Anomalies and Financial Distress

by

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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. 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 among high and low credit risk firms as well as during periods of deteriorating, stable, and improving credit conditions.

Asset pricing theories prescribe that riskier assets should command higher returns. Existing theories, however, leave unexplained a host of empirically documented cross-sectional patterns in stock returns, classified as anomalies. Specifically, the literature has documented that in the cross-section future stock returns are positively related to past returns (Jegadeesh and Titman 1993, 'price momentum'), unexpected earnings (Ball and Brown 1968, 'earnings momentum'), and book-to-market (Fama and French 1992, 'value effect'). Further, stock returns are negatively related to firm size (Fama and French 1992), accruals (Sloan 1996), credit risk (Dichev 1998, Campbell, Hilscher, and Szilagyi 2008, and Avramov, Chordia, Jostova, and Philipov 2009a), dispersion in analysts' earnings forecasts (Diether, Malloy, and Scherbina 2002), capital investments (Titman, Wei, and Xie 2004), asset growth (Cooper, Gulen, and Schill 2008), and idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang 2006).

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 anomalies and, in particular, assess the implications of financial distress for the profitability of anomaly-based trading strategies. Financial distress leads to sharp responses in stock and bond prices[1] and this pattern could potentially be related to the dynamics of anomalies.

We are motivated to examine financial distress following Fama and French (1993) who suggest that the size and value factors proxy for a priced distress factor. However, Campbell, Hilscher, and Szilagyi (2008) find that while distressed firms have high loadings on the SMB and HML factors, they generate lower, not higher, returns, and argue against the existence of a priced distress factor. Moreover, consistent with the anomalies literature, Daniel and Titman (1997) argue that it is the size and value characteristics, not SMB and HML factor loadings, that impact stock returns. In this paper, we consider financial

[1] 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.

distress to be a characteristic and examine its impact on stock returns and the profitability of anomalies. The potential implications of financial distress for market anomalies have not yet been comprehensively explored. This paper attempts to fill this gap.

We focus on financial distress, rather than other possibly correlated characteristics, because financial distress has direct implications for a firm's future performance. For example, there may be triggers in bond covenants that stipulate coupon rate increases if rating drops below a certain grade. Creditors may abandon low rated firms. Financial distress could result in loss of customers, suppliers, and key employees. Further, managerial time may be spent on dealing with financial distress rather than focusing on value enhancing projects. There are regulatory restrictions on the minimum ratings of firms in which some institutions can invest. These restrictions may be difficult to tie to other firm characteristics such as size, illiquidity, or volatility, which are not directly tied to the firm's borrowing capacity and costs. In addition, a credit rating downgrade offers a directly observable measure of deteriorating firm conditions. As a result, financial distress, as proxied by credit rating downgrades, is likely to be the primary ex-ante indicator of real implications for a firm's future performance.

Methodologically, our analysis of characteristics-based anomalies relies on portfolio sorts and cross-sectional regressions, as in Fama and French (2008). 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 all rated firms. 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, it is significant among low-rated stocks. The accruals strategy is an exception – while more profitable among low-rated firms, it is robust across all credit risk groups. Note that credit risk is not merely a proxy for size or illiquidity. The results from double sorts on rating and size (or illiquidity) show that the anomalies are reasonably robust among all size (and illiquidity) groups.

The profitability of the price momentum, earnings momentum, credit risk, dispersion, idiosyncratic volatility, and capital investments anomalies derives exclusively from periods of financial distress. All these strategies provide statistically insignificant and economically small profits when periods around credit rating downgrades (from six months before to six months after a downgrade) are excluded from the sample. None of these strategies produces significant profits during stable or improving credit conditions. In contrast, the value anomaly is significant only during stable or improving credit conditions and is mostly attributable to long positions in low-rated stocks. Accruals is again an exception. It is profitable during deteriorating, stable, and improving credit conditions.

The distinct patterns of the accruals and value effects suggest that both 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, the accruals strategy is unrelated to financial distress and the value 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.

We find that financial distress causes the anomalies' conditioning variables for the low-rated stocks to take extreme values, which in turn puts these distressed low-rated stocks on the short side of the trading strategies. These distressed stocks subsequently realize extremely low returns thus producing the anomalous profits from the short side of the trading strategy. Financial distress thus provides the link between the anomalies' conditioning variables and the subsequent profitability of the anomaly-based trading strategy.

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

1 Data

The asset-pricing anomalies we study require data on stock return, credit rating, and a variety of equity characteristics. 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 RatingsXpress) on WRDS. Combining the S&P company rating in Compustat and RatingsXpress 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 rated firms in October 1985, when the sample begins and 2,196 in December 2008 when the sample ends. The maximum number of firms, 2,497, is recorded in April 2000. The sample size changes based on the conditioning variable used for the anomalies.[2]

The definition of a company's Long Term Issuer credit rating is identical in both Compustat and RatingsXpress 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. *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

[2]Details about the number of firms based on the conditioning variable used are available upon request.

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, 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 sorted 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 (C1) has an average rating of A+, the medium-rated portfolio (C2) has an average rating of BBB-, and the lowest-rated portfolio (C3) has an average rating of B+.

Not surprisingly, the average firm size decreases monotonically with credit rating. The highest-rated stocks have an average market cap of $3.30 billion, while the lowest-rated stocks

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

have an average capitalization of \$0.35 billion. The book-to-market [BM] ratio increases monotonically with credit risk, from 0.52 in C1 to 0.64 in C3. The average stock price also decreases monotonically with increasing credit risk from \$38.07 for C1 to \$12.47 for C3. Notice also that institutions hold fewer shares of low-rated stocks. Institutional holding amounts to 59% of shares outstanding (an average holding of \$1.95 billion) for high-rated stocks and 49% (an average holding of \$0.17 billion) for the low-rated stocks.

High-rated firms are considerably more liquid than low-rated firms. The average monthly dollar trading volume decreases from \$284 million for the highest-rated to \$53 million for the lowest-rated NYSE/AMEX and from \$73 million for the highest-rated to \$40 million for the lowest-rated stocks Nasdaq stocks. Moreover, the Amihud (2002) illiquidity measure is 0.02 and 0.12 for the highest-quality NYSE/AMEX and NASDAQ stocks, respectively. For the lowest-rated stocks the illiquidity measure is 0.44 and 0.48 for NYSE/AMEX and NASDAQ. 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 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).

Next, we analyze several variables that proxy for uncertainty about firm's future fundamentals. In particular, the average number of analysts following a firm 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)[4] also decrease monotonically from 0.58 for the highest to 0.14 for the lowest rated stocks. Dispersion in analysts EPS forecasts in-

[4]SUE is 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.

creases 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, increases monotonically from 0.54 for the highest-rated to 1.17 for the lowest-rated stocks.

Market betas increase monotonically from 0.82 for the highest-rated to 1.31 for the lowest-rated stocks – the lowest-rated stocks have more market risk than the higher-rated stocks. However, the CAPM alphas decrease from 0.30% per month for the highest-rated stocks to -0.60% for the lowest-rated stocks, while the Fama-French alphas decrease from 0.11% to -0.80%. The SMB beta also increases from -0.06 for the highest-rated to 0.82 for the lowest-rated stocks. Both the market and the SMB betas 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. This is the credit risk puzzle that we shall address in the context of financial distress.

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

Our analysis of anomalies is based on portfolio sorts and cross-sectional regressions. Focusing on the former, portfolio returns are value-weighted as well as equally-weighted across stocks. Equally-weighted portfolio returns can be dominated by tiny (microcap) stocks which account for a very low fraction 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, and, thus we present both.

We run the analysis for all rated stocks as well as within subsets based on market capitalization and credit ratings. In particular, we implement trading strategies within 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 above the median NYSE capitalization. We note that while microcap stocks represent 17.78% of the total number of rated stocks, they account for only 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 represent 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 large firms are more likely to be rated.

Similarly, we run the analysis within credit rating terciles: C1 (highest quality), C2 (medium quality), and C3 (worst quality). The anomalies are also studied within subsamples based on the interaction of the three size and three credit rating groups.

Anomaly profits are based on size and book-to-market adjusted stock returns, as in Fama and French (2008).[5] The 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, each month t, we rank stocks into quintile portfolios 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. 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

[5] We have checked that our results are robust to using raw, rather than size and book-to-market adjusted returns. In fact, the raw anomaly profits are stronger and are again concentrated in high credit risk firms.

calculated as the equally- or value-weighted average return of its constituent stocks. When the holding period, K, is longer than a month, 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 this methodology applies to all strategies, different strategies use different conditioning variables and may also differ with respect to the holding period.

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 SUE and is 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 (P1), selling the worst-rated quintile (P5), and holding both for a month.

As in Diether, Malloy, and Scherbina (2002), the dispersion 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 forecast. The strategy involves buying P1 (lowest dispersion), selling P5 (highest dispersion), and holding them for one month.

Idiosyncratic volatility (IV) is computed as the sum of the stock's squared daily returns from CRSP minus the sum of the squared daily market returns, as in Campbell, Lettau, Malkiel, and Xu (2001). The strategy conditions on prior month IV and involves buying P1 (lowest volatility), selling P5 (highest volatility), and holding both for one month.

Following Cooper, Gulen, and Schill (2008), the asset growth anomaly conditions on the percentage change in total assets from December of year $t-2$ to December of year $t-1$. The strategy involves buying P1 (lowest asset growth), selling P5 (highest growth), and holding both from July of year t through June of year $t+1$.

As in Titman, Wei, and Xie (2004), the capital investments 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 $t-2$. It involves buying P1 (lowest investments), selling P5 (highest investments), and holding both positions from July of year t through June of year $t+1$.

Accruals is computed following Sloan (1996). There is a four-month lag between formation and holding periods to ensure that all accounting variables to calculate accruals are in the investor's information set. The strategy involves buying the lowest accruals portfolio (P1), selling the highest accruals portfolio (P5), and holding them for the next 12 months.

The value strategy conditions on book-to-market as of December of year $t-1$. It 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. For each anomaly, we compute the fraction of market capitalization captured by our sample of rated firms relative to the entire CRSP sample. Our sample captures 89.35% of market capitalization of the overall CRSP sample for price momentum; 90.72% for earnings momentum; 90.44% for the dispersion anomaly; 89.30% for the idiosyncratic volatility anomaly; 88.64% for the asset growth anomaly; 88.60% for the 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, we compare anomaly profits in rated firms (see Table 2) and in all CRSP firms (see Table 2A in the appendix). Anomaly profits are comparable, suggesting that our sample of rated firms adequately represents the overall CRSP universe. Indeed, this paper focuses on credit rating as a proxy for credit conditions, as the rating provides us with a publicly available, non-model-specific, measure of credit risk and financial distress.[6]

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 each anomaly. Panel A exhibits the size- and BM-adjusted equally-weighted portfolio returns, while Panel B presents the corresponding value-weighted returns.

We first examine anomaly-based 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 stocks earning -74 bps and the winner stocks earning 27 bps. The earnings momentum strategy yields 44 bps monthly profits. The credit risk strategy generates 71 bps per month. 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 profit is 27 bps per month. All these anomalies' profits are economically and statistically significant. The value strategy delivers the lowest return – a statistically insignificant -15 bps per month. Given that we use size- and BM-adjusted returns it is not surprising that in the overall sample the value strategy's profits are indistinguishable from zero. For the overall sample of rated firms, except for the value effect, all trading strategies are profitable.

Next, we examine trading strategies implemented among microcap, small, and big firms. Both earnings and price momentum generate profits that monotonically diminish with mar-

[6]In Table 2A, we use Altman's Z-score instead of credit ratings to proxy for financial distress. The caveat with using Altman's Z-score is that it uses past returns and is thus somewhat endogenous. Moreover, not all firms have accounting data in Compustat to compute the Z-scores, so the reduction in number of firms from Z-score is even larger. Thus, ratings are a much better filter than Z-scores when isolating the firms driving most anomalies. In any case, we show in Figure 2 that the Z-score and downgrades are highly correlated.

ket capitalization. The profits of the earnings momentum strategy are 135 bps and of the price momentum strategy 187 bps per month for microcap stocks. For small stocks the earnings momentum strategy returns 68 bps and for big stocks it returns 14 bps, while the price momentum strategy returns 103 bps for small stocks and 57 bps for big stocks. The P1 portfolio (the short side of the strategy) leads to the large differences across the size-sorted portfolios. Focusing on earnings momentum, P1 returns -99, -41, and -4 bps per month for microcap, small, and big stocks, respectively. In contrast, the long side of the strategy (P5) delivers earnings momentum returns of 37, 27, and 10 bps per month for the corresponding size groups. For price momentum, P1 returns -144, -76, and -34 bps per month and P5 returns 43, 27, and 23 bps per month for microcap, small, and big stocks. 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 profits that monotonically diminish across the size groups, with the highest profits attributable to microcap stocks and the lowest to big stocks. The dispersion strategy earns 111, 75, and 34 bps per month in microcap, small, and big stocks, respectively. The idiosyncratic volatility strategy profits decrease from 82 bps per month in microcap to 59 bps in big stocks. The asset growth strategy delivers monthly profits that decrease from 118 bps in microcap to 41 bps in big stocks while the capital investments strategy delivers profits that decrease from 75 bps in microcap to 24 bps in big stocks. Once again, the return differential between microcap and big stocks on the short side of the strategy is larger than that on the long side. For instance, focusing on the asset growth strategy, the return differential between microcap and big stocks is 109 bps on the short side and 32 bps on the long side. The accruals strategy yields 31, 38, and 21 bps per month in microcap, small, and big firms. Note that among big stocks only the price momentum, asset growth, and accruals-based trading strategies are profitable at the 5% level.

Since our objective is to examine the impact of credit risk on anomalies, we further partition the sample into high-rated (C1), medium-rated (C2), and low-rated (C3) stocks. The evidence shows that the impact of credit conditions is striking. For instance, the price momentum strategy' profits are 26, 41, and 193 bps per month, while the asset growth strategy' profits are 15, 26 and 76 bps in high, medium, and low-rated stocks, respectively.

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

Remarkably, all strategies (except value) are profitable among low-rated, C3, stocks. The highest profit (2.62% per month) is earned by the price momentum strategy in low-rated microcap stocks. The next highest profit (1.84% per month) is also earned by the price momentum strategy in low-rated small stocks. Even big low-rated stocks deliver a significant (at the 10% level) price momentum profit of 81 bps per month. All trading strategies are profitable among low-rated microcap and small stocks. The only exception is the dispersion strategy in small stocks which is profitable only at the 10% level. Among low-rated big stocks, only the idiosyncratic volatility, accruals and value strategies are profitable. The value strategy provides statistically and economically significant profits (103 bps per month) only in low-rated big stocks. Note that although returns are adjusted by the 'unconditional' returns of their matching size- and BM portfolios, conditioning on credit risk, the value effect still appears significant in certain subsamples.

Differences in profitability between low- and high-rated firms are economically and statistically significant (at the 5% level) for almost all trading strategies (unreported results). The only exceptions are the dispersion strategy, for which this difference is significant at the 10% level, and the value strategy, for which it is not statistically significant.

We should point out that despite the various sorting procedures in Table 2, the results are based on well populated portfolios. Sorting on credit risk terciles and anomaly variable quintiles divides our firms into 15 portfolios. We have an average of 1,931 rated firms per month which leaves an average of 129 firms in each of the 15 credit rating and anomaly-sorted portfolio. The main conclusion that anomaly profits are driven by high credit risk firms is based on these very well populated portfolios. When we further subdivide into three size groups in parts of Table 2, we get an average of 43 stocks per portfolio (the finest sort in the paper). Note that while this double sort on credit risk and size checks the importance of firm size versus ratings for the anomalies, it is not crucial to our main conclusions.

Panel B of Table 2 is the value-weighted counterpart of Panel A. Indeed, the value-weighted profits are often lower, suggesting a role for small firms. For instance, the overall price momentum profits in Panel B are 64 bps compared to 100 bps in Panel A. Nevertheless, profits are typically significant among low-rated firms. Moreover, profits generally increase with worsening credit rating. Only the idiosyncratic volatility, asset growth, capital investments and value strategies are profitable among low-rated big stocks.

Quite prominent in the results is the overwhelming impact of the short side of the strategies. To illustrate, consider the anomaly profits of the small rated stocks in Panel B – for price momentum the long side earns 27 bps per month and the short side 79 bps. Recall that all the returns in Table 2 are size and BM-adjusted. Thus, these returns should be zero as long as it is the size and value characteristics that drive returns. However, both the long and the short side of the strategies earn non-zero returns with the short side earning substantially higher returns. For earnings momentum the corresponding long and short position returns are 20 and 42 bps respectively; for credit risk the long and short returns are 4 and 64 bps; for dispersion they are 38 and 39 bps; for idiosyncratic volatility they are 9 and 72 bps; for asset growth they are 3 and 58 bps ; and for capital investments they are 4 and 67 bps per month. Thus, the short side of the trading strategy yields higher profits than the long side.

Another way to see the importance of the short side of the strategy is to examine the return differential across the lowest- and the highest-rated stocks. Consider the price momentum strategy. The size- and BM-adjusted value-weighted return of the winner portfolio is 21 bps per month among C1 stocks and 8 bps among C3 stocks. This represents a return differential of 13 bps. On the other hand, the return differential across the loser stocks is 108 [114-6] bps. The short side of the strategy is clearly the primary source of momentum profitability. Consider now earnings momentum. The return differential between the long portfolios in low and high-rated stocks is 14 bps while the return differential between the short portfolios is much larger at 63 bps. For credit risk, the return differential between low- and high-rated long portfolios is 37 bps and 64 bps for short portfolios; for dispersion the return differential between the long portfolios is 23 bps and between the short portfolios it is 44 bps; for idiosyncratic volatility the return differential is 12 bps for the long and 151 bps for the short portfolios; for asset growth the return differential is 16 bps for the long and 73 bps for the short portfolios; for capital investments the return differential is 4 bps for the long and 93 bps for the short portfolios. Only in the case of accruals are the long and short portfolio return differentials similar, 51 bps versus 69 bps. This further reinforces the distinctive patterns of the accruals strategy – except for accruals, the short side of the strategy provides the bulk of profitability. Note that the long side of the strategy is also profitable, although not as much as the short side.

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 strategy is the primary source of anomaly profits; (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.

Table 2 provides results from double sorts on size and credit ratings. We find that even after controlling for firm size, it is credit ratings (which proxy for something that is economically fundamental) that drive the anomaly profits. We have considered another double sort based on illiquidity and credit ratings and find similar results (unreported). The results suggest that credit ratings are not simply proxies for firm size or illiquidity.

To further pinpoint the segment of firms driving the anomalies' profits, we document in Table 3 the equally-weighted size- and BM-adjusted profits for various credit rating subsamples as we sequentially exclude the worst-rated stocks. The starting point is the full sample with all ratings (AAA-D) – profits are identical to those exhibited in Panel A of Table 2. Table 3 shows that the profitability of the different anomalies declines as the lowest-rated stocks are excluded from the sample. The earnings momentum strategy profits monotonically diminish from 0.44% in the overall sample to a statistically insignificant 0.17% per month while the price momentum strategy profits decline from 1.00% to 0.36% per month as firms rated BB- or below are eliminated. The asset growth strategy is reduced to an insignificant 19 bps when firms rated BB+ and below are removed from the sample. The accruals strategy is an exception, remaining statistically significant throughout – the maximum profitability (29 bps) is realized when stocks rated CC and below are excluded. Except for accruals, the 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.[7]

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 anomalies in particular. Specifically, profitability typically rises with worsening credit conditions. Moreover, the short side of the trading strategy generates most of the profits.

Studying the impact of credit rating changes is our next task. Rating changes have already been analyzed in the context of empirical asset-pricing. In particular, Hand, Holthausen,

[7] 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.

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 implications of credit rating downgrades for all market anomalies have not yet been explored. Below we show that credit rating downgrades are indeed crucial for understanding the source of anomaly profits.

3.1 Credit Rating Downgrades

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 different patterns across credit risk groups. For one, the number of downgrades in the highest-rated group is 2,485 (8.94 per month on average), while the corresponding figure for the lowest-rated group is much larger at 3,147 (11.32 per month). Moreover, the average size of a downgrade among the lowest-rated stocks is 2.14 notches, whereas the average downgrade among the highest-rated stocks is 1.75 notches.

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 a rather dramatic -14.08% for the worst-rated. In the six-month period before and after the downgrade, the lowest-rated firms deliver average returns of -25.99% and -16.69%. The corresponding returns for the highest-rated stocks are 2.09% and 5.39%. In the year before and after the downgrade, the return for the lowest-rated stocks is -32.44% and -13.26%, while they are 5.53% and 11.86% for the highest-quality stocks.

Table 4 also documents the number of delisted firms across the rating terciles. Over 6, 12 and 24 months after a downgrade, the number of delistings among the highest-rated stocks are 63, 96 and 154, while the corresponding figures are 289, 484 and 734 among 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, these numbers suggest that delisting events could be a direct consequence of financial distress.

We have examined downgrades during expansions and recessions and also during periods with positive and negative market returns. We have also examined pairwise correlation of downgrades. The results suggest that downgrades are idiosyncratic events and do not cluster together. We have also examined investment grade and non-investment grade stocks – the average size of the downgrade is larger, the time between downgrades is shorter and the returns are substantially more negative for non-investment grade stocks. All these results are available upon request.

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

3.2 Impact of Downgrades on Anomalies

Table 5 repeats the analysis from Table 2 but focusing on periods of stable or improving credit conditions. For each downgraded stock, we exclude observations from six months before the downgrade to six months after the downgrade. Of course, our analysis 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] Panels A and B of Table 5 present the equally-weighted and the 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 and the medium-rated big stocks.

The accruals strategy is robust in periods of improving or stable credit conditions. For instance, across all stocks, the accruals strategy returns 32 bps per month (as opposed to 27 bps in Table 2). The strategy results in profits 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 accruals is profitable for some size groups across the different rating categories.

The value strategy is also profitable at 26 bps (t-statistic of 2.53) when periods around downgrades are eliminated, as opposed to an insignificant -15 bps over the entire sample period. The value strategy generates significant 61 bps per month among low-rated and 85 bps among big low-rated stocks, suggesting that low-rated stocks that survive financial distress earn positive abnormal returns. Although returns are adjusted by the 'unconditional' returns of their matching size and BM portfolios, value stocks earn higher returns when conditioning on non-distress periods.

The value-weighted portfolio returns (Panel B) display similar patterns as the equally-

[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.

weighted ones (Panel A). Apart from accruals and value, only the asset growth strategy is profitable and that too only in low-rated microcap and medium-rated big stocks.[9] All other strategies provide insignificant returns regardless of the conditioning on size or credit rating.

Recall from Table 2 that a large fraction of profitability is due to the short side of the strategies. Here, the short side does not play such a crucial role. To illustrate, the difference in P1 returns (the short side) across high and low-rated stocks for the price momentum strategy is 15 bps compared to 108 bps in Panel B of Table 2. Moreover, the long side generates only 1bp difference. Similarly, for earnings momentum the short and the long sides both yield 13 bps. The short side yields 1bp and the long side yields 22 bps for credit risk; for dispersion the short and the long sides yield 33 bps and 5 bps; 59 bps and 1 bps for the short and long sides for idiosyncratic volatility; 17 bps and 6 bps for asset growth, and 40 bps and 29 bps for capital investments. All of these differences are far smaller than when the downgrade period was included. 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 strategies derive their profits from the strongly negative returns around financial distress. In particular, a large fraction of profitability emerges from the short side. 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's BM ratio rises due to falling market value. This leads to the inclusion of low-rated distressed stocks on the long side of the strategy. If such firms get

[9] Collins and Kim (2011) suggest that a significant portion of the asset growth anomaly can be ascribed to mergers, and this may be the reason for why the asset growth strategy is sometimes profitable.

downgraded, they realize abysmally low returns and the strategy could become unprofitable. Instead if the firm rebounds, the strategy succeeds. Indeed, the value effect seems to emerge from long positions in low-rated firms that survive financial distress and subsequently realize relatively high returns.

Figure 1 examines the anomalies' conditioning variables around downgrades. The first panel shows the equally-weighted monthly returns for the high-rated (C1) and the low-rated (C3) stocks around downgrades. The monthly returns are negative for the C3 stocks from around eighteen months before the downgrade to nine months after. The return is as low as -14% in the month of downgrade. A profitable price momentum strategy would require going short 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 remain negative until about twelve months after the downgrade. A profitable earnings momentum strategy would require going short 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.

Figure 1 illustrates that financial distress causes the anomalies' conditioning variables for the low-rated stocks to take extreme values, which in turn puts these distressed low-rated stocks on the short side of the trading strategies. These distressed stocks subsequently realize extremely low returns thus producing the anomalous profits from the short side of the trading strategy. Financial distress thus provides the link between the anomalies' conditioning variables and the subsequent profitability of the anomaly-based trading strategy.

Given that accruals depend on 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 BM ratio increases around downgrades (reaching a maximum of over 1.8) among C3 stocks. However, the value strategy involves buying the high BM stocks. Thus, unlike the other strategies which go short the C3 stocks, the value strategy goes long the high BM C3 stocks around downgrades. The bet is that these high BM stocks survive financial distress and provide high subsequent returns.

3.3 Distinguishing the Impact of Downgrades from Past Returns

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. We have implicitly assumed that it is financial distress that leads to the negative returns. While both these statements could be true, we will now show that a downgrade is informative even after controlling for past returns. This could be because the downgrade itself leads to serious consequences for the firm. We address this in a number of ways.

First, note in Figure 1, that the most negative return, -14%, occurs during the month of downgrade suggesting that the downgrade is informative or potentially leads to selling by institutions that cannot hold low-rated stocks. 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. 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 2B, 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 larger than two standard deviations above the mean is considered a downgrade. This downgrade measure, 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 in Table 5A in the appendix are similar to those in Table 5, suggesting that our results are driven by financial distress and not by past returns.

Examining industry-adjusted financial ratios further confirms that firms are experiencing financial distress around downgrades. We find that, around downgrades, the low-rated stocks experience considerable deterioration in their profit margin, interest coverage and asset turnover relative to their industry.[10] Results are available upon request.

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 Nini, Smith, and Sufi (2009) from company 10-K or 10-Q filings and provided on Amir Sufi's webpage. The actual financial covenants violation is an exogenous variable, 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

[10] Note that, unlike leverage, these ratios are unrelated to past returns.

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. Moreover, the fact that the covenant violations reach a maximum right around the downgrade suggests that the downgrade event may itself cause deterioration in the financial condition leading to the violations.

In sum, the evidence points to financial distress as the determinant of falling stock prices around downgrades. Financial distress also causes the anomalies' conditioning variables of low-rated stocks to go to extremes, putting these distressed stocks on the short side of the trading strategies. These distressed stocks subsequently realize extremely low returns generating the anomalous profits from the short side of the strategy. Financial distress provides the link between the anomalies' conditioning variables and their subsequent profitability.

3.4 Regression Analysis

In this section, we scrutinize the asset-pricing anomalies using regression analysis. In particular, we consider the following cross-sectional specification:

$$r^*_{it} = a_t + b_t\, Z_{i,t-lag} + e_{it}, \tag{2}$$

where r^*_{it} is the size- and BM-adjusted return[11] on stock i at time t and $Z_{i,t-lag}$ is the value of the conditioning variable for stock i 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

[11]We have also used risk-adjusted return (using Fama-French factors) as the dependent variable as in Brennan, Chordia, and Subrahmanyam (1998) and the results are quite similar to those reported.

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 value 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 6 reports the Fama-MacBeth coefficient estimates and t-statistics from a separate univariate regression of future returns on a past anomaly variable. We also include dummy variables D_{NIG} and D_{IG} to denote the period from six months prior to six months after a downgrade for non-investment and investment grade stocks, respectively.

Table 6 Panel A exhibits the cross-sectional regression coefficients for all stocks. The evidence is similar to that based on returns from portfolio sorts, reported in Table 2. In particular, the coefficient estimates for past returns (0.86) and standardized unexpected earnings (0.11) are positive and significant, consistent with the price and earnings momentum anomalies. The coefficient estimates for credit risk (-0.06), analyst dispersion (-0.31), idiosyncratic volatility (-8.76), asset-growth (-0.47), capital investments (-0.57), and accruals (-3.89) are negative and significant, again consistent with prior results. Given that we adjust the returns for size and BM it is not surprising that the coefficient for the BM ratio is insignificant in the cross-sectional regressions in the overall sample.

Next we introduce dummy variables for the period around downgrades. We start with a dummy for non-investment grade stocks only. The coefficient on the dummy variable is significantly negative across the board, consistent with the negative returns realized around 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 estimate is uniformly smaller in absolute value. With both dummy variables, only the asset growth, accruals, and value strategies are profitable.

Overall, the regression evidence is consistent with our portfolio-based findings 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 downgrades.

Note that the coefficients for the BM ratio actually increase and become significant as the dummy variables for periods around downgrades are introduced in the regression. Indeed, the value strategy is profitable during periods of stable or improving credit conditions. This indicates that the value anomaly 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 BM ratio thus rises. This leads to a temporally negative relation between BM and stock returns during periods of financial distress. This negative relationship makes the value strategy unprofitable around periods of financial distress.

Panel B, C, and D of Table 6 present the regression evidence for microcap, small, and big stocks, respectively. For microcap stocks, only the coefficients for earnings momentum and asset growth are significant in the presence of the downgrade dummies. For small stocks, the coefficients for earnings momentum and capital investments are significant, though smaller, when downgrade dummies are included. Accruals and BM are significant when downgrade periods are removed consistent with our portfolio-based results. For big stocks, only accruals and asset growth are significant in the presence of the downgrade dummies.

The evidence suggests that the accruals and value anomalies become stronger when periods around 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 downgrade dummy variables are included. 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 downgrades.

While Table 6 analyzes univariate regressions, we next consider multivariate cross-sectional regressions combining all anomaly variables. We present Fama-Macbeth coefficients from regressions of size- and BM-adjusted returns on various combinations of anomaly variables with firm size as a control variable. It is evident from Table 7 that over our sample period, firm size is insignificant across all specifications.

Regressions (1) and (2) show that before introducing the downgrade dummies, the anomaly variables that produce statistically significant (at the 5% level) coefficients 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 the findings of Chordia and Shivakumar (2006) that price and earnings momentum interact. Capital investments is insignificant in the presence of the other anomaly variables.

Introducing dummy variables for periods of financial distress, we find that the only two profitable anomalies are accruals and value. The value anomaly is profitable when the high BM stocks survive financial distress, whereas accruals is significant with and without conditioning on financial distress.

4 Conclusions

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 all these anomalies disappears when firms rated BB+ or below are excluded from the sample. Remarkably, the eliminated firms

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

represent only 9.7% of the market capitalization of rated firms. Indeed, the profitability of these anomalies is concentrated in a small sample of low-rated stocks facing deteriorating credit conditions. Moreover, 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 profits.

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 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. 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. 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 5% 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

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 RatingXpress. 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 known when investing. 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). 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 matching size-BM portfolio 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. The last two columns report the percentage of total firms or total market cap represented by each specific subsample.

Sample	Momentum	SUE	Credit Risk	Dispersion	Idio Vol	Asset Growth	Investment	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)		
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)		
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)		
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)		
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)		
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)		
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)		
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)		
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)		
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)		
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)		
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)		
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)		
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)		
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)		

Table 4
Downgrades, 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. We analyze downgrades by credit rating tercile, sorted on firm rating at the end of month $t-1$.

	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
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

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

We repeat the analysis in Table 2 after removing return observations from six months prior to six months after a downgrade.

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

Each month t, we run univariate cross-sectional regressions of monthly size and book-to-market 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 on COMPUSTAT or Standard and Poor's RatingXpress:

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

Returns are size and book-to-market adjusted 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. Each firm characteristic, $Z_{i,t-lag}$, 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 5% level). Each panel also provides results from regressions including downgrade dummies:

$$r^*_{it} = a_t + b_t Z_{it-1} + d_{t,IG} D_{IG} + d_{t,NIG} D_{NIG} + e_{it},$$

where D_{IG} (D_{NIG}) is a dummy variable which takes the value of 1 from six months prior to six months after a downgrade 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	0.86	0.11	-0.06	-0.31	-8.76	-0.47	-0.57	-3.89	-0.01
	(**2.26**)	(**3.85**)	(**-2.62**)	(**-2.93**)	(**-3.25**)	(**-3.68**)	(**-2.63**)	(**-2.95**)	(-0.27)
b	0.18	0.06	0.01	-0.03	-1.40	-0.40	-0.36	-4.98	0.13
	(0.49)	(**2.07**)	(0.64)	(-0.37)	(-0.55)	(**-3.17**)	(-1.35)	(**-3.88**)	(**2.74**)
d_{NIG}	-3.80	-3.31	-3.76	-3.91	-3.72	-3.64	-3.47	-3.46	-3.71
	(**-14.93**)	(**-10.36**)	(**-14.21**)	(**-11.03**)	(**-15.21**)	(**-12.06**)	(**-11.88**)	(**-10.78**)	(**-11.94**)
b	0.06	0.04	-0.00	-0.02	-1.73	-0.42	-0.41	-5.05	0.14
	(0.17)	(1.53)	(-0.04)	(-0.18)	(-0.68)	(**-3.39**)	(-1.55)	(**-3.94**)	(**2.84**)
d_{IG}	-0.95	-0.85	-0.96	-0.90	-0.97	-0.97	-0.93	-0.80	-0.94
	(**-10.27**)	(**-8.12**)	(**-8.66**)	(**-8.19**)	(**-9.71**)	(**-9.52**)	(**-9.12**)	(**-6.78**)	(**-8.99**)
d_{NIG}	-3.86	-3.35	-3.73	-3.94	-3.74	-3.67	-3.50	-3.49	-3.74
	(**-15.11**)	(**-10.46**)	(**-14.25**)	(**-11.08**)	(**-15.24**)	(**-12.12**)	(**-11.92**)	(**-10.82**)	(**-12.00**)

Table 6 (continued)

Panel B: Micro Stocks

	Momentum	SUE	Credit Risk	Dispersion	Idio Vol	Asset Growth	Investment	Accruals	BM
b	1.75	0.27	-0.07	-0.76	-7.96	-0.81	-0.50	-0.19	0.02
	(**4.03**)	(**3.55**)	(**-2.52**)	(**-3.25**)	(**-2.61**)	(**-2.78**)	(-1.48)	(-0.06)	(0.19)
b	0.62	0.15	0.02	-0.32	-0.49	-0.72	-0.27	-2.04	0.15
	(1.52)	(1.93)	(0.76)	(-1.36)	(-0.17)	(**-2.45**)	(-0.82)	(-0.62)	(1.63)
d_{NIG}	-4.22	-3.82	-4.39	-5.02	-4.39	-4.30	-4.32	-3.96	-4.39
	(**-12.81**)	(**-7.33**)	(**-12.91**)	(**-8.56**)	(**-13.25**)	(**-11.49**)	(**-12.14**)	(**-9.39**)	(**-11.88**)
b	0.59	0.15	0.01	-0.35	-0.75	-0.72	-0.30	-2.03	0.15
	(1.45)	(1.93)	(0.41)	(-1.46)	(-0.25)	(**-2.46**)	(-0.90)	(-0.61)	(1.59)
d_{IG}	-1.05	-0.90	-1.05	-0.80	-1.09	-1.13	-1.26	-1.22	-1.04
	(**-3.50**)	(**-2.42**)	(**-3.58**)	(**-2.15**)	(**-3.63**)	(**-3.69**)	(**-4.16**)	(**-2.97**)	(**-2.70**)
d_{NIG}	-4.26	-3.84	-4.39	-5.03	-4.41	-4.33	-4.35	-3.99	-4.41
	(**-12.96**)	(**-7.40**)	(**-12.90**)	(**-8.59**)	(**-13.33**)	(**-11.61**)	(**-12.23**)	(**-9.44**)	(**-11.88**)

Panel C: Small Stocks

	Momentum	SUE	Credit Risk	Dispersion	Idio Vol	Asset Growth	Investment	Accruals	BM
b	0.97	0.17	-0.07	-0.23	-17.42	-0.48	-0.74	-4.07	-0.01
	(**2.31**)	(**4.26**)	(**-2.63**)	(**-2.36**)	(**-3.57**)	(**-2.82**)	(**-3.09**)	(**-1.96**)	(-0.10)
b	0.33	0.11	0.02	0.06	-7.82	-0.41	-0.50	-5.76	0.06
	(0.81)	(**2.83**)	(0.83)	(0.40)	(-1.70)	(-1.81)	(**-2.15**)	(**-2.85**)	(0.79)
d_{NIG}	-3.55	-3.00	-3.53	-3.62	-3.44	-3.41	-3.14	-3.27	-3.40
	(**-11.17**)	(**-8.00**)	(**-10.57**)	(**-8.35**)	(**-11.17**)	(**-9.52**)	(**-8.63**)	(**-8.25**)	(**-9.42**)
b	0.20	0.09	0.00	0.10	-8.26	-0.35	-0.52	-5.97	0.11
	(0.51)	(**2.36**)	(0.08)	(0.65)	(-1.60)	(-1.64)	(**-2.26**)	(**-2.93**)	(1.42)
d_{IG}	-1.38	-1.34	-1.42	-1.42	-1.45	-1.45	-1.38	-1.06	-1.57
	(**-7.98**)	(**-6.31**)	(**-7.51**)	(**-6.78**)	(**-8.14**)	(**-7.91**)	(**-6.65**)	(**-3.57**)	(**-8.30**)
d_{NIG}	-3.57	-3.02	-3.47	-3.64	-3.43	-3.40	-3.13	-3.29	-3.40
	(**-11.25**)	(**-8.06**)	(**-10.50**)	(**-8.41**)	(**-11.16**)	(**-9.51**)	(**-8.65**)	(**-8.30**)	(**-9.42**)

Panel D: Big Stocks

	Momentum	SUE	Credit Risk	Dispersion	Idio Vol	Asset Growth	Investment	Accruals	BM
b	-0.12	0.05	-0.03	-0.36	-7.96	-0.40	-0.39	-5.69	0.07
	(-0.27)	(1.76)	(**-2.09**)	(**-2.05**)	(**-2.13**)	(**-2.83**)	(-1.46)	(**-4.05**)	(1.17)
b	-0.43	0.03	0.00	-0.20	-1.95	-0.34	-0.26	-6.02	0.16
	(-0.97)	(1.36)	(0.02)	(-1.20)	(-0.29)	(**-2.50**)	(-0.99)	(**-4.38**)	(**2.64**)
d_{NIG}	-3.42	-2.57	-3.15	-3.39	-3.20	-2.90	-2.49	-3.09	-3.18
	(**-8.37**)	(**-5.09**)	(**-7.90**)	(**-6.50**)	(**-8.59**)	(**-6.64**)	(**-5.74**)	(**-5.59**)	(**-6.93**)
b	-0.64	0.02	-0.01	-0.16	-1.29	-0.37	-0.31	-6.12	0.20
	(-1.44)	(0.71)	(-0.27)	(-0.95)	(-0.19)	(**-2.71**)	(-1.20)	(**-4.43**)	(**3.21**)
d_{IG}	-0.87	-0.71	-0.84	-0.72	-0.84	-0.83	-0.78	-0.68	-0.82
	(**-9.17**)	(**-6.40**)	(**-8.00**)	(**-6.36**)	(**-8.50**)	(**-7.92**)	(**-7.58**)	(**-5.22**)	(**-7.58**)
d_{NIG}	-3.43	-2.56	-3.09	-3.34	-3.17	-2.86	-2.47	-3.06	-3.16
	(**-8.39**)	(**-5.09**)	(**-7.81**)	(**-6.43**)	(**-8.52**)	(**-6.58**)	(**-5.70**)	(**-5.51**)	(**-6.88**)

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

Each month t, we run multivariate cross-sectional regressions of monthly size and book-to-market-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 on COMPUSTAT or Standard and Poor's RatingXpress:

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

The firm characteristics, $\mathbf{Z}_{i,t-lag}$, are all the conditioning variable described in Table 6, lagged as prescribed by each specific anomaly and D_{IG} (D_{NIG}) is a dummy variable which takes the value of 1 from six months prior to six months after a downgrade 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 5% level). Returns are size and BM–adjusted as in Table 6. 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	-0.29	0.08	-0.04	-0.21	-11.11	-0.51	-0.07	-7.52	0.11	-0.06			6.06
	(-0.71)	(**2.93**)	(**-2.13**)	(-1.70)	(**-2.07**)	(**-2.71**)	(-0.26)	(**-5.73**)	(1.09)	(-0.73)			
2	-0.29	0.08		-0.29	-10.17	-0.53	-0.11	-7.64	0.12	-0.05			5.43
	(-0.70)	(**2.80**)		(**-2.36**)	(**-1.97**)	(**-2.83**)	(-0.37)	(**-5.80**)	(1.16)	(-0.64)			
3	-0.76	0.05	0.00	-0.09	-6.99	-0.30	-0.10	-7.71	0.23	-0.03	-0.93	-3.25	7.05
	(-1.83)	(1.91)	(0.14)	(-0.79)	(-1.30)	(-1.62)	(-0.34)	(**-5.89**)	(**2.15**)	(-0.40)	(**-6.99**)	(**-10.16**)	
4	-0.49		0.01	-0.00	-9.07	-0.23	-0.17	-7.67	0.21	-0.01	-0.81	-3.46	6.35
	(-1.28)		(0.52)	(-0.02)	(-1.95)	(-1.50)	(-0.71)	(**-6.16**)	(**2.09**)	(-0.06)	(**-6.31**)	(**-11.29**)	
5		0.02	0.01	-0.02	-5.88	-0.28	-0.05	-8.06	0.22	0.01	-0.86	-3.11	5.66
		(0.84)	(0.56)	(-0.20)	(-1.08)	(-1.51)	(-0.16)	(**-5.94**)	(**2.01**)	(0.11)	(**-6.36**)	(**-9.32**)	

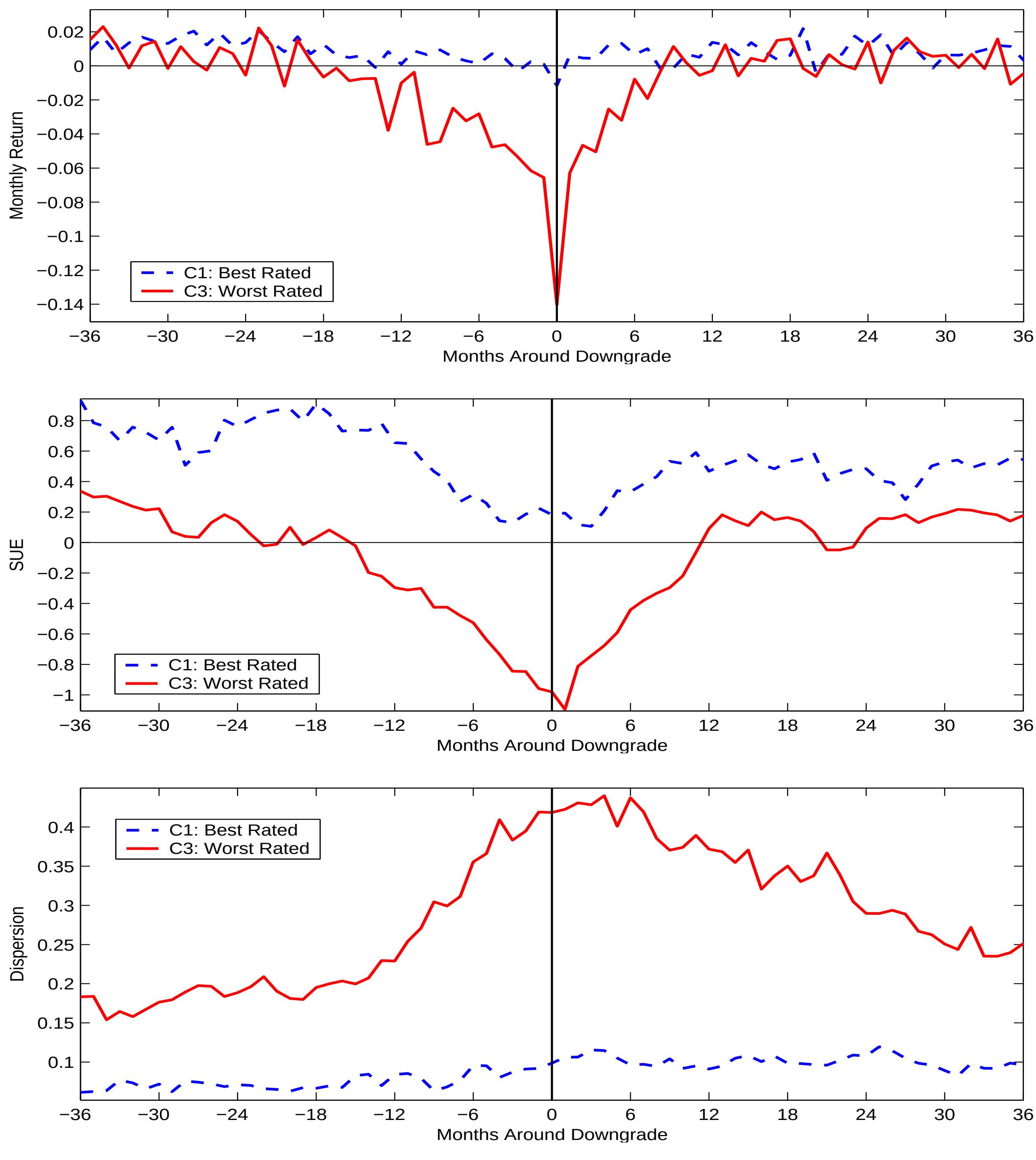

Figure 1. Conditioning Variables around Downgrades. Each month t, all stocks rated by Standard & Poor's with available return data in CRSP are divided into terciles based on credit rating. Within each tercile, we find firms that have been downgraded in month t and compute their equally weighted average 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.

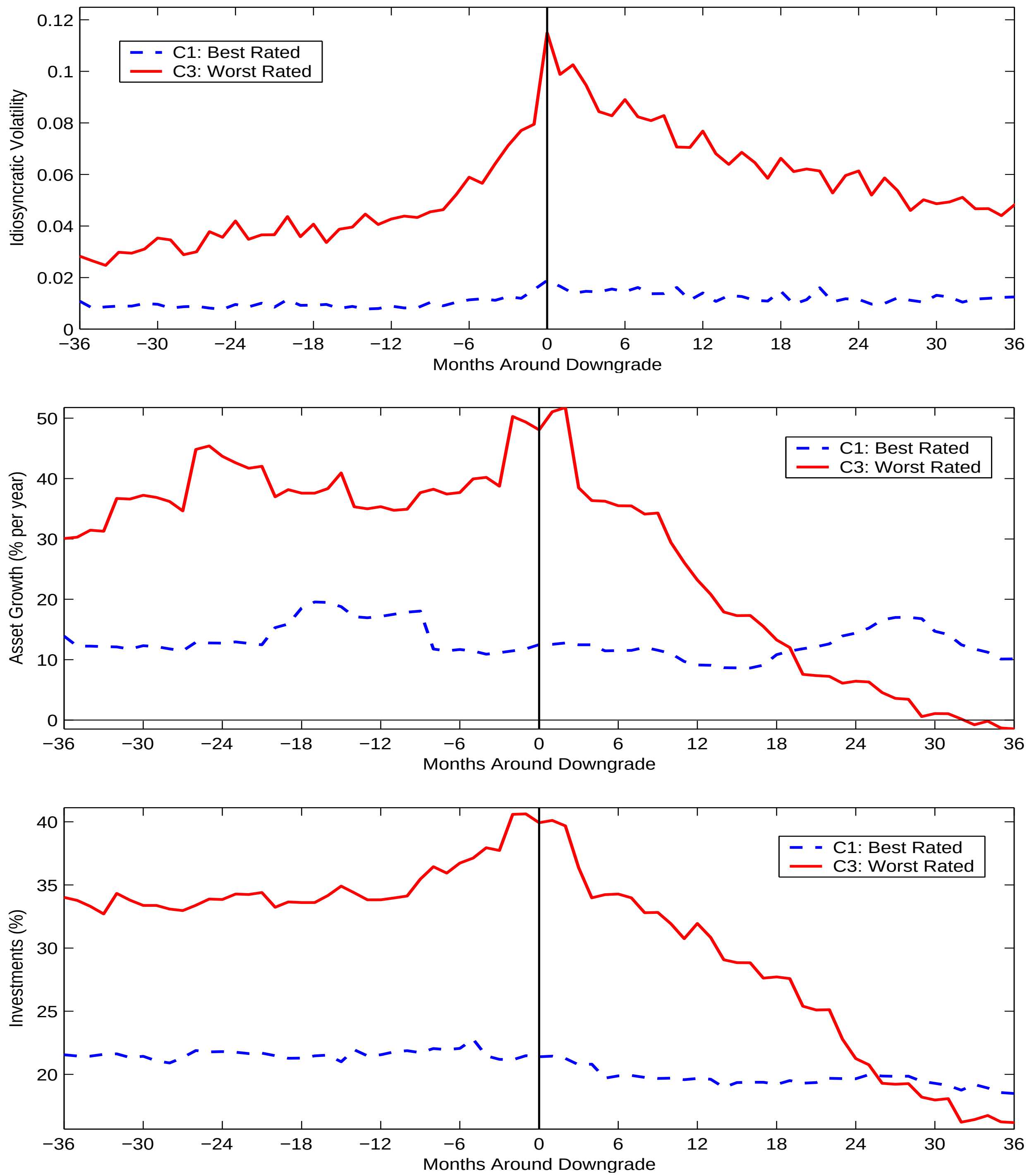

Figure 1(continued). Conditioning Variables around Downgrades.

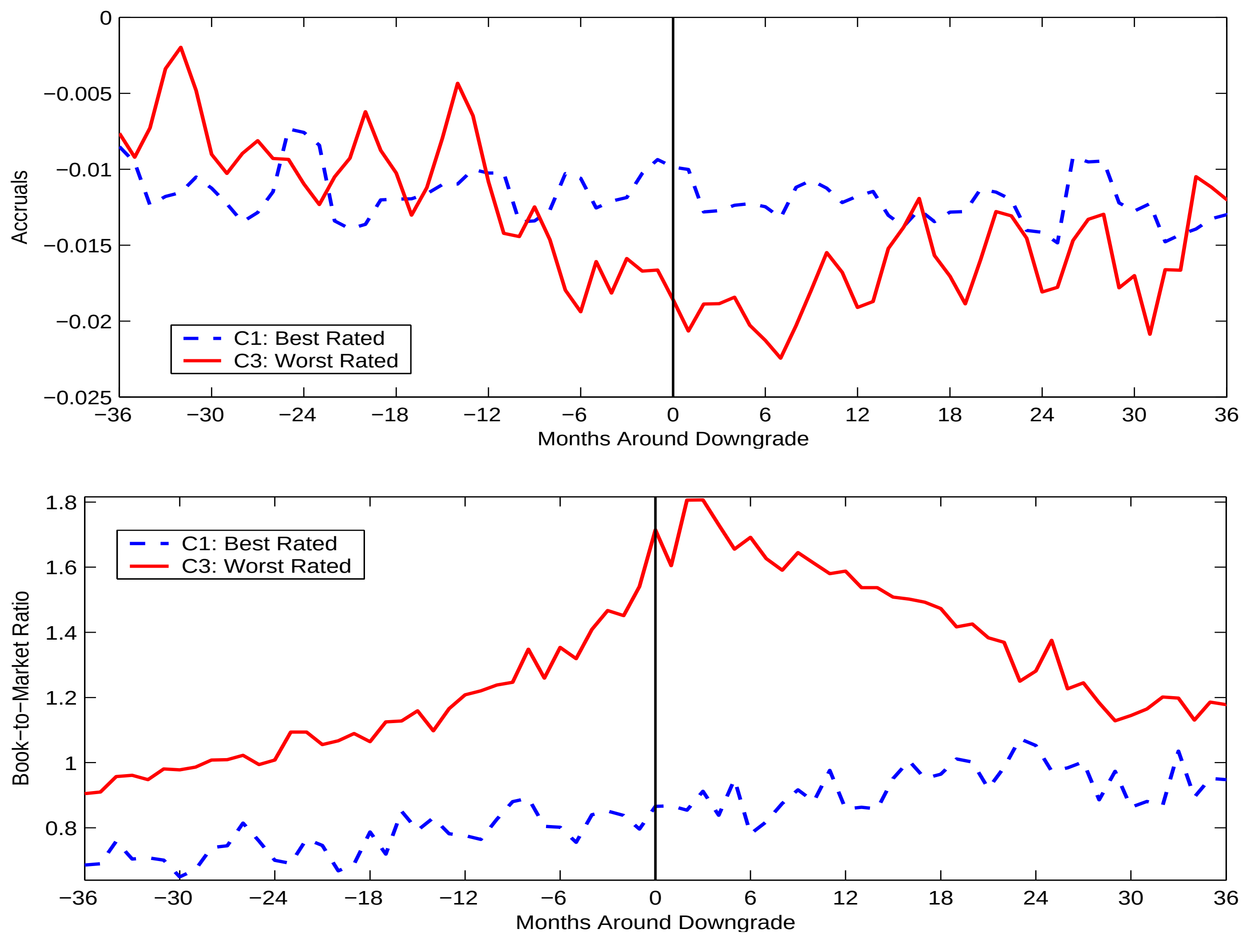

Figure 1(continued). Conditioning Variables around Downgrades.

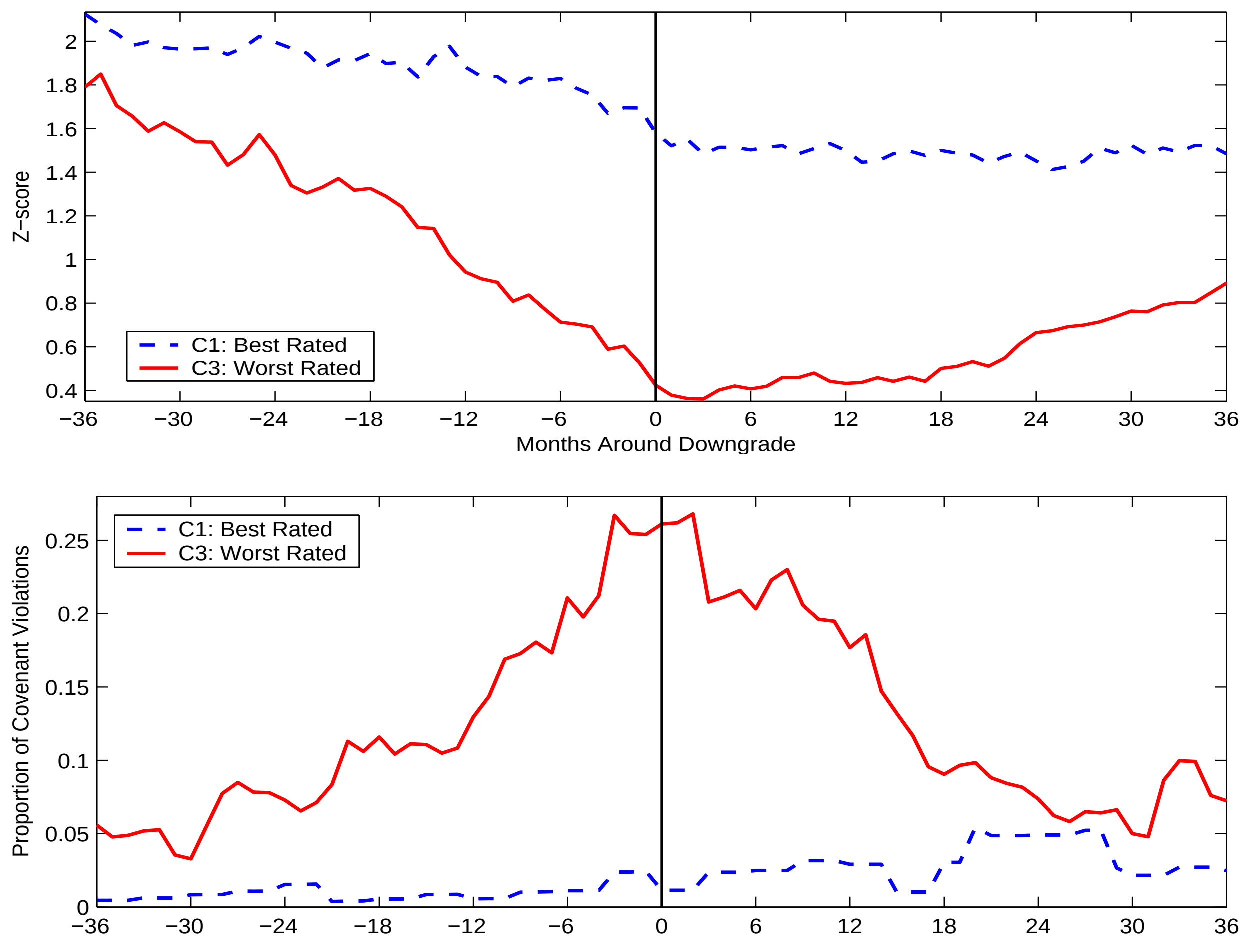

Figure 2. Z-scores and Proportion of Covenant Violations around Downgrades. Each month t, all stocks rated by Standard & Poor's with available return data in CRSP are divided into terciles based on credit rating. Within each tercile, we find firms that have been downgraded in month t and compute their 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
Profits from Asset-Pricing Anomalies in All Firms

We repeat the analysis in Table 2 considering all firms listed on NYSE, Amex, and Nasdaq over the period October 1985 to December 2008. Stocks priced below $1 at the beginning of the month are removed. All return adjustments and cut-offs for the size groups are the same as in Table 2. For the Credit Risk anomaly, we use here Z-scores rather than credit ratings, since these are available for both rated and unrated firms.

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	P5-P1	P1-P5	P1-P5	P1-P5	P1-P5	P1-P5	P5-P1
All Firms	P1	-1.14	-0.54	-1.48	0.38	-0.03	-0.33	-0.29	-0.33	-0.46
	P5	0.18	0.28	-0.17	-0.47	-1.33	-0.84	-0.73	-0.53	-0.34
	Strategy	1.32	0.82	1.31	0.85	1.30	0.52	0.44	0.20	0.13
		(**7.01**)	(**6.86**)	(**8.44**)	(**4.60**)	(**5.43**)	(**4.90**)	(**3.10**)	(**4.13**)	(1.43)
Micro	P1	-1.33	-0.79	-1.64	0.50	-0.24	-0.47	-0.44	-0.43	-0.79
	P5	0.12	0.46	-0.19	-0.64	-1.38	-1.07	-0.88	-0.67	-0.39
	Strategy	1.45	1.25	1.45	1.14	1.13	0.60	0.43	0.24	0.39
		(**8.78**)	(**9.53**)	(**8.88**)	(**6.10**)	(**4.52**)	(**5.69**)	(**3.57**)	(**5.15**)	(**3.06**)
Small	P1	-0.91	-0.40	-1.32	0.39	0.10	-0.05	-0.09	-0.19	-0.31
	P5	0.28	0.36	-0.14	-0.33	-1.52	-0.63	-0.55	-0.33	-0.26
	Strategy	1.18	0.76	1.17	0.72	1.62	0.58	0.46	0.14	0.04
		(**5.00**)	(**5.09**)	(**5.46**)	(**3.37**)	(**5.00**)	(**4.10**)	(**2.58**)	(1.92)	(0.35)
Big	P1	-0.53	-0.12	-0.53	0.26	0.06	0.06	-0.01	-0.08	-0.13
	P5	0.27	0.10	-0.07	-0.26	-1.12	-0.43	-0.34	-0.14	-0.01
	Strategy	0.79	0.22	0.46	0.52	1.19	0.48	0.33	0.06	0.12
		(**2.82**)	(1.51)	(**2.64**)	(**2.04**)	(**2.87**)	(**2.88**)	(1.36)	(0.63)	(0.97)

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	P5-P1	P1-P5	P1-P5	P1-P5	P1-P5	P1-P5	P5-P1
All Firms	P1	-0.63	-0.18	-0.89	0.16	0.08	0.08	0.03	-0.05	-0.09
	P5	0.28	0.07	-0.01	-0.41	-1.35	-0.35	-0.28	-0.16	-0.11
	Strategy	0.91	0.25	0.89	0.57	1.44	0.42	0.31	0.11	-0.02
		(**3.39**)	(1.52)	(**4.93**)	(**2.12**)	(**4.04**)	(**2.36**)	(1.08)	(0.99)	(-0.18)
Micro	P1	-1.26	-0.65	-1.70	0.45	-0.10	-0.31	-0.29	-0.27	-0.61
	P5	0.23	0.42	-0.12	-0.63	-1.53	-0.98	-0.81	-0.54	-0.40
	Strategy	1.50	1.07	1.58	1.08	1.43	0.67	0.51	0.26	0.21
		(**7.87**)	(**7.21**)	(**8.18**)	(**5.18**)	(**5.21**)	(**5.71**)	(**3.47**)	(**4.39**)	(1.83)
Small	P1	-0.88	-0.39	-1.35	0.37	0.11	-0.06	-0.07	-0.16	-0.25
	P5	0.28	0.31	-0.10	-0.37	-1.50	-0.63	-0.57	-0.31	-0.28
	Strategy	1.16	0.70	1.24	0.74	1.60	0.56	0.50	0.15	-0.03
		(**4.76**)	(**4.52**)	(**5.60**)	(**3.25**)	(**4.80**)	(**3.70**)	(**2.63**)	(1.88)	(-0.22)
Big	P1	-0.51	-0.14	-0.68	0.15	0.08	0.12	0.05	-0.02	-0.08
	P5	0.29	0.06	0.01	-0.40	-1.28	-0.27	-0.17	-0.09	-0.03
	Strategy	0.80	0.20	0.69	0.55	1.36	0.39	0.22	0.07	0.05
		(**2.72**)	(1.12)	(**3.52**)	(1.88)	(**3.03**)	(**1.99**)	(0.69)	(0.53)	(0.44)

Table 2B

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)