Why Do Firms Manage Earnings?

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Abstract

I examine earnings management of firms using a sample of all firms with sufficient data availability covering the period 1980 to 1997. The objective is to answer what goals managers pursue when they manage the firms' earnings and how investors react to observable earnings management. Earnings can be thought of as a combination of cash flows and adjustments. The stated purpose of these adjustments is to better reflect "true" economic performance in the earnings numbers. Managers, however, have some discretion over the adjustments they make. They can, for example, increase current earnings to either signal good future performance (signaling), or to hide bad past performance (manipulation). Discretionary current accruals (DCA) are used as a proxy for voluntary earnings management. The analyses show that high DCA predict low future returns but are also associated with high current and past returns. Additionally, DCA exhibit negative autocorrelation. Overall, this is evidence that, at least, some firms manipulate their earnings successfully.

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Corporate earnings receive a great deal of attention from both investors and corporate managers. They are the measure of choice in communicating a company's performance and value to the public. Quarterly earnings announcements frequently cause significant stock price movements. In short, corporate earnings seem to provide valuable information. Not surprisingly, business schools' and firms' accounting departments are entirely dedicated to earnings and many analysts on Wall Street earn their money analyzing and predicting earnings.

One way to assess the value and accuracy of the information contained in earnings is to examine the relationship between earnings and subsequent stock returns. Lev (1989) provides an overview of two decades of empirical accounting research and finds a low correlation between earnings and stock returns. Based on this, he questions the usefulness of earnings to investors and raises the issue of the low quality, i.e., low information content, of reported earnings. Greig (1992) shows that fundamental analysis using accounting items has no significant incremental power to predict earnings when he controls for firm size and risk measured by the CAPM beta. Zarowin (1989) tests whether the stock market overreacts to extreme earnings. He finds that over the 36 months following the extreme earnings event the firms with the lowest earnings outperform the highest earners but his result disappears when he controls for firm size.

Contrary to the evidence of a low usefulness of earnings to predict stock returns, Ou and Penman (1989) document the existence of significant abnormal returns to a trading strategy that uses the prediction of the sign of unexpected earnings per share (EPS) under the assumption that EPS follows a random walk with drift. Similarly, Holthausen and Larcker (1992) find excess returns with a trading strategy based on a logit model that predicts the sign of the subsequent year excess return from accounting ratios. Lamont (1998) shows that on an aggregate level high dividends forecast high returns while high earnings forecast low returns.

The conflicting evidence on the information content of earnings and its usefulness for investors requires taking a closer look at what determines stock returns and what constitutes reported earnings. If stock markets are reasonably, e.g., semi-strong form efficient, trading strategies based on accounting numbers should not consistently yield excess returns. The reason is very simple: accounting numbers are observable and should therefore immediately be incorporated into stock prices. So unless markets are assumed to be inefficient the excess returns found in previous studies cannot be explained. Consequently, the answers might be in the way earnings are reported.

There is a distinct difference between stock prices and earnings. Many investors in a market setting determine the former while the latter are produced by a small number of corporate managers. While it is difficult to influence market prices, accounting principles and standards require managers to adjust earnings. Accruals are frequently used to move reported earnings away from a cash flow measure to an economic value measure. The stated goal is to make earnings a measure of "true" economic value.[1] Dechow (1994) describes under which conditions accruals improve earnings' ability to measure firm performance. She measures true performance through stock returns.

The critical difference between accruals and most other accounting numbers on the one hand and stock returns on the other is that managers have a lot of discretion when deciding on the size and timing of accruals. Considering the large attention that EPS and meeting analysts' earnings forecasts receive managers have huge incentives to deliver the "right" earnings and ample discretion to do so. Therefore, earnings might be more of a reflection of managers' incentives and expectations than of economic performance. The mixture of incentives and expectations makes it a lot harder to analyze earnings and incorporate the information into stock prices because the earnings variables are measured with error. Anecdotal evidence supports this idea. Recently, Fortune magazine dedicated its title story to earnings management under the headline: "Recipe For Jail" (see Loomis (1999)). The Wall Street Journal titled its 'Heard on the Street' column with: "Earnings Management Spurs Selloffs Now" (see Pulliam (1999)). So there

[1] There are further refinements, like the EVA measure (Economic Value Added), that claim to measure true performance better than earnings.

seems to be little doubt that earnings are managed.[2] The interesting questions now are if and how the manipulation can be discovered and what the implications for current and future stock prices are.

Sloan (1996) shows that stock prices do not fully reflect the information in accruals and cash flows about future earnings. He cautions, however, that his findings do not necessarily imply the existence of profitable trading strategies. Houge and Loughran (1999) extend Sloan's analysis. They form portfolios based on accruals and cash flows and find consistently positive excess returns that are robust to the Fama and French (1992, 1993) three-factor model. They conclude that the market overestimates the earnings quality with high accruals and underestimates the persistence of cash flows. My study differs from Houge and Loughran in three ways. First, it focuses on managerial incentives instead of trading strategies. Second, it uses discretionary current accruals (DCA) that measure abnormal accruals instead of total accruals that are scaled by firm size only[3]. Third, I also examine prior and current returns in addition to future returns. This allows me to determine how successful earnings manipulation is while it is performed. For example, if high DCA predict low future returns, low current returns would indicate an under-reaction to new information while high current returns would indicate successful earnings manipulation.

Teoh, Welch, and Wong (1998a) examine the performance of initial public offerings (IPO). Their measure of earnings measurement, discretionary current accruals, is a modification of the Jones (1991) measure and the same measure used here. If there is earnings management it makes most sense just before an equity issue because the issuer makes money selling overpriced stock. Therefore, it would be easiest to detect when using a sample of IPOs. Teoh, Welch, and Wong

[2] "Managed", as used here, can be signaling (conveying true firm value to investors) or manipulation (misleading investors regarding true firm value).

[3] The use of DCA instead of total accruals is important because total accruals might just proxy for industry effects, as accruals usually increase in growing firms and growing firms usually cluster I growing industries. Additionally, growing industries are likely to exhibit high stock returns. Therefore, using total accruals to predict returns might simply detect positive momentum.

find that the firms with the most aggressive accruals prior to the IPO have the worst returns of the subsequent three years. This finding suggests earnings manipulation. Teoh, Welch, and Wong (1998b) repeat their analysis with a sample of seasoned equity offerings and get a similar result. Since firms conducting seasoned equity offerings are usually larger, older, and better covered by analysts the underperformance of high accrual firms in this sample poses an even greater challenge to the efficient market hypothesis than the IPO sample result. In a similar analysis, Rangan (1998) documents that earnings management during the year of the seasoned equity offering predicts both earnings changes and stock returns in the subsequent year. The main distinction between my study and the Teoh et al. papers is that they focus on equity offerings, although they also detect an earnings management effect when they use a sample of all firms, and that they do not examine prior returns.

In other related papers, Beaver, McNichols, and Nelson (1999) show that there does not seem to be any earnings management prior to equity issuing in the property casualty industry and DuCharme, Malatesta, and Sefcik (1999) examine the relationship between earnings management around equity offerings and subsequent shareholder lawsuits.

This paper seeks to extend the previous literature along two dimensions. First, since equity offerings occur quite infrequently but earnings announcements generally receive significant attention each quarter, earnings manipulation is likely to be present more frequently than just prior to equity offerings. Therefore, I focus on the rationale for earnings management of all firms, in particular firms that do not plan equity offerings. Second, I analyze current and prior returns to evaluate the success of earnings management.

Both my portfolio and individual firms analyses provide evidence of low future returns for high DCA firms, and vice versa. In addition, while the firms have low DCA there returns are abnormally low. The results clearly indicate successful earnings manipulation. This also implies some market inefficiency. In addition, firms in extreme DCA groups move back and forth between extremes and DCA exhibit negative autocorrelation.

It seems that some firms try to hide bad performance through earnings management while others do not engage in that practice. Consider two identical firms with identical "true" earnings of \$100 and assume that investors use a discount factor of 0.1 to compute the value of the firm. The market value of the firms at year –1 is \$1,000. In year 0, firm A reports the true earnings and investors value the firm at \$1,000. In year 1, firm A again reports the true earnings of \$100 and investors still value the firm at \$1,000. Firm B, on the other hand engages in earnings manipulation and reports earnings of \$110 in year 0. Investors, not taking the earnings management into account value the firm at \$1,100. In year 1, however, firm B is unable to maintain the earnings adjustments and reports earnings of \$90, leading investors to value the firm at \$900. As a consequence, the stock of the firm not engaging in earnings management has returns of 0% in both years, while firm B's return is 10% during the earnings manipulation and a negative 18.18% in the year following the earnings manipulation when it has to reverse its earnings adjustments (accruals). The simplified example shows what I observe in the data. It is surprising that the earnings management seems to work because the DCA used to proxy for the earnings management are observable.

The issue of earnings management and over-reliance of analysts on reported EPS might be able to explain other phenomena observed in stock prices that do not seem to be consistent with efficient markets, e.g., contrarian investment strategies, momentum strategies, and strategies based on systematic errors in analysts forecasts (see Lakonishok, Shleifer, and Vishny (1994), Chopra, Lakonishok, and Ritter (1992), Chan, Jegadeesh, and Lakonishok (1996), and La Porta (1996)).

The remainder of the paper is organized as follows. Section I describes the earnings management measure and develops the hypotheses. The sample is described in Section II. Section III presents the empirical results and Section IV concludes with a summary and future research ideas.

I. Earnings management measures and stock prices

A) Accrual-based measures of earnings management

The appendix describes how I measure and estimate the accrual-based proxies for earnings management. I basically follow Teoh, Welch, and Wong's (1998a, 1998b) methodology that is based on Jones (1991). Reported earnings are the sum of the cash flow from operations and the total accruals:

$$\text{Net income} = \text{Cash flow from operations} + \text{Total accruals} \qquad (1)$$

In particular the accruals are subject to management's discretion. The accrual adjustments reflect transactions that are known or expected at the present time to impact future cash flows. Examples are allowances for warranties, obsolescence, or bad debt. When the firm sells a product it is reasonable to expect that some items will fail and become subject to the firm's warranty. So when a sale takes place a certain amount needs to be recorded in the warranty accrual account that reflects the expected future expenses associated with the warranty for faulty products. The firm might decide to accrue expenses at a rate of, e.g., 3% of sales. This reduces current income. The firm, however, has a lot of discretion regarding the amount it accrues. If 3% is reasonable, 2.5% or 4% also sound quite reasonable. Since the firm is allowed to change its accrual amounts over time it can generate income or hide income to a certain level by simply changing its assumptions regarding the "correct" accrual amounts. There is, of course, a tradeoff. Increasing earnings in the current period lowers earnings in future periods, and vice versa.

Accruals can be classified into current accruals and long-term accruals. Current accruals adjust short-term assets and liabilities (e.g., provision for bad debt) while long-term accruals adjust long-term net assets (e.g., depreciation). It has been argued in the accounting literature that current accruals provide more discretion for the firm than long-term accruals (e.g., Guenther (1994)). Therefore, at this point the focus of the analysis is on current accruals.

Following Teoh, Welch, and Wong's (1998a) approach I calculate current accruals for each firm. Then the changes in accruals, scaled by the total assets of the firm, are regressed on the change in sales. These regressions are performed separately for each industry. Using the coefficients of these regressions the nondiscretionary accruals are calculated as the fitted values. The discretionary accruals for each firm are the actual accruals minus the nondiscretionary accruals. The appendix describes the procedure in detail.

B) Hypothesis development

If firms manage earnings and the earnings management is not fully observed and understood by investors a portfolio that is long in stocks with the smallest accruals and short in stocks with the highest accruals should provide long-term abnormal excess returns (manipulation). If the earnings management is fully, immediately, and correctly incorporated into stocks prices such a portfolio should not earn excess returns.

If firms increase DCA because their true economic performance is otherwise not correctly reflected in earnings (signaling) the stock price might increase while the firm has high DCA but the DCA should not have any effect on future returns if the investors interpret the DCA correctly. If investors regard the high DCA as an earnings manipulation future returns of high DCA firms should be high because, on average, good news will be revealed.

If firms increase their DCA to hide their inferior performance the earnings management should not have any effect if investors anticipate the firms' motivation. If investors do not correctly anticipate the firm's behavior high DCA should lead to high returns during the manipulation and low future returns. Exhibit 1 summarizes the relationship between DCA and returns for high-DCA firms. This paper tries to determine if firms use DCA for signaling or manipulation purposes.

II. Sample selection and data

The sample contains all firms that have the necessary data availability in Compustat and CRSP starting in 1980 and ending in 1997. To be included in the sample, a firm must have at least two adjacent years of Compustat data (to calculate accruals) as well as three years of subsequent and one year of prior CRSP returns. This leaves the years 1981 through 1994 as the base years where I can analyze the effects of earnings management. Overall, 37,285 firm years of data remain, 16,594 firm years in the period 1981 to 1987 and 20,691 from 1988 to 1994. Table 1 shows the firms in the sample by year and industry.

Differing firm year-ends and the lag between a firm's year-end and the public announcement of results (annual report) require caution when using Compustat data. Generally, Compustat defines a year to contain all firm years ending between June 1 of that calendar year and May 31 of the following calendar year. Compustat year 1992, e.g., contains the data of firm years that ended between June 1, 1992 and May 31, 1993.

I make some simplifying assumptions regarding the firm year and lag time. The event year, Year 0, is defined as the period from June 1 to May 31 of the year following the accrual calculation. I assume that all information contained in the annual report is known on June 1 of the following year. In the example of year 1992, I assume that the annual report information is public knowledge on June 1, 1993. This assumption is certainly unrealistic for firm year-ends after January 31 but gives a generous lag time for all other firms.[4] The event window covers the twelve months of the Compustat year and is denoted Year 0. The preceding year is denoted Year-1 while the following years are Year 1, Year 2, and Year 3 (see Exhibit 2 for a timeline).

Observations are dropped when any one of the data items is missing. This might induce some look-ahead bias because firms that do not have three years of subsequent returns do not enter the sample. This creates a problem when these firms went bankrupt, merged, or got acquired. It is not clear, however, in what direction this bias affects the results.

III. Empirical Analysis

A) Future Returns

1. Portfolio Returns

The first question I try to answer is whether discretionary current accruals scaled by total assets (DCA) affect future returns. Based on the DCA I form ten portfolios on June 1 of each year from 1981 to 1994. A simple sorting on DCA also induces a strong sorting on firm size in that firms in the extreme DCA deciles tend to be much smaller than the firms in the medium DCA deciles. Therefore, I first sort the sample into ten size deciles and then sort each size decile into DCA deciles. The DCA decile group determines into what portfolio the firm enters. Table 2 shows the means of some portfolio characteristics over the entire sample period and two sub-periods. The average DCA over all years and all portfolios is 0.0039, while the lowest accrual portfolio averages -0.1619 and the highest one averages 0.1615. The average ratio of book value of equity to market value of equity over all portfolios and all years is 1.95. It seems that the higher accrual firms have a lower book-to-market ratio with the highest accrual portfolio's mean of 1.39 and the second highest portfolio's mean of 1.65. The book-to-market ratio does not seem to impose a strict ordering on the intermediate portfolios although the central portfolios have higher averages.[5]

The market value of the equity (adjusted for inflation) differs between portfolios but the differences are not statistically different. The average firm in the lowest accrual portfolio has a market value of $573.8 million and the average firm in the highest accrual portfolio has a market capitalization of $635.3 million. In contrast, the center portfolios, 4 through 6, have an average firm market value between $733.5 million and $797.4 million. This shows that the controlling for size in the sort procedure and the portfolio selection works relatively well.

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[4] Firm year-ends between February 1 and May 31 account for about 15% of the sample.
[5] There is a large dispersion of book-to-market ratios within each portfolio. The differences between portfolios appear to be insignificant and I control for book-to-market effects.

The portfolios are formed on June 1 of year 1 and are rebalanced on June 1 of every year.[6] The portfolios are as close to equally sized in the number of firms as possible and contain between 210 and 316 firms. I calculate value-weighted[7] monthly returns for each portfolio beginning with June of Year 1 and ending with May of Year 1.[8] I then run the following regression for each portfolio

$$r_{pt} - r_{ft} = \alpha_p + m\,(r_{mt} - r_{ft}) + s\,(SML_t) + h\,(HML_t) + \varepsilon_{pt}$$

with p = Low, 2, 3, …, High

where r_{pt} is the return on portfolio p at time t, r_{ft} is the risk-free rate at time t, r_{mt} is the return on the value-weighted CRSP market index at time t, SML_t is the return on the Fama-French size portfolio at time t, HML_t is the return on the Fama-French book-to-market portfolio at time t, α_p is the intercept of portfolio p, and ε_{pt} is the error term.[9]

Table 3 presents the result of the regressions using the entire dataset from 1981 to 1994. The regression for each portfolio employs 168 monthly return observations. The α's for the lowest accrual portfolios (Low through 3) are positive and significant. In contrast, the α's for the higher accrual portfolios (7 through High) are negative although only the α for High is significantly different from zero. The intermediate portfolios have insignificant α's. Since these are time-series regressions it is not surprising that the coefficient on the market is highly significant and close to one. With one exception, the coefficient on SML is significant while only three out of ten coefficients on HML are statistically different from zero. SML and HML pick up variations between portfolios due to size and book-to-market that were not perfectly eliminated through the sorting procedure. Overall, the coefficients on SML and HML do not indicate

[6] These are not "true" buy-and-hold returns because we hold the portfolio weights constant as of June 1 of Year 1.
[7] Using value-weighted instead of equally-weighted returns biases the results against finding DCA effects on future returns because smaller firms tend to have more extreme DCA's.
[8] Remember, the "year" begins on June 1 and ends on May 31.
[9] Eugene Fama and Kenneth French generously supplied the time-series of their factor returns.

imbalances in the portfolios due to size or book-to-market. The adjusted R^2's are between .84 and .90.

So far the analysis supports the hypothesis that low accrual firms outperform high accrual firms over a subsequent 12-month period. As a robustness check I form a portfolio that is long on the Low portfolio and short on the High portfolio. Again the excess return of this hedge portfolio is regressed on the excess return of the market, HML, and SML. Consistent with the earlier results, the intercept of this regression is positive (0.53) and significant at the 1%-level. Furthermore, this portfolio is no longer exposed to market risk, size, or book-to-market effects because the coefficients on the market, SML, and HML are insignificant. In addition, the adjusted R^2 is only 0.02. These results suggest that the hedge portfolio offers a virtually risk-free monthly return of, on average, 0.53% per month on a zero net-investment portfolio. This indicates that lower discretionary accrual firms enjoy higher returns than lower discretionary accrual firms. The result might indicate an inefficient use of accounting information by investors.

To verify the robustness of the results the sample is split roughly in half. I repeat the analysis separately for the years 1981 to 1987 and 1988 to 1994. Each regression now has 84 observations. In the 1981 to 1987 period (Table 4), the intercepts become insignificant with the exception of portfolio 6, which has a significantly positive α (0.39). Inspection of the point estimates for the intercepts still reveals generally decreasing returns with increasing accruals but the coefficients lack significance. The hedge portfolio of Low minus High has an α of 0.43 but with a t-value of 1.53 it is insignificant at conventional levels.

In the 1988 to 1994 period (Table 5), the lower DCA portfolios exhibit positive α's (with portfolio 2 being significant) while most of the higher DCA portfolios have negative α's. In particular, the α on High is -0.43 and significant at the 1%-level. Consistent with the earlier results the α's of the lower accrual portfolios generally tend to be higher than those of the higher accrual portfolios. The hedge portfolio Low minus High has an α of 0.56 that is significant at the

1%-level. The size of the α is almost identical to the α of the entire sample. The coefficients on the market, SML, and HML are insignificant and the adjusted R^2 is very small at -0.04. This suggests that the hedge portfolio earns excess returns without being exposed to any residual risk due to the market, size, or book-to-market.

The existence of higher returns for lower accrual firms in the first year following the firms' accrual decision has been established. Next, I check if these higher returns persist beyond the first year. I repeat the analysis above but this time the portfolios are rebalanced every three years, i.e., the firms are sorted and grouped into portfolios on June 1 of 1982, 1985, 1988, 1991, and 1994. This results in 180 observations per portfolio where each firm remains in the portfolio for three years after each regrouping. The results in Table 6 basically confirm the one-year analysis. The α's on the lower accrual portfolios are positive while the α's on the higher accrual portfolios are negative. All but two coefficients, however, are insignificant. For the hedge portfolio Low minus High the α is 0.29 and insignificant. The coefficients on the market, SML, and HML in the hedge portfolio regression are not significant. While there are still higher returns for the lower accrual portfolios their significance is much less than in the one-year return analysis. This finding suggests that most of the higher returns are realized in the first 12 to 24 month following firms' earnings management.

Again, I split the sample in half and repeat the analysis. This provides 90 observations per regression. Table 7 contains the results of regressions using monthly returns from June 1982 to November 1989 where the portfolio is rebalanced on June 1 of 1982, 1985, and 1988. The intercepts and coefficients exhibit a familiar pattern with the lower DCA portfolios' α's being positive and the higher DCA portfolios' α's being negative. Only the α's for portfolios Low, 3, 6, and 9 are significant.[10] The hedge portfolio's α has a point estimate of 0.58 and is significant at the 10%-level, thereby confirming the one-year post formation results.

Table 8 shows the results for the second half of the sample, covering returns from December 1989 to May 1997. Nine out of ten α's are insignificant. Although it appears that the lower accrual portfolios tend to have larger α's than the higher accrual portfolios (in particular 3 vs. 8 and 4 vs. 7) there is no statistical support for this conclusion. The hedge portfolio Low minus High has an insignificant α and even a slightly negative point estimate. Part of the reason for the insignificance is the low and significant α of -0.11 of the Low portfolio. Therefore, the three-year post formation returns in the second half of the sample do not support the earlier results. However, this result is not too disturbing since it is based on portfolios that had been sorted only three times.

In summary, portfolio formation based on discretionary current accruals shows that, even after controlling for market, size, and book-to-market risk factors, firms with lower discretionary current accruals exhibit higher future returns than firms with higher discretionary current accruals. The return differential is strongest for the extreme discretionary accrual firms. In the next section, I will use individual firms as opposed to portfolios to further examine the impact of discretionary current accruals on future returns.

2. Individual Stock Return

I examine individual firm three-year buy-and-hold returns. Similarly to the earlier analysis the returns are measured from June 1 of Year 1 through May 31 of Year 3. Four indicator variables replace the portfolio formation. The DCA portfolios are collapsed into quintiles and assigned the indicator variables accordingly. The lowest accrual quintile is indicated by the variable LOWEST, the second lowest quintile by LOW, the highest by

[10] The positive and significant coefficient on portfolio 6 also appears in Table 4 and is difficult to explain.

HIGHEST, and the second highest by HIGH. Since I combine all firm years into one regression I control for market movements with MARKET. This variable represents the three-year buy-and-hold return on the equally-weighted CRSP market index. Since size and book-to-market are correlated with returns the logarithm of market value (SIZE) and the logarithm of the book-to-market ratio (B/M) are included as control variables.

Table 9 shows the results of the regression of three-year buy-and hold returns on the explanatory variables described above. I also include year-dummy variables and industry group dummy variables as controls but do not report their coefficients. The second column of Table 9 shows the regression over the entire sample period from 1981 to 1993, i.e., the returns cover the period from June 1981 to May 1997. Using each firm year with its three-year return results in 34,132 observations. Since the return periods are overlapping the observations are not independent. Therefore, the t-statistics should be interpreted with caution because they are likely to be overstated.

The results confirm the portfolio analysis. The coefficient on LOWEST is 10.10 and significant at the 1%-level. LOW has a significant coefficient of 8.59, HIGH an insignificant coefficient of 0.01, and HIGHEST a coefficient of -5.72 with 5%-significance. The point estimates indicate that the average stock in the lowest accrual group outperforms the average stock in the highest accrual group by about 14.3% over the subsequent three years. The control variables coefficients are consistent with expectations. B/M is positive, SIZE negative, and the coefficient on the market close to one. An F-test of the equality of the coefficients on LOWEST and HIGHEST is strongly rejected.

As before I split the sample in half. The third column of Table 9 shows the results for the regression using the 16,594 observations from 1981 to 1987 (returns from June 1981 to May 1990). The results are very similar to the entire sample result.

It certainly warrants further investigation.

The fourth column uses the 17,538 observations from 1988 to 1993 (returns from June 1988 to May 1997). The results here are weaker but still have the same direction as the earlier results. Of the accrual dummy variables only LOWEST is significant. However, the coefficient point estimate on HIGHEST is quite negative, though not significant. Still, an F-test rejects the equality of LOWEST and HIGHEST at the 1%-level. Therefore, I regard the individual firm evidence as supportive of the portfolio results.

The caveat of the overlapping return observations, however, remains. To check if this misspecification induces invalid significance I repeat the analysis above but run the regressions separately for each year.[11] Table 10 shows the results of the 14 regressions. While the significance of the variables is substantially reduced the point estimate of LOWEST is always higher than the point estimate on HIGHEST. In addition, the two-sided F-tests of the equality of HIGEST and LOWEST are rejected in seven out of fourteen years. Overall, this is evidence that, while the t-statistics in the combined regressions might be overstated, the results are qualitatively reliable.

Since I do not want to rely on potentially overstated statistics I repeat the analysis in Table 9 but this time using one-year buy-and-hold returns instead of three-year ones. The analysis in Table 11 serves two purposes. First, the problem with overlapping returns disappears. Second, I am able to evaluate when the return effect of DCA is strongest, in the short-run (one year) or the medium range (one year to three years). The second column contains the results over the entire sample period from 1981 to 1994 with 37,285 observations. The results strongly support the earlier analyses. The coefficient on LOWEST is 5.19, on LOW is 2.24, on HIGH is 0.63, and on HIGHEST is -2.35. In addition, LOWEST, LOW, and HIGHEST are significant at 1%, 10% and 5%, respectively. The control variables are as expected and all highly significant. B/M is positive, SIZE is negative, and MARKET close to one. Not surprisingly, the F-test of equality between Lowest and Highest is strongly rejected. Column three and four present the results for the sub-periods. Qualitatively, the coefficients do not change from the entire sample. However, the 16,594 observations from 1981 to 1987 cause LOW to be significant at the 1%-level and HIGHEST to be significant at the 1%-level. The period 1988 to 1994 covers 20,691 observations. Here, LOWEST remains significant at the 1%-level while the other indicator variables are insignificant. Still, the F-test of equality of LOWEST and HIGHEST is strongly rejected in both sub-periods. This leads to the conclusion that the return effect of DCA is strongest during the first year after the earnings management. It also seems that the significance levels are not caused by serially or spuriously correlated returns. However, to further test the robustness of the results and to exclude inadequate expected return adjustments or spurious correlations as the source of the results I perform Fama-MacBeth regressions.

The analysis in Table 12 follows the Fama and MacBeth (1973) methodology. I create five pools of observations, each covering 12 months in event time. The first group contains the monthly returns during Year -1 (see Exhibit 1 for a timeline), the second group the monthly returns during Year 0, etc. Then all observations within a pool are put into calendar time and each regression includes only the observations from one calendar month. This leads to 168 monthly regressions per pool. The table presents the average coefficients of the 168 regressions. The t-statistics are calculated as $\mu(t_m) / \left\lfloor \sigma(t_m) / \sqrt{168-1} \right\rfloor$. Looking at years 1, 2, and 3, the earlier results get full confirmation. In Year 1, the coefficients are 0.41 on LOWEST, 0.05 on LOW, -0.03 on HIGH, and -0.09 on HIGHEST. They are all significant with the exception of HIGH. As expected, the coefficient on B/M is positive and significant and the one on SIZE negative and significant. In year 2 and 3 the indicator variables become mainly insignificant.

At this point, I have established that firms with lower discretionary current accruals have lower future returns and vice versa. This is in particular true for the first year following the manipulation. The result is somewhat disturbing because all information regarding accruals is

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[11] Of course, the market return or year dummies are not included as explanatory variables.

perfectly observable once the annual report is published. In an efficient market, such return differences should not be based on publicly observable information. In the following sections I will further investigate the accrual behavior and try to explain why such returns exist.

B) Past Returns

1. Fama-MacBeth Regressions

An interesting question is whether past returns induce firms to manage their earnings in a certain way. It is possible that poor returns make management anxious to report something positive, in this case, good earnings. High discretionary accruals are certainly a way to make earnings look better. If this were true one would expect firms with low prior returns to end up in the high accrual groups. In contrast, firms might manage their earnings for several years and run up their accruals. If investors do not pay adequate attention to the manipulation one would expect firms with high prior returns to enter the high accrual groups.

I try to test these two hypotheses using the Fama-MacBeth regression results in Table 12. Using the same variables as described above I examine the pre-sorting returns instead of the post-sorting returns. This is somewhat unusual and certainly not an implementable trading strategy because the information used to sort the stocks is only known after the returns have occurred. Additionally, the causality assumed in the earlier regressions is reversed. The rationale for performing this analysis is to understand the time-series of the returns of the firms in the different DCA groups and, more important, to evaluate the degree of success of the earnings manipulation.

The second column of Table 11 shows the results for Year-1. The coefficients are striking. LOWEST is negative at -0.25 and highly significant. HIGHEST, on the other hand, is positive at .15 but not significant. In Year 0 and Year 1 the coefficients reverse signs. LOWEST is positive and significant and HIGHEST is negative and significant. This suggests that investors penalize firms that do not inflate their earnings using DCA just before and during the period of the earnings management. After the earnings manipulation becomes obvious, and “true” earnings are revealed, the returns reverse. This is the clearest evidence so far that DCA are used to mislead investors. During the manipulation they cause comparatively higher returns that cannot be sustained once the market recognizes the true value of the firm.[12] This alone does not necessarily point to market inefficiency because the high accruals could signal superior future performance but, as already shown above, this is not the case. In the next section I verify this result using pooled individual firm observations.

2. Individual Stock Returns

I again run the same kind of regressions as in Table 11 above. The only difference is that I use the buy-and-hold returns preceding the earnings management, i.e., during Year-1, instead of the returns during Year 1. Column two presents the results for the entire sample from 1981 to 1994. The results confirm the Fama-MacBeth analysis. LOWEST is negative at -1.79 and significant, HIGHEST is positive at 4.55 and significant, and the F-test of equality is strongly rejected. B/M, SIZE, and MARKET have the expected signs and are significant. The results for the sub-periods do not change qualitatively. This analysis confirms the Fama-MacBeth results and verifies my hypothesis. Firms manipulating earnings enjoy higher returns while they are manipulating and lower returns afterwards. The return pattern over time suggests that the earnings manipulation is quite successful. This return behavior is also consistent with some momentum and reverse momentum in stock returns. In this sense, earnings manipulation might be one reason these mysterious return patterns exist. In the next section, the time-series of DCA are examined.

[12] In Year-1, the coefficient on B/M is negative and the coefficient on SIZE negative which is exactly opposite from the later years. One reason might be that I take the value of B/M and SIZE at the end of

C) Discretionary Current Accrual Patterns

1. Time-Series Regressions

The first step in analyzing the pattern of DCA is to look at how past DCA are related to future DCA. Over the long run, there almost necessarily has to be some negative autocorrelation in DCA because accounting procedures and principles prevent firms from running up their discretionary accruals indefinitely. So what goes up must come down, and vice versa. It is an interesting empirical question, however, whether firms build up their accruals over a few years and then keep them steady or reduce them, or whether firms have a tendency to reverse the direction of their accrual from year to year. While the observed pattern might not determine what induces the discretionary accruals it provides a guide to where to look for explanations.

For each year from 1985 to 1994 I regress the current year's DCA of each firm on the previous four years of its DCA. Table 14 shows the coefficient on the prior year's DCA to be a negative -0.13 on average with an average t-statistic of -5.52. This coefficient is significant at the 1%-level for each year, except for 1986. The coefficients on the two years prior DCA are also mainly negative but much less significant and smaller in size with an average of 0.05 and an average t-value of -1.90. The earlier years' DCA are largely insignificant. This suggests that, on average, firms reverse the direction of their accrual within one to two years. They seem to use accruals as a temporary adjustment that is going to be reversed soon. This, in fact, is the intended use of accruals. The results in Table 14 do not reveal if the frequent changes of direction in DCA reflect true economic performance or if they are economically justified. This question was answered above by looking at the return pattern. The next section further investigates the pattern of DCA.

Year 0. Therefore, there is some misspecification in the Year-1 and Year 0 regressions.

2. Transition Probabilities

On average, DCA are negatively correlated. This is an unconditional result so it is of interest to determine how DCA change in the following year conditional on the DCA in the current year. I group all firm year observations into deciles each year on June 1 and tabulate the movements from the current year's group to the following year's group. Table 15, Panel A, displays the number of moves that occur in each transition pair. Table 15, Panel B, presents the results in percentages and Panel C collapses the deciles to quintiles. Inspection reveals an interesting pattern. Firms in the extreme quintiles have a tendency to remain in either one of the extreme quintiles while firms in the center quintiles tend to stay within those center quintiles. For example, 22.1% of the firms in the lowest DCA quintile stay in the same quintile in the following year while 26.1% move to the highest quintile. Even more astonishing, 28.2% of the firms in the highest DCA quintile move to the lowest DCA quintile while 23.9% remain in the highest DCA quintile. Of the firms in the center quintiles only about one in three move to one of the extreme DCA deciles.

These patterns seem to suggest that there are two types of firms: one group with moderate accruals and another group of firms whose DCA swing back and forth between the most extreme groups. The identification of the movers and what their motives might be are interesting topics for future research.

IV. Conclusion

There are three main results:

1) High DCA firms underperform low DCA firms over the following three years and, in particular, over the following year.
2) High DCA firms outperform low DCA firms during and just prior to the period of high DCA.

3) DCA are negatively correlated and firms in either extreme group tend to move between extreme groups while firms with medium DCA continue to show medium DCA.

Combined these results suggest that some firms successfully manage their earnings in the sense that when their DCA (and presumably earnings) are high their returns are high, and vice versa. Another group of firms seems to mainly stay away from this kind of earnings management.

Are DCA an efficient way to signal future performance or are DCA used to manipulate earnings and stock prices? Do investors fully understand the impact of DCA? The fact that DCA have a tendency to bounce between extremes and that a trading strategy based on DCA, at least in theory, allows excess returns suggest some form of market inefficiency. The high returns during periods of high DCA and subsequent lower returns strongly suggest earnings manipulation through DCA by firms. On the other hand, these return reversals could simply be a momentum effect. The question then becomes if the correlation between DCA and momentum is spurious or if earnings management contributes to momentum and momentum reversal.

There are several issues for further research and future versions of this paper. Since firms move quickly from one DCA group to the next the time period chosen for return observations is crucial for the results. If firms increase DCA and their stock moves immediately higher and it then moves immediately lower when they decrease DCA it is possible that these movements reflect the latest assessment of future performance. Therefore, an analysis with a smaller frequency, e.g. quarters, might yield additional insights. A more detailed analysis of the extreme DCA movers and their performance could provide additional insights. An important extension in a future version of this paper would be a sorting procedure that controls for momentum and book-to-market in addition to size. The motives of earnings managers also deserve further attention. One motivation could be the desire of managers to beat earnings benchmarks, i.e., to meet analysts' earnings forecasts or to report positive earnings. Dechow, Richardson, and Tuna (2000) find some evidence that accruals are used to beat these benchmarks. However, it seems that managing earnings is a widespread phenomenon that is not limited to cases where firms find themselves close to a benchmark when earnings reports are due. To put a structure on different motivations and investor reactions a convincing theory of earnings management would also be extremely useful.

Appendix

The accrual calculations follow Teoh, Welch, and Wong (1998a). Four variables are calculated using Compustat: discretionary current accruals (DCA), nondiscretionary current accruals (NDCA), discretionary long-term accruals (DLA), and nondiscretionary long-term accruals (NDLA). The calculations use Compustat's annual items (item numbers in parentheses). The total accruals AC are:

AC = Net income (172) - Cash flows from operations (308)

When cash flow from operations (308) is not available (generally before 1988), AC is calculated as:

AC = Funds flow from operations (110)- current accruals CA

Current accruals CA are calculated as:

CA = Δ[accounts receivables (2) + inventories (3) + other current assets (68)]

- Δ[accounts payable (70) + tax payable (71)

+ other current liabilities (72)]

Nondiscretionary accruals are the fitted values of a cross-sectional OLS regression on sales (12) scaled by total assets TA (6) by industry. I use 2-digit SIC codes:

$$\frac{CA_{j,t}}{TA_{j,t-1}} = a_0\left(\frac{1}{TA_{j,t-1}}\right) + a_1\left(\frac{\Delta Sales_{j,t}}{TA_{j,t-1}}\right) + \varepsilon_{j,t}$$

where j $\in$ estimation sample.

Nondiscretionary current accruals are:

$$NDCA_{j,t} = \hat{a}_0\left(\frac{1}{TA_{j,t-1}}\right) + \hat{a}_1\left(\frac{\Delta Sales_{j,t} - \Delta TR_{j,t}}{TA_{j,t-1}}\right)$$

where TR are trade receivables (151).

The discretionary current accruals are then:

$$DCA_{j,t} = \frac{CA_{j,t}}{TA_{j,t-1}} - NDCA_{j,t}$$

The long-term discretionary and nondiscretionary accruals are calculated in a similar fashion:

$$\frac{AC_{j,t}}{TA_{j,t-1}} = b_0\left(\frac{1}{TA_{j,t-1}}\right) + b_1\left(\frac{\Delta Sales_{j,t}}{TA_{j,t-1}}\right) + b_2\left(\frac{PPE_{j,t}}{TA_{j,t-1}}\right) + \varepsilon_{j,t}$$

where PPE = gross property, plant, and equipment (7) as an additional explanatory variable.

Nondiscretionary total accruals NDTAC are:

$$NDTAC_{j,t} = \hat{b}_0\left(\frac{1}{TA_{j,t-1}}\right) + \hat{b}_1\left(\frac{\Delta Sales_{j,t}}{TA_{j,t-1}}\right) + \hat{b}_2\left(\frac{PPE_{j,t}}{TA_{j,t-1}}\right)$$

Nondiscretionary long-term accruals NLA are:

$NLA_{j,t} = NDTAC_{j,t} - NDCA_{j,t}$

Discretionary long-term accruals are then:

$$DLA_{j,t} = \frac{AC_{j,t} - CA_{j,t}}{TA_{j,t-1}} - NLA_{j,t}$$

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Table1: Sample Distribution Across Industries And Time

This table describes the industry and SIC composition of the sample. The industry grouping follows Teoh, Welch, and Wong (1998a), Table 1. Firms with sufficient data availability in Compustat and CRSP are selected in each of the 14 years. The next to last column adds the total number of firms in the sample belonging to the specific industry over the entire sample period. The last column contains the percentage share of that industry of the entire sample. The number of firms in the sample increases continuously from 2105 in 1981 to 3153 in 1994. The total sample contains 37,285 firm-year observations.

Industry	SIC	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	Total	Total %
Oil and Gas	13, 29	138	155	143	139	127	127	132	133	134	148	145	149	151	144	1965	**5.3**
Food Products	20	71	70	70	69	69	67	72	85	92	94	91	93	97	91	1131	**3.0**
Paper and Paper Products	24-27	160	155	144	142	157	145	148	147	141	139	145	145	153	159	2080	**5.6**
Chemical Products	28	118	130	134	139	158	159	169	188	200	211	217	221	256	276	2576	**6.9**
Manufacturing	30-34	221	220	204	188	192	190	190	200	202	211	218	212	214	213	2875	**7.7**
Computer Hardware & Software	35, 73	278	305	316	330	386	394	406	429	427	432	436	425	440	459	5463	**14.7**
Electronic Equipment	36	186	199	204	208	229	230	232	236	243	240	243	248	261	271	3230	**8.7**
Transportation	37, 39, 40-42, 44, 45	155	154	148	147	159	163	166	169	173	180	188	190	197	199	2388	**6.4**
Scientific Instruments	38	144	167	174	173	195	190	199	218	221	217	221	222	241	250	2832	**7.6**
Communications	48	29	30	35	36	47	47	47	50	54	61	60	57	69	67	689	**1.8**
Electric and Gas Services	49	31	32	166	167	171	178	179	174	180	186	186	189	186	171	2196	**5.9**

Industry	SIC	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	Total	Total %
Durable Goods	50	72	74	74	78	78	81	83	88	95	99	100	98	108	98	1226	**3.3**
Retail	53, 54, 56, 57, 59	106	96	91	85	99	100	120	130	134	140	142	144	164	172	1723	**4.6**
Eating and Drinking Establishments	58	34	36	38	40	46	44	46	46	46	48	50	54	61	60	649	**1.7**
Financial Services	61, 62, 64, 65	27	28	26	32	40	45	42	41	35	34	38	44	41	43	516	**1.4**
Entertainment Services	70, 78, 79	39	40	41	38	42	42	46	56	56	56	54	54	56	51	671	**1.8**
Health	80	10	10	12	16	24	35	44	54	48	44	53	57	66	70	543	**1.5**
Other	1, 7, 10, 12, 14-17, 21-23, 46, 47, 51, 52, 55, 60, 63, 67, 72, 75, 76, 82, 83, 87, 99	286	279	274	284	299	312	316	351	356	353	358	350	355	359	4532	**12.2**
Total		2105	2180	2294	2311	2518	2549	2637	2795	2837	2893	2945	2952	3116	3153	37285	**100.0**

Table 2: Portfolio Characteristics

Portfolios based on the market value of equity (Size) and discretionary current accruals (DCA) are formed at the end of each Compustat year (May 31). For example, the 1981 portfolios are formed on May 31, 1982. All firms are initially sorted into ten, as equally sized as possible, groups. Then, each group is sorted by DCA into 10 subgroups. Finally, firms are assigned to the portfolios based on their DCA subgroup ranking. The portfolio with the lowest DCA is termed 'Lowest', the one with the highest DCA 'Highest'. The first column of each category shows the mean over the entire sample period, the second column the mean over the first half, and the third column the mean over the second half of the sample period. The last row of the table contains the mean of the respective category over all ten portfolios. The DCA clearly exhibit the desired order. Size varies between portfolios but not in a systematic way and the differences between portfolios are insignificant (tests not reported here). Since the sorting procedure does not control for book-to-market there are differences between the portfolios. Most pronounced is the low book-to-market ratio of the highest DCA portfolio. This difference does not seem to be too significant (tests not reported here) but all further analyses control for book-to-market effects.

	DCA			Book-to-market			Size (MV of equity)		
	1981-1994	1981-1987	1988-1994	1981-1994	1981-1987	1988-1994	1981-1994	1981-1987	1988-1994
	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
Lowest	-0.1619	-0.1609	-0.1628	1.95	1.98	1.91	573.8	513.0	634.7
2	-0.0620	-0.0623	-0.0617	2.01	2.04	1.97	720.2	587.5	853.0
3	-0.0337	-0.0344	-0.0330	2.14	2.23	2.05	694.5	593.2	795.8
4	-0.0157	-0.0157	-0.0157	2.28	2.33	2.23	797.4	709.3	885.5
5	-0.0022	-0.0015	-0.0029	2.27	2.39	2.16	733.5	573.9	893.2
6	0.0106	0.0118	0.0094	2.10	2.19	2.02	776.7	678.7	874.7
7	0.0253	0.0270	0.0236	1.97	1.98	1.96	683.7	524.7	842.8
8	0.0446	0.0468	0.0424	1.78	1.81	1.75	648.4	504.2	792.6
9	0.0735	0.0761	0.0708	1.65	1.77	1.54	751.6	707.6	795.6
Highest	0.1615	0.1647	0.1583	1.39	1.51	1.27	635.3	560.8	709.8
Total	0.0039	0.0050	0.0028	1.95	2.02	1.89	701.0	594.9	807.1

Table 3: Monthly Time-Series Regression Of One-Year Post Formation Returns With Annual Rebalancing 1981-1994

The equation $r_{pt} - r_{ft} = alpha + m * Market_t + s * SML_t + h * HML_t + \varepsilon_t$, where p denotes the portfolios 'Low' through 'High', Market is the value-weighted CRSP return, SML and HML are the Fama-French factors, and ε an error term is estimated. The regression is run separately for each portfolio and uses 168 monthly returns. Portfolios are rebalanced on June 1 of each year. The base year refers to the fiscal year that is the basis for the sorting. For example, the 1981 portfolio is formed on June 1, 1982 data and the return on the 1981 portfolio is taken monthly starting on June 1, 1982, and ending on May 31, 1983. The last row presents the regression results for a hedge portfolio that is long in Low and short in High. Alphas are in percent per month. The lower DCA portfolios tend to have positive and significant alphas while the higher DCA portfolios have negative alphas. The hedge portfolio has a highly significant alpha of 0.53 % per month and only insignificant loadings on the other factors. T-statistics are in parentheses and ***, **, and * denote significance at the 1%, 5%, and 10%-level, respectively.

Portfolio	alpha	m	s	h	Adj. R2
Low	0.1924	0.9539	0.1827	-0.1932	0.9011
	(1.661)*	(32.028)***	(3.772)***	(-3.629)*	
2	0.2769	0.9279	-0.0865	-0.1631	0.9081
	(2.672)***	(34.816)***	(-1.995)**	(-3.423)***	
3	0.2253	0.9474	-0.0487	0.0183	0.8676
	(1.822)*	(29.792)***	(-0.941)	(0.322)	
4	0.0747	0.8866	-0.1514	0.0776	0.8635
	(0.644)	(29.686)***	(-3.116)***	(1.453)	
5	0.0876	0.9088	-0.2315	0.0212	0.8628
	(0.725)	(29.240)***	(-4.579)***	(0.382)	
6	0.1194	0.9035	-0.2258	0.0177	0.8717
	(1.043)	(30.672)***	(-4.713)***	(0.335)	
7	-0.0009	0.9022	-0.1854	-0.0491	0.8379
	(-.007)	(26.237)***	(-3.315)***	(-0.800)	
8	-0.0286	0.9711	-0.0321	-0.0179	0.8682
	(-0.224)	(29.534)***	(-0.600)	(-0.224)	
9	-0.0264	0.9951	-0.1044	-0.0507	0.8873
	(-0.219)	(32.193)***	(-2.076)**	(-0.917)	
High	-0.3339	1.0206	0.2527	-0.2418	0.8850
	(-2.430)***	(28.875)***	(4.396)***	(-3.827)**	
Low - High	0.5263	-0.0667	-0.0700	0.0486	0.0233
	(3.165)***	(-1.559)	(-1.006)	(0.635)	

Table 4: Monthly Time-Series Regression Of One-Year Post Formation Returns With Annual Rebalancing 1981-1987

The equation $r_{pt} - r_{ft} = alpha + m * Market_t + s * SML_t + h * HML_t + \varepsilon_t$, where p denotes the portfolios 'Low' through 'High', Market is the value-weighted CRSP return, SML and HML are the Fama-French factors, and ε an error term is estimated. The regression is run separately for each portfolio and uses 84 monthly returns. Portfolios are rebalanced on June 1 of each year. The base year refers to the fiscal year that is the basis for the sorting. For example, the 1981 portfolio is formed on June 1, 1982 data and the return on the 1981 portfolio is taken monthly starting on June 1, 1982, and ending on May 31, 1983. The last row presents the regression results for a hedge portfolio that is long in Low and short in High. Alphas are in percent per month. The lower DCA portfolios tend to have positive alphas while the two highest DCA portfolios have negative alphas. The hedge portfolio has a highly significant alpha of 0.43 % per month and only insignificant loadings on the other factors. T-statistics are in parentheses and ***, **, and * denote significance at the 1%, 5%, and 10%-level, respectively.

Portfolio	alpha	m	s	h	Adj. R2
Low	0.2230	0.9325	0.1528	-0.1669	0.9033
	(1.155)	(21.758)***	(1.863)*	(-1.846)	
2	0.1796	0.9725	-0.0847	-0.0414	0.9192
	(1.050)	(25.602)***	(-1.165)	(-0.516)	
3	0.1534	0.9729	0.0035	0.0881	0.8938
	(0.794)	(22.679)***	(0.043)	(0.973)	
4	0.1725	0.9214	-0.1006	0.1443	0.8856
	(0.927)	(22.308)***	(-1.272)	(1.655)	
5	0.0086	0.9387	-0.1074	0.0982	0.8894
	(0.045)	(22.446)	(-1.342)	(1.113)	
6	0.3870	0.8990	-0.2221	-0.0521	0.9073
	(2.281)**	(23.863)***	(-3.08)***	(-0.656)	
7	0.1361	0.9434	-0.1129	-0.0291	0.9189
	(0.823)	(25.695)***	(-1.607)	(-0.375)	
8	0.1257	0.9815	-0.0006	-0.0472	0.9083
	(0.674)	(23.687)***	(-0.007)	(-0.540)	
9	-0.0339	1.0028	-0.1871	-0.0755	0.9190
	(-0.191)	(24.493)***	(-2.485)**	(-0.909)	
High	-0.2046	1.0058	0.2847	-0.2872	0.8870
	(-0.860)	(19.037)***	(2.815)***	(-2.576)**	
Low - High	0.4276	-0.0733	-0.1318	0.1203	0.0601
	(1.526)	(-1.178)	(-1.107)	(0.916)	

Table 5: Monthly Time-Series Regression Of One-Year Post Formation Returns With Annual Rebalancing 1988-1994

The equation $r_{pt} - r_{ft} = alpha + m * Market_t + s * SML_t + h * HML_t + \varepsilon_t$, where p denotes the portfolios 'Low' through 'High', Market is the value-weighted CRSP return, SML and HML are the Fama-French factors, and ε an error term is estimated. The regression is run separately for each portfolio and uses 84 monthly returns. Portfolios are rebalanced on June 1 of each year. The base year refers to the fiscal year that is the basis for the sorting. For example, the 1988 portfolio is formed on June 1, 1989 data and the return on the 1988 portfolio is taken monthly starting on June 1, 1989, and ending on May 31, 1990. The last row presents the regression results for a hedge portfolio that is long in Low and short in High. Alphas are in percent per month. The lower DCA portfolios tend to have positive and significant alphas while the higher DCA portfolios have negative alphas. The hedge portfolio has a highly significant alpha of 0.56% per month and only insignificant loadings on the other factors. T-statistics are in parentheses and ***, **, and * denote significance at the 1%, 5%, and 10%-level, respectively.

Portfolio	alpha	m	s	h	Adj. R2
Low	0.1283	1.0102	0.2046	-0.2357	0.8989
	(0.928)	(23.018)***	(3.624)***	(-3.734)***	
2	0.3026	0.8751	-0.0641	-0.2703	0.8893
	(2.462)**	(22.436)***	(-1.278)	(-4.819)***	
3	0.2553	0.9175	-0.0790	-0.0284	0.8066
	(1.549)	(17.535)***	(-1.173)	(-0.377)	
4	-0.0494	0.8254	-0.1804	0.0129	0.8065
	(-0.339)	(17.858)***	(-3.034)***	(0.194)	
5	0.2486	0.8498	0.5369	0.2243	0.9241
	(2.449)**	(26.201)***	(12.954)***	(4.843)***	
6	-0.0846	0.8746	-0.2397	0.0558	0.7981
	(-0.539)	(17.561)***	(-3.741)***	(0.779)	
7	-0.1215	0.8075	-0.2359	-0.0637	0.6687
	(-0.584)	(12.232)***	(-2.778)***	(-0.671)	
8	-0.1467	0.9284	-0.0606	0.0020	0.7776
	(-0.810)	(16.160)***	(-0.819)	(0.024)	
9	0.0057	0.9709	-0.0346	-0.0428	0.8179
	(0.034)	(18.032)***	(-0.499)	(-0.554)	
High	-0.4315	1.0304	0.2162	-0.2057	0.8765
	(-2.758)***	(20.746)	(3.383)***	(-2.880)***	
Low - High	0.5599	-0.0201	-0.0116	-0.0300	-0.0350
	(2.871)***	(-0.325)	(-0.145)	(-0.377)	

Table 6: Monthly Time-Series Regression Of Three-Year Post Formation Returns With Rebalancing Every Three Years 1981-1994

The equation $r_{pt} - r_{ft} = alpha + m * Market_t + s * SML_t + h * HML_t + \varepsilon_t$, where p denotes the portfolios 'Low' through 'High', Market is the value-weighted CRSP return, SML and HML are the Fama-French factors, and ε an error term is estimated. The regression is run separately for each portfolio and uses 180 monthly returns. Portfolios are rebalanced on June 1 every three years, i.e., 1981, 1984, 1987, 1990, and 1993. The base year refers to the fiscal year that is the basis for the sorting. For example, the 1981 portfolio is formed on June 1, 1982 data and the return on the 1981 portfolio is taken monthly starting on June 1, 1982, and ending on May 31, 1985. The last row presents the regression results for a hedge portfolio that is long in Low and short in High. Alphas are in percent per month. The lower DCA portfolios tend to have positive alphas while the higher DCA portfolios have negative alphas. The hedge portfolio has an (insignificant) alpha of 0.29 % per month and only insignificant loadings on the other factors. T-statistics are in parentheses and ***, **, and * denote significance at the 1%, 5%, and 10%-level, respectively.

Portfolio	alpha	m	s	h	Adj. R2
Low	0.1511	0.9703	0.1511	-0.0795	0.8413
	(1.047)	(25.918)***	(2.579)**	(-1.210)	
2	0.1467	0.9590	-0.0719	-0.0576	0.8724
	(1.208)	(30.448)***	(-1.459)	(-1.042)	
3	0.3658	0.9056	0.0270	-0.0704	0.8799
	(3.252)***	(31.022)***	(0.590)	(-1.374)	
4	0.1352	0.9597	-0.0991	0.1598	0.8611
	(1.127)	(30.836)***	(-2.034)**	(2.925)***	
5	0.0203	0.9262	-0.1384	0.0968	0.8350
	(0.157)	(27.519)***	(-2.628)***	(1.638)***	
6	0.0273	0.9238	-0.0190	0.0555	0.8528
	(0.221)	(28.841)***	(-0.379)	(0.987)	
7	-0.2337	0.9402	-0.1428	-0.0102	0.8213
	(-1.642)	(25.458)***	(-2.471)***	(-0.157)	
8	-0.2163	1.0441	0.0584	0.1302	0.8681
	(-1.667)*	(31.015)***	(1.109)	(2.203)**	
9	-0.0352	0.9818	-0.1095	-0.0255	0.8924
	(-0.316)	(33.946)***	(-2.421)**	(-0.502)	
High	-0.1381	0.9545	0.1246	-0.1532	0.8506
	(-0.989)	(26.325)***	(2.196)**	(-2.406)**	
Low - High	0.2892	0.0158	0.0265	0.0736	-0.0129
	(1.499)	(0.316)	(0.338)	(0.838)	

Table 7: Monthly Time-Series Regression Of Three-Year Post Formation Returns With Rebalancing Every Three Years 1981-1987

The equation $r_{pt} - r_{ft} = alpha + m * Market_t + s * SML_t + h * HML_t + \varepsilon_t$, where p denotes the portfolios 'Low' through 'High', Market is the value-weighted CRSP return, SML and HML are the Fama-French factors, and ε an error term is estimated. The regression is run separately for each portfolio and uses 90 monthly returns. Portfolios are rebalanced on June 1 every three years, i.e., 1981, 1984, and 1987. The base year refers to the fiscal year that is the basis for the sorting. For example, the 1981 portfolio is formed on June 1, 1982 data and the return on the 1981 portfolio is taken monthly starting on June 1, 1982, and ending on May 31, 1985. The 1987 portfolio returns end on November 30, 1989 (to get an even split in the sample). The last row presents the regression results for a hedge portfolio that is long in Low and short in High. Alphas are in percent per month. The lower DCA portfolios tend to have positive and significant alphas while the higher DCA portfolios have negative alphas. The hedge portfolio has a significant alpha of 0.58 % per month and only insignificant loadings on the other factors. T-statistics are in parentheses and ***, **, and * denote significance at the 1%, 5%, and 10%-level, respectively.

Portfolio	alpha	m	s	h	Adj. R2
Low	0.3834	0.9740	0.2231	-0.0103	0.8648
	(1.762)*	(19.548)***	(2.423)**	(-.100)	
2	0.2305	0.9843	0.0257	-0.0708	0.9327
	(1.548)	(28.860)***	(0.408)	(-1.010)	
3	0.3536	0.8950	0.1089	0.0123	0.8744
	(1.880)*	(20.787)***	(1.369)	(0.139)	
4	0.1010	1.0106	-0.1220	0.2352	0.8831
	(0.534)	(23.339)***	(-1.525)	(2.644)***	
5	-0.0409	0.9787	-0.0841	0.1760	0.8763
	(-0.213)	(22.285)***	(-1.036)	(1.950)*	
6	0.2966	0.9473	0.0476	0.0003	0.9017
	(1.715)*	(23.927)***	(0.650)	(0.003)	
7	-0.1566	0.9979	-0.0350	-0.0849	0.9110
	(-0.893)	(24.854)***	(-0.472)	(-1.029)	
8	-0.2784	1.1033	-0.0167	0.1348	0.9048
	(-1.463)	(25.310)***	(-0.208)	(1.505)	
9	-0.3016	1.0677	-0.0773	0.1336	0.9102
	(-1.698)*	(26.248)***	(-1.029)	(1.598)	
High	-0.1989	0.9664	0.0495	-0.1683	0.8698
	(-0.917)	(19.444)***	(0.539)	(-1.648)	
Low - High	0.5823	0.1736	0.1736	0.1580	-0.0060
	(1.894)*	(0.109)	(1.334)	(1.093)	

Table 8: Monthly Time-Series Regression Of Three-Year Post Formation Returns With Rebalancing Every Three Years 1987-1993

The equation $r_{pt} - r_{ft}$ = alpha + m * $Market_t$ + s * SML_t + h * HML_t + ε_t, where p denotes the portfolios 'Low' through 'High', Market is the value-weighted CRSP return, SML and HML are the Fama-French factors, and ε an error term is estimated. The regression is run separately for each portfolio and uses 90 monthly returns. Portfolios are rebalanced on June 1 every three years, i.e., 1987, 1990, and 1993. The base year refers to the fiscal year that is the basis for the sorting. For example, the 1990 portfolio is formed on June 1, 1991 data and the return on the 1990 portfolio is taken monthly starting on June 1, 1991, and ending on May 31, 1994. The 1987 portfolio returns start on December 1, 1989 (to get an even split in the sample). The last row presents the regression results for a hedge portfolio that is long in Low and short in High. Alphas are in percent per month. The lower DCA portfolios tend to have positive alphas while the higher DCA portfolios have negative alphas. The hedge portfolio has an insignificant alpha of -0.04 % per month and only insignificant loadings on the other factors. T-statistics are in parentheses and ***, **, and * denote significance at the 1%, 5%, and 10%-level, respectively.

Portfolio	alpha	m	s	h	Adj. R2
Low	-0.1061	0.9729	0.0920	-0.1525	0.8049
	(-0.555)	(16.357)***	(1.238)	(-1.808)*	
2	0.0982	0.8966	-0.1420	-0.0484	0.7652
	(0.519)	(15.239)***	(-1.932)*	(-0.581)	
3	0.3249	0.9507	-0.0415	-0.1343	0.8947
	(2.563)**	(24.107)***	(-0.843)	(-2.401)**	
4	0.1615	0.8775	-0.0712	0.0908	0.8143
	(1.072)	(18.724)***	(-1.217)	(1.367)	
5	0.0754	0.8409	-0.1701	0.0317	0.7473
	(0.426)	(15.268)***	(-2472)**	(0.405)	
6	-0.1773	0.8468	-0.0657	0.0848	0.7629
	(-1.045)	(16.043)***	(-0.996)	(1.133)	
7	-0.2142	0.7919	-0.2113	0.0501	0.6496
	(-1.028)	(12.211)***	(-2.608)**	(0.544)	
8	-0.1178	0.9259	0.1311	0.1201	0.7938
	(-0.675)	(17.060)***	(1.933)*	(1.560)	
9	0.1943	0.8583	-0.1169	-0.1486	0.8731
	(1.528)	(21.700)***	(-2.367)**	(2.649)**	
High	-0.0655	0.9292	0.1866	-0.1417	0.8110
	(-0.358)	(16.311)***	(2.621)**	(-1.754)*	
Low - High	-0.0406	0.0436	-0.0946	-0.0108	-0.0193
	(-0.172)	(0.594)	(-1.031)	(-0.104)	

Table 9: Three-Year Individual Firm Buy-and-Hold Returns 1981 To 1993

The regression equation $$r_t = \alpha + \beta_1 * Lowest_t + \beta_2 * Low_t + \beta_3 * High_t + \beta_4 * Highest_t + \beta_5 * B/M_t + \beta_6 * Size_t + \beta_7 * Market_t + \sum_{i=1}^{T-1} YearDummy_i + \sum_{i=1}^{17} IndustryDummy_i + \varepsilon_t$$ is estimated. $Lowest_t$ is a dummy equal to 1 when the firm is in the lowest DCA quintile at time t and zero otherwise, Low_t equals 1 when the firm is in the second lowest DCA quintile, and $Highest_t$ and $High_t$ are similar dummy variables for the highest and second highest DCA quintile, respectively. B/M_t is the logarithm of ratio of book equity to market equity at the time of the annual sorting, $Size_t$ is the logarithm of the firm's market value, adjusted for inflation, at the time of the annual sorting, $Market_t$ is the return on the equally-weighted CRSP market index, $YearDummy_i$ (results not reported) are indicator variables for the year of the sorting, and $IndustryDummy_i$ (results not reported) are indicator variables for the various industry groups (see Table 1). This is a pooled regression with overlapping return observations. As in the portfolio regressions, firms are sorted into DCA deciles each year (here the deciles are collapsed into quintiles). Then the return over the 36 months following the sorting is regressed on the appropriate explanatory variables. For example, the 1981 sorting is performed on June 1, 1982 data and the 36-month buy-and-hold return on the 1981 sort is calculated from June 1, 1982, to May 31, 1985. The second column has the results over the entire sample period, the third column over the first half, and the fourth column over second half of the sample period. The numbers are in percent over the 3-year return period. The last row contains an F-test of the equality of Lowest and Highest. Overall, Lowest is positive and significant while Highest is negative and, with one exception, significant. Equality of Lowest and Highest is rejected at the 1%-level. T-statistics are in parentheses and ***, **, and * denote significance at the 1%, 5%, and 10%-level, respectively. Due to the overlap in the return observations they are likely to be overstated.

Period	**81 - 93**	**81 - 87**	**88 - 93**
Observations	34,132	16,594	17,538
Lowest	10.1001	7.0986	12.7257
	(3.794)***	(2.553)**	(2.874)***
Low	8.5874	10.9290	6.1444
	(3.254)***	(3.957)***	(1.403)
High	0.0097	1.1438	-1.1284
	(0.004)	(-0.413)	(-0.257)
Highest	-5.7247	-8.2973	-2.4517
	(-2.129)**	(-2.951)***	(-0.549)
B/M	17.4331	16.5051	15.4810
	(17.642)***	(15.552)***	(9.602)***
Size	-2.6086	2.9430	-7.3291
	(-6.142)***	(6.489)***	(-10.562)***
Market	0.9404	0.9571	1.4545
	(18.492)***	(25.639)***	(11.120)***
Adj. R2	0.0417	0.1099	0.0306
F-test			
Lowest = Highest	36.08***	31.24***	12.01***

Table 10: Three-Year Individual Firm Buy-and-Hold Returns Using Annual Regressions 1981 To 1993

This table repeats the analysis of Table 9 but runs the regressions separately for each year. The regression equation $r_t = \alpha + \beta_1 * Lowest_t + \beta_2 * Low_t + \beta_3 * High_t + \beta_4 * Highest_t + \beta_5 * B/M_t + \beta_6 * Size_t + \sum_{i=1}^{17} IndustryDummy_i + \varepsilon_t$ is estimated separately each year. $Lowest_t$ is a dummy equal to 1 when the firm is in the lowest DCA quintile at time t and zero otherwise, Low_t equals 1 when the firm is in the second lowest DCA quintile, and $Highest_t$ and $High_t$ are similar dummy variables for the highest and second highest DCA quintile, respectively. B/M_t is the logarithm of ratio of book equity to market equity at the time of the annual sorting, $Size_t$ is the logarithm of the firm's market value, adjusted for inflation, at the time of the annual sorting, and $IndustryDummy_i$ (results not reported) are indicator variables for the various industry groups (see Table 1). As in the portfolio regressions, firms are sorted into DCA deciles each year (here the deciles are collapsed into quintiles). Then the return over the 36 months following the sorting is regressed on the appropriate explanatory variables. For example, the 1981 sorting is performed on June 1, 1982 data and the 36-month buy-and-hold return on the 1981 sort is calculated from June 1, 1982, to May 31, 1985. The numbers are in percent over the 3-year return period. The last row contains an F-test of the equality of Lowest and Highest. Overall, Lowest is larger than Highest in every year and the equality of Lowest and Highest is rejected in seven out of the fourteen years at statistically significant levels. T-statistics are in parentheses and ***, **, and * denote significance at the 1%, 5%, and 10%-level, respectively.

Period	1981	1982	1983	1984	1985	1986	1987
Observations	2,105	2,180	2,294	2,311	2,518	2,549	2,637
Lowest	28.372	1.922	3.237	0.243	4.235	4.657	13.242
	(2.688)***	(0.279)	(0.401)	(0.042)	(0.764)	(0.824)	(1.671)*
Low	19.304	11.936	6.885	2.010	2.022	18.036	14.477
	(1.890)*	(1.728)*	(0.867)	(0.344)	(0.368)	(3.234)***	(1.844)*
High	-0.279	7.366	6.730	-13.652	1.335	3.612	7.742
	(-0.026)	(1.065)	(0.845)	(-2.321)**	(0.242)	(0.647)	(0.988)
Highest	-9.589	-18.737	-2.720	-14.265	-3.799	-3.198	3.947
	(-0.889)	(-2.688)***	(-0.336)	(-2.386)**	(-0.675)	(-0.564)	(0.496)
B/M	27.239	19.078	12.716	18.309	19.046	7.301	-1.404
	(6.660)***	(7.606)***	(4.032)***	(7.629)***	(8.938)***	(3.425)***	(-0.466)
Size	-5.661	5.099	8.920	6.775	4.425	3.256	0.706
	(-3.148)***	(4.434)***	(6.633)***	(6.956)***	(4.984)***	(3.649)***	(0.569)
Adj. R2	0.1110	0.1362	0.1062	0.0849	0.0709	0.0419	0.0171
F-test Lowest = Highest	12.80***	8.90***	0.57	6.11**	2.18*	1.99	1.41

Period	1988	1989	1990	1991	1992	1993	1994
Observations	2,795	2,837	2893	2,945	2,952	3,116	3,153
Lowest	5.523	9.962	20.553	14.629	6.594	23.136	11.217
	(0.715)	(1.01)	(1.830)*	(1.637)	(0.442)	(2.247)**	(1.154)
Low	3.683	3.430	12.839	15.868	-14.689	19.643	-0.508
	(0.482)	(0.352)	(1.153)	(1.795)*	(-0.998)	(1.915)*	(-0.053)
High	-9.219	-1.387	-3.308	1.321	3.610	7.388	0.261
	(-1.197)	(-0.142)	(-0.296)	(0.148)	(0.245)	(0.722)	(0.027)
Highest	-0.305	-12.546	15.535	4.582	-31.037	12.859	-14.302
	(-0.039)	(-1.262)	(1.370)	(0.502)	(-2.064)**	(1.235)	(-1.466)
B/M	-0.919	12.448	21.307	18.874	9.816	22.146	29.209
	(-0.305)	(3.282)***	(5.528)***	(6.169)***	(1.834)*	(5.600)***	(7.592)***
Size	-4.260	-13.116	-12.072	-3.654	-10.199	-0.185	-3.912
	(-3.497)***	(-8.538)***	(-6.981)***	(-2.627)***	(-4.380)***	(-0.112)	(-2.543)**
Adj. R2	0.0325	0.0472	0.0456	0.0586	0.0392	0.0260	0.0317
F-test Lowest = Highest	0.57	5.35**	0.20	1.26	6.50**	1.01	7.11***

Table 11: One-year Individual Firm Buy-and-Hold Returns 1981 To 1994

The regression equation

$$r_t = \alpha + \beta_1 * Lowest_t + \beta_2 * Low_t + \beta_3 * High_t + \beta_4 * Highest_t + \beta_5 * B/M_t + \beta_6 * Size_t + \beta_7 * Market_t + \sum_{i=1}^{T-1} YearDummy_i + \sum_{i=1}^{17} IndustryDummy_i + \varepsilon_t$$

is estimated. $Lowest_t$ is a dummy equal to 1 when the firm is in the lowest DCA quintile at time t and zero otherwise, Low_t equals 1 when the firm is in the second lowest DCA quintile, and $Highest_t$ and $High_t$ are similar dummy variables for the highest and second highest DCA quintile, respectively. B/M_t is the logarithm of ratio of book equity to market equity at the time of the annual sorting, $Size_t$ is the logarithm of the firm's market value, adjusted for inflation, at the time of the annual sorting, $Market_t$ is the return on the equally-weighted CRSP market index, $YearDummy_i$ (results not reported) are indicator variables for the year of the sorting, and $IndustryDummy_i$ (results not reported) are indicator variables for the various industry groups (see Table 1). This is a pooled regression with non-overlapping return observations. As in the portfolio regressions, firms are sorted into DCA deciles each year (here the deciles are collapsed into quintiles). Then the return over the 12 months following the sorting is regressed on the appropriate explanatory variables. For example, the 1981 sorting is performed on June 1, 1982 data and the 12-month buy-and-hold return on the 1981 sort is calculated from June 1, 1982, to May 31, 1983. The second column has the results over the entire sample period, the third column over the first half, and the fourth column over second half of the sample period. The numbers are in percent over the 1-year return period. The last row contains an F-test of the equality of Lowest and Highest. Overall, Lowest is positive and significant while Highest is negative and, with one exception, significant. Equality of Lowest and Highest is rejected at the 1%-level. T-statistics are in parentheses and ***, **, and * denote significance at the 1%, 5%, and 10%-level, respectively.

Period	**81 - 94**	**81 - 87**	**88 - 94**
Observations	37,285	16,594	20,691
Lowest	5.1930	4.5730	5.8267
	(4.469)***	(3.249)***	(3.315)***
Low	2.2353	3.7548	1.1178
	(1.941)*	(2.686)***	(0.643)
High	0.6262	1.2073	0.1574
	(0.542)	(0.861)	(0.090)
Highest	-2.3475	-2.4882	-2.0774
	(-2.001)**	(-1.748)*	(-1.172)
B/M	4.2065	5.9515	2.4025
	(9.704)***	(11.079)***	(3.714)***
Size	-2.8818	-0.8743	-4.3404
	(-15.555)***	(-3.809)***	(-15.733)***
Market	1.1651	1.0167	1.0857
	(33.442)***	(61.575)***	(22.684)***
Adj. R2	0.1150	0.2576	0.0487
F-test Lowest = Highest	43.03***	25.65***	20.70***

Table 12: Fama-MacBeth Regressions

Columns two through six report average time series coefficients of 168 monthly regressions:

$$r_t = \alpha + \beta_1 * Lowest_t + \beta_2 * Low_t + \beta_3 * High_t + \beta_4 * Highest_t + \beta_5 * B/M_t + \beta_6 * Size_t + \sum_{i=1}^{17} IndustryDummy_i + \varepsilon_t$$

As before, firms are re-sorted every year on June 1. Year-1 refers to the return in the 12 months year prior to the base year, Year 0 to the 12 returns during the base year, Year 1 to the 12 months following the base year, etc. For example, using the 1981 sorting, firms are assigned to groups on June 1, 1982. Year-1 contains the 12 monthly returns of this group from June 1, 1980 to May 31, 1981, Year 0 from June 1, 1981 to May 31, 1982, Year 1 from June 1, 1982 to May 31, 1983, etc. The t-statistics (in parentheses) are computed as $\mu(t_m)/\lfloor\sigma(t_m)/\sqrt{168-1}\rfloor$. The numbers are percent per month. Low DCA firms seem to have lower returns and high DCA firms higher returns during Year-1. In Year 0 and Year 1 the relationship reverses. Beyond Year 1 the significance of variables declines considerably. ***, **, and * denote significance at the 1%, 5%, and 10%-level, respectively.

Period	**Year -1**	**Year 0**	**Year 1**	**Year 2**	**Year 3**
Observations	168	168	168	168	168
Lowest	-0.2542	0.3386	0.4115	0.0618	0.1100
	(-3.2971)***	(2.4307)**	(3.4846)***	(-.4031)	(0.4830)
Low	-0.0382	0.1142	0.1499	0.0546	0.1887
	(-1.0987)	(1.1892)	(2.4705)**	(0.3242)	(2.7783)***
High	-0.0253	-0.1769	0.0766	-0.0310	-0.0046
	(-0.6317)	(-2.8039)***	(0.9686)	(-1.0445)	(-0.2526)
Highest	0.1490	-0.3213	-0.1358	-0.0870	-0.0868
	(0.7417)	(-4.2735)***	(-2.0926)**	(-1.8572)*	(-1.5176)
B/M	-1.1391	-0.4539	0.2169	0.1922	0.1883
	(-11.7856)***	(-4.1986)***	(3.6393)***	(3.5816)***	(3.6748)***
Size	0.0846	-0.0418	-0.1918	-0.0775	-0.0445
	(3.0341)***	(.5258)	(-2.3590)**	(-.3542)	(0.2042)
Intercept	1.5443	1.6562	2.3248	1.4936	1.4865
	(1.3336)	(1.9786)**	(3.3581)***	(1.8177)*	(1.9539)*

Table 13: One-year Prior Individual Firm Buy-and-Hold Returns 1981 To 1994

The regression equation
$$r_t = \alpha + \beta_1 * Lowest_t + \beta_2 * Low_t + \beta_3 * High_t + \beta_4 * Highest_t + \beta_5 * B/M_t + \beta_6 * Size_t + \beta_7 * Market_t + \sum_{i=1}^{T-1} YearDummy_i + \sum_{i=1}^{17} IndustryDummy_i + \varepsilon_t$$
is estimated. $Lowest_t$ is a dummy equal to 1 when the firm is in the lowest DCA quintile at time t and zero otherwise, Low_t equals 1 when the firm is in the second lowest DCA quintile, and $Highest_t$ and $High_t$ are similar dummy variables for the highest and second highest DCA quintile, respectively. B/M_t is the logarithm of ratio of book equity to market equity at the time of the annual sorting, $Size_t$ is the logarithm of the firm's market value, adjusted for inflation, at the time of the annual sorting, $Market_t$ is the return on the equally-weighted CRSP market index, $YearDummy_i$ (results not reported) are indicator variables for the year of the sorting, and $IndustryDummy_i$ (results not reported) are indicator variables for the various industry groups (see Table 1). This is a pooled regression with non-overlapping return observations. As in the portfolio regressions, firms are sorted into DCA deciles each year (here the deciles are collapsed into quintiles). Then the return over the 12 months prior to the base year of the sorting is regressed on the appropriate explanatory variables. For example, the 1981 sorting is performed on June 1, 1982 data and the 12-month prior buy-and-hold return on the 1981 sort is calculated from June 1, 1980, to May 31, 1981. The second column has the results over the entire sample period, the third column over the first half, and the fourth column over second half of the sample period. The numbers are in percent over the 1-year return period. The last row contains an F-test of the equality of Lowest and Highest. Overall, Lowest is negative and, with one exception, significant while Highest is positive and significant. Equality of Lowest and Highest is rejected at the 1%-level. T-statistics are in parentheses and ***, **, and * denote significance at the 1%, 5%, and 10%-level, respectively.

Period	**81 - 94**	**81 - 87**	**88 - 94**
Observations	37,285	16,594	20,691
Lowest	-1.7942	-2.9578	-0.8067
	(-1.742)*	(-1.802)*	(-0.619)
Low	-0.4026	-1.0766	0.1359
	(-0.394)	(-0.660)	(0.105)
High	0.0519	-2.0780	2.5231
	(0.507)	(-1.270)	(1.951)*
Highest	4.5472	3.7557	5.4445
	(4.373)***	(2.262)**	(4.142)***
B/M	-18.8280	-19.4547	-18.6758
	(-49.013)***	(-31.049)***	(3.714)***
Size	1.7109	2.0245	1.4726
	(10.422)***	(7.561)***	(7.199)***
Market	1.1092	1.1477	0.8421
	(51.618)***	(42.236)***	(19.406)***
Adj. R2	0.2165	0.2861	0.1154
F-test Lowest = Highest	38.76***	17.04***	23.55***

Table 14: Time-Series DCA

Each year the equation $DCA_t = \alpha_t + \beta_1 * DCA_{t-1} + \beta_2 * DCA_{t-2} + \beta_3 * DCA_{t-3} + \beta_4 * DCA_{t-4} + \varepsilon_t$ is estimated. The second to last row presents the average coefficients over the 10 annual regressions and the last row the average t-statistic. T-statistics are in parentheses and ***, **, and * denote significance at the 1%, 5%, and 10%-level, respectively. Current year DCA seems to be negatively related to the two prior years' DCA. The coefficients beyond two years prior are mainly insignificant.

Year	DCA(year-1)	DCA(year-2)	DCA(year-3)	DCA(year-4)	Intercept	Adj. R2	Obs.
1985	-0.1451	-0.0781	-0.0479	-0.0615	0.0035	0.0188	1476
	(-4.862)***	(-2.659)***	(-1.620)	(-1.957)*	(1.444)		
1986	0.0107	-0.0891	0.0080	-0.0413	0.0053	0.0059	1536
	(0.439)	(-3.168)***	(0.284)	(-1.482)	(2.186)**		
1987	-0.1828	-0.0692	-0.0624	0.0245	0.0025	0.033	1714
	(-7.083)***	(-2.894)***	(-2.201)**	(0.865)	(1.018)		
1988	-0.1426	-0.0914	-0.0289	0.0171	0.0048	0.0241	1721
	(-5.901)***	(-3.222)***	(-1.183)	(0.634)	(2.009)**		
1989	-0.2441	-0.0686	-0.0487	0.0296	0.0028	0.0586	1875
	(-10.621)***	(-3.014)***	(-1.874)*	(1.274)	(1.244)		
1990	-0.1112	-0.0698	-0.0144	0.0042	-0.0036	0.0146	1937
	(-5.326)***	(-3.251)***	(-0.691)	(0.181)	(-1.764)*		
1991	-0.1448	-0.0189	0.0107	-0.0142	-0.0045	0.0177	2016
	(-6.251)***	(-0.828)	(0.491)	(-0.696)	(-2.228)**		
1992	-0.1047	-0.0355	-0.0606	-0.0101	-0.0015	0.0154	2173
	(-5.304)***	(-1.801)*	(-3.090)***	(-0.523)	(-0.815)		
1993	-0.1324	0.0195	0.0041	-0.0260	0.0027	0.016	2207
	(-6.038)***	(0.952)	(0.206)	(-1.330)	(1.463)		
1994	-0.0895	0.0183	0.0578	0.0276	0.0051	0.0112	2133
	(-4.255)***	(0.882)	(3.027)***	(1.492)	(2.985)***		
Average	-0.1286	-0.0483	-0.0182	-0.0050	0.0017		
Average t	-5.5202	-1.9003	-0.6651	-0.1542	0.7542		

Table 15: Transition Matrices

The three panels show how firms move between DCA deciles in adjacent years. Panel A shows the absolute number of firms over the entire sample period. To be included a firm must have at least two adjacent years of complete data. This results in 31,460 observed transitions. Panel B presents the numbers of Panel A as a percentage of the firms in each decile in the base Year. Panel C collapses the deciles to quintiles and also reports percentages. Some clustering can be observed. Firms in the two extreme quintiles Lowest and Highest tend to stay in their quintile or move to the other extreme quintile. Firms in the central quintiles 2, 3, and 4 tend to stay within the central quintiles.

Panel A

		Year+1										
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Total**
	Lowest	447	324	249	199	204	194	247	321	359	593	3,137
	2	313	303	306	294	261	299	315	359	362	325	3,137
	3	249	302	325	338	333	343	321	360	349	246	3,166
Year	**4**	223	283	328	371	386	406	367	341	261	186	3,152
	5	201	279	314	412	447	424	370	329	222	184	3,182
	6	205	320	335	387	417	345	376	294	252	201	3,132
	7	224	332	392	345	352	386	337	279	267	226	3,140
	8	275	328	386	339	326	271	327	323	318	256	3,149
	9	365	366	320	270	267	257	294	322	357	300	3,118
	Highest	694	340	272	200	166	193	207	237	350	488	3,147
	Total	3,196	3,177	3,227	3,155	3,159	3,118	3,161	3,165	3,097	3,005	31,460

Panel B

		Year+1										
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Total**
	Lowest	14.2	10.3	7.9	6.3	6.5	6.2	7.9	10.2	11.4	18.9	100.0
	2	10.0	9.7	9.8	9.4	8.3	9.5	10.0	11.4	11.5	10.4	100.0
	3	7.9	9.5	10.3	10.7	10.5	10.8	10.1	11.4	11.0	7.8	100.0
Year	**4**	7.1	9.0	10.4	11.8	12.2	12.9	11.6	10.8	8.3	5.9	100.0
	5	6.3	8.8	9.9	12.9	14.0	13.3	11.6	10.3	7.0	5.8	100.0
	6	6.5	10.2	10.7	12.4	13.3	11.0	12.0	9.4	8.0	6.4	100.0
	7	7.1	10.6	12.5	11.0	11.2	12.3	10.7	8.9	8.5	7.2	100.0
	8	8.7	10.4	12.3	10.8	10.4	8.6	10.4	10.3	10.1	8.1	100.0
	9	11.7	11.7	10.3	8.7	8.6	8.2	9.4	10.3	11.4	9.6	100.0
	Highest	22.1	10.8	8.6	6.4	5.3	6.1	6.6	7.5	11.1	15.5	100.0

Panel C

		Year+1					
		1	**2**	**3**	**4**	**5**	**Total**
	Lowest	22.1	16.7	15.3	19.8	26.1	100.0
	2	16.7	21.6	23.2	22.0	16.5	100.0
Year	**3**	15.9	22.9	25.9	21.7	13.6	100.0
	4	18.4	23.2	21.2	20.1	17.0	100.0
	Highest	28.2	17.0	14.1	16.9	23.9	100.0

Exhibit 1: Relationship Of DCA And Returns For High-Low DCA Firms

Investor Beliefs	Current Returns		Future Returns: High	Future Returns: Average	Future Returns: Low
Market believes firm is Signaling		High	Signaling (partially successful)	Signaling (successful)	Manipulation (successful)
Equal probability on Signaling and Manipulation	Current Returns	Average	Signaling (partially successful)	Ambiguous (efficient market reaction)	Manipulation (partially successful)
Market believes Manipulation		Low	Signaling (unsuccessful)	Manipulation (unsuccessful)	Manipulation (partially successful)

- Signaling: Proper accrual accounting that adjusts to "true" earnings
- Manipulation: Improper accrual accounting that overstates "true" earnings

- Successful: Investors interpret adjusted earnings as "true" earnings and stock price moves accordingly
- Unsuccessful: Investors do not interpret reported earnings as "true" earnings and stock price does not react as intended by manager

Investor Beliefs	Current Returns		Future Returns: High	Future Returns: Average	Future Returns: Low
Market believes firm is Signaling		High		Separating Equilibrium	
Equal probability on Signaling and Manipulation	Current Returns	Average		Pooling Equilibrium	
Market believes Manipulation		Low		Separating Equilibrium	

Exhibit 2: Timeline