, we show that the earnings momentum, credit risk, dispersion, idiosyncratic volatility, and the capital investments based anomalies are unprofitable amongst big firms for all rating categories. Among big firms, the price momentum anomaly becomes unprofitable at the 10% level as firms rated B+ and below are eliminated from the sample. These firms account only for 1.82% (96.51%-94.69%) of the market capitalization of firms in our sample. Among big firms, only the accruals anomaly displays significant profitability as all non-investment grade stocks are excluded.

Considering small market capitalization firms, the profitability of all anomalies disappears when stocks rated BB+ and lower comprising 1.81% (3.03%-1.22%) 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.[6]

Thus far, the analysis has exclusively focused on credit rating levels. The overall evidence suggests that credit risk has a major impact on the cross-section of stock returns in general and market anomalies in particular. Specifically, investment profitability typically rises with worsening credit conditions. Moreover, the short side of the trading generates most of the profits.

Studying the impact of credit rating changes is our next task. 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 fall sharply following credit rating downgrades, while credit rating upgrades play virtually no role. However, the potential implications of credit rating downgrades for all the market anomalies have not yet been explored. Below we show that credit rating downgrades are indeed crucial for understanding the source of market anomalies.

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. The evidence suggests that rating downgrades exhibit differential patterns across credit risk groups. For one, the number of downgrades in the highest-rated portfolio is 2,485 (8.94 per month on average), while the corresponding figure for the lowest-rated portfolio is much larger at 3,147 (11.32 per month on average). Moreover, the average size of a downgrade amongst the lowest-rated stocks is 2.14 points (moving from $B+$ to $B-$), whereas the average downgrade amongst the highest-rated stocks is lower at 1.75 points (moving from $A+$ to $A-$).

Next, 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 -1.15% for the best-rated stocks, while it is -14.08% for the worst-rated. In the six-

[6] While we have presented the equally-weighted results, the value-weighted results show that an even smaller fraction of the low-rated firms drive the anomaly profits.

month period before (after) the downgrade, the lowest-rated firms deliver an average return of -25.99% (-16.69%). The corresponding figure for the highest-rated stocks is 2.09% (5.39%). 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 -32.44% (-13.26%), while the return for the highest-quality stocks is 5.53% (11.86%).

Panel A of Table 4 also documents the number of delisted firms across the various rating deciles. Over 6 (12) [24] months after a downgrade, the number of delistings amongst the highest-rated stocks are 63 (96) [154], while the corresponding figures are 289 (484) [734] amongst the lowest-rated stocks. The probability of delisting of a low rated firm over 6 months following a downgrade is 9.2% (289 delistings out of 3,147 downgrades) while it is only 2.5% (63 delistings out of 2,485 downgrades) for the high rated firms. 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 10 (13); a high-rated firm experiences on average 9 (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 -20.30% (-9.96%) 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 about the same during up (2.16 points) and down (2.11 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 -7.76% (-4.76%) in up (down) market. The corresponding return for high-rated firms is 1.10% (-1.37%) in up (down) market.

We also examine downgrades during expansions and recessions as defined by NBER. This analysis is merely suggestive as there are only 28 months of recessions in our sample. We find that the low-rated firms have an average of 19 downgrades per month during recessions and 11 during expansions. Also, the returns of low-rated stocks for the month of the downgrade during recessions is -16.60% while the return for the month of the downgrade during expansions is -13.70%.

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. Specifically, 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 (7.28%) than in the high-rated firms (2.73%). 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 2008. The evidence further shows that for almost every category of number of downgrades (N ranging between one and ten), the average size per downgrade is 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 3-month returns for the non-investment grade stocks average -17.32% (-21.84%) per downgrade by the sixth downgrade (N=6). On the other hand, for the investment grade stocks, the 3-month returns average -3.96% (-0.64%) per downgrade in the 3 months before (after) a downgrade. For each downgrade frequency, we have also examined (results are not reported) the cumulative returns during periods of expansions versus recessions as well as periods when the market excess returns are positive versus negative. Not surprisingly, returns for non-investment grade stocks are far more negative during recessions as well as periods of negative market returns.

Overall, the lowest-rated stocks experience significant price drops around downgrades, whereas, unconditionally, the highest-quality stocks realize positive returns.[7] 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.[8] Panel A (B) of Table 5 presents the equally-weighted (value-weighted) size- and BM-adjusted returns for the various strategies.

Panel A shows that, except for accruals and value, the economic and statistical significance of all trading strategies diminishes strongly when only periods of stable or improving conditions are considered. Price momentum, credit risk, dispersion, idiosyncratic volatility, and capital investments are unprofitable overall, as well as in all credit risk- and size-sorted subsamples. Earnings momentum is unprofitable overall and in all subsamples, except for low-rated microcap stocks. Only the asset growth strategy returns are statistically significant in the overall sample, although they drop from 54 bps (Table 2) to 27 bps (Table 5) per month when periods around downgrades are removed. Moreover, the asset growth profitability disappears from all, but the low-rated microcap stocks and the medium-rated big stocks, subsamples.

[7] 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.

[8] 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.

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 32 bps per month overall (as opposed to 27 bps in Table 2). The strategy results in payoffs of 52, 32, and 24 bps per month for the microcap, small, and big firms, respectively (as compared to 31, 38, and 21 bps in Table 2). Only the accruals based trading strategy is profitable for some size groups across the different rating categories.

The value strategy is also more profitable at 26 bps (t-statistic of 2.53) when the period around downgrades is eliminated, as opposed to an insignificant -15 bps per month for the entire sample. The value strategy provides a significant size- and BM-adjusted return of 61 bps per month among low-rated stocks and 85 bps per month among big low-rated stocks, suggesting that low-rated stocks that survive financial distress earn positive abnormal returns.

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 asset growth strategy is profitable and that too only for the low-rated microcap and medium-rated big stocks. All other strategies provide insignificant returns regardless of the conditioning on size or credit rating.

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 15 basis points as compared to 108 basis points in Panel B of Table 2. Moreover, the long side of the trade generates only a one basis point difference. Similarly, for the earnings momentum strategy the short (long) side of the trade yields 13 (13) basis points per month. The short (long) side of the trade yields one (22) basis points for the credit risk anomaly, 33 (5) basis points for the dispersion anomaly, 59 (one) basis points for the idiosyncratic volatility anomaly, 17 (6) for the asset growth anomaly and 40 (29) for the capital investments anomaly. All of these differences are far smaller than when the downgrade period was included in the sample. In the case of the value anomaly, a larger fraction of the profits 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 further 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 eighteen months before the downgrade to nine months after. The return is as low as -14% 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 C3 stocks becomes increasingly negative from about fifteen months prior to the downgrade, reaching a minimum of -1 in the downgrade month, and remains negative until about twelve months after the downgrade. A profitable earnings momentum strategy would require going short in the C3 stocks. Analyst forecast dispersion, idiosyncratic volatility, asset growth, and investments increase around downgrades for C3 stocks. Thus, forecast dispersion, idiosyncratic volatility, asset-growth, and investments for C3 stocks are high when the returns are low and a profitable strategy would require going short the high dispersion, high idiosyncratic volatility, high asset growth, or high capital investments, C3 stocks.

Given that the accruals anomaly is a result of managerial discretion, there is no discernible pattern in accruals across the high- or 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 1.8) among 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.

There is an important concern about potential endogeneity because we are looking ahead to identify distress periods. It could be the case that the rating agencies look at past returns before downgrading. Thus, the negative returns could be driving the downgrade while we have implicitly assumed that it is financial distress that leads to the negative returns. We address this endogeneity in a number of ways.

First, note from Figure 1, that the most negative return, around -14%, occurs during the month of the downgrade suggesting that the downgrade is informative or possibly the downgrade leads to selling by institutions that cannot hold low-rated securities. To further check that it is indeed financial distress that drives the returns, we plot Altman's Z-scores around downgrades in the top panel of Figure 2. Note that the Z-score of C3 firms reaches a minimum around downgrades suggesting that we are indeed capturing financial distress. However, the Z-score uses past returns as one of the variables. Thus, we have not yet completely addressed the endogeneity issue.

Next, we compute return-adjusted ratings and rating changes to ensure that our rating measures are not contaminated by past returns. Specifically, each month, we run cross-sectional regressions of rating levels on cumulative past six-month returns. The past six-month-return-adjusted rating is computed as the intercept and residual from these cross-sectional regressions. We then repeat the analysis of Table 2, sorting stocks on their return-adjusted ratings, rather than on raw ratings. The results, presented in the appendix in Table 2A, are similar to those in Table 2, suggesting that ratings rather than past returns impact the profitability of anomalies. Furthermore, we replicate the results of Table 5 by adjusting rating changes as follows. We regress all rating changes on past six-month returns. The past six-month-return-adjusted rating change is the intercept and residual from this regression. A past-returns-adjusted rating change that is larger than two standard deviations above the mean is considered a downgrade. This measure of downgrade, which is independent of past returns, is what we use to identify the period of financial distress. We then repeat the analysis in Table 5, but remove periods around past-returns-adjusted downgrades, rather than raw downgrades. The results, presented in the appendix in Table 5A, are quite similar to those in Table 5, suggesting once again that our results are indeed driven by financial distress and not by past returns.

Examining industry-adjusted financial ratios is essential to confirm that firms are indeed experiencing financial distress around downgrades. In particular, we examine the profit margin, interest coverage, and asset turnover around downgrades. Profit margin is defined as net income over sales; interest coverage is defined as EBIT over interest expense; and asset turnover is defined as sales over total assets. We do not examine any leverage ratios because these are likely to be driven by past returns since the market capitalization declines due to the large negative returns before a downgrade. Table 6 presents the median industry-adjusted ratio from eight quarters before to eight quarters after the downgrade. It is clear that, around downgrades, the low-rated stocks experience considerable deterioration in their underlying business relative to their industry as measured by the profit margin, interest coverage, and asset turnover.

Finally, we examine covenant violations around rating downgrades. Covenant violations can show whether downgrades are associated with financial problems. Covenant violations data is compiled by Professor Amir Sufi from company 10-K or 10-Q filings and provided on his webpage.[9] The data represents a binary variable: 0 for no covenant violations for the fiscal quarter and 1 if a violation of a financial covenant has been reported in that fiscal quarter. It covers the period from June 1996 to June 2008. The data is described in detail in the appendix of Nini, Sufi, and Smith (2009). The data captures actual violations of financial covenants and is an exogenous variable which is not based on a model, past returns, or any other firm characteristic. The average percentage of firms with covenant violations for our sample of rated firms is 3.86% (0.84%/2.42%/6.57% for C1/C2/C3 firms).

The bottom plot in Figure 2 presents the proportion of C1 and C3 firms with covenant violations around downgrades. The percentage of C3 firms with covenant violations reaches a maximum around downgrades and is as high as 26.80% in the three months around the downgrade. In contrast, the maximum percentage of covenant violations in C1 firms is 5.43% and occurs more than 18 months after the downgrade. The figure confirms that high credit risk firms face real financial distress around downgrades.

In sum, the evidence altogether points to financial distress as the determinant of

[9] http://faculty.chicagobooth.edu/amir.sufi/data.htm

falling stock prices prior to downgrade. It is financial distress that is indeed driving the profitability of the examined anomalies.

3.3 Regression Analysis

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

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

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 for stocks with at least 24 months of non-missing returns data,[10] and $C_{i,t-lag}$ is the value of the conditioning variable underlying a specific trading strategy, lagged as prescribed by the corresponding anomaly. Specifically, momentum uses the past six-month cumulative returns as the independent variable after a one-month lag. SUE are based on the last reported EPS over the past 4 months. Credit risk, dispersion, and idiosyncratic volatility condition on variables from the past month. For the asset-growth, investments, and book-to-market anomalies, we use conditioning variables as of December of year $t-1$ for returns between July of year t to June of year $t+1$. Returns of month t are regressed on quarterly Accruals 4 months prior.

Each column in Table 7 reports the results from a separate univariate regression of future returns on a past anomaly variable and shows the time-series average of these cross-sectional regression coefficients, b_t. We then add 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.

Table 7 Panel A exhibits the cross-sectional regression coefficients for all stocks. 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 (0.77) and standardized unexpected earnings (0.12) are positive and significant, consistent with the

[10]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).

price and earnings momentum anomalies. The coefficient estimates for credit risk (-0.07), analyst dispersion (-0.32), idiosyncratic volatility (-7.96), asset-growth (-0.37), capital investments (-0.51), and accruals (-3.98) are negative and significant, again consistent with prior results. The coefficient estimate for the book-to-market ratio is insignificant in the cross-sectional regressions.

Next we introduce dummy variables for the six-month period around downgrades.[11] 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 asset growth, the accruals, and the value strategies are profitable. Then we consider both dummies for investment grade and non-investment 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 asset growth, accruals, and value strategies result in positive payoffs, whereas none of the other strategies is profitable.

Overall, the regression 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, idiosyncratic volatility, and capital investments anomalies are driven by falling stock prices around credit ratings downgrades.

Note that the coefficients for the book-to-market ratio actually increase and become significant 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. This negative relationship makes the value strategy unprofitable around periods of financial distress.

Panel B, C, and D of Table 7 presents the regression evidence for microcap, small, and big stocks, respectively. Only the coefficients for earnings momentum and asset growth are significant for microcap stocks in the presence of the downgrade dummy variables.

[11] We have also interacted the downgrade dummy variables with credit rating as well as with liquidity and the results were similar.

For small stocks, the earnings momentum and capital investments anomalies still produce positive payoffs when downgrade dummies are included although the payoffs are smaller than without downgrade dummies. Accruals and the value anomalies are profitable in small stocks when downgrade periods are removed consistent with our portfolio-based results. For big stocks, only the accruals and asset growth trading strategies are profitable in the presence of the downgrade dummy variables.

The evidence suggests that the accruals and value anomalies become stronger when periods around rating downgrades are removed. Further, the accruals anomaly is profitable for big stocks, which account for over 96% of the sample by market capitalization. All other anomalies display diminishing coefficient estimates as the dummy variables for downgrade periods are introduced into the regression. Except for the accruals, value and asset growth anomalies, profitability of all other anomalies is attributable to negative returns realized on the short side of the trade around credit rating downgrades.

While Table 7 focuses on univariate regressions, we next consider multivariate cross-sectional asset pricing regressions combining all anomalies. We present Fama-Macbeth coefficients in five regressions of risk-adjusted returns on various combinations of the anomaly variables with firm size employed as a control variable. It is evident from Table 8 that over our sample period, firm size is insignificant across all five specifications.

Regressions (1) and (2) show that before introducing the dummy variables for the periods of financial distress, the anomaly variables that provide statistically significant (at the 5% level) profits are earnings momentum, credit risk, idiosyncratic volatility and accruals.[12] The dispersion anomaly is profitable only in the absence of the credit risk anomaly, consistent with Avramov, Chordia, Jostova, and Philipov (2009b). The price momentum anomaly is statistically insignificant in the presence of the earnings momentum anomaly, consistent with Chordia and Shivakumar (2006) who show the two anomalies interact. Asset growth and investments are insignificant in the presence of the other anomaly variables.

Introducing dummy variables for periods of financial distress, we find that the only two anomalies that are profitable are accruals and the value anomaly. The value anomaly is profitable when the high book-to-market stocks survive financial distress, whereas the accruals anomaly is significant regardless of whether the returns are conditioned

[12]We have experimented excluding other anomaly variables and the results are consistent with the ones presented here.

on periods of financial distress or not. In the presence of downgrade dummies, both earnings and price momentum are insignificant (regressions (4) and (5)).

The questions that arise at this stage are: (i) Why are these negative returns around financial distress 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 in taking short positions.

3.4 Short-Sale Constraints and Illiquidity

Impediments to trading such as short selling costs and poor liquidity could establish non-trivial hurdles for exploiting market anomalies. Hence, we examine how short-sale 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) liquidity, 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 liquidity could make it difficult to trade in and out of positions. We examine illiquidity using the Amihud (2002) measure noted earlier.

Table 9 presents the mean and median measures of institutional holdings, shares outstanding, and illiquidity for portfolios sorted on credit ratings and firm size. Among all rated stocks, not surprisingly, big stocks are more liquid and they have more shares outstanding and higher institutional holdings.

Conditioning on credit ratings, we show that low-rated stocks are substantially more illiquid. For instance, the median Amihud measure increases monotonically from 0.02 (0.12) for the high-rated NYSE/AMEX (Nasdaq) stocks to 0.44 (0.48) 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 80.39 million for the high-rated stocks to 26.59 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 9). 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.

We have shown that it is difficult to short-sell the low rated stocks. Recall that there are fewer analysts following the low rated stocks and there is higher forecast dispersion as well. Table 1 also documents that the analyst revisions decline from -0.02% for the high rated stocks to -0.14% for the low rated stocks (these differences in forecast revisions are stronger when we examine quintile or decile portfolios formed by sorting on ratings). Thus, while analysts are generally optimistic, they are more optimistic about the prospects of the low rated stocks. Thus, not only is it difficult to short sell the low rated stocks, but in an informationally poor environment (fewer analysts with higher forecast dispersion) the analysts are considerably more optimistic about the prospects of these firms.

4 Conclusions

The empirically documented price momentum, earnings momentum, credit risk, analysts' forecasts dispersion, idiosyncratic volatility, asset growth, capital investments, 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, idiosyncratic volatility, asset growth, and investments 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 9.7% of the market capitalization of the rated firms. Indeed, the profitability of price momentum, earnings momentum, credit risk, dispersion, idiosyncratic volatility, asset growth, and investments 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. During stable or improving credit conditions, none of the above strategies delivers significant payoffs, except for the asset growth anomaly. Even the profitability of the latter diminishes significantly, and disappears from all, but the low-rated microcap and the medium-rated big stocks, subsamples.

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. Moreover, analysts are more optimistic about the prospects of the low rated firms than those of the high rated firms.

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 or improving 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 t, all stocks rated by Standard & Poor's are divided into terciles based on their credit rating. Stocks priced below \$1 are removed. The top part of Panel A reports the average S&P numeric (and letter equivalent) rating for each group, where the numeric rating is 1=AAA, 2=AA+, ..., 21=C, 22=D. For each tercile, we compute the cross-sectional median characteristic for month $t+1$. The sample period is October 1985 to December 2008. Panel A reports the time-series average of these monthly medians. Institutional share is the percentage of shares outstanding owned by institutions. Dollar volume is the monthly dollar trading volume. Amihud's illiquidity is computed, as in Amihud (2002) (see eq. (1)). Analyst revisions is 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 EPS reported this quarter minus the EPS four quarters ago, divided by the standard deviation of EPS changes over the last eight quarters. Dispersion is the standard deviation in analysts EPS forecasts standardized by the absolute value of the consensus forecast. Leverage is the ratio of book value of long-term debt to common equity. Investments is measured as the current year's capital expenditures over the prior year Property, Plant and Equipment. Asset growth represents the percentage change in total assets from the prior year. In Panel B, CAPM and Fama and French (1993) alphas and betas are obtained from time-series regressions of the credit risk tercile portfolio excess returns on the factor returns. 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
Average S&P Letter Rating	A+	BBB-	B+
Average S&P Numeric Rating	5.55	9.64	14.39
Size (\$billions)	3.30	1.26	0.35
Book-to-Market Ratio	0.52	0.62	0.64
Price (\$)	38.07	26.40	12.47
Institutional Share	0.59	0.61	0.49
Dollar Volume - NYSE/AMEX (\$ mln)	284.34	147.27	53.28
Dollar Volume - Nasdaq (\$ mln)	73.07	84.64	39.57
Illiquidity-NYSE/Amex ($\times 10^7$)	0.02	0.05	0.44
Illiquidity - Nasdaq ($\times 10^7$)	0.12	0.19	0.48
Number of Analysts	14.04	9.30	5.28
Analyst Revisions (%)	-0.02	-0.11	-0.14
SUE	0.58	0.33	0.14
Dispersion in Analysts EPS Forecasts	0.03	0.05	0.11
LT Debt/Equity	0.54	0.77	1.17
Investments (%)	18.07	17.99	22.22
Asset Growth (%)	8.01	7.93	9.53

PANEL B: Portfolio Alphas and Betas

	C1	C2	C3	C1-C3
CAPM Alpha (%/month)	0.30	0.21	-0.60	0.90
	(**2.96**)	(1.71)	(**-3.06**)	(**4.12**)
CAPM Beta	0.82	0.95	1.31	-0.48
	(**37.46**)	(**34.68**)	(**30.17**)	(**-10.06**)
FF93 Alpha (%/month)	0.11	-0.05	-0.80	0.91
	(1.69)	(-0.58)	(**-6.49**)	(**6.81**)
Mkt Beta	0.96	1.08	1.32	-0.37
	(**59.33**)	(**56.48**)	(**44.78**)	(**-11.42**)
SMB Beta	-0.06	0.28	0.82	-0.89
	(**-3.00**)	(**11.07**)	(**21.12**)	(**-20.88**)
HML Beta	0.41	0.60	0.47	-0.06
	(**16.47**)	(**19.95**)	(**10.24**)	(-1.16)

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. We exclude stocks priced below \$1 at the beginning of the month. 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. The asset-growth anomaly conditions on the percentage change in total assets from December of year t-2 to December of year t-1, and uses this percentage for holding period returns between July of year t and June of year $t + 1$. Similarly the investments anomaly conditions on the ratio of annual capital expenditures to Property, Plant and Equipment as of December of year t-1, and uses this ratio for holding period returns between July of year t and June of year $t + 1$. 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 2008. 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 independently sorted portfolios using NYSE size and BM quintiles as of December of year t-1. Value-weighted portfolio returns are then calculated for each of 25 Size and BM sorted portfolios using all NYSE, Amex, and Nasdaq firms from July of year t to June of year t+1. We then subtract the monthly return of the size-BM 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	Asset Growth	Investment	Accruals	BM
Strategy		P5-P1	P5-P1	P1-P5	P1-P5	P1-P5	P1-P5	P1-P5	P1-P5	P5-P1
All Rated	P1	-0.74	-0.29	0.08	0.21	0.04	0.03	-0.04	0.01	-0.12
	P5	0.27	0.15	-0.63	-0.41	-0.78	-0.51	-0.49	-0.26	-0.27
	Strategy	1.00	0.44	0.71	0.62	0.81	0.54	0.45	0.27	-0.15
		(**4.07**)	(**3.15**)	(**3.61**)	(**2.94**)	(**2.71**)	(**4.43**)	(**2.45**)	(**3.43**)	(-1.26)
Micro Rated	P1	-1.44	-0.99	-0.12	0.10	-0.33	-0.18	-0.27	-0.27	-0.63
	P5	0.43	0.37	-0.81	-1.00	-1.16	-1.36	-1.03	-0.58	-0.49
	Strategy	1.87	1.35	0.68	1.11	0.82	1.18	0.75	0.31	0.14
		(**7.30**)	(**4.32**)	(**2.08**)	(**2.75**)	(**2.46**)	(**4.96**)	(**2.66**)	(**2.01**)	(0.31)
Small Rated	P1	-0.76	-0.41	0.02	0.36	0.10	0.07	0.02	0.05	-0.25
	P5	0.27	0.27	-0.57	-0.38	-0.65	-0.55	-0.60	-0.33	-0.27
	Strategy	1.03	0.68	0.58	0.75	0.75	0.62	0.63	0.38	-0.03
		(**3.73**)	(**3.46**)	(**2.00**)	(**2.99**)	(**2.21**)	(**3.89**)	(**2.99**)	(**3.35**)	(-0.12)
Big Rated	P1	-0.34	-0.04	0.11	0.18	0.05	0.14	0.02	0.08	-0.07
	P5	0.23	0.10	-0.33	-0.16	-0.54	-0.27	-0.22	-0.13	0.03
	Strategy	0.57	0.14	0.43	0.34	0.59	0.41	0.24	0.21	0.10
		(**2.05**)	(0.91)	(1.29)	(1.36)	(1.67)	(**2.74**)	(1.14)	(**2.56**)	(0.70)
C1 All	P1	-0.04	0.00	0.05	0.25	0.08	0.15	0.05	0.15	0.13
	P5	0.21	0.16	0.12	-0.06	0.02	-0.00	0.05	0.02	-0.07
	Strategy	0.26	0.16	-0.07	0.31	0.06	0.15	-0.00	0.14	-0.20
		(1.33)	(1.20)	(-0.94)	(1.71)	(0.28)	(1.41)	(-0.01)	(**2.30**)	(-1.13)
C1 Micro	P1	-0.32	-0.35	0.06	0.48	0.28	-0.12	-0.15	0.15	0.26
	P5	0.28	0.89	-0.03	-0.39	-0.80	0.13	-0.13	-0.10	-0.01
	Strategy	0.68	1.13	0.16	0.60	0.68	-0.35	-0.05	0.33	-2.03
		(1.53)	(1.25)	(0.44)	(0.76)	(1.35)	(-0.76)	(-0.09)	(1.02)	(-0.33)
C1 Small	P1	-0.51	-0.39	-0.02	-0.13	0.17	0.16	0.02	-0.17	-0.19
	P5	0.20	-0.04	-0.18	-0.27	-0.28	0.08	-0.05	-0.08	-0.04
	Strategy	0.72	0.35	0.16	0.08	0.45	0.08	0.09	-0.09	0.68
		(1.41)	(0.96)	(0.79)	(0.17)	(1.48)	(0.22)	(0.21)	(-0.61)	(0.74)
C1 Big	P1	0.03	0.04	0.06	0.26	0.05	0.15	0.06	0.19	0.13
	P5	0.23	0.16	0.18	0.03	0.09	0.03	0.09	0.05	0.01
	Strategy	0.20	0.12	-0.12	0.23	-0.04	0.12	-0.03	0.14	-0.12
		(1.02)	(0.88)	(-1.41)	(1.21)	(-0.15)	(1.06)	(-0.17)	(**2.15**)	(-0.72)
C2 All	P1	-0.18	-0.09	0.02	0.12	0.03	0.09	0.01	0.07	0.01
	P5	0.23	0.09	0.05	-0.06	-0.06	-0.17	-0.07	-0.12	-0.04
	Strategy	0.41	0.18	-0.04	0.18	0.09	0.26	0.09	0.19	-0.05
		(1.85)	(1.13)	(-0.38)	(0.93)	(0.36)	(**2.24**)	(0.50)	(**2.31**)	(-0.39)
C2 Micro	P1	-0.17	-0.34	0.03	-0.05	-0.45	-0.10	0.06	-0.38	-1.51
	P5	0.17	-0.20	-0.05	-0.43	-0.17	0.10	-0.01	-0.42	-0.09
	Strategy	0.37	0.05	-0.06	0.36	-0.16	-0.35	0.18	0.04	1.22
		(0.80)	(0.08)	(-0.17)	(0.59)	(-0.33)	(-0.51)	(0.30)	(0.11)	(1.20)
C2 Small	P1	-0.21	-0.16	-0.32	0.05	-0.01	-0.02	-0.08	0.08	0.00
	P5	0.21	0.19	0.03	-0.20	-0.14	-0.29	-0.24	-0.07	-0.06
	Strategy	0.42	0.35	-0.35	0.25	0.13	0.27	0.16	0.15	-0.06
		(1.80)	(1.76)	(-1.64)	(0.93)	(0.47)	(1.44)	(0.73)	(1.21)	(-0.16)
C2 Big	P1	-0.18	-0.05	0.10	0.14	0.07	0.16	0.08	0.06	0.01
	P5	0.28	0.06	0.10	0.10	-0.05	-0.13	-0.02	-0.16	0.12
	Strategy	0.46	0.11	0.00	0.04	0.12	0.30	0.10	0.22	0.11
		(1.92)	(0.65)	(0.01)	(0.16)	(0.47)	(**2.29**)	(0.58)	(**2.06**)	(0.74)
C3 All	P1	-1.55	-0.78	-0.16	0.17	-0.05	-0.08	-0.20	-0.16	-0.47
	P5	0.37	0.19	-1.06	-0.52	-1.57	-0.85	-0.98	-0.61	-0.49
	Strategy	1.93	0.97	0.90	0.69	1.51	0.76	0.78	0.45	-0.02
		(**5.59**)	(**5.17**)	(**4.43**)	(**2.62**)	(**4.47**)	(**3.68**)	(**3.26**)	(**3.34**)	(-0.10)
C3 Micro	P1	-1.95	-1.32	-0.09	-0.18	-0.25	-0.13	-0.48	-0.25	-0.75
	P5	0.67	0.08	-1.29	-1.40	-1.93	-1.55	-1.45	-0.70	-0.65
	Strategy	2.62	1.40	1.20	1.23	1.69	1.42	0.96	0.45	0.10
		(**7.83**)	(**4.09**)	(**4.04**)	(**2.72**)	(**4.86**)	(**4.36**)	(**2.55**)	(**2.34**)	(0.25)
C3 Small	P1	-1.48	-0.65	-0.06	0.36	0.14	-0.04	0.03	-0.05	-0.29
	P5	0.36	0.34	-1.04	-0.22	-1.32	-0.72	-0.92	-0.54	-0.60
	Strategy	1.84	0.99	0.98	0.58	1.46	0.69	0.95	0.48	-0.31
		(**4.56**)	(**3.81**)	(**2.91**)	(1.80)	(**3.27**)	(**2.74**)	(**3.56**)	(**2.78**)	(-1.13)
C3 Big	P1	-0.76	-0.36	-0.29	-0.14	-0.17	-0.03	-0.11	0.01	-0.59
	P5	0.04	0.04	-0.11	-0.20	-1.56	-0.49	-0.57	-0.65	0.44
	Strategy	0.81	0.40	-0.19	0.06	1.37	0.46	0.46	0.66	1.03
		(1.76)	(1.27)	(-0.46)	(0.16)	(**2.52**)	(1.51)	(1.26)	(**2.14**)	(**2.65**)

Table 2 (continued)

Panel B: Value-Weighted Size and BM adjusted Returns

Anomaly		Momentum	SUE	Credit Risk	Dispersion	Idio Vol	Asset Growth	Investment	Accruals	BM
Strategy		P5-P1	P5-P1	P1-P5	P1-P5	P1-P5	P1-P5	P1-P5	P1-P5	P5-P1
All Rated	P1	-0.37	-0.12	0.05	0.10	0.02	0.19	0.06	0.11	-0.02
	P5	0.28	0.06	-0.61	-0.36	-0.57	-0.27	-0.20	-0.13	-0.12
	Strategy	0.64	0.18	0.66	0.46	0.59	0.46	0.25	0.24	-0.11
		(**2.33**)	(0.98)	(**2.21**)	(1.69)	(1.63)	(**2.43**)	(1.08)	(**2.20**)	(-1.05)
Micro Rated	P1	-1.35	-0.90	-0.13	0.02	-0.22	-0.22	-0.22	-0.22	-0.59
	P5	0.33	0.32	-0.86	-0.99	-1.18	-1.26	-1.04	-0.56	-0.54
	Strategy	1.68	1.22	0.72	1.03	0.95	1.04	0.82	0.34	0.05
		(**6.14**)	(**3.71**)	(1.93)	(**2.44**)	(**2.63**)	(**3.87**)	(**2.58**)	(1.94)	(0.11)
Small Rated	P1	-0.79	-0.42	0.04	0.38	0.09	0.03	0.04	0.07	-0.27
	P5	0.27	0.20	-0.64	-0.39	-0.72	-0.58	-0.67	-0.35	-0.31
	Strategy	1.06	0.62	0.67	0.76	0.81	0.61	0.71	0.42	-0.04
		(**3.76**)	(**3.08**)	(**2.27**)	(**2.93**)	(**2.31**)	(**3.65**)	(**3.11**)	(**3.41**)	(-0.19)
Big Rated	P1	-0.32	-0.09	0.05	0.09	0.02	0.20	0.06	0.11	-0.01
	P5	0.28	0.06	-0.44	-0.34	-0.53	-0.25	-0.16	-0.12	-0.07
	Strategy	0.59	0.15	0.48	0.43	0.55	0.45	0.21	0.23	-0.06
		(**2.12**)	(0.84)	(1.34)	(1.52)	(1.44)	(**2.29**)	(0.89)	(**2.06**)	(-0.50)
C1 All	P1	-0.06	-0.05	0.06	0.23	0.06	0.16	0.01	0.10	0.01
	P5	0.21	0.13	0.07	-0.02	-0.07	-0.03	-0.04	-0.03	-0.06
	Strategy	0.27	0.18	-0.01	0.25	0.13	0.20	0.06	0.13	-0.07
		(1.19)	(0.92)	(-0.08)	(1.00)	(0.48)	(1.01)	(0.27)	(1.15)	(-0.46)
C1 Micro	P1	-0.38	-0.41	0.10	0.49	0.29	0.03	0.02	0.15	0.26
	P5	0.11	0.84	-0.25	-0.32	-0.79	0.02	-0.15	-0.10	-0.03
	Strategy	0.57	1.27	0.41	0.47	0.70	-0.05	0.03	0.31	-1.41
		(1.21)	(1.28)	(1.02)	(0.52)	(1.19)	(-0.09)	(0.06)	(1.02)	(-0.23)
C1 Small	P1	-0.51	-0.45	-0.03	-0.19	0.16	0.18	0.11	-0.14	-0.19
	P5	0.21	-0.08	-0.15	-0.32	-0.18	0.13	-0.08	-0.05	-0.03
	Strategy	0.72	0.38	0.12	0.09	0.34	0.05	0.20	-0.09	0.65
		(1.38)	(1.02)	(0.59)	(0.19)	(1.10)	(0.13)	(0.46)	(-0.58)	(0.71)
C1 Big	P1	-0.06	-0.04	0.06	0.23	0.06	0.16	0.01	0.10	0.01
	P5	0.21	0.13	0.07	-0.02	-0.07	-0.03	-0.04	-0.03	-0.05
	Strategy	0.27	0.17	-0.02	0.25	0.13	0.20	0.05	0.13	-0.06
		(1.18)	(0.90)	(-0.10)	(0.98)	(0.48)	(1.01)	(0.26)	(1.15)	(-0.40)
C2 All	P1	-0.36	-0.30	0.09	0.13	0.14	0.25	0.08	0.08	-0.10
	P5	0.39	-0.14	0.01	-0.15	-0.24	-0.32	-0.02	-0.23	0.11
	Strategy	0.75	0.16	0.08	0.28	0.39	0.58	0.10	0.31	0.21
		(**2.61**)	(0.72)	(0.54)	(1.01)	(1.21)	(**2.83**)	(0.37)	(**2.14**)	(1.24)
C2 Micro	P1	-0.22	-0.41	-0.03	0.02	-0.39	-0.35	0.00	-0.46	-1.52
	P5	0.13	-0.22	-0.17	-0.66	-0.35	0.09	0.18	-0.35	-0.13
	Strategy	0.39	0.11	-0.07	0.62	0.10	-0.58	-0.06	-0.11	1.05
		(0.81)	(0.21)	(-0.18)	(0.94)	(0.20)	(-0.83)	(-0.10)	(-0.32)	(1.06)
C2 Small	P1	-0.24	-0.17	-0.30	0.10	-0.00	-0.02	-0.06	0.12	-0.06
	P5	0.17	0.17	-0.01	-0.17	-0.27	-0.28	-0.40	-0.07	-0.05
	Strategy	0.41	0.34	-0.29	0.27	0.27	0.26	0.34	0.19	0.00
		(1.72)	(1.61)	(-1.63)	(0.96)	(0.95)	(1.28)	(1.38)	(1.36)	(0.01)
C2 Big	P1	-0.36	-0.31	0.10	0.13	0.16	0.27	0.09	0.08	-0.10
	P5	0.41	-0.15	0.04	-0.14	-0.23	-0.32	-0.00	-0.24	0.15
	Strategy	0.76	0.16	0.07	0.26	0.39	0.59	0.10	0.32	0.25
		(**2.62**)	(0.69)	(0.42)	(0.93)	(1.20)	(**2.80**)	(0.36)	(**2.10**)	(1.37)
C3 All	P1	-1.14	-0.68	-0.31	-0.00	-0.06	-0.00	0.05	-0.41	-0.65
	P5	0.08	-0.01	-0.71	-0.46	-1.58	-0.76	-0.97	-0.72	-0.07
	Strategy	1.22	0.67	0.40	0.45	1.52	0.76	1.02	0.31	0.58
		(**2.91**)	(**2.14**)	(1.26)	(1.28)	(**3.25**)	(**2.59**)	(**2.81**)	(1.42)	(**2.06**)
C3 Micro	P1	-1.87	-1.30	0.00	-0.24	-0.18	-0.15	-0.42	-0.21	-0.76
	P5	0.61	-0.03	-1.36	-1.35	-2.10	-1.43	-1.52	-0.66	-0.66
	Strategy	2.47	1.27	1.36	1.11	1.93	1.28	1.10	0.44	0.10
		(**6.88**)	(**3.44**)	(**4.14**)	(**2.39**)	(**4.89**)	(**3.61**)	(**2.68**)	(**2.05**)	(0.23)
C3 Small	P1	-1.56	-0.64	-0.09	0.44	0.09	-0.09	0.01	-0.03	-0.30
	P5	0.37	0.24	-1.01	-0.31	-1.33	-0.85	-0.97	-0.62	-0.75
	Strategy	1.94	0.88	0.92	0.75	1.41	0.76	0.98	0.59	-0.45
		(**4.54**)	(**3.19**)	(**2.58**)	(**2.13**)	(**2.90**)	(**2.87**)	(**3.22**)	(**2.89**)	(-1.61)
C3 Big	P1	-0.77	-0.60	-0.33	-0.34	-0.11	0.08	0.06	-0.30	-0.69
	P5	-0.05	-0.04	-0.30	-0.39	-1.73	-0.62	-0.84	-0.72	0.30
	Strategy	0.72	0.56	-0.03	0.06	1.59	0.71	0.91	0.41	0.99
		(1.70)	(1.45)	(-0.08)	(0.13)	(**2.61**)	(**1.97**)	(**2.07**)	(1.29)	(**2.28**)

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.

Sample Sample	Momen- tum	SUE	Credit Risk	Disper- sion	Idio Vol	Asset Growth	Invest- ment	Accruals	BM	% of Firms	% of MV
All (AAA-D)	1.00	0.44	0.71	0.62	0.81	0.54	0.45	0.27	-0.15	100.00	100.00
	(**4.07**)	(**3.15**)	(**3.61**)	(**2.94**)	(**2.71**)	(**4.43**)	(**2.45**)	(**3.43**)	(-1.26)		
Micro (AAA-D)	1.87	1.35	0.68	1.11	0.82	1.18	0.75	0.31	0.14	17.78	0.46
	(**7.30**)	(**4.32**)	(**2.08**)	(**2.75**)	(**2.46**)	(**4.96**)	(**2.66**)	(**2.01**)	(0.31)		
Small (AAA-D)	1.03	0.68	0.58	0.75	0.75	0.62	0.63	0.38	-0.03	27.26	3.03
	(**3.73**)	(**3.46**)	(**2.00**)	(**2.99**)	(**2.21**)	(**3.89**)	(**2.99**)	(**3.35**)	(-0.12)		
Big (AAA-D)	0.57	0.14	0.43	0.34	0.59	0.41	0.24	0.21	0.10	54.97	96.51
	(**2.05**)	(0.91)	(1.29)	(1.36)	(1.67)	(**2.74**)	(1.14)	(**2.56**)	(0.70)		
All (AAA-C)	0.93	0.41	0.60	0.57	0.73	0.54	0.45	0.28	-0.12	99.26	99.93
	(**3.81**)	(**2.94**)	(**3.19**)	(**2.75**)	(**2.44**)	(**4.43**)	(**2.45**)	(**3.55**)	(-1.05)		
Micro (AAA-C)	1.76	1.31	0.58	1.04	0.69	1.16	0.83	0.35	0.05	17.18	0.45
	(**6.85**)	(**4.23**)	(**2.02**)	(**2.56**)	(**2.06**)	(**4.91**)	(**2.99**)	(**2.26**)	(0.11)		
Small (AAA-C)	0.94	0.64	0.46	0.69	0.66	0.64	0.61	0.39	-0.01	27.15	3.02
	(**3.46**)	(**3.28**)	(1.83)	(**2.79**)	(**2.00**)	(**4.02**)	(**2.92**)	(**3.46**)	(-0.02)		
Big (AAA-C)	0.54	0.13	0.41	0.33	0.58	0.40	0.23	0.21	0.11	54.92	96.46
	(1.94)	(0.89)	(1.26)	(1.33)	(1.65)	(**2.67**)	(1.10)	(**2.49**)	(0.77)		
All (AAA-CC)	0.93	0.41	0.60	0.57	0.73	0.54	0.45	0.28	-0.12	99.25	99.93
	(**3.79**)	(**2.91**)	(**3.19**)	(**2.74**)	(**2.43**)	(**4.43**)	(**2.45**)	(**3.55**)	(-1.05)		
Micro (AAA-CC)	1.74	1.27	0.58	1.04	0.68	1.16	0.83	0.36	0.05	17.18	0.45
	(**6.80**)	(**4.13**)	(**2.02**)	(**2.56**)	(**2.05**)	(**4.89**)	(**2.99**)	(**2.32**)	(0.12)		
Small (AAA-CC)	0.94	0.64	0.46	0.69	0.66	0.64	0.62	0.39	-0.01	27.15	3.02
	(**3.46**)	(**3.28**)	(1.83)	(**2.79**)	(**2.00**)	(**4.02**)	(**2.92**)	(**3.45**)	(-0.03)		
Big (AAA-CC)	0.54	0.13	0.41	0.33	0.58	0.40	0.23	0.21	0.11	54.92	96.46
	(1.95)	(0.89)	(1.27)	(1.33)	(1.66)	(**2.67**)	(1.10)	(**2.49**)	(0.77)		
All (AAA-CCC-)	0.90	0.39	0.57	0.58	0.71	0.53	0.44	0.29	-0.12	99.05	99.92
	(**3.68**)	(**2.78**)	(**3.09**)	(**2.75**)	(**2.38**)	(**4.33**)	(**2.38**)	(**3.77**)	(-1.02)		
Micro (AAA-CCC-)	1.65	1.29	0.55	1.04	0.65	1.11	0.78	0.40	0.04	17.02	0.45
	(**6.46**)	(**4.18**)	(**1.99**)	(**2.57**)	(1.95)	(**4.73**)	(**2.82**)	(**2.63**)	(0.10)		
Small (AAA-CCC-)	0.92	0.62	0.42	0.70	0.66	0.62	0.61	0.40	-0.02	27.12	3.02
	(**3.40**)	(**3.20**)	(1.73)	(**2.81**)	(**1.99**)	(**3.89**)	(**2.89**)	(**3.53**)	(-0.07)		
Big (AAA-CCC-)	0.52	0.12	0.40	0.34	0.58	0.39	0.22	0.21	0.11	54.90	96.45
	(1.91)	(0.79)	(1.27)	(1.37)	(1.66)	(**2.65**)	(1.09)	(**2.58**)	(0.76)		
All (AAA-CCC)	0.88	0.38	0.54	0.57	0.69	0.53	0.43	0.29	-0.11	98.83	99.91
	(**3.60**)	(**2.72**)	(**2.94**)	(**2.72**)	(**2.30**)	(**4.37**)	(**2.33**)	(**3.69**)	(-0.96)		
Micro (AAA-CCC)	1.62	1.30	0.53	1.01	0.61	1.10	0.75	0.43	0.06	16.86	0.45
	(**6.32**)	(**4.24**)	(**1.96**)	(**2.49**)	(1.86)	(**4.74**)	(**2.69**)	(**2.73**)	(0.13)		
Small (AAA-CCC)	0.91	0.60	0.38	0.69	0.65	0.61	0.59	0.38	-0.01	27.07	3.01
	(**3.34**)	(**3.08**)	(1.66)	(**2.79**)	(1.95)	(**3.85**)	(**2.79**)	(**3.42**)	(-0.05)		
Big (AAA-CCC)	0.51	0.12	0.38	0.34	0.56	0.40	0.23	0.21	0.11	54.90	96.45
	(1.88)	(0.80)	(1.20)	(1.37)	(1.61)	(**2.69**)	(1.12)	(**2.54**)	(0.77)		
All (AAA-CCC+)	0.82	0.35	0.47	0.54	0.60	0.52	0.41	0.29	-0.10	98.31	99.87
	(**3.39**)	(**2.53**)	(**2.60**)	(**2.59**)	(**2.02**)	(**4.35**)	(**2.21**)	(**3.78**)	(-0.84)		
Micro (AAA-CCC+)	1.53	1.22	0.42	1.00	0.47	1.13	0.69	0.43	-0.09	16.51	0.44
	(**6.07**)	(**3.93**)	(1.52)	(**2.47**)	(1.42)	(**4.79**)	(**2.47**)	(**2.74**)	(-0.19)		
Small (AAA-CCC+)	0.86	0.57	0.31	0.65	0.57	0.58	0.58	0.38	-0.04	26.96	3.00
	(**3.19**)	(**2.97**)	(1.12)	(**2.61**)	(1.72)	(**3.70**)	(**2.75**)	(**3.41**)	(-0.18)		
Big (AAA-CCC+)	0.49	0.10	0.35	0.32	0.53	0.39	0.22	0.21	0.10	54.84	96.42
	(1.81)	(0.71)	(1.15)	(1.31)	(1.53)	(**2.68**)	(1.09)	(**2.59**)	(0.74)		
All (AAA-B-)	0.75	0.33	0.42	0.52	0.51	0.47	0.38	0.28	-0.09	97.39	99.77
	(**3.12**)	(**2.37**)	(**2.38**)	(**2.51**)	(1.75)	(**4.00**)	(**2.09**)	(**3.70**)	(-0.79)		
Micro (AAA-B-)	1.37	1.28	0.37	0.99	0.37	0.94	0.72	0.43	-0.13	15.93	0.43
	(**5.49**)	(**4.20**)	(1.15)	(**2.47**)	(1.14)	(**4.04**)	(**2.66**)	(**2.73**)	(-0.27)		
Small (AAA-B-)	0.79	0.53	0.26	0.61	0.47	0.53	0.51	0.34	-0.06	26.74	2.99
	(**3.00**)	(**2.74**)	(0.96)	(**2.50**)	(1.48)	(**3.42**)	(**2.44**)	(**3.20**)	(-0.23)		
Big (AAA-B-)	0.47	0.10	0.43	0.34	0.50	0.37	0.20	0.21	0.08	54.71	96.36
	(1.75)	(0.70)	(1.42)	(1.37)	(1.47)	(**2.55**)	(0.98)	(**2.55**)	(0.60)		

Table 3 (continued)

Sample	Momentum	SUE	Credit Risk	Dispersion	Idio Vol	Asset Growth	Investment	Accruals	BM	% of Firms	% of MV
All (AAA-B)	0.65	0.30	0.34	0.46	0.40	0.42	0.31	0.26	-0.13	94.96	99.42
	(**2.83**)	(**2.16**)	(**2.01**)	(**2.26**)	(1.41)	(**3.77**)	(1.81)	(**3.60**)	(-1.06)		
Micro (AAA-B)	1.18	1.30	0.31	0.85	0.28	0.99	0.75	0.37	-0.37	14.62	0.39
	(**4.89**)	(**4.34**)	(0.99)	(**2.16**)	(0.87)	(**4.29**)	(**2.83**)	(**2.38**)	(-0.74)		
Small (AAA-B)	0.71	0.48	0.19	0.59	0.38	0.43	0.38	0.31	-0.18	25.97	2.90
	(**2.72**)	(**2.52**)	(0.72)	(**2.41**)	(1.24)	(**2.98**)	(1.91)	(**2.95**)	(-0.71)		
Big (AAA-B)	0.42	0.10	0.28	0.30	0.40	0.33	0.17	0.22	0.03	54.36	96.12
	(1.63)	(0.66)	(1.01)	(1.25)	(1.20)	(**2.40**)	(0.89)	(**2.72**)	(0.18)		
All (AAA-B+)	0.53	0.25	0.27	0.32	0.26	0.34	0.27	0.27	-0.15	90.14	98.62
	(**2.40**)	(1.88)	(1.71)	(1.62)	(1.01)	(**3.17**)	(1.64)	(**3.69**)	(-1.20)		
Micro (AAA-B+)	0.84	1.22	0.26	0.66	0.17	0.74	0.78	0.51	-0.33	12.06	0.33
	(**3.59**)	(**3.71**)	(0.82)	(1.43)	(0.57)	(**3.12**)	(**2.88**)	(**2.96**)	(-0.63)		
Small (AAA-B+)	0.59	0.39	0.11	0.47	0.21	0.35	0.33	0.35	-0.29	24.49	2.74
	(**2.43**)	(**2.13**)	(0.44)	(1.59)	(0.74)	(**2.43**)	(1.72)	(**3.26**)	(-1.13)		
Big (AAA-B+)	0.40	0.10	0.29	0.25	0.27	0.31	0.14	0.19	0.02	53.59	95.55
	(1.63)	(0.69)	(1.16)	(1.07)	(0.87)	(**2.37**)	(0.78)	(**2.47**)	(0.14)		
All (AAA-BB-)	0.42	0.20	0.14	0.30	0.14	0.28	0.19	0.20	-0.14	80.38	97.24
	(**2.00**)	(1.52)	(1.03)	(1.62)	(0.57)	(**2.71**)	(1.24)	(**3.17**)	(-1.05)		
Micro (AAA-BB-)	0.59	0.75	0.14	0.60	0.05	0.27	0.46	0.28	-0.86	7.95	0.22
	(**2.29**)	(1.79)	(0.42)	(1.45)	(0.14)	(0.96)	(1.40)	(1.56)	(-1.05)		
Small (AAA-BB-)	0.52	0.33	0.05	0.22	0.15	0.38	0.31	0.26	-0.28	20.45	2.34
	(**2.37**)	(1.86)	(0.20)	(1.02)	(0.58)	(**2.66**)	(1.69)	(**2.62**)	(-0.96)		
Big (AAA-BB-)	0.35	0.10	0.26	0.24	0.14	0.27	0.12	0.16	0.00	51.98	94.69
	(1.49)	(0.72)	(1.36)	(1.09)	(0.49)	(**2.35**)	(0.73)	(**2.19**)	(0.01)		
All (AAA-BB)	0.36	0.17	0.00	0.26	0.04	0.29	0.12	0.17	-0.11	71.34	95.36
	(1.74)	(1.33)	(0.04)	(1.41)	(0.16)	(**2.92**)	(0.76)	(**2.93**)	(-0.79)		
Micro (AAA-BB)	0.36	0.78	-0.06	0.73	-0.05	0.41	0.42	0.11	-0.86	5.52	0.14
	(1.30)	(1.60)	(-0.18)	(1.55)	(-0.14)	(1.21)	(1.09)	(0.41)	(-0.79)		
Small (AAA-BB)	0.48	0.32	-0.03	0.10	0.04	0.49	0.31	0.15	-0.22	16.09	1.85
	(**2.18**)	(1.74)	(-0.11)	(0.45)	(0.17)	(**3.35**)	(1.57)	(1.54)	(-0.63)		
Big (AAA-BB)	0.33	0.10	0.04	0.23	0.03	0.25	0.07	0.17	-0.01	49.73	93.38
	(1.48)	(0.77)	(0.33)	(1.06)	(0.14)	(**2.22**)	(0.41)	(**2.48**)	(-0.07)		
All (AAA-BB+)	0.30	0.14	-0.01	0.25	-0.03	0.26	0.08	0.16	-0.13	64.39	93.04
	(1.51)	(1.13)	(-0.13)	(1.43)	(-0.11)	(**2.58**)	(0.49)	(**2.92**)	(-0.89)		
Micro (AAA-BB+)	0.15	0.90	0.20	0.71	-0.25	0.22	0.24	0.29	-1.52	4.62	0.11
	(0.50)	(1.82)	(0.56)	(1.47)	(-0.70)	(0.55)	(0.57)	(1.11)	(-0.99)		
Small (AAA-BB+)	0.43	0.29	-0.00	0.08	0.02	0.49	0.23	0.08	-0.47	12.76	1.44
	(**2.04**)	(1.63)	(-0.00)	(0.38)	(0.10)	(**3.30**)	(1.12)	(0.79)	(-1.22)		
Big (AAA-BB+)	0.28	0.10	0.02	0.22	-0.05	0.23	0.06	0.16	-0.01	47.01	91.49
	(1.36)	(0.73)	(0.14)	(1.07)	(-0.21)	(**2.17**)	(0.36)	(**2.55**)	(-0.06)		
All (AAA-BBB-)	0.28	0.09	0.03	0.25	0.03	0.19	0.04	0.16	-0.14	58.83	90.29
	(1.45)	(0.74)	(0.38)	(1.44)	(0.14)	(1.60)	(0.23)	(**2.89**)	(-0.97)		
Micro (AAA-BBB-)	0.16	0.59	0.40	0.76	0.15	-0.00	0.06	-0.29	-1.02	4.03	0.10
	(0.39)	(1.19)	(0.98)	(1.47)	(0.33)	(-0.00)	(0.13)	(-1.08)	(-0.90)		
Small (AAA-BBB-)	0.41	0.22	0.05	0.11	0.08	0.27	0.28	0.15	-0.25	10.80	1.22
	(1.66)	(1.22)	(0.25)	(0.47)	(0.33)	(1.50)	(1.26)	(1.21)	(-0.43)		
Big (AAA-BBB-)	0.27	0.06	0.02	0.15	-0.02	0.17	0.01	0.15	-0.06	44.00	88.97
	(1.33)	(0.45)	(0.20)	(0.80)	(-0.08)	(1.44)	(0.07)	(**2.33**)	(-0.41)		
All (AAA-BBB)	0.26	0.10	0.06	0.27	0.01	0.16	0.05	0.14	-0.16	50.61	85.83
	(1.37)	(0.87)	(0.78)	(1.41)	(0.06)	(1.48)	(0.30)	(**2.50**)	(-1.06)		
Micro (AAA-BBB)	0.03	0.67	0.31	0.48	-0.02	-0.08	0.32	-0.12	-0.63	3.53	0.08
	(0.07)	(1.29)	(0.84)	(0.91)	(-0.04)	(-0.20)	(0.72)	(-0.41)	(-0.52)		
Small (AAA-BBB)	0.46	0.16	0.03	-0.01	0.18	0.28	0.25	0.16	0.60	8.17	0.88
	(1.43)	(0.83)	(0.17)	(-0.03)	(0.75)	(1.37)	(1.06)	(1.06)	(0.80)		
Big (AAA-BBB)	0.23	0.08	0.06	0.20	-0.04	0.15	0.02	0.12	-0.13	38.91	84.86
	(1.19)	(0.64)	(0.65)	(1.08)	(-0.18)	(1.02)	(0.10)	(**1.96**)	(-0.84)		
All (AAA-BBB+)	0.26	0.07	0.02	0.27	0.03	0.15	0.05	0.12	-0.16	40.15	78.42
	(1.34)	(0.60)	(0.33)	(1.57)	(0.13)	(1.26)	(0.27)	(**2.16**)	(-0.94)		
Micro (AAA-BBB+)	0.42	0.52	0.11	0.04	0.22	0.26	0.16	0.02	-4.61	2.82	0.06
	(1.01)	(0.89)	(0.40)	(0.06)	(0.47)	(0.68)	(0.35)	(0.06)	(-1.08)		
Small (AAA-BBB+)	0.45	0.05	0.16	-0.18	0.23	0.19	0.22	0.00	0.60	5.57	0.57
	(1.33)	(0.21)	(0.84)	(-0.54)	(0.88)	(0.81)	(0.80)	(0.02)	(0.95)		
Big (AAA-BBB+)	0.23	0.05	-0.01	0.17	-0.01	0.15	0.03	0.12	-0.09	31.76	77.79
	(1.13)	(0.43)	(-0.11)	(0.92)	(-0.06)	(1.20)	(0.15)	(**1.96**)	(-0.54)		

Table 4

Downgrade Characteristics, Delistings, and Returns by Credit Rating Groups

The table focuses on stocks with at least one downgrade and priced at least $1 at the beginning of the month. 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.

PANEL A: By Credit Rating Portfolio

	Rating Group (C1=Lowest , C3=Highest Risk)		
	C1	C2	C3
Number of Downgrades	2,485	2,441	3,147
Downgrades/month	8.94	8.78	11.32
Size of Downgrades	1.75	1.77	2.14
r_{t-1}	0.10	-4.06	-6.56
r_t	-1.15	-3.45	-14.08
r_{t+1}	0.62	-1.32	-6.29
$r_{t-6:t-1}$	2.09	-8.60	-25.99
$r_{t+1:t+6}$	5.39	-3.44	-16.69
$r_{t-12:t-1}$	5.53	-6.87	-32.44
$r_{t+1:t+12}$	11.86	1.43	-13.26
$r_{t-24:t-1}$	17.00	-3.97	-31.14
$r_{t+1:t+24}$	28.09	17.28	-0.95
Delisted over $(t+1:t+6)$	63	109	289
Delisted over $(t+1:t+12)$	96	172	484
Delisted over $(t+1:t+24)$	154	312	734
Downgrades/month ($r_{mt}>0$)	8.51	7.87	9.92
Size of Downgrades	1.70	1.84	2.16
r_{t-1}	1.10	-3.34	-7.76
r_t	1.84	0.56	-9.96
r_{t+1}	1.24	-0.40	-1.73
Downgrades/month ($r_{mt}<0$)	9.59	9.93	13.40
Size of Downgrades	1.82	1.65	2.11
r_{t-1}	-1.37	-4.98	-4.76
r_t	-5.51	-8.51	-20.30
r_{t+1}	-0.27	-2.47	-12.97
Downgrades/month (Expansions)	8.40	8.29	10.51
Size of Downgrades	1.72	1.78	2.14
r_{t-1}	1.03	-2.50	-5.59
r_t	0.23	-2.90	-13.70
r_{t+1}	0.15	-0.79	-5.68
Downgrades/month (Recessions)	13.07	13.59	19.22
Size of Downgrades	1.72	1.56	2.21
r_{t-1}	-5.97	-13.33	-13.02
r_t	-10.09	-6.70	-16.60
r_{t+1}	3.78	-4.64	-10.24
Downgrade Correlation (%)	2.73	4.64	7.28
Downgrade Correlation (±3 months) (%)	1.91	2.27	3.98
Downgrade Correlation (±6 months) (%)	1.99	2.21	4.52

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	592	626	2.04	2.25			-0.78	-14.69	-2.58	-14.73	2.05	-23.64	0.88	-14.63
N=2	333	385	1.68	2.03	47.56	22.30	-2.53	-14.74	-0.72	-20.57	-4.07	-25.29	2.75	-22.55
N=3	228	190	1.56	1.77	41.02	18.43	-1.78	-17.01	-4.02	-23.60	-3.72	-26.64	-2.04	-24.52
N=4	119	74	1.37	1.59	35.57	23.59	-2.06	-10.30	1.09	-15.49	-2.41	-13.72	4.80	-18.07
N=5	56	34	1.41	1.56	36.19	18.76	-2.72	-14.33	-1.12	-11.53	-4.39	-23.13	1.36	-10.62
N=6	21	8	1.40	1.38	31.01	14.60	-3.96	-17.32	-0.64	-21.84	-4.56	-29.96	1.56	-24.40
N=7	10	3	1.24	1.62	30.18	16.17	-3.77	-9.28	-0.09	-11.41	-2.82	-19.90	3.61	-11.87
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	2		1.28		31.06		-13.58		6.17		-16.50		4.84	
N=10	1		2.20		13.89		1.03		7.15		-0.86		14.40	
Obs.							8,770	7,460	11,268	8,919	17,515	14,876	19,182	14,447

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	Asset Growth	Investment	Accruals	BM
Strategy		P5-P1	P5-P1	P1-P5	P1-P5	P1-P5	P1-P5	P1-P5	P1-P5	P5-P1
All Rated	P1	0.23	0.23	0.19	0.28	0.14	0.36	0.28	0.44	0.15
	P5	0.42	0.32	0.18	0.30	0.15	0.09	0.01	0.11	0.40
	Strategy	0.19	0.09	0.00	-0.02	-0.01	0.27	0.27	0.32	0.26
		(0.80)	(0.75)	(0.01)	(-0.09)	(-0.04)	(**2.45**)	(1.47)	(**4.17**)	(**2.53**)
Micro Rated	P1	0.34	0.03	0.07	0.39	-0.10	0.53	0.39	0.79	0.16
	P5	0.80	0.56	0.32	0.30	0.30	-0.20	-0.11	0.27	0.47
	Strategy	0.46	0.53	-0.24	0.09	-0.39	0.74	0.50	0.52	0.32
		(1.40)	(1.78)	(-0.73)	(0.21)	(-1.10)	(**2.57**)	(1.69)	(**2.82**)	(0.64)
Small Rated	P1	0.21	0.24	0.07	0.46	0.21	0.49	0.31	0.43	0.33
	P5	0.46	0.47	0.13	0.49	0.21	0.22	0.01	0.11	0.35
	Strategy	0.25	0.23	-0.07	-0.03	0.00	0.27	0.30	0.32	0.02
		(0.94)	(1.26)	(-0.23)	(-0.11)	(0.01)	(1.79)	(1.40)	(**2.76**)	(0.07)
Big Rated	P1	0.21	0.26	0.22	0.23	0.14	0.27	0.19	0.30	0.09
	P5	0.30	0.24	0.08	0.15	0.00	0.11	0.06	0.06	0.39
	Strategy	0.09	-0.02	0.14	0.08	0.14	0.16	0.13	0.24	0.30
		(0.34)	(-0.13)	(0.45)	(0.32)	(0.40)	(1.20)	(0.66)	(**3.12**)	(**2.43**)
C1 All	P1	0.17	0.22	0.13	0.27	0.14	0.21	0.15	0.24	0.17
	P5	0.28	0.17	0.22	0.16	0.25	0.12	0.17	0.11	0.18
	Strategy	0.11	-0.05	-0.09	0.11	-0.11	0.09	-0.03	0.13	0.02
		(0.58)	(-0.39)	(-1.14)	(0.59)	(-0.54)	(0.77)	(-0.16)	(**2.18**)	(0.12)
C1 Micro	P1	-0.27	0.17	0.14	0.47	0.35	0.37	-0.20	0.05	3.54
	P5	0.19	-0.24	0.05	-0.05	-0.36	-0.04	-0.05	-0.05	0.54
	Strategy	0.54	-0.84	0.15	-0.06	0.39	0.50	-0.27	0.34	-4.45
		(1.37)	(-1.29)	(0.41)	(-0.10)	(0.84)	(1.03)	(-0.49)	(1.04)	(-0.98)
C1 Small	P1	-0.29	-0.08	0.04	-0.14	0.27	0.08	0.09	-0.13	0.72
	P5	0.18	-0.18	-0.02	0.00	-0.20	0.22	-0.05	-0.01	0.07
	Strategy	0.48	-0.23	0.07	-0.20	0.42	-0.14	0.17	-0.12	0.09
		(1.64)	(-0.88)	(0.30)	(-0.43)	(1.35)	(-0.37)	(0.41)	(-0.81)	(0.07)
C1 Big	P1	0.24	0.27	0.15	0.28	0.11	0.20	0.17	0.28	0.16
	P5	0.29	0.19	0.26	0.23	0.33	0.17	0.22	0.14	0.20
	Strategy	0.04	-0.08	-0.11	0.06	-0.22	0.04	-0.05	0.14	0.04
		(0.23)	(-0.60)	(-1.38)	(0.29)	(-0.95)	(0.30)	(-0.30)	(**2.06**)	(0.30)
C2 All	P1	0.35	0.24	0.15	0.21	0.14	0.29	0.22	0.30	0.19
	P5	0.30	0.27	0.32	0.25	0.33	0.10	0.13	0.09	0.24
	Strategy	-0.05	0.03	-0.17	-0.05	-0.19	0.19	0.09	0.21	0.05
		(-0.23)	(0.25)	(-1.83)	(-0.24)	(-0.79)	(1.53)	(0.54)	(**2.46**)	(0.41)
C2 Micro	P1	0.09	-0.34	-0.12	-0.04	-0.37	-0.64	0.06	0.11	-0.84
	P5	-0.16	0.10	0.16	-0.30	-0.44	0.14	0.30	-0.25	-0.52
	Strategy	-0.45	0.22	-0.33	-0.12	-0.03	-0.61	-0.03	0.38	-0.13
		(-1.23)	(0.42)	(-0.88)	(-0.17)	(-0.05)	(-0.96)	(-0.06)	(0.97)	(-0.12)
C2 Small	P1	0.41	0.27	-0.12	0.20	0.10	0.30	0.20	0.23	0.18
	P5	0.34	0.37	0.41	0.32	0.42	0.21	0.12	0.23	0.20
	Strategy	-0.06	0.10	-0.53	-0.12	-0.32	0.09	0.09	0.00	0.02
		(-0.30)	(0.53)	(-1.23)	(-0.46)	(-1.15)	(0.44)	(0.36)	(0.03)	(0.05)
C2 Big	P1	0.30	0.28	0.24	0.22	0.19	0.38	0.27	0.30	0.17
	P5	0.33	0.24	0.32	0.37	0.34	0.11	0.13	0.03	0.37
	Strategy	0.04	-0.04	-0.08	-0.15	-0.15	0.27	0.14	0.27	0.20
		(0.16)	(-0.25)	(-0.68)	(-0.67)	(-0.59)	(**2.00**)	(0.78)	(**2.57**)	(1.28)
C3 All	P1	0.18	0.17	0.19	0.34	0.22	0.40	0.43	0.63	0.07
	P5	0.63	0.56	0.29	0.62	0.03	0.07	-0.09	0.11	0.68
	Strategy	0.45	0.39	-0.10	-0.27	0.19	0.32	0.53	0.52	0.61
		(1.15)	(1.89)	(-0.48)	(-1.02)	(0.56)	(1.82)	(1.90)	(**3.84**)	(**3.38**)
C3 Micro	P1	0.57	-0.09	0.33	0.14	0.10	0.73	0.50	0.87	0.31
	P5	1.07	0.72	0.40	0.53	0.17	-0.13	-0.15	0.27	0.66
	Strategy	0.50	0.81	-0.07	-0.38	-0.06	0.86	0.65	0.60	0.36
		(0.97)	(**2.24**)	(-0.24)	(-0.70)	(-0.16)	(**2.06**)	(1.55)	(**2.80**)	(0.77)
C3 Small	P1	-0.03	0.34	0.34	0.51	0.43	0.35	0.44	0.53	0.29
	P5	0.59	0.58	0.29	0.92	0.15	0.27	0.00	0.07	0.62
	Strategy	0.62	0.24	0.05	-0.41	0.27	0.08	0.44	0.46	0.33
		(1.51)	(0.95)	(0.17)	(-1.25)	(0.59)	(0.37)	(1.58)	(**2.48**)	(1.15)
C3 Big	P1	0.14	0.12	-0.03	-0.04	-0.01	0.12	0.24	0.45	-0.26
	P5	0.21	0.37	0.23	0.50	-0.60	0.08	-0.11	-0.03	0.60
	Strategy	0.07	0.25	-0.28	-0.52	0.59	0.03	0.35	0.48	0.85
		(0.16)	(0.83)	(-0.71)	(-1.33)	(1.08)	(0.12)	(0.94)	(1.60)	(**2.05**)

Table 5 (continued)

Panel B: Value Weighted Size and BM adjusted Returns

Anomaly		Momentum	SUE	Credit Risk	Dispersion	Idio Vol	Asset Growth	Investment	Accruals	BM
Strategy		P5-P1	P5-P1	P1-P5	P1-P5	P1-P5	P1-P5	P1-P5	P1-P5	P5-P1
All Rated	P1	0.12	0.21	0.17	0.15	0.10	0.33	0.18	0.31	0.09
	P5	0.31	0.17	-0.02	0.05	-0.09	0.12	0.02	0.04	0.31
	Strategy	0.19	-0.04	0.19	0.09	0.19	0.21	0.16	0.27	0.22
		(0.68)	(-0.25)	(0.66)	(0.36)	(0.52)	(1.11)	(0.68)	(**2.47**)	(**2.22**)
Micro Rated	P1	0.18	0.04	-0.01	0.40	-0.05	0.51	0.35	0.72	0.19
	P5	0.66	0.41	0.23	0.30	0.28	-0.25	-0.09	0.17	0.37
	Strategy	0.47	0.37	-0.24	0.09	-0.34	0.76	0.44	0.55	0.19
		(1.60)	(1.26)	(-0.73)	(0.22)	(-0.90)	(**2.58**)	(1.42)	(**2.78**)	(0.38)
Small Rated	P1	0.23	0.24	0.06	0.47	0.19	0.46	0.31	0.48	0.37
	P5	0.46	0.38	0.10	0.48	0.16	0.14	-0.02	0.09	0.28
	Strategy	0.23	0.14	-0.04	-0.01	0.03	0.32	0.33	0.39	-0.09
		(0.85)	(0.74)	(-0.14)	(-0.04)	(0.09)	(1.80)	(1.46)	(**3.25**)	(-0.37)
Big Rated	P1	0.11	0.21	0.17	0.14	0.10	0.32	0.17	0.30	0.09
	P5	0.30	0.16	-0.03	-0.00	-0.13	0.12	0.04	0.03	0.32
	Strategy	0.19	-0.04	0.20	0.15	0.23	0.20	0.14	0.26	0.23
		(0.69)	(-0.28)	(0.57)	(0.53)	(0.59)	(1.03)	(0.57)	(**2.35**)	(**2.03**)
C1 All	P1	0.20	0.25	0.15	0.25	0.13	0.22	0.09	0.27	0.06
	P5	0.27	0.16	0.14	0.17	0.13	0.17	0.10	0.08	0.16
	Strategy	0.07	-0.09	0.01	0.08	-0.01	0.05	-0.01	0.19	0.10
		(0.31)	(-0.49)	(0.06)	(0.33)	(-0.03)	(0.26)	(-0.03)	(1.57)	(0.85)
C1 Micro	P1	-0.28	0.13	0.14	0.48	0.42	0.35	-0.21	0.09	3.54
	P5	0.08	-0.23	-0.12	-0.12	-0.45	-0.09	-0.03	-0.04	0.36
	Strategy	0.43	-0.71	0.32	0.16	0.60	0.56	-0.41	0.37	-4.45
		(1.05)	(-1.09)	(0.79)	(0.23)	(1.12)	(1.08)	(-0.71)	(1.23)	(-0.98)
C1 Small	P1	-0.27	-0.10	0.04	-0.20	0.24	0.00	0.13	-0.11	0.72
	P5	0.19	-0.18	0.01	-0.06	-0.14	0.26	-0.07	0.02	0.08
	Strategy	0.46	-0.21	0.02	-0.23	0.33	-0.25	0.21	-0.14	0.00
		(1.57)	(-0.80)	(0.11)	(-0.47)	(1.05)	(-0.65)	(0.49)	(-0.90)	(0.00)
C1 Big	P1	0.20	0.26	0.15	0.25	0.13	0.22	0.09	0.27	0.06
	P5	0.27	0.16	0.14	0.17	0.13	0.17	0.10	0.08	0.17
	Strategy	0.07	-0.09	0.01	0.08	-0.01	0.05	-0.01	0.19	0.10
		(0.31)	(-0.51)	(0.06)	(0.32)	(-0.03)	(0.27)	(-0.03)	(1.56)	(0.86)
C2 All	P1	0.18	0.10	0.25	0.27	0.25	0.44	0.26	0.29	0.12
	P5	0.44	0.16	0.35	0.14	0.20	0.01	0.20	-0.07	0.30
	Strategy	0.26	0.06	-0.10	0.13	0.05	0.43	0.06	0.36	0.18
		(0.93)	(0.33)	(-0.68)	(0.50)	(0.15)	(1.86)	(0.23)	(**2.64**)	(1.01)
C2 Micro	P1	0.03	-0.45	-0.23	-0.03	-0.33	-0.88	0.03	0.00	-0.84
	P5	-0.24	0.06	0.01	-0.45	-0.39	0.10	0.30	-0.19	-0.56
	Strategy	-0.46	0.31	-0.34	0.10	-0.04	-0.79	-0.05	0.21	-0.21
		(-1.16)	(0.59)	(-0.87)	(0.13)	(-0.07)	(-1.17)	(-0.08)	(0.57)	(-0.20)
C2 Small	P1	0.38	0.25	-0.06	0.28	0.10	0.30	0.24	0.26	0.17
	P5	0.30	0.34	0.37	0.31	0.28	0.24	0.02	0.25	0.21
	Strategy	-0.08	0.10	-0.42	-0.03	-0.18	0.06	0.21	0.01	0.04
		(-0.40)	(0.49)	(-1.48)	(-0.10)	(-0.63)	(0.28)	(0.86)	(0.05)	(0.10)
C2 Big	P1	0.16	0.09	0.26	0.26	0.26	0.45	0.26	0.28	0.12
	P5	0.45	0.15	0.37	0.13	0.21	0.01	0.20	-0.10	0.32
	Strategy	0.28	0.06	-0.11	0.13	0.06	0.44	0.06	0.38	0.20
		(1.01)	(0.30)	(-0.69)	(0.46)	(0.17)	(**1.96**)	(0.22)	(**2.67**)	(1.05)
C3 All	P1	0.05	0.12	-0.07	0.20	0.12	0.28	0.38	0.28	-0.28
	P5	0.28	0.29	0.15	0.50	-0.46	-0.00	-0.30	-0.02	0.66
	Strategy	0.23	0.18	-0.22	-0.30	0.58	0.29	0.68	0.30	0.93
		(0.56)	(0.61)	(-0.79)	(-0.89)	(1.26)	(1.10)	(1.80)	(1.45)	(**3.21**)
C3 Micro	P1	0.37	-0.09	0.44	0.10	0.08	0.68	0.49	0.81	0.48
	P5	0.94	0.53	0.40	0.42	0.19	-0.19	-0.26	0.18	0.57
	Strategy	0.57	0.62	0.04	-0.31	-0.11	0.87	0.75	0.63	0.10
		(1.26)	(1.70)	(0.13)	(-0.58)	(-0.23)	(**2.10**)	(1.78)	(**2.64**)	(0.22)
C3 Small	P1	-0.00	0.40	0.32	0.56	0.35	0.36	0.39	0.62	0.32
	P5	0.61	0.46	0.32	0.83	0.08	0.15	-0.03	0.00	0.55
	Strategy	0.61	0.07	0.00	-0.27	0.28	0.21	0.42	0.62	0.23
		(1.42)	(0.25)	(0.01)	(-0.77)	(0.54)	(0.92)	(1.34)	(**3.14**)	(0.81)
C3 Big	P1	0.08	0.02	-0.15	-0.14	0.02	0.20	0.31	0.26	-0.38
	P5	0.14	0.26	0.02	0.47	-0.59	0.11	-0.34	0.05	0.54
	Strategy	0.07	0.24	-0.18	-0.58	0.59	0.09	0.65	0.21	0.91
		(0.14)	(0.63)	(-0.46)	(-1.35)	(0.96)	(0.29)	(1.41)	(0.65)	(1.93)

Table 6
Industry-Adjusted Financial Ratios Around Downgrades

The table focuses on stocks with at least one downgrade and priced at least $1 in the month prior to the downgrade. Financial ratios are industry-adjusted by subtracting from each firm ratio the median ratio for the industry to which the firm belongs, based on the 20 industries of Moskowitz and Grinblatt (1999). Each month, downgrades are assigned to a credit risk group based on the firm rating prior to the downgrade. We compute the median industry-adjusted financial ratio from 8 quarters before to 8 quarters after the downgrade across all downgrades in a particular credit risk group for that month. The table reports the time-series average of these median industry-adjusted ratios. Ratios are calculated from the Quarterly Compustat files. Profit margin is Net Income over Sales ($NIQ_q/SALEQ_q$) in %. Interest Coverage is EBIT over Interest Expense ($(PIQ_q+XINTQ_q)/XINTQ_q$. Total Asset Turnover is Sales over Total Assets ($SALEQ_q/ATQ_{q-1}$) in %.

	Profit Margin			Interest Coverage			Asset Turnover		
Quarter	C1	C2	C3	C1	C2	C3	C1	C2	C3
-8	0.92	-0.97	-4.51	3.00	0.36	-1.37	1.17	1.54	1.27
-7	0.61	-1.08	-4.13	2.80	0.79	-1.86	0.88	1.27	0.65
-6	0.89	-1.67	-5.42	2.52	0.44	-1.73	0.37	1.21	0.58
-5	0.78	-2.63	-6.02	2.57	-0.34	-2.62	0.04	1.27	0.07
-4	0.79	-2.83	-7.29	2.90	-0.51	-2.20	0.09	0.96	-1.22
-3	0.81	-2.50	-7.14	2.01	-0.80	-2.09	0.70	0.25	-1.80
-2	0.58	-2.86	-9.94	2.17	-1.53	-3.28	0.14	0.32	-1.72
-1	-2.02	-5.44	-10.25	1.51	-1.92	-3.08	0.40	0.01	-1.54
0	-0.96	-5.01	-10.72	1.09	-1.84	-3.21	0.68	0.14	-1.42
1	-1.44	-4.11	-10.58	1.06	-1.87	-1.80	0.55	-0.24	-1.03
2	-0.57	-4.94	-11.22	0.99	-1.59	-3.50	0.14	-0.22	-1.83
3	-1.07	-3.45	-8.01	0.95	-2.18	-3.04	0.19	0.28	-1.50
4	-0.63	-3.56	-8.09	1.45	-1.12	-2.56	0.20	0.60	-0.72
5	-0.89	-3.29	-7.39	0.93	-1.27	-2.81	0.26	0.46	-1.14
6	-0.45	-1.94	-7.24	0.82	-0.60	-2.45	-0.02	0.73	-0.90
7	-1.31	-2.76	-5.82	0.84	-0.89	-1.46	0.02	0.74	-0.32
8	0.29	-1.55	-5.66	1.12	-0.65	-1.77	0.12	1.05	1.24

Table 7
Cross-Sectional Regressions of Risk-Adjusted Returns on Anomaly Variables

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:

$$r^*_{it} = a_t + b_t C_{i,t-lag} + e_{it}.$$

Each firm characteristic, $C_{i,t-lag}$, is a conditioning variable described in Table 2, lagged as prescribed by each specific anomaly. Momentum uses the past six-month cumulative returns as the independent variable. SUE uses the SUE calculated based on the last reported EPS over the past 4 months. Credit risk, dispersion, and idiosyncratic volatility condition on variables from the past month. For the asset-growth, investments, and book-to-market anomalies, we use conditioning variables as of December of year $t-1$ for returns between July of year t to June of year $t+1$. Returns of month t are regressed on quarterly Accruals 4 months prior. 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: All Stocks

	Momentum	SUE	Credit Risk	Dispersion	Idio Vol	Asset Growth	Investment	Accruals	BM
b	0.77	0.12	-0.07	-0.32	-7.96	-0.37	-0.51	-3.98	-0.01
	(**2.23**)	(**3.77**)	(**-3.58**)	(**-3.97**)	(**-3.15**)	(**-4.05**)	(**-2.02**)	(**-3.20**)	(-0.20)
b	-0.12	0.06	0.01	-0.05	-0.29	-0.32	-0.32	-4.90	0.15
	(-0.35)	(**2.09**)	(0.35)	(-0.61)	(-0.12)	(**-3.55**)	(-1.29)	(**-4.03**)	(**2.68**)
D_{NIG}	-3.82	-3.37	-3.66	-3.96	-3.76	-3.37	-3.06	-3.30	-3.40
	(**-16.47**)	(**-10.99**)	(**-14.94**)	(**-12.71**)	(**-16.52**)	(**-11.54**)	(**-10.34**)	(**-10.94**)	(**-11.66**)
b	-0.22	0.04	-0.01	-0.03	-0.59	-0.34	-0.37	-4.94	0.16
	(-0.67)	(1.54)	(-0.42)	(-0.39)	(-0.24)	(**-3.87**)	(-1.50)	(**-4.07**)	(**2.89**)
D_{IG}	-0.89	-0.87	-0.87	-0.83	-0.88	-0.89	-0.89	-0.82	-0.89
	(**-9.30**)	(**-8.29**)	(**-8.21**)	(**-7.56**)	(**-8.81**)	(**-8.63**)	(**-8.66**)	(**-6.98**)	(**-8.39**)
D_{NIG}	-3.88	-3.41	-3.63	-3.98	-3.78	-3.40	-3.09	-3.33	-3.43
	(**-16.70**)	(**-11.11**)	(**-14.96**)	(**-12.76**)	(**-16.56**)	(**-11.60**)	(**-10.39**)	(**-10.98**)	(**-11.72**)

Table 7 (continued)

Panel B: Micro Stocks

	Momentum	SUE	Credit Risk	Dispersion	Idio Vol	Asset Growth	Investment	Accruals	BM
b	1.07	0.41	-0.10	-0.41	-6.17	-0.77	-0.34	-2.08	0.06
	(**2.23**)	(**4.35**)	(**-3.22**)	(**-2.12**)	(**-2.16**)	(**-2.35**)	(-0.53)	(-0.69)	(0.48)
b	-0.38	0.24	-0.01	-0.06	1.00	-0.70	-0.03	-3.64	0.15
	(-0.78)	(**2.64**)	(-0.20)	(-0.27)	(0.35)	(**-2.14**)	(-0.05)	(-1.19)	(1.23)
d_{NIG}	-4.41	-3.82	-4.19	-5.19	-4.38	-4.08	-3.99	-3.91	-4.13
	(**-14.61**)	(**-8.62**)	(**-13.13**)	(**-9.43**)	(**-14.53**)	(**-11.49**)	(**-10.85**)	(**-9.88**)	(**-11.26**)
b	-0.38	0.25	-0.01	-0.08	0.81	-0.71	-0.10	-3.74	0.15
	(-0.79)	(**2.65**)	(-0.40)	(-0.39)	(0.29)	(**-2.16**)	(-0.15)	(-1.22)	(1.26)
d_{IG}	-0.38	-0.44	-0.36	-0.19	-0.44	-0.84	-0.97	-0.55	-0.88
	(-0.94)	(-0.85)	(-0.92)	(-0.44)	(-1.15)	(**-2.31**)	(**-2.70**)	(-1.10)	(-1.60)
d_{NIG}	-4.45	-3.85	-4.20	-5.20	-4.41	-4.11	-4.03	-3.93	-4.14
	(**-14.82**)	(**-8.70**)	(**-13.19**)	(**-9.46**)	(**-14.65**)	(**-11.60**)	(**-10.95**)	(**-9.89**)	(**-11.27**)

Panel C: Small Stocks

	Momentum	SUE	Credit Risk	Dispersion	Idio Vol	Asset Growth	Investment	Accruals	BM
b	1.08	0.21	-0.08	-0.30	-14.60	-0.28	-1.05	-3.70	0.03
	(**2.84**)	(**3.88**)	(**-3.42**)	(**-2.20**)	(**-3.62**)	(**-2.00**)	(**-3.16**)	(-1.89)	(0.33)
b	0.26	0.12	-0.01	-0.02	-5.07	-0.21	-0.81	-5.16	0.11
	(0.73)	(**2.63**)	(-0.50)	(-0.19)	(-1.32)	(-1.49)	(**-2.54**)	(**-2.71**)	(1.28)
d_{NIG}	-3.56	-3.27	-3.46	-3.75	-3.56	-3.18	-2.80	-3.05	-3.12
	(**-13.17**)	(**-9.31**)	(**-11.66**)	(**-10.47**)	(**-13.87**)	(**-9.04**)	(**-7.48**)	(**-8.26**)	(**-8.84**)
b	0.15	0.11	-0.03	0.00	-5.51	-0.25	-0.86	-5.40	0.17
	(0.42)	(**2.28**)	(-1.50)	(0.02)	(-1.44)	(-1.78)	(**-2.67**)	(**-2.81**)	(**1.97**)
d_{IG}	-1.25	-1.30	-1.35	-1.31	-1.32	-1.28	-1.24	-0.95	-1.47
	(**-7.18**)	(**-5.80**)	(**-7.24**)	(**-6.31**)	(**-7.49**)	(**-6.82**)	(**-5.69**)	(**-3.06**)	(**-7.63**)
d_{NIG}	-3.59	-3.27	-3.39	-3.77	-3.55	-3.17	-2.80	-3.08	-3.12
	(**-13.30**)	(**-9.34**)	(**-11.61**)	(**-10.56**)	(**-13.84**)	(**-9.02**)	(**-7.48**)	(**-8.32**)	(**-8.84**)

Panel D: Big Stocks

	Momentum	SUE	Credit Risk	Dispersion	Idio Vol	Asset Growth	Investment	Accruals	BM
b	-0.10	0.05	-0.04	-0.34	-13.49	-0.28	-0.13	-5.47	0.05
	(-0.26)	(1.83)	(**-2.21**)	(**-2.50**)	(**-2.35**)	(**-2.83**)	(-0.46)	(**-4.19**)	(0.62)
b	-0.48	0.03	-0.00	-0.16	-6.76	-0.24	-0.04	-5.69	0.08
	(-1.32)	(1.20)	(-0.16)	(-1.17)	(-1.22)	(**-2.45**)	(-0.13)	(**-4.40**)	(1.13)
d_{NIG}	-3.38	-3.05	-3.14	-3.41	-3.20	-2.84	-2.29	-2.76	-3.05
	(**-9.99**)	(**-6.99**)	(**-9.10**)	(**-8.01**)	(**-10.36**)	(**-7.31**)	(**-5.87**)	(**-5.74**)	(**-7.78**)
b	-0.67	0.01	-0.01	-0.12	-6.34	-0.26	-0.09	-5.75	0.13
	(-1.86)	(0.48)	(-0.65)	(-0.90)	(-1.15)	(**-2.75**)	(-0.32)	(**-4.44**)	(1.80)
d_{IG}	-0.82	-0.74	-0.77	-0.71	-0.78	-0.75	-0.75	-0.70	-0.76
	(**-9.06**)	(**-7.00**)	(**-7.55**)	(**-6.51**)	(**-8.04**)	(**-7.29**)	(**-7.35**)	(**-5.68**)	(**-7.20**)
d_{NIG}	-3.39	-3.04	-3.08	-3.38	-3.18	-2.80	-2.26	-2.72	-3.02
	(**-10.02**)	(**-6.97**)	(**-9.00**)	(**-7.96**)	(**-10.30**)	(**-7.23**)	(**-5.82**)	(**-5.65**)	(**-7.71**)

Table 8
Joint Cross-Sectional Regressions
of Risk-Adjusted Returns on All Anomaly Variables

Each month t, we run multivariate cross-sectional regressions of monthly risk-adjusted stock returns on lagged firm characteristics 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:

$$r^*_{it} = a_t + \mathbf{b}_t \mathbf{C}_{i,t-lag} + d_{t,IG} D_{IG} + d_{t,NIG} D_{NIG} + e_{it}.$$

The firm characteristics, $\mathbf{C}_{i,t-lag}$, are all the conditioning variable described in Table 7, lagged as prescribed by each specific anomaly and 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. Market capitalization, $Size_{i,t-lag}$, is also included in the regression as a control, lagged as in Fama and French (1993). The table reports the results from the joint multivariate regression and shows the time-series average of these cross-sectional regression coefficients, $\mathbf{b}_t$, with their associated sample t-statistics in parentheses (bold if significant at the 95% confidence level). We risk-adjust returns as in Table 7. The time-series average adjusted-R^2 from the joint cross-sectional regressions are reported in the last column.

	Momentum	SUE	Credit Risk	Dispersion	Idio Vol	Asset Growth	Investment	Accruals	BM	Size	D_{IG}	D_{NIG}	Adj. R^2(%)
1	-0.41	0.09	-0.04	-0.20	-11.62	-0.29	-0.20	-6.89	0.15	-0.08			5.15
	(-1.04)	(**3.02**)	(**-2.02**)	(-1.55)	(**-2.26**)	(-1.65)	(-0.56)	(**-5.11**)	(1.37)	(-0.99)			
2	-0.36	0.09		-0.26	-11.92	-0.33	-0.24	-7.00	0.14	-0.02			4.78
	(-0.94)	(**2.90**)		(**-2.01**)	(**-2.38**)	(-1.83)	(-0.68)	(**-5.14**)	(1.34)	(-0.31)			
3	-0.89	0.06	-0.02	-0.07	-7.50	-0.31	-0.22	-7.04	0.28	-0.05	-0.94	-3.14	6.17
	(**-2.31**)	(**2.08**)	(-1.10)	(-0.53)	(-1.45)	(-1.69)	(-0.62)	(**-5.25**)	(**2.66**)	(-0.65)	(**-7.42**)	(**-9.48**)	
4	-0.56		-0.02	-0.06	-7.73	-0.23	-0.32	-7.60	0.22	-0.02	-0.85	-3.15	5.43
	(-1.55)		(-0.92)	(-0.47)	(-1.80)	(-1.54)	(-0.94)	(**-5.90**)	(**2.22**)	(-0.29)	(**-6.88**)	(**-9.68**)	
5		0.03	-0.01	0.02	-6.30	-0.25	-0.05	-7.28	0.23	-0.01	-0.88	-2.96	4.91
		(1.11)	(-0.53)	(0.14)	(-1.21)	(-1.37)	(-0.14)	(**-5.32**)	(**2.13**)	(-0.10)	(**-6.80**)	(**-8.56**)	

Table 9
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) and low level of shares outstanding. Amihud's Illiquidity measure, computed as in eq. (1)), is presented separately for NYSE/AMEX and Nasdaq stocks.

	Institutional Ownership (%)		Shares Outstanding (mln)		Illiquidity NYSE/AMEX		Illiquidity Nasdaq	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
All Rated	54.06	57.15	97.94	45.39	1.27	0.05	4.35	0.26
Micro Rated	40.32	38.59	15.33	10.95	8.79	2.24	12.30	2.81
Small Rated	51.53	53.12	33.48	25.74	0.68	0.25	1.44	0.28
Big Rated	59.68	62.47	159.40	95.75	0.07	0.02	0.48	0.03
C1 All	56.53	59.23	152.26	80.39	0.24	0.02	2.28	0.12
C1 Micro	44.54	43.83	5.72	3.58	3.22	1.49	8.11	2.98
C1 Small	45.41	41.88	23.96	20.37	0.38	0.23	1.74	0.42
C1 Big	58.92	60.97	191.87	113.98	0.03	0.01	0.36	0.03
C2 All	57.19	60.89	83.37	46.47	0.60	0.05	2.55	0.19
C2 Micro	42.59	42.13	11.06	8.91	6.90	1.77	9.56	3.47
C2 Small	53.27	55.76	30.14	25.18	0.62	0.22	1.43	0.33
C2 Big	61.38	65.15	123.13	78.30	0.08	0.02	0.59	0.04
C3 All	48.17	49.19	48.85	26.59	3.85	0.44	6.15	0.48
C3 Micro	39.33	38.00	18.44	13.79	10.39	2.66	13.03	2.88
C3 Small	52.48	54.27	40.07	29.57	0.84	0.31	1.39	0.22
C3 Big	57.60	60.85	123.44	87.77	0.19	0.04	0.96	0.03

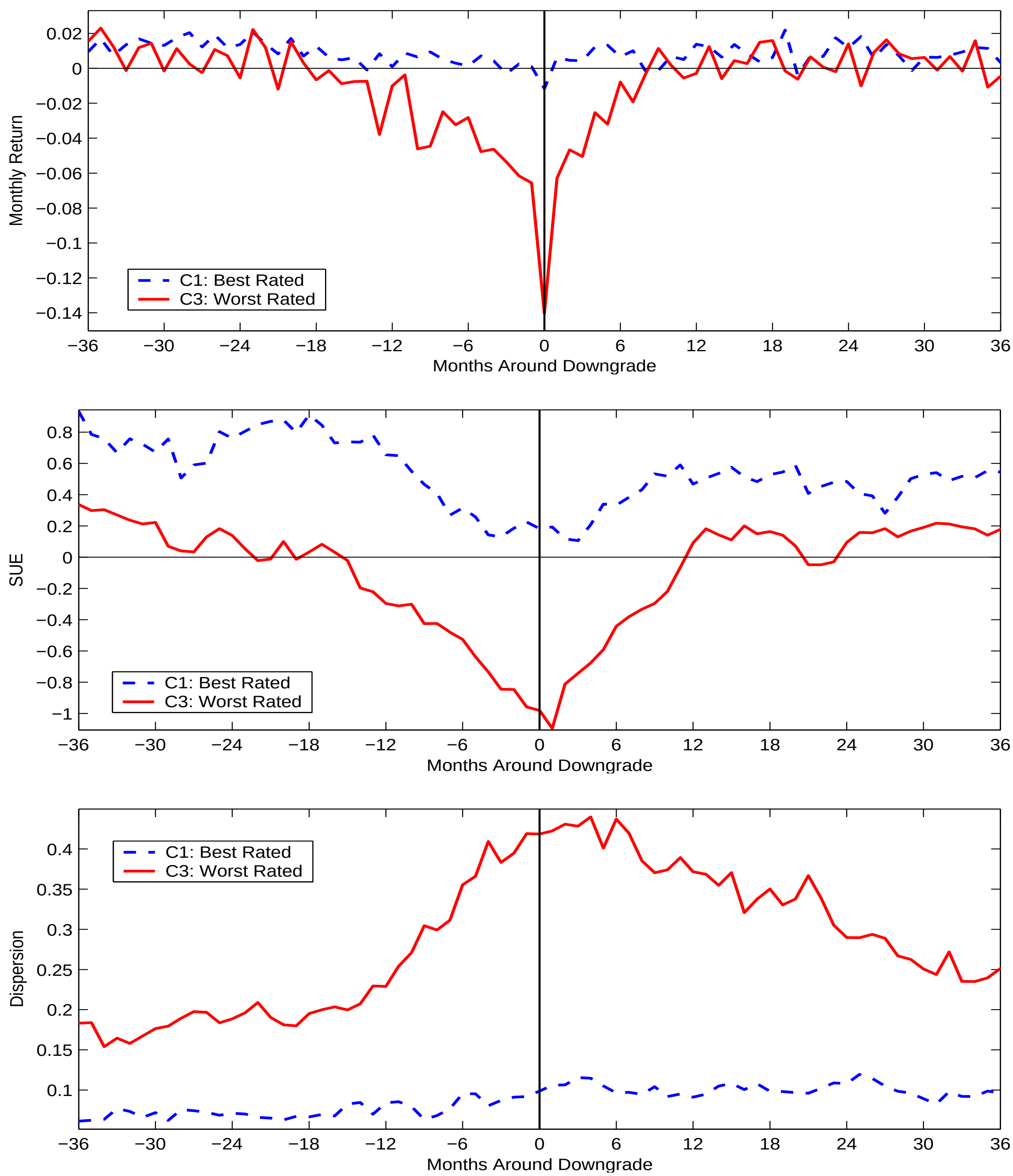

Figure 1. Conditioning Variables around Downgrades. Each month t, all stocks rated by Standard & Poor's with available return data in CRSP are divided into terciles based on credit rating. Within each tercile, we find firms that have been downgraded in month t and compute their equally weighted average firm conditioning variable based on each anomaly over each month from $t - 36$ to $t + 36$. We repeat this every month. The figure presents these average monthly conditioning variables for the best (C1) and worst (C3) rated terciles around rating downgrades. Month 0 is the month of downgrade. The conditioning variables are described in detail in Table 2. The sample period is October 1985 to December 2008.

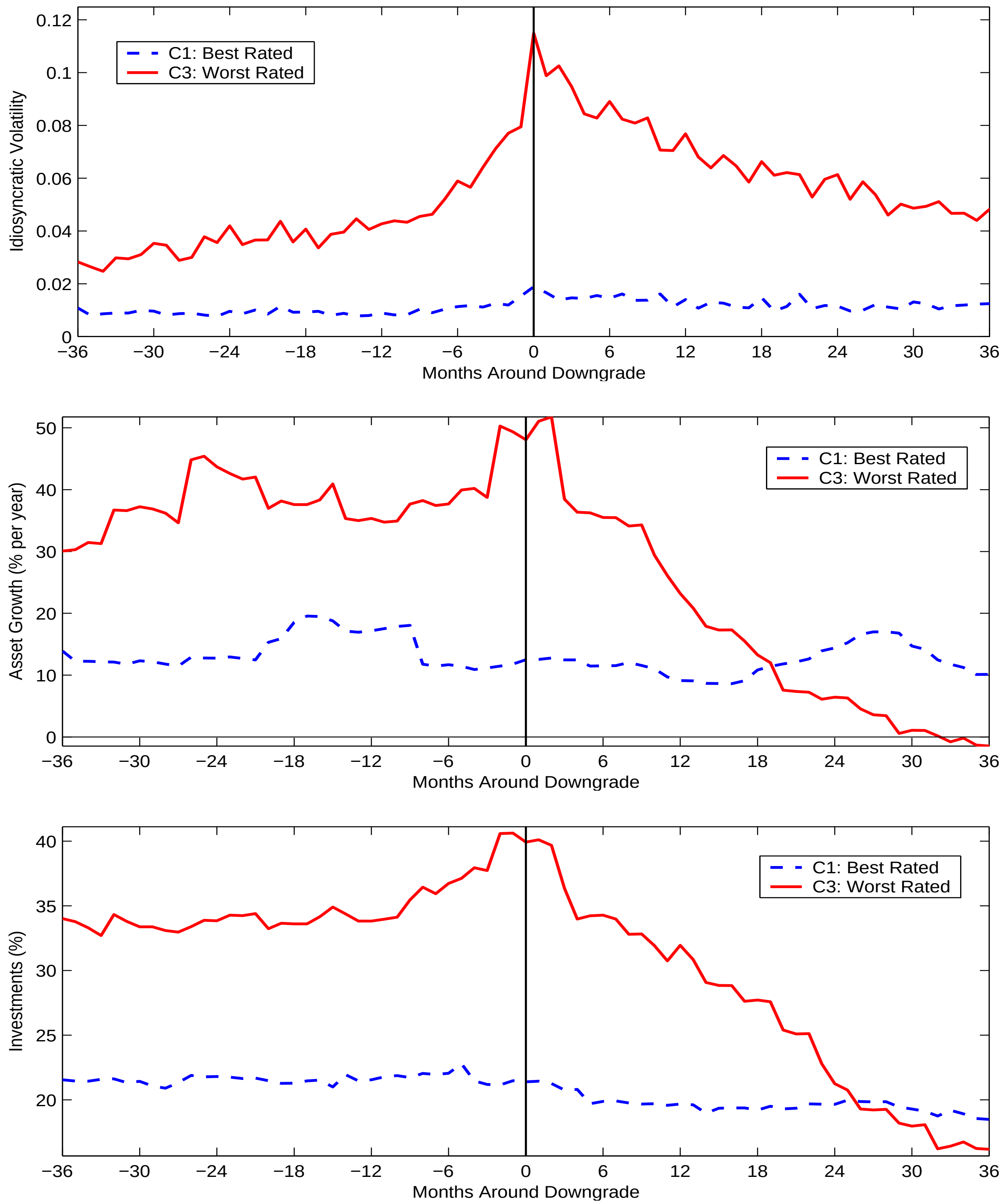

Figure 1(continued). Conditioning Variables around Downgrades.

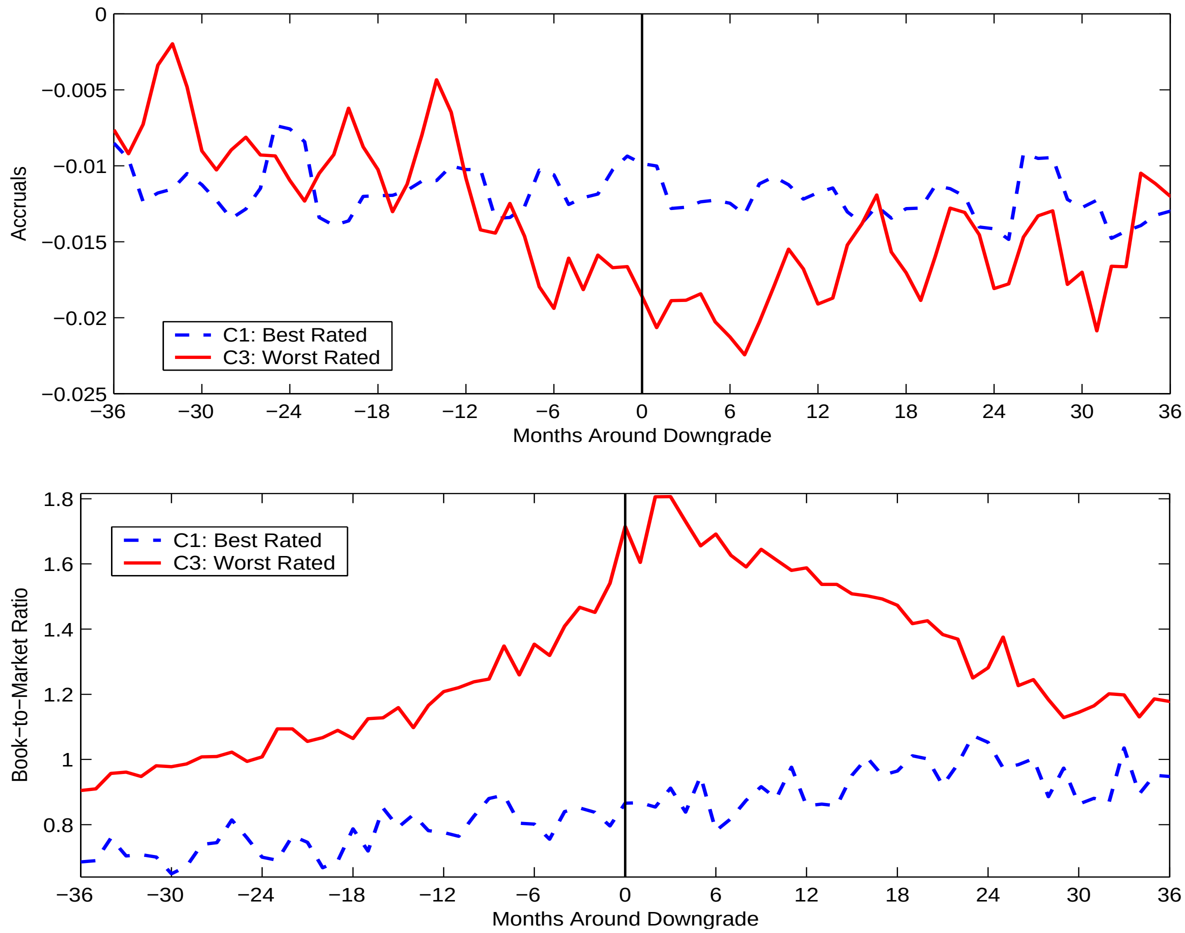

Figure 1(continued). Conditioning Variables around Downgrades.

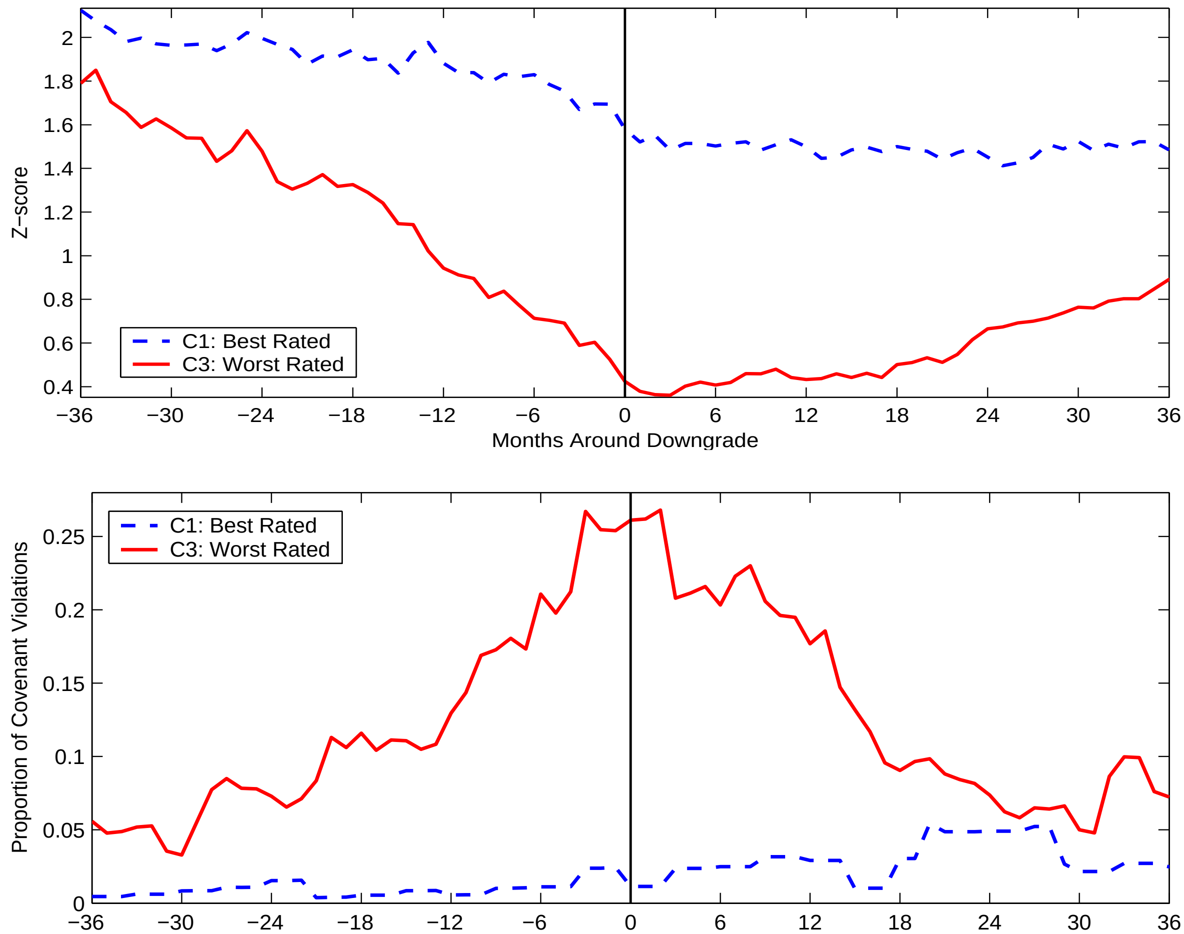

Figure 2. Z-scores and Proportion of Covenant Violations around Downgrades. Each month t, all stocks rated by Standard & Poor's with available return data in CRSP are divided into terciles based on credit rating. Within each tercile, we find firms that have been downgraded in month t and compute their equally weighted average z-scores and covenant violations rates over each month from $t-36$ to $t+36$. We repeat this every month. The figure presents these average monthly z-scores and covenant violations rates for the best (C1) and worst (C3) rated terciles around rating downgrades. Month 0 is the month of downgrade. Data on covenant violations is obtained from Professor Amir Sufi's website at *http://faculty.chicagobooth.edu/amir.sufi/data.htm*. The data consists of 0s and 1s, 1 (0) indicating a (no) covenant violation. The sample period is October 1985 to December 2008 for z-scores and June 1996 to June 2008 for covenant violations.

Appendix

Table 2A
Anomaly Profits Sorted by Past-Returns-Adjusted Ratings

We run monthly cross-sectional regressions of rating levels, $Rating_{it}$, on cumulative past-six-month returns. The past-returns-adjusted rating, $Rating^{*}_{it}$, is the intercept and residual from these cross-sectional regressions. We then repeat the analysis in Table 2, where C1, C2, and C3 represent terciles sorted each month on past-returns-adjusted ratings, $Rating^{*}_{it}$, rather than on raw ratings, $Rating_{it}$, as in Table 2. Results are presented for equally-weighted size- and book-to-market-adjusted returns.

Anomaly		Momentum	SUE	Credit Risk	Dispersion	Idio Vol	Asset Growth	Investment	Accruals	BM
All Rated	P1	-0.74	-0.29	0.08	0.21	0.04	0.03	-0.04	0.01	-0.12
	P5	0.27	0.15	-0.62	-0.41	-0.78	-0.51	-0.49	-0.26	-0.27
	Strategy	1.00	0.44	0.70	0.62	0.81	0.54	0.45	0.27	-0.15
		(**4.07**)	(**3.15**)	(**3.55**)	(**2.94**)	(**2.71**)	(**4.42**)	(**2.45**)	(**3.43**)	(-1.26)
Micro Rated	P1	-1.44	-0.99	-0.12	0.10	-0.34	-0.18	-0.27	-0.27	-0.63
	P5	0.43	0.37	-0.80	-1.00	-1.16	-1.36	-1.03	-0.58	-0.49
	Strategy	1.87	1.35	0.68	1.11	0.82	1.18	0.75	0.31	0.14
		(**7.30**)	(**4.33**)	(**2.06**)	(**2.75**)	(**2.46**)	(**4.95**)	(**2.65**)	(**2.01**)	(0.31)
Small Rated	P1	-0.76	-0.41	0.02	0.36	0.10	0.07	0.02	0.05	-0.24
	P5	0.27	0.27	-0.55	-0.39	-0.65	-0.55	-0.60	-0.33	-0.27
	Strategy	1.03	0.68	0.57	0.75	0.74	0.62	0.63	0.38	-0.03
		(**3.73**)	(**3.46**)	(**1.98**)	(**2.99**)	(**2.21**)	(**3.89**)	(**2.99**)	(**3.36**)	(-0.12)
Big Rated	P1	-0.34	-0.04	0.11	0.18	0.05	0.13	0.02	0.08	-0.07
	P5	0.23	0.10	-0.32	-0.16	-0.54	-0.27	-0.22	-0.13	0.03
	Strategy	0.57	0.14	0.43	0.34	0.60	0.41	0.23	0.21	0.10
		(**2.05**)	(0.91)	(1.28)	(1.35)	(1.67)	(**2.74**)	(1.14)	(**2.57**)	(0.70)
C1 All	P1	-0.05	0.06	0.05	0.27	0.13	0.23	0.07	0.16	0.10
	P5	0.24	0.15	0.15	-0.06	-0.00	-0.01	0.00	0.02	-0.02
	Strategy	0.29	0.09	-0.10	0.33	0.13	0.23	0.07	0.13	-0.12
		(1.37)	(0.64)	(-0.87)	(1.79)	(0.54)	(**2.25**)	(0.37)	(**2.36**)	(-0.72)
C1 Micro	P1	-0.02	-0.09	0.07	-0.17	0.25	0.23	0.11	-0.10	4.30
	P5	0.25	0.51	0.27	-0.80	0.01	-0.05	-0.62	-0.22	-0.08
	Strategy	0.31	0.48	-0.12	-0.04	-0.03	0.49	0.75	0.34	-5.25
		(0.77)	(0.63)	(-0.35)	(-0.06)	(-0.06)	(1.09)	(1.59)	(0.95)	(-1.01)
C1 Small	P1	-0.38	-0.34	-0.02	-0.38	0.21	0.07	-0.09	-0.01	-1.51
	P5	0.30	-0.13	-0.14	-0.32	-0.36	0.03	-0.20	-0.17	0.04
	Strategy	0.67	0.20	0.12	-0.07	0.57	0.05	0.11	0.16	1.95
		(1.36)	(0.60)	(0.52)	(-0.18)	(1.90)	(0.16)	(0.28)	(0.91)	(**2.37**)
C1 Big	P1	0.00	0.10	0.07	0.30	0.10	0.27	0.10	0.18	0.11
	P5	0.25	0.16	0.20	0.07	0.06	0.01	0.05	0.07	0.03
	Strategy	0.25	0.06	-0.14	0.23	0.04	0.26	0.05	0.11	-0.08
		(1.16)	(0.42)	(-1.17)	(1.16)	(0.17)	(**2.30**)	(0.26)	(1.78)	(-0.45)
C2 All	P1	-0.34	-0.12	-0.05	0.07	-0.00	0.03	0.00	0.06	-0.09
	P5	0.18	0.08	-0.02	-0.03	-0.16	-0.23	-0.05	-0.22	-0.07
	Strategy	0.52	0.20	-0.03	0.10	0.16	0.26	0.06	0.28	0.02
		(**2.11**)	(1.27)	(-0.17)	(0.46)	(0.59)	(**2.09**)	(0.31)	(**3.16**)	(0.15)
C2 Micro	P1	-0.64	-0.45	-0.23	0.30	-0.48	-0.41	0.36	-0.49	-2.06
	P5	-0.06	-0.20	-0.57	-0.22	-0.69	-0.64	-0.91	-0.66	-0.28
	Strategy	0.54	0.31	0.23	0.66	0.30	0.07	1.27	0.18	1.80
		(1.35)	(0.61)	(0.62)	(0.92)	(0.56)	(0.11)	(1.78)	(0.60)	(1.45)
C2 Small	P1	-0.30	-0.08	-0.07	0.09	-0.02	0.13	0.11	0.08	0.03
	P5	0.16	0.33	0.04	0.03	-0.08	-0.30	-0.12	-0.17	-0.19
	Strategy	0.45	0.41	-0.11	0.06	0.06	0.42	0.22	0.25	-0.22
		(1.68)	(1.94)	(-0.51)	(0.22)	(0.20)	(**2.15**)	(0.87)	(**2.04**)	(-0.71)
C2 Big	P1	-0.29	-0.10	-0.00	0.05	0.02	0.04	-0.02	0.08	-0.09
	P5	0.20	0.01	0.02	0.03	-0.18	-0.16	0.01	-0.23	0.17
	Strategy	0.49	0.11	-0.02	0.03	0.20	0.21	-0.02	0.31	0.27
		(1.82)	(0.63)	(-0.10)	(0.12)	(0.65)	(1.49)	(-0.12)	(**2.87**)	(1.76)
C3 All	P1	-1.63	-0.84	-0.18	0.14	-0.11	-0.11	-0.20	-0.17	-0.48
	P5	0.40	0.20	-1.10	-0.59	-1.62	-0.90	-1.01	-0.61	-0.54
	Strategy	2.03	1.04	0.92	0.73	1.50	0.79	0.81	0.44	-0.06
		(**5.82**)	(**5.37**)	(**3.76**)	(**2.71**)	(**4.39**)	(**3.63**)	(**3.22**)	(**3.09**)	(-0.35)
C3 Micro	P1	-1.99	-1.37	-0.49	-0.17	-0.25	-0.16	-0.53	-0.23	-0.69
	P5	0.74	0.08	-1.33	-1.37	-1.90	-1.58	-1.45	-0.69	-0.67
	Strategy	2.73	1.46	0.85	1.20	1.65	1.41	0.92	0.46	0.02
		(**7.81**)	(**4.23**)	(**2.84**)	(**2.57**)	(**4.73**)	(**4.30**)	(**2.36**)	(**2.29**)	(0.05)
C3 Small	P1	-1.47	-0.73	-0.03	0.30	0.11	-0.07	0.04	-0.03	-0.30
	P5	0.33	0.33	-1.02	-0.33	-1.37	-0.80	-0.96	-0.54	-0.62
	Strategy	1.80	1.06	0.99	0.62	1.48	0.74	1.00	0.52	-0.33
		(**4.41**)	(**3.98**)	(**2.62**)	(1.87)	(**3.24**)	(**2.74**)	(**3.64**)	(**2.90**)	(-1.16)
C3 Big	P1	-0.72	-0.31	-0.28	0.01	-0.31	0.02	0.02	-0.11	-0.56
	P5	0.21	0.05	-0.12	-0.17	-1.31	-0.45	-0.51	-0.79	0.18
	Strategy	0.93	0.36	-0.17	0.18	1.01	0.47	0.53	0.68	0.74
		(1.86)	(1.10)	(-0.34)	(0.44)	(1.75)	(1.44)	(1.34)	(**2.27**)	(1.78)

Table 5A

Anomaly Profits after Removing Past-Returns-Adjusted Rating Downgrades

Rating changes, $\Delta Rating_{it}$, are regressed on the firm's cumulative past-six-month returns. The past-return-adjusted rating change, $\Delta Rating^*_{it}$, is the intercept and residual from this regression. We consider past-return-adjusted rating changes larger than 2 standard deviations above the mean to be past-return-adjusted rating downgrades, i.e. if $\Delta Rating^*_{it} > \mu_{(\Delta Rating^*_{it})} + 2\sigma_{(\Delta Rating^*_{it})} \Rightarrow \Delta Rating^*_{it} \equiv Downgrade^*_{it}$. We repeat the analysis in Table 5, but remove six months of returns before and after past-returns-adjusted downgrades, $Downgrades^*_{it}$, rather than raw downgrades. C1, C2, and C3 are sorted on $Rating^*_{it}$. Results are presented for equally-weighted size- and BM-adjusted returns.

Anomaly		Momentum	SUE	Credit Risk	Dispersion	Idio Vol	Asset Growth	Investment	Accruals	BM
All Rated	P1	0.22	0.23	0.19	0.28	0.14	0.36	0.28	0.43	0.15
	P5	0.42	0.32	0.18	0.30	0.15	0.09	0.01	0.11	0.40
	Strategy	0.20	0.09	0.00	-0.02	-0.01	0.27	0.27	0.32	0.25
		(0.83)	(0.74)	(0.01)	(-0.09)	(-0.02)	(**2.44**)	(1.48)	(**4.13**)	(**2.51**)
Micro Rated	P1	0.31	0.03	0.07	0.39	-0.10	0.53	0.39	0.78	0.16
	P5	0.80	0.54	0.30	0.30	0.28	-0.20	-0.11	0.27	0.45
	Strategy	0.48	0.50	-0.23	0.09	-0.38	0.74	0.50	0.51	0.30
		(1.48)	(1.70)	(-0.68)	(0.21)	(-1.06)	(**2.56**)	(1.69)	(**2.75**)	(0.61)
Small Rated	P1	0.22	0.24	0.07	0.46	0.21	0.49	0.32	0.43	0.34
	P5	0.46	0.47	0.15	0.49	0.21	0.22	0.01	0.11	0.35
	Strategy	0.25	0.23	-0.08	-0.03	-0.00	0.27	0.31	0.32	0.02
		(0.94)	(1.25)	(-0.28)	(-0.12)	(-0.01)	(1.79)	(1.42)	(**2.76**)	(0.08)
Big Rated	P1	0.21	0.26	0.22	0.23	0.14	0.27	0.19	0.30	0.09
	P5	0.30	0.24	0.09	0.15	0.00	0.11	0.06	0.06	0.39
	Strategy	0.09	-0.02	0.13	0.08	0.13	0.16	0.13	0.24	0.30
		(0.35)	(-0.13)	(0.40)	(0.32)	(0.39)	(1.20)	(0.66)	(**3.12**)	(**2.44**)
C1 All	P1	0.24	0.30	0.15	0.29	0.19	0.32	0.18	0.24	0.15
	P5	0.29	0.19	0.31	0.21	0.29	0.13	0.14	0.14	0.24
	Strategy	0.05	-0.11	-0.16	0.08	-0.11	0.19	0.04	0.11	0.08
		(0.26)	(-0.93)	(-1.56)	(0.47)	(-0.46)	(1.68)	(0.19)	(**2.04**)	(0.68)
C1 Micro	P1	-0.02	-0.09	0.15	-0.16	0.35	0.24	0.06	0.02	4.78
	P5	0.23	0.29	0.10	-0.42	-0.25	-0.25	-0.41	-0.20	0.41
	Strategy	0.29	0.09	0.19	-0.51	0.48	0.72	0.56	0.37	-2.60
		(0.81)	(0.13)	(0.55)	(-0.93)	(1.05)	(1.94)	(1.15)	(0.98)	(-0.92)
C1 Small	P1	-0.01	0.01	0.05	-0.39	0.27	0.32	0.06	0.02	-0.53
	P5	0.39	-0.11	0.07	-0.01	0.05	0.22	-0.14	0.06	0.17
	Strategy	0.40	-0.14	-0.03	-0.40	0.23	0.09	0.20	-0.04	1.08
		(1.48)	(-0.56)	(-0.12)	(-1.04)	(0.73)	(0.29)	(0.53)	(-0.25)	(1.04)
C1 Big	P1	0.31	0.33	0.16	0.32	0.17	0.33	0.21	0.28	0.15
	P5	0.30	0.21	0.36	0.32	0.36	0.18	0.20	0.17	0.26
	Strategy	-0.01	-0.12	-0.20	-0.00	-0.19	0.16	0.00	0.12	0.10
		(-0.04)	(-1.01)	(-1.80)	(-0.01)	(-0.82)	(1.28)	(0.01)	(1.87)	(0.85)
C2 All	P1	0.34	0.21	0.07	0.16	0.11	0.26	0.23	0.37	0.13
	P5	0.28	0.30	0.38	0.32	0.35	0.10	0.19	0.08	0.31
	Strategy	-0.06	0.09	-0.31	-0.16	-0.24	0.16	0.04	0.29	0.18
		(-0.26)	(0.65)	(-1.00)	(-0.79)	(-0.91)	(1.27)	(0.22)	(**3.18**)	(1.42)
C2 Micro	P1	0.16	-0.46	-0.30	0.57	-0.23	-0.45	0.42	0.38	0.44
	P5	-0.01	0.16	0.20	-0.16	0.01	-0.67	-0.55	0.08	-0.25
	Strategy	-0.17	0.69	-0.55	0.63	-0.26	0.54	1.06	0.34	-0.33
		(-0.41)	(1.37)	(-1.37)	(0.78)	(-0.43)	(0.76)	(1.49)	(1.04)	(-0.25)
C2 Small	P1	0.45	0.33	0.08	0.27	0.10	0.33	0.35	0.42	0.47
	P5	0.30	0.42	0.54	0.59	0.61	0.15	0.29	0.19	0.26
	Strategy	-0.15	0.09	-0.46	-0.32	-0.52	0.18	0.06	0.23	-0.21
		(-0.57)	(0.50)	(-1.16)	(-1.13)	(-1.71)	(0.88)	(0.25)	(1.78)	(-0.66)
C2 Big	P1	0.24	0.18	0.10	0.13	0.13	0.31	0.21	0.32	0.08
	P5	0.27	0.24	0.29	0.26	0.28	0.12	0.20	-0.02	0.39
	Strategy	0.03	0.06	-0.18	-0.13	-0.15	0.19	0.01	0.34	0.32
		(0.14)	(0.38)	(-0.96)	(-0.56)	(-0.51)	(1.38)	(0.04)	(**3.15**)	(1.93)
C3 All	P1	0.07	0.15	0.13	0.29	0.14	0.43	0.44	0.62	0.04
	P5	0.66	0.53	0.30	0.58	0.03	0.01	-0.11	0.08	0.68
	Strategy	0.59	0.38	-0.17	-0.28	0.11	0.41	0.55	0.54	0.64
		(1.46)	(**2.07**)	(-0.72)	(-1.02)	(0.30)	(**2.13**)	(**2.16**)	(**3.83**)	(**3.53**)
C3 Micro	P1	0.54	-0.07	-0.10	0.14	0.11	0.75	0.49	0.91	0.43
	P5	1.11	0.64	0.36	0.66	0.22	-0.11	-0.10	0.25	0.68
	Strategy	0.57	0.70	-0.46	-0.52	-0.12	0.85	0.60	0.66	0.26
		(1.12)	(**1.98**)	(-1.44)	(-0.92)	(-0.28)	(**2.03**)	(1.41)	(**2.92**)	(0.54)
C3 Small	P1	-0.12	0.29	0.29	0.44	0.35	0.39	0.46	0.53	0.19
	P5	0.58	0.56	0.39	0.75	0.20	0.17	-0.05	0.02	0.58
	Strategy	0.70	0.27	-0.10	-0.32	0.15	0.23	0.50	0.51	0.39
		(1.63)	(1.00)	(-0.27)	(-0.92)	(0.30)	(0.99)	(1.78)	(**2.75**)	(1.35)
C3 Big	P1	0.11	0.18	-0.02	0.04	-0.19	0.17	0.22	0.33	-0.22
	P5	0.41	0.40	0.33	0.45	-0.28	0.02	-0.08	-0.16	0.59
	Strategy	0.30	0.21	-0.36	-0.42	0.09	0.15	0.31	0.50	0.79
		(0.59)	(0.72)	(-0.77)	(-1.03)	(0.16)	(0.52)	(0.78)	(1.79)	(1.83)