The Rational Part of Momentum*

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Abstract

The returns of different momentum deciles closely track a concurrent measure of the change in fundamental value calculated from analysts' earnings estimates. This concurrence of price and value occurs in the momentum periods and during the familiar reversal period. In addition, stock returns appear to predict future changes in fundamental value, up to a year in advance. These two findings indicate that the primary explanation of momentum is likely to be rational since this behavior is consistent with models of capital market equilibrium with heterogeneous expectations, particularly those models where the expectations and actions of informed investors move prices before those who are less well informed.

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Momentum Effect, Noisy Rational Expectations

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The Rational Part of Momentum

Recent papers have investigated the relationship between momentum in stock returns (Jagadeesh and Titman, 1993, 2002) and earnings, often focusing on the post earnings announcement drift phenomenon (Ball and Brown, 1968).[1] Much of the emphasis has been on the extent to which analysts' estimates can predict future returns. To investigate the rationality of momentum, this paper reverses the question and considers the extent to which stock returns predict future analysts' expectations.

First, we build an estimate of a stock's fundamental value based on analysts' expectations. We then show that the return of each stock return decile tracks the concurrent rate of change in the decile's fundamental value. Not only are decile returns and value changes monotonic in the six month ranking periods and the periods immediately preceding and following the ranking period, they follow each other closely when the familiar reversal occurs a year and a half after the ranking period. This concurrent co-movement of price and fundamental value is striking and consistent with rationality: price should reflect fundamental value.

However, we find another more subtle aspect of rationality. When we redefine the momentum deciles to reduce errors in our estimate of changing fundamental value, the stock return deciles appear to predict future changes in fundamental value. While we find some evidence that analysts' estimates tend to predict future changes in stock price, the more pronounced effect works in the opposite direction; stock returns appear to predict future changes in analysts' estimates as much as a year into the future.

There are several possible explanations for this predictability, but we believe the most plausible is a simple one, for which there is ample theoretical support. That is, some investors spend time and money to gain, and trade on, useful non-public information before other, less well informed, investors gain the information and trade on it.

[1] A growing literature suggests the momentum and PEAD anomalies are linked, e.g., Chan, Jagadeesh and Lakonishok (1999); Van Dijk and Huibers, 2002; Hong, Lee and Swaminathan (2003); Chordia and Shivakumar (JFE, 2006).

Differing investor expectations are a necessary condition for this explanation. Models of capital market equilibrium with heterogeneous expectations (e.g., Fama and French, 2007, Rubinstein, 1974, Lintner, 1969) suggest how prices or past returns could predict both future returns and future fundamental values. In particular, consider a model in which some investors become "informed" in the sense that they deduce the correct mean of next year's stock's price. Other investors remain "uninformed" and have incorrect estimates of the mean. As Fama and French argue the informed investors are likely to have positive alphas and the uninformed, negative alpha's (p. 673).[2]

A more revealing version of this argument is suggested by the interaction of information and prices in "On the Impossibility of Informationally Efficient Markets," (Grossman and Stiglitz, hereafter GS, 1980). GS first show that, when information is costly, no market mechanism ensures that prices fully reflect all available information. Stated differently, if the Efficient Markets Hypothesis held and prices did reflect all information, there would no incentive to collect costly information. Hence, prices will not reflect the costly information. Fama (1991, p. 1575) acknowledged the point in his second review of the efficient markets literature. "Since there are surely positive information and trading costs, the extreme version of the market efficiency hypothesis is surely false."

[2] For example, if initially all investors assume that next period the expected price of a stock is 11 and the appropriate discount rate is 10%, the current market price will be 10. Next, to add heterogeneous expectations, assume that a subset of investors suddenly discovers new information that leads them to believe the stock will have higher future cash flows so that the mean of its price next period is 14. If the market reopens, then as long as some investors remain uninformed, the current stock price will not rise as much as the informed investors believe is warranted.

How much the price increases will depend on the relative wealth, risk aversion and different price expectations of both types of investors as well as their other portfolio holdings. Suppose that the current price rises to 11.5, thereby creating a positive, abnormal return. If next period's price equals 14, which is the mean of the informed investors' distribution, a second abnormally positive return will follow the first.

In sum, if some investors become informed before others, one abnormal return will be followed by another. That is, there will be a momentum effect. Further, since prices are determined by discounting future cash flows, the cash flows expected by the uninformed investors in one period will be the cash flows expected by the informed investors in the previous period.

In the noisy rational expectations equilibrium modeled by GS (see also Lucas, 1972), a subset of investors collects costly, and useful, information and trades on it. Their trades move prices. The uninformed investors try to take advantage of the situation. They know that a stock whose price has just gone up is more likely to have a higher expected return than a stock that has gone down. They buy the stock, but not enough so that the price fully reflects the information. Their purchases are too small because they are hampered by the normal randomness of prices (which GS model as supply shocks) and their own risk aversion.

As a result prices partially reflect the information of informed traders. In the next period when the information is revealed, price fully adjusts, thereby creating the momentum effect.

In practice, we believe that a highly competent subset of professional investors fill the role of the informed investors in the above models. Most professional investors predict future earnings, and many use present value techniques to predict future stock prices. To the extent they are successful; they buy or sell stocks before changes in fundamental value are fully incorporated in stock prices. Their trades move prices, but not so much that prices fully reflect the information these investors have gathered and interpreted.

Security analysts employed by brokerage firms provide the information to the uninformed investors. Like professional investors, security analysts carefully research companies and estimate earnings and future cash flows; but they trade very little on the information they generate. Instead, they work to disseminate it widely so that the information they generate is subsequently impounded in prices. Our data suggests they are successful. Over the six month intervals we investigate, changes in our measure of analysts' expectations are significantly correlated with contemporaneous changes in stock price[3].

[3] We show below that analysts' expectations also anticipate future price changes, but that effect is smaller than the correlation between changes in analysts' expectations and concurrent price change.

Hong and Stein (1999) present a theoretical model that, like GS, has two types of investors. While their model is one with boundedly rational agents, rather than a rational expectations one, Hong and Stein's "news watchers" are like the informed investors in GS, while their momentum investors are similar to the uninformed investors in GS. A test of their model appears in Hong, Lim and Stein (2000) which investigates the effect of analyst coverage on the size and speed of momentum profits. Our study can be viewed as complementary in that we focus on the interaction between the information that analysts provide and momentum.

To investigate the earnings/momentum link, we use a modified present value framework to estimate changes in a stock's fundamental value. Our measure of fundamental value is similar to but different from earlier present value models of equity valuation (e.g., Edwards and Bell, 1961, and Miller and Modigliani, 1966), but, like them, allows the use of security analysts' expectations.

The next section describes our estimate of the change in fundamental value. Section II discusses the data we use. Section III provides initial evidence suggesting the potential of our measure of fundamental value to explain the momentum effect. Section IV investigates the momentum effect directly by showing how prices and fundamental values of different momentum deciles change together over time from a year before the formation of the momentum deciles until a year and a half after. Section V presents a similar story for deciles ranked on change in value. Section VI provides a check to see whether our results could be explained by assuming that analysts' expectations simply track past rates of return. Section VII tests momentum hypotheses based on behavioral arguments and also estimates how far into the future professional investors appear to predict fundamental value. Section VIII contains concluding comments and final remarks on the literature.

I. Representing Changes in Fundamental Value with Analysts' Estimates

Since our tests concern rates of return, we do not need to measure fundamental value directly. We only need to measure the rate of change in fundamental value. We then relate that to the rate of change in price. However, in order to motivate our rate of change measure we will begin with a multi-period dividend discount formula. In particular, we assume that V, the fundamental value per share of a firm's equity is given by

$$V_i = \sum_{t=1}^{\infty} \frac{D_{it}}{(1+r)^t} \qquad [1]$$

Where D_{it} = annual dividends per share expected by the average or representative investor, and

r = risk-adjusted discount rate[4], or equivalently,

$$V_i = \frac{\lambda E_{i1}}{1+r} + \frac{\lambda E_{i2}}{(1+r)^2} + \sum_{t=3}^{\infty} \frac{\lambda_{it} E_{it}}{(1+r)^t} \qquad [2]$$

Where E_{it} = annual earnings per share for the ith firm in period t as expected by the representative investor, and

λ_{it} = dividend payout ratio as expected by the representative investor, where we have assumed the first two λ's are equal for simplicity.

We next assume that in many instances, news that effects fundamental value in a cross-sectional analysis also effects expected earnings within in the next two years. Implicit in this view is also the assumption that valuation-sensitive news that only affects

[4] The discount rate used was fixed at 10%. Similar results were obtained using a fixed industry discount rate suggested by Fama & French, 1997, and with a time varying discount rate equaling 6% plus the 10 year Treasury bond rate.

information beyond two years is less likely and often more difficult to assess, so its impact on valuation is less.

Mechanically, denote the first two terms on the right hand side of [2] A and the last term B. We assume B is proportional to A, i.e., B = γA, or

$$V_i = (1+\gamma)\left[\frac{\lambda E_{i1}}{1+r} + \frac{\lambda E_{i2}}{(1+r)^2}\right] \qquad [3]$$

We define R_{it}^{v} as the rate of change in fundamental value, or smoothed earnings estimates. In a cross-sectional of stock returns, macro factors, such as the level of the overall stock market, will be common for all stocks. As a result we assume that, cross-sectionally, R_{it}^{v} will be proportional to the change in a firm's fundamental value[5].

$$1+R_{it}^{v} \sim (V_{it}/V_{it-1}). \qquad [4]$$

Notice that since λ and $(1+\gamma)$ appear multiplicatively in both numerator and dominator of [4] they are not required in the definition of R_{it}^{v}. In sum, we approximate the cross-sectional change in fundamental value by changes in expectations about firm-specific, near-term events.

Analysts commonly estimate earnings for the current fiscal year, the following fiscal year, and sometimes more. They typically estimate a long-run growth estimate as well. The time interval we use in estimating R_{it}^{v} is six months, i.e., in [4], t is six months after

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[5] For a practitioner-oriented view of R_{it}^{v} consider the following: let P_{mt} represent the average prices of the stocks in the market at period t. Let V_{mt} represent the average of V_i, from [2], for all the stocks in the market. Then P_{mt}/V_{mt} is a type of market P/E ratio. Assume that the corresponding P/E ratio for each stock moves proportionally with the market's P/E ratio. Equation [2] then implies

$$1+R_{it}^{v} = (V_{it}/V_{it-1})[(P_{mt}/V_{mt})/(P_{mt-1}/V_{mt-1})]. \qquad [4']$$

Since we use [4'] cross-sectionally, the market term is the [4'] is the same for every firm. This implies that in cross-sectional analysis $1+R_{t}^{v}$ is proportional to the firm specific term, (V_{it}/V_{it-1}), or equation [4] above.

t-1. Our measure requires estimates for earnings one year hence and two years hence. In each month, for each firm in our sample we estimate expected earnings one year hence and two years hence using the following formulas.

$$E_{it+1} = w \cdot FY1 + (1 - w) \cdot FY2 \quad \text{and} \qquad [5]$$

$$E_{it+2} = w \cdot FY2 + (1\text{-}w) \cdot FY2 \cdot (1 + LTG) \qquad [6]$$

where E_{it} is company i's expected earnings for period t constructed each month with the weighted average of FY1 and FY2, the analyst average estimates[6] for earnings for fiscal year 1 and 2 respectively. LTG is the consensus long term growth[7], and *w* is the fraction of months remaining in the current fiscal year. Using [5] and [6], we create monthly proxies for earnings one and two years ahead.

Defining R_{it}^{v} in this manner has several advantages. A six month interval allows us to use a time interval used in many previous studies. A six month interval is also long enough to allow meaningful changes in fundamental value.

In addition, smoothing earnings over two years allows us to update changing expectations on a regular basis and track the relation between prices and expectations as stocks in different momentum deciles evolve over time. The smoothing process also makes it more likely that our measure will capture changes in relating to the firm's longer run profitability. Thus, it helps mitigate issues relating to transitory earnings (Kothari, 2001).

However, because our measure of expectations looks out only two years, it may miss the full impact of some important changes. For example, the discovery of an oil field or a new drug may impact long-run fundamentals but may not affect near-term earnings estimates. In Section V we use an averaging process to reduce error in our measure.

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[6] We also computed very similar results using the median instead of the mean of FY1 and FY2.
[7] When LTG is not available we assign the industry (three digit SIC) average long term growth rate, similar results obtained when assigning 0% to the missing LTG estimates.

II. Data and Variable Construction

Our sample is composed of firms listed in the Center for Research in Securities Prices (CRSP) tapes for the period of 1985 to 2006 for which there are also security analyst estimates of future earnings in the IBES database. To be consistent with previous literature, we focus on common equity and exclude REIT's, ADR's, limited partnerships, and closed-end funds. Since the tests in this paper are based on holding periods of six months,[8] we include in our sample only firms that have analyst estimates for both fiscal year 1 and 2 six months before the formation date of our momentum deciles and six months after formation.

Table 1 contains the characteristics of our sample. In an average every month we cover 1,977 firms. Before 1990, the average number of firms was 1,036. It rose to 2,674 in the second half of the 90's and then decreased to 2,318 in the following decade. In terms of size and book-to-market quintiles, the sample appears slightly skewed toward smaller low book-to-market stocks. However, the apparent skew is largely attributable to the fact that the Fama French breakpoints are based on NYSE stocks, while our sample includes Nasdaq and AMEX stocks as well. Panel F shows that the sample covers a wide range of industries. Over the sample period the percent of manufacturing and non-durable industries decreased slightly, while business equipment increased.

III. An Initial Look at Evidence

In this section we show that, as expected, the momentum effect occurs in our data. We also show the power of our rate of change in fundamental value to explain contemporaneous returns.

[8] Test periods of 3, and 9 months were also conducted with similar results.

First, both the momentum literature and the noisy rational expectations model suggest that past returns should predict future returns. That is, b_1 in the following regression should be positive (the momentum effect).

$$R_{it} = a_1 + b_1 R_{it-1} + e_t \qquad [7]$$

Table 2 presents average monthly cross-sectional regression estimates, using six month returns, so that R_{it} represents one six month return and R_{it-1} represents the six month return immediately preceding it with a one month lag between the two periods. Given that the holding periods are 6 months long and the regressions are estimated every month, the observations overlap. Therefore reported *t*-statistics are computed with Newey-West (1987) standard errors, using a lag length of one less than the holding-period horizon. This statistic is designed to correct for moving average errors induced by the overlapping observations. Equation [7] appears as the first regression in Panel A of Table 2. The R^2 is low 0.014, but the t Statistic is significant (5.19).

The remaining regressions in Panel A show that R_{it-2} is insignificant and R_{it-3} has a significant, but negative sign. The negative sign is consistent with the familiar reversal effect in the momentum literature (e.g., Jegadeesh and Titman, 1993). We shall return to it later in the discussion of momentum.

The second regression of Panel B shows that when returns are regressed against last period's change in fundamental value, $R_{i,t-1}^v$, the R^2 is even lower (.0046), though the t Statistic is significant at 2.52. However, when last period's return is included in the regression, its coefficient remains significant while the coefficient on $R_{i,t-1}^v$ falls to a third of its former value and becomes insignificant (t = .97). This suggests that much of the information in $R_{i,t-1}^v$ is subsumed in past return.

Finally, Panel C includes regressions where return is regressed on concurrent $R_{i,t}^v$.

$$R_{it} = a_2 + b_2 R_{it}^v + e_{2t} \ . \qquad [8]$$

R^2 equals .11 and the t Statistic on $R_{i,t}^v$ equals a highly significant 16.9. We believe this suggests that investors, whose activities are reflects in return, and analysts, whose expectations are reflected in $R_{i,t}^v$, are reacting to the same news about future corporate profitability. Further, when past return is added to the regression, the coefficient on past return becomes insignificant, suggesting that the information in past return is largely subsumed by the current change in fundamental value.

A noisy rational expectations interpretation of these results is that in period t-1, informed investors correctly anticipated much of the information contained in next period's R_{it}^v. The trading activity of these informed investors causes R_{t-1} to partially reflect next period R^v. Then in period t, analysts publish their expectations, and uninformed investors trade based on the now public information in R_{it}^v. This explains the momentum effect.

In sum, Table 2 provides initial evidence consistent with the momentum effect, the noisy rational expectations hypothesis and the power of our measure of fundamental value to explain concurrent stock returns. The next section presents a more dramatic view of these issues by tracing the time paths of both fundamental value and the returns of stocks sorted into momentum deciles.

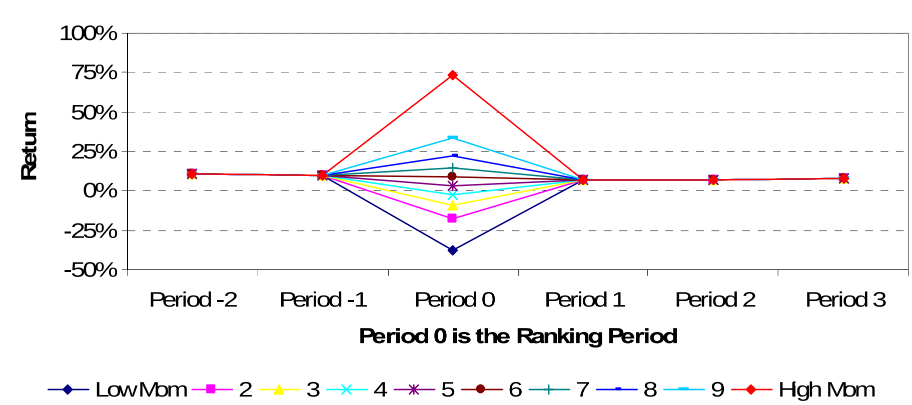
IV. The Time Path of Momentum Deciles

A. Returns

We create overlapping momentum deciles by ranking stocks each month according to their trailing 6-month returns. We will call each 6-month ranking period, Period 0, e.g., for the six month period beginning January, 2000 and ending June, 2000, we rank the stocks as of their six month return at the end of June. We then calculate 6-month returns for the stocks in each Period 0 decile for five additional periods. The 6-month period immediately proceeding the ranking period is Period -1 (in the example, July, 1999 through December, 1999); the 6-month period before that is Period -2. We skip one month between period 0 and the next 6-month period (Period 1), as is common in the momentum literature, to avoid bid-ask bounce problems (as well as lags in analysts' earnings changes). Immediately following Period 1 are the two final 6-month periods, Periods 2 and 3. Counting the month we skipped after the ranking period, our data covers 37 months for each momentum decile. Each month begins another (overlapping) ranking period, In our example, the next Period 0 would start at the beginning of February, 2000. To adjust for overlapping observations, we use Newey-West standard errors to calculate our t-statistics.

If the data met the test of strong form market efficiency, and assuming each decile is well-diversified, a plot of the momentum deciles would look like Figure 1. In Period 0, the stocks are ranked into deciles by returns. Therefore in the ranking period, the deciles differ by construction. In an efficient markets' interpretation, the return differences in Period 0 reflect the idiosyncratic returns of the underlying stocks, presumably the result of a news event. The market should fully reflect the news event in Period 0, and that news should not affect returns in other periods.

Figure 1
Hypothetical Returns for Momentum Deciles
Under the Assumption of Market Efficiency

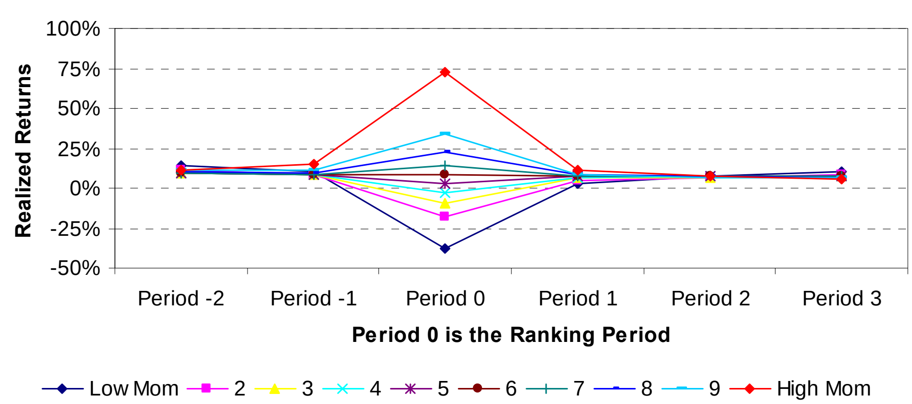


In periods other than the ranking month, each decile simply represents a more or less random sample of 10% of the stocks in the market. In these non-ranking periods, each decile should earn the market rate of return. Only in the ranking period should the deciles, by construction, differ from the market return.

Before and after Period 0, the returns of all deciles should equal the average return in the market.

Table 3 presents the actual results using our data. Figure 2, which is based on the first panel in Table 3, presents a graphical summary of the actual returns of the momentum deciles. It is similar to Figure 1, and, visually, suggests rough correspondence with market efficiency. But Figure 2 differs from Figure 1 in a number of important respects. We will start with Period 1, the ranking period, and move forward in time before considering the earlier periods.

Figure 2
Returns for Momentum Deciles



Period 0 is the ranking period. As expected, deciling stocks on 6-month returns results in huge return differentials. Return differentials this large are most likely the result of investors reacting to significant new information. The heterogeneity of the returns suggests that the news is company-specific, or at most industry-specific.

Period 1 shows the familiar momentum effect. The deciles in Period 1 line up just as they did in Period 0. Stocks in decile 10 had higher returns than stocks in decile 9 and so on, monotonically down to decile 1. The difference in returns between deciles 10 and 1 is large, 8.1% per six month period and the t statistic of the difference is a statistically significant 5.4.

A noisy rational expectations interpretation is that some investors became informed and traded stocks in Period 0. Those stocks then subsequently out- or under-performed in Period 1. We investigate this interpretation more fully below when we present the changes in fundamental value over these periods.

By **Period 2** the t statistic of top decile average return minus the bottom decile return is negative and insignificant, and the returns within the deciles are roughly similar. Deciles returns in Period 1 do not predict decile returns in Period 2. By the end of this period, 13 months after the ranking period, the information that moved prices in Periods 0 and 1 seem to be fully imbedded in stock prices.

In **Period 3**, the familiar reversal effect is evident (as it was in the regressions of Table 2). The decile returns are again monotonic, but in the opposite direction. Stocks that 19 months earlier had the highest returns, now have the lowest and underperformed the lowest momentum decile by a statistically significant -4.5% (t statistic = -3.7).

In part the reversal effect is probably due to survivorship. To be in the Period 3 analysis, a firm must survive until Period 3. The Period 3 returns in Table 3 and Figure 2, are not realizable returns, rather they are conditional returns, conditional on the survival of the firm until Period 3. It is not surprising that bottom decile firms, who may have flirted with bankruptcy, but survived, have high returns. However, survivorship does not seem to explain the swan dive taken by the former high flyers in the top deciles. In the next subsection, we show the close relation of the reversal effect to fundamental value and resume discussion of survivorship issues.

Next, consider the returns in **Period -1,** the period before the ranking period. The decile returns in Period -1 or any period before Period 0 are not realizable as an investment strategy since they are based on a sort that occurs in Period 0. Nevertheless, as we argued above, under the hypothesis of Market Efficiency as depicted in Figure 1, the decile returns in Period -1 should be independent of those in Period 0. However they are not, and the actual relationship between Period 0 and Period -1 might be called the reverse momentum effect. The top decile resulting from the ranking in Period 0 outperforms the bottom decile in Period -1 by 4.7% (t statistic = 3.12). Though somewhat peculiar, this reverse momentum effect would seem as great a challenge to market efficiency as the more familiar momentum effect. On the other hand, a noisy rational expectations interpretation of this reverse momentum effect is that, in Period -1, informed investors successfully traded stocks that subsequently out- or under-performed in Period 0.

Although the payoffs to these informed Period -1 investors seem large, they reflect the mechanical construction of the momentum deciles constructed in Period 0. Many stocks had returns as high (or low) as the extreme decile portfolios did in Period -1. On average these stocks did not earn extreme returns in Period 0. We are simply looking at the stocks that subsequently did earn high returns. Nonetheless, even for these stocks, Market Efficiency implies there should be no reverse momentum effect.

Period -2 is odder still. A year before the ranking period, the extreme deciles all had high returns while the middle deciles had below average returns, the difference between top and bottom deciles is -2.8% but it is statistically insignificant. To cast further light on the time path followed by the momentum deciles, the next subsection shows the relation between momentum and R_{it}^{v}, our measure of the change in fundamental value.

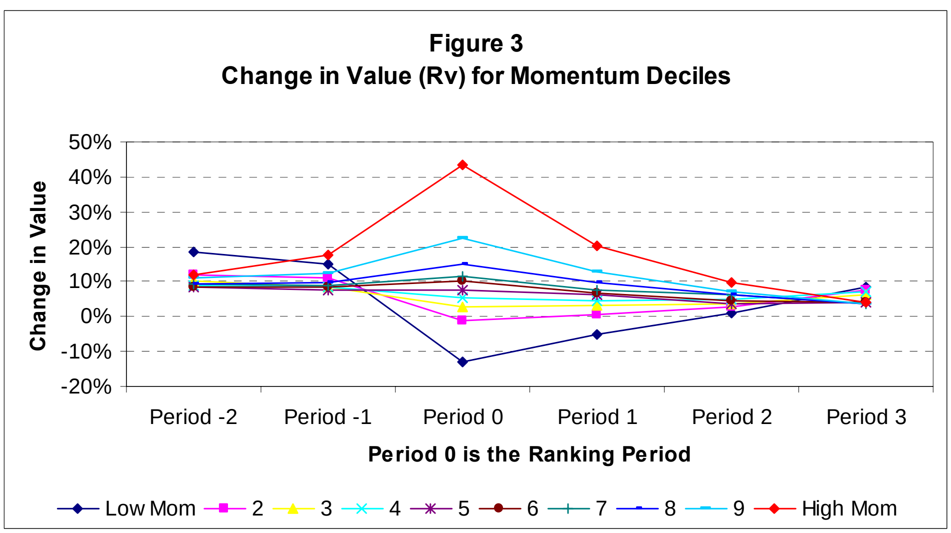
The third panel of Table 3 shows that adjusting for risk has little effect on the results. Excess returns relative to Fama French size and book-to-value portfolios show the same results discussed above, although in most cases the t statistics, though significant, are less so. For example, in Period 1 the excess return from top minus bottom momentum deciles is 6.34% with a t-statistic of 4.01; while in Period 2 the alphas are statistically insignificant, but in Period 3 they show a reversal effect of -3.52% with a significant t-statistic of 3.04.

B. Fundamental Value by Momentum Deciles

For each of the above momentum deciles, Figure 3 and the second panel of Table 3 present each decile's average R^v, our estimate of the change in fundamental value. They trace the path of the R^v's for each momentum decile from a year and a half before the formation of each momentum decile (period -2) until a year and seven months after formation (period 3).

If there were no predictability in the time series of the R^v's, Figure 3 would look like Figure 1. However, though Figure 3 resembles Figure 2, it does not look like Figure 1. The monotonicity of the R^v's in Periods 0 and 1 suggest predictability in the time series of analysts earnings revisions and thus in our R^v's. Further, there seems to be greater predictability in the high momentum deciles, which had above-average R^v's for Periods -1, 0, 1 and 2, or a little over two years.

The individual periods tell an interesting story. As before, we will begin with **Period 0** and work forward before considering the pre-ranking periods.



In **Period 0** the R^v's for the different momentum deciles line up in exactly the same order as did their stock returns. The highest momentum decile had the highest increase in fundamental value exceeding that of the lowest decile by 56.2%. The difference is statistically significant (t statistic = 28.3)[9]. This suggests that the primary driver of the large differences in the **Period 0** returns is captured by the estimated change in fundamental value that also occurred in **Period 0**.

As mentioned in the previous section, there is modest evidence that analysts' estimates, and thus our R^v's, may be affected by stock price changes. While some trend following may account for a little of our measure of changing fundamental value, it is unlikely to explain much. The increases (decreases) in fundamental value in the extreme deciles in Period 0 appear too large for an analyst to justify if there is no fundamental evidence supporting such dramatic changes.

Further, the monotonicity of the R^v's would require that most, if not virtually all analysts, ignore fundamentals and change their earnings estimates to correspond to price moves. Finally, if price movements were driving changes in analysts' expectations, we would expect to find long discussions of momentum in analysts' reports. Instead, they focus on company prospects for future earnings, cash flow and the relation of price to fundamentals.

Similarly, the changes in fundamental value in **Period 1** mirror the returns in period 1. However, the Period 1 fundamental returns are larger than the price returns in Period 1, and are monotonically in line with the momentum deciles of Period 0. A noisy rational expectations interpretation is that the price changes in Period 0 reflect not only the change in fundamental value occurring in Period 0 but also the expectations by informed investors that fundamental value will continue to change in Period 1. As the information underlying those expectations becomes more widely apparent, analysts, and thus Rv, reflect it. The informed investors benefit from their foresight and trading activity as the returns in Period 1 validate their Period 0 trades (the momentum effect).

[9] Compared with the actual returns for the difference in momentum deciles, this return is relatively low. This phenomenon is similar to the low values of "earnings response coefficients" in the accounting literature (Kothari, 2001). It also reflects that the extreme decile stocks are largely growth stocks as we show below.

There may be a second, more mechanical reason, for the wider spread in the R^v deciles in Period 1 that is related to the way we construct R^v. As equation [3] shows, our measure depends only on expected earnings over the next two years. It may be that some of information expected by analysts in Period 0 effect earnings shortly beyond two years. By Period 1 some of that information affects our measure of R^v and causes the wider dispersion of the Period 1 deciles. This argument may also affect R^v in Period 2.

A similar phenomenon, "prices lead earnings," is familiar in the accounting literature (Kothari, 2001). There it refers to reported earnings, which are reported later than the earnings expectations we analyze. Figure 3 suggests that "prices lead analysts' expectations of future earnings." A final interpretation is that analysts' expectations simply follow past price change, an issue to which we return in Section VI.

In **Period 2** the pattern of the R^v's, partially extends the pattern of Period 1, but the extreme deciles have begun moving toward the mean. By **Period 3**, which ends over a year and a half after the momentum deciles were established, a reversal in the R^v's is evident, which corresponds with the reversal in their stock returns. The bottom four deciles have an average R^v of 7.3%, while the top six have an average of 3.9%.

Fundamental value in Period 3 suggests that the reversal in price returns is not a return to rational pricing after a period when prices overshoot fundamentals (as suggested by e.g., Daniel et al, 1998). To the extent that the results are not due to survivorship bias[10], investors appear to react to changing fundamentals. The expectations of these fundamentals may be over-extrapolations, but this data suggests the return reversal mirrors changing fundamentals. Notice too that these changes in fundamental value

[10] We were able to reduce the reversal effect to a degree by revising the initial way we did the study. Initially, to be included in any period, a firm had to be in the sample for the entire period. In our revision, we required only that a firm be in the sample during periods 0 and 1. We assumed any proceeds from the last price at which the firm traded were invested in the remaining stocks in its decile. Its revised R^v equaled its R. This reduced survivorship and reversal, but as is apparent in the Tables and Figures, the reversal remains.

cannot be interpreted as the result of analysts changing their earnings expectations to ratify past returns.

V. Ranking Stocks into R^v Deciles

In this section instead of ranking stocks by returns in Period 0, we rank them into deciles based on R^v, the percent change in fundamental value. Then, just as we did in the previous sections, we follow these deciles through time in terms of both R^v and R. If our hypotheses are correct, a more powerful link between stock price and fundamental value should be apparent when we sort the stocks into R^v deciles. This is because our measure of fundamental value, R^v, is based on near term earnings estimates and will be most powerful when information about fundamentals changes near-term earnings (the next two or three years).

When we ranked on returns, the extreme deciles likely contained, not only stocks with large changes in near-term earnings estimates, but also stocks whose valuation-sensitive information focused only on longer term cash flows. That is, the extreme deciles in the R ranking likely contained stocks that either had won or lost long-term contracts, had drugs or other products approved or not, found extensive mineral deposits, etc. Since our measure is unlikely to respond to that type of information, we would expect that in momentum rankings the link between stock price and fundamentals will appear weaker than it actually is.

However, when we rank stocks by R^v, it is likely that stocks whose returns have only been affected by changing long run fundamentals will be randomly distributed among the deciles. In an R^v ranking, R^v is more likely to be the primary driver of stock returns, and if the noisy rational expectations hypothesis is correct we should expect that prices should appear to be a better predictor of changes in fundamental value. Note: Jim I think that you saying that Rv is the driver could be interpreted as predictability????

Table 4 and Figures 4 and 5 show the time path of R^v and R. Figure 4 shows the path of fundamental value. In Figure 4 the changes in fundamental value seem less predictable than in the momentum ranking. Here it looks as if analysts were surprised, particularly in the extreme deciles. If the Rv's were independent of each other, Figure 4 would look like Figure 1. However, although it is similar, the highest deciles in Period 0 are also the highest in Periods –2 through Period 1. The lowest two deciles in Period 0 were also the lowest in the two years beginning in Period -2. However mirroring Figure 3, by Periods 1 and 2, the lowest decile in Period 0 is now the highest in terms of changing fundamental value.

The reversal in the lowest decile appears sooner than was apparent in the momentum sorts. In particular, the lowest decile bounces back in the period immediately following the ranking period. Further, as Table 4 and Figure 5 show, the corresponding stock return for that decile do not reverse until periods 2 and 3. This may be related to excessive pessimism by analysts about bottom decile stocks in Period 0 or to major earnings write-downs by managers, which analysts subsequently corrected in Period 1. It is important to note that returns in Period 2 and 3 in excess of Fama French portfolios are all statistically insignificant.

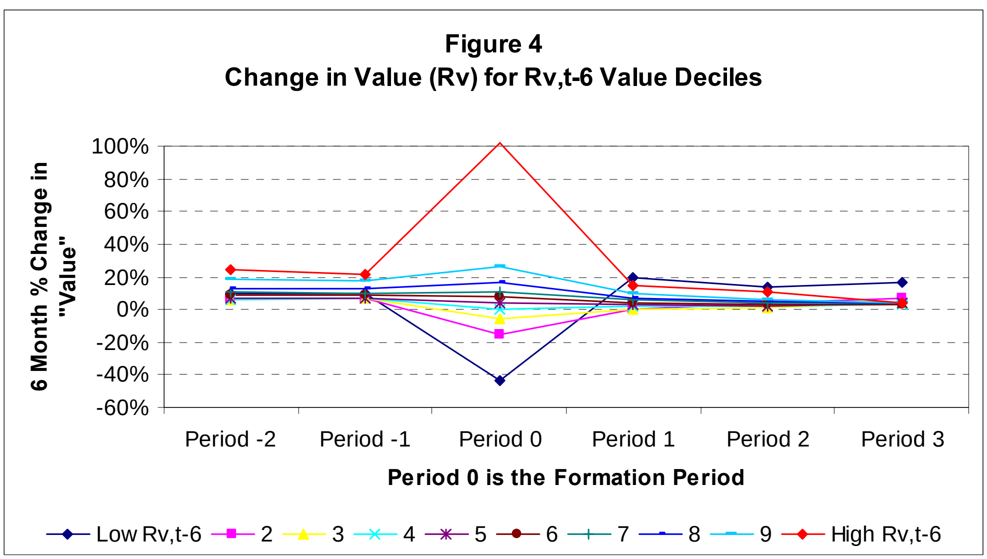
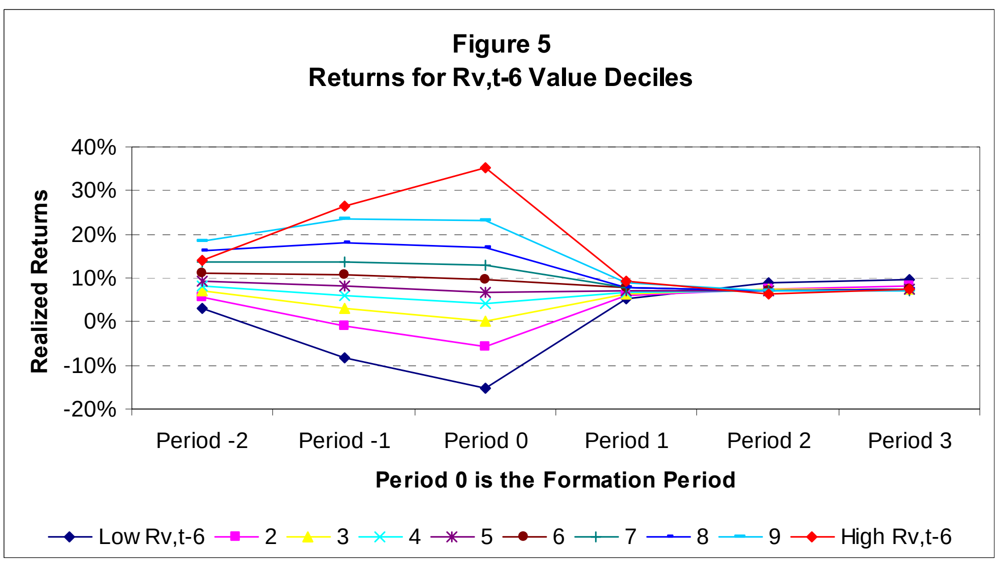


Figure 5 shows the returns corresponding to the value deciles and these returns appear consistent with a noisy rational expectations market. Compared to Figure 2, prices predict the forthcoming Period 0 changes sooner and to a larger extent.

Recall that the returns in Figure 2, where stocks were ranked on the returns themselves, approximated market efficiency. On the other hand, Figure 5, which shows the returns when stocks are ranked by the change in fundamental value, does not look like market efficiency at all. High (low) ranking deciles in Period -2 continue to be high (low) ranking deciles for the next three six month periods.

An interpretation of Figure 5 in the spirit of noisy rational expectations is that, as early as Period -2, some informed investors predicted the large changes in fundamental value that security analysts reported in Period 0. Then, in Period -1, additional investors became informed (and/or the previously informed investors become more confident) causing Period -1 returns to deviate even more from average.

Security analysts then disseminate the information in Period 0 and the price moves dramatically as most of the uninformed investors react. Finally, a few of the uninformed do not react until Period 1, causing a small momentum effect in Period 1.



Simple correlations between decile returns are consistent with a stronger link between current returns and future changes in value when using an R^v ranking. Consider the correlations of R in one period with R^v one or two periods later. For the two period ahead prediction, this indicates how well returns in one six month period, for clarity, say January to June, predict changes in fundamental value the following January to June. For the momentum deciles (Figures 2 and 3), the correlation for one period predictions is .63; for two periods, .17. For the fundamental deciles (Figures 4 and 5) the correlations rise to .73 and .29.

VI. Do Prices Predict Fundamentals or Do Analysts Chase Prices?

The results so far, and particularly Figure 5, suggest that prices lead analysts' expectations and, thus our measure of R^v. We believe the data suggests a noisy rational expectations equilibrium. That is informed, or professional, investors either obtain information more quickly or analyze existing data better than the average analyst. These professional investors make their decisions and move prices before analysts publish their opinions.

Nevertheless, another interpretation is that analysts' expectations of earnings simply follow prices. If say, a stock's return relative to the market is positive, analysts increase their published expectations. Under this interpretation, the high concurrent correlation between returns and our measure of the change in fundamental value simply reflects analysts publishing expectations that ratify recent price changes.

We will call this possibility the extrapolative hypothesis. That is, current changes in analysts' expectations move in the same direction as lagged returns[11]. It is not possible to

[11] There is some evidence prior stock movements partially explain changes in analyst's earnings expectations, but that fundamentals are more important. For example, Stickel (1990) shows that a stock's return over the interval between an analyst's prior estimates and her current estimate has statistically significant explanatory power. However, he also shows that its importance is small and weak (R^2 increases from .37 to .38), and that the behavior of other analysts is far more dominant. Subsequent work, such as

cleanly distinguish the extrapolative hypothesis from a noisy rational expectations explanation because both hypotheses imply some degree of extrapolation. The extrapolative hypothesis implies that all a security analyst does, On the other hand, if rational expectations are noisy, analysts base forecasts on their assessment of company fundamentals. However, since they realize that returns convey information about current and future fundamentals, their expectations should also reflect lagged returns.

It is relatively easy to cast substantial doubt on an extreme version of the extrapolative hypothesis, particularly over the six month intervals we have investigated. In particular, suppose that over the past six months a stock's return has been relatively high. If the extrapolative hypothesis is true, then analysts' should increase their expectations of earnings, regardless of what is happening currently.

For example, suppose we look at the change in earnings expectations one month after the end of the six month ranking period. If a company's lagged return was relatively high, then regardless of what is happening currently, analysts' expectations should rise and should be independent of the actual return over that one month interval. That is, if we look at high momentum stocks, the change in analysts' earnings estimates should be reflect past return, but not current return.

On the other hand, if the noisy rational expectations view is correct, we should expect the current change in analysts' expectations to reflect both past and current returns. And as the observation period after the ranking period lengthens from one month to three and six months, the more analysts' expectations should appear to track concurrent rather than past returns.

To investigate this, we independently sort stocks each month into deciles based their past six month return (momentum deciles) as well as their realized returns over the next 1, 3

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that by Keane and Runkel (1998) and others (e.g., Lim, 2001) suggest that analysts' earnings estimates are focused on predicting earnings and not driven primarily by stock prices.

and 6 months. We then calculate the average realized R^v's (change in value, as measured by the change in analysts' expectations) for each of the 100 bins for the following 1, 3 and 6 month periods. Each bin has between 12 and 30 firms on average. Table 5 in the appendix shows how R^v, our measure of fundamental value changes over each of those intervals.

Table 5 does not support an extreme version of the extrapolative hypothesis over any subsequent horizon. The table below summarizes Table 5. Instead of deciles, it simply divides the sample in half, the five top deciles and the bottom five. The six numbers in the top left corner show what happens to the stocks that had relatively high rates of return in the last six months, and also had relatively high returns in the subsequent 1,3 or 6 month period. The top line shows that stocks that did well in both the initial six month period and in the subsequent one month period a return in that subsequent month of 7.7% above the equally weighted average of all stocks in our sample. R^v was also above average for those stocks, as we would expect either under either hypothesis.

However, follow the top line across the table to the low return quadrant to the high momentum stock that underperformed in the subsequent one month period. Already in this first subsequent month the difference in analysts' expectations suggests a noisy rational expectation explanation rather than the extrapolative hypothesis. The R^v_{t+1} is below average and significantly below the average for all high momentum stocks (t stat = -12.6). If analysts were simply extrapolating past returns, the t statistic would have been 0 (and the change in value would be above average).

The remaining cells in the Table also support the noisy rational expectations explanation. For stocks where momentum works (the upper left six cells and the lower right six cells) fundamental value tracks both past and present return. For the cells in the off diagonals, fundamental value tracks concurrent price change more closely as the observation interval increases. By the time six months have elapsed, which is the window we used for our analysis, the differences in R^v_{t+1} are striking.

Nevertheless, even at six months, Table 5 suggests that the stocks for which momentum did not work still reflect some of the initial momentum. Perhaps some analysts are still extrapolating the optimism or pessimism in past returns, or perhaps they have not yet observed the evolution of fundamentals expected by professional investors.

		High Rt+1		Low Rt+1	
		R_{t+1} - Average R_{t+1}	R^v_{t+1} - Average R^v_{t+1}	R_{t+1} - Average R_{t+1}	R^v_{t+1} - Average R^v_{t+1}
High R_t	**1 month**	7.70%	0.92%	-7.74%	-0.93%
High R_t	**3 months**	13.97%	3.64%	-14.24%	-3.72%
High R_t	**6 months**	20.46%	8.22%	-21.71%	-8.71%
Low R_t	**1 month**	8.29%	1.36%	-8.31%	-1.37%
Low R_t	**3 months**	14.48%	4.96%	-14.34%	-4.88%
Low R_t	**6 months**	21.52%	10.34%	-20.39%	-9.74%

VII. The Prediction Horizon of Informed Investors

The theoretical arguments and empirical results suggest that, because of the activity of professional investors, prices anticipate future changes in fundamental value. If so, current stock price should reflect not only current fundamental value but future fundamental value as well. Current price should also reflect the activity of noise traders whose actions are independent of any estimates of fundamental value.

It is simplest to capture this in a multiplicative model, so we can then take logarithms and derive a regression equation. Let P_t and V_t represent current price and fundamental value respectively.

In a perfect market, with homogeneous expectations, where V_t accurately measures those expectations, $P_t = V_t$ and, over any period of time, $R_t = R^v_t$. However, suppose that all investors know the current V_t while a few can accurately predict V_{t+1}. Then current price will be a function involving the beliefs of those who know only V_t and those who know V_t and V_{t+1} (and thereby R^v_{t+1}). The pricing function will also reflect the number of investors in each group, their wealth levels, aversion to risk and any possible constraints they face. In this case we might represent current price as

$$P_t = V_t(1+R^v_{t+1})^{\beta_1}\ , \qquad [9]$$

where and β_1 reflect the relative effect of the two types of investors on price. If all investors know V_t and no one knows V_{t+1}, then $\beta_1 = 0$. If all investors know both V_t and V_{t+1}, then $\beta_1 = 1$. If some know V_{t+1} and other do not, then β_1 will lie between 0 and 1. Notice that this is a different way of presenting our view of how the momentum effect works. At any time, the current price reflects not only current fundamental value (as perceived by the representative investor) but future value as well.

We can generalize equation [9] to allow some investors who may not know even V_t, as well as some investors who can predict not only V_{t+1} but V_{t+2} or V_{t+3}. Assuming that a noisy rational expectations equilibrium is a reasonable approximation to reality, it is interesting to ask how far into the future can investors and thus current prices anticipate future fundamental value. Let β_1, β_2 and β_3, reflect the relative importance of future changes in fundamental value in determining current price. Also let β_0 and λ be parameters to reflect the relative importance of traders whose decisions do not depend on any estimates of fundamental value ("noise traders"). In the following equation, it is reasonable to expect $\beta_1 > \beta_2 > \beta_3$.

$$P_t = \lambda_t V_t^{\beta_0}(1+R^v_{t+1})^{\beta_1}(1+R^v_{t+2})^{\beta_2}(1+R^v_{t+3})^{\beta_3}e_t \qquad [10]$$

Since $1+R_t = P_t / P_{t-1}$, taking logarithms, differences, and using lower case letters to denote a logarithmic variable, e.g., $r = \ln(1+R)$, yields

$$r_t = \alpha + \beta_0 r_{vt} + \beta_1(r_{vt+1}-r_{vt}) + \beta_2(r_{vt+2}-r_{vt+1}) + \beta_3(r_{vt+3}- r_{vt+2}) + u_t\ , \qquad [11]$$

where we reflect the influence of noise traders by α, a constant, and u_t, a random error term. Since $u_t = \ln(e_t) - \ln(e_t)$, we would expect it to display negative autocorrelation if we were to estimate [11] in a time series. However, we estimate the equation cross-sectionally.

The following two regressions show that β_1 and $\beta_2 > 0$, but $\beta_3 < 0$. The positivity of β_1 and β_2 suggests that current prices impound (accurate) predictions of future changes in expected fundamental value one year hence (two periods).

$$R_{i,t} = \alpha + \beta_0 R_{v,t} + \beta_1 dR_{v,t+1} + \beta_2 dR_{v,t+2} + \beta_3 dR_{v,t+3} + \varepsilon_{i,t}$$

Months	Intercept	$R_{v,t}$	$dR_{v,t+1}$	$dR_{v,t+2}$	$dR_{v,t+3}$	Avg # Obs	R^2
250	0.0704	0.3433	0.1434	0.0383		1900	0.12339
	4.89	18.94	13.46	6.27			
244	0.0740	0.3456	0.1291	0.0109	-0.0183	1720	0.1329
	5.09	16.90	9.79	1.08	-2.45		

The negativity of β_3 is consistent with the familiar reversal effect and is inconsistent with rational expectations. However, as different regressions involve more and more periods in the future, there is a survivorship issue – the sample size keeps decreasing. Although we have used standard procedures to deal with this, it should be borne in mind that a regression requiring r_{vt+3} is a conditional regression. That is, the observations only involve firms that have survived more one year after the observation of r_t. If a number of firms have gone bankrupt, or were delisted, during this period, although they were properly represented in prior regressions, they are not represented in this one. This suggests that β_3 may be biased downward and that the suggested reversal may be more apparent than real.

VIII. Concluding Comments

The similarity between actual returns and changes in fundamental value is striking and suggests that the primary force underlying the momentum effect is changing company fundamentals as reflected in analysts' expectations. Further, when stocks are ranked into deciles based on the change in fundamental value, stock returns appear to predict subsequent changes in fundamental value well in advance.

These finding are consistent with capital market equilibrium models where rational investors have heterogeneous expectations, particularly models with noisy rational expectations. In our view, these models suggest that that sophisticated investors have predicted these changes in fundamental value before security analysts, and that they have traded on their predictions. Others trade after they too receive the information, thereby creating momentum in returns.

The linkage between price and value casts doubt on the primacy of several behavioral and/or technical explanations of momentum. In particular, prospect theory and the disposition effect suggest investors sell winners too early and hold losers too long so that prices slowly react to fundamentals and thus, significantly diverge from fundamentals (e.g., Kahneman and Tversky, 1979; Shefrin and Stattman, 1985; Grinblatt and Han, 2005). In contrast, our findings suggest that prices mirror current changes in fundamentals, and anticipate future changes in fundamentals.

Other theories posit that momentum occurs because technical traders react to unusual price movements by seeking to ride a trend and over-extrapolate underlying fundamentals (e.g., Delong et al, 1990). Daniel et al (1998) suggest that the behavior of over-confident investors causes over-extrapolation. Again, our work suggests that, by and large, prices track and anticipate underlying fundamentals. While these behavioral/technical explanations may account for some portion of the momentum effect, they do not seem to be the driving force.

This paper shares similarities with recent research on futures prices by Boudoukh et al (2007) who contest the view of Delong et al (1990). Delong et al argued that fundamentals had little effect on the frozen concentrated orange juice futures market. They based their argument on the fact that regressions relating futures prices to temperature that appeared in Roll (1984) have low R^2's.

Later research by Boudoukh et al show that when temperatures remain above 36^{o}, Delong et al are correct; temperature change has little effect on futures prices. However, movements in temperature near and below the freezing point have a significant impact on supply because they can destroy orange crops. These freezing temperatures also have dramatic effects on price, just as economic theory would predict. In concert with our findings, changing fundamentals drive prices.

In a similar way, separating stock returns into momentum deciles and focusing on the extreme deciles forces a researcher to study stocks at a time when something highly significant affected their prices. Neoclassical finance suggests the significant event should relate directly to the valuation of future corporate cash flows. Behavioral finance might allow for some impact by fundamentals but would hold that there should be additional and significant behavioral effects that would be considered irrational in a neoclassical context. We find that fundamentals appear to be the predominant force.

The findings of Hong, Lee and Swaminathan (2003) (HLS) can be interpreted as added evidence supporting a noisy rational expectations equilibrium. In particular, if information is costless and the price system highly informative, there is unlikely to be a noisy rational equilibrium or a momentum effect. An important instance of this can occur when corporate insiders, who do have costless information about their own corporations, can trade freely on that information. HLS studied 11 countries. In those countries where investor protection was low and corruption was high (and, presumably, insider trading largely unimpeded), there was neither post-earnings-announcement-drift nor a momentum effect, as the GS analysis would suggest.

The noisy rational expectations model is attractive in terms of assumptions and implications. In the first place, it requires the plausible assumption that the acquisition and interpretation of information about equity pricing requires skill and resources. In the second, it implies that the less well informed investors base their investment decisions, in part, on past returns

While our work supports the notion that the evolution of prices is consistent with the above models as well as with present value theory, it does not support the efficient markets hypothesis. Prices do not fully reflect all available information. Instead, the data suggests that prices partially reflect two types of information: (1) information that is readily available (from analysts' expectations) and interpretable by a large group of investors, and (2) the predictions of a group of "informed" investors, who rely on information that is harder to obtain and/or more difficult to interpret.

This interpretation of price and value has implications beyond momentum, post earnings announcement drift and the broader anomalies literature. It suggests that the behavioral hypotheses that rely on investor reactions to past price movements may be less important than hypotheses about how investors form expectations about stock fundamentals.

It may also relate to the literature on the excess volatility of the equity market (see, e.g., Shiller, 2003). Much of that work is based on a measure of fundamental value equal to the present value of the future dividends of companies that survive. Stock prices appear to move far too much relative to the slow and smooth movements of discounted actual dividends. The results here suggest that, at the individual stock level, the volatility of the fundamental value is far larger than suggested by discounted dividends. It may be that, even in the aggregate, fundamental values are more volatile and more closely tied to stock prices. If better estimates of fundamental value are highly volatile, perhaps the stock market behaves appropriately, in that stock prices reflect estimates of fundamental value. However, it may also be true that investors' estimates of fundamental value are excessively volatile.

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Table 1: Sample size and distribution mapped into Fama French quintiles and 12 industry classifications

The sample is composed of common equity firms that have both IBES earnings estimates for fiscal year 1 and year 2, and that can be matched to CRSP tapes. Every month firms are classified into their corresponding Fama French book to market and size quintile based on the information available on the last month of June. Panel A presents the average number of firms analyzed per month, the 5x5 size – book to market grid and the average for each quintile. Panels B to E show the sample distribution for different time periods. Panel F shows the sample distribution when firms are classified using Fama French 12 industry sectors.

Panel A: Sample Distribution from 1985 to 2006

Avg # Firms 1977	Low B/M	2	3	4	High B/M	Total Size
Small	6.1%	6.4%	6.1%	6.0%	5.9%	**30.5%**
2	6.5%	5.6%	5.0%	3.9%	2.5%	**23.5%**
3	5.7%	4.2%	3.7%	2.6%	1.5%	**17.7%**
4	4.7%	3.6%	3.0%	2.2%	1.2%	**14.6%**
Big	5.4%	3.1%	2.3%	1.8%	1.1%	**13.7%**
Total B/M	**28.5%**	**22.8%**	**20.2%**	**16.4%**	**12.0%**	**100.0%**

Panel B: Sample Distribution from 1985 to 1989

Avg # Firms 1036	Low B/M	2	3	4	High B/M	Total Size
Small	7.3%	7.4%	5.3%	3.8%	3.8%	**27.7%**
2	8.0%	5.8%	4.7%	2.7%	2.3%	**23.6%**
3	6.6%	3.9%	3.5%	2.5%	1.9%	**18.5%**
4	4.1%	3.5%	3.3%	2.4%	1.5%	**14.8%**
Big	4.5%	3.3%	3.1%	2.7%	1.8%	**15.5%**
Total B/M	**30.6%**	**24.0%**	**19.9%**	**14.2%**	**11.3%**	**100.0%**

Panel C: Sample Distribution from 1990 to 1994

Avg # Firms 1739	Low B/M	2	3	4	High B/M	Total Size
Small	6.6%	6.2%	4.7%	4.8%	6.3%	**28.6%**
2	7.2%	6.5%	5.3%	3.9%	3.3%	**26.2%**
3	5.7%	4.4%	3.8%	2.8%	1.4%	**18.2%**
4	4.4%	3.2%	3.1%	2.4%	1.2%	**14.4%**
Big	4.6%	3.1%	2.6%	1.6%	0.7%	**12.6%**
Total B/M	**28.6%**	**23.5%**	**19.6%**	**15.5%**	**12.8%**	**100.0%**

Panel D: Sample Distribution from 1995 to 2000

Avg # Firms 2674	Low B/M	2	3	4	High B/M	Total Size
Small	5.3%	5.8%	7.1%	7.5%	7.4%	**33.1%**
2	6.0%	4.9%	4.9%	4.3%	2.4%	**22.5%**
3	5.6%	4.2%	3.5%	2.6%	1.3%	**17.1%**
4	5.1%	3.6%	2.8%	2.0%	1.1%	**14.6%**
Big	6.0%	3.0%	1.8%	1.2%	0.8%	**12.7%**
Total B/M	**28.0%**	**21.4%**	**20.1%**	**17.6%**	**12.9%**	**100.0%**

Panel E: Sample Distribution from 2001 to 2006						
Avg # Firms						
2318	**Low B/M**	**2**	**3**	**4**	**High B/M**	**Total Size**
Small	5.6%	6.3%	7.3%	7.5%	5.8%	**32.4%**
2	5.0%	5.2%	5.2%	4.7%	1.9%	**22.0%**
3	5.0%	4.4%	3.9%	2.4%	1.3%	**17.0%**
4	5.0%	3.9%	2.9%	2.0%	1.0%	**14.7%**
Big	6.3%	3.0%	1.9%	1.6%	1.1%	**13.9%**
Total B/M	**26.9%**	**22.7%**	**21.2%**	**18.2%**	**11.0%**	**100.0%**

Panel F: Sample Distribution Per Industry Sector					
Industry	**(1985 - 2006)**	**(1985 - 1989)**	**(1990 - 1994)**	**(1995 - 2000)**	**(2001 - 2006)**
Non-Durables	8.45%	10.68%	9.49%	7.29%	6.70%
Durables	2.03%	2.35%	1.99%	1.99%	1.80%
Manufacturing	10.26%	11.68%	10.33%	10.07%	9.06%
Energy	3.74%	3.03%	4.27%	3.71%	3.94%
Chemicals	2.51%	3.48%	2.75%	2.01%	1.95%
BusinessEquip	16.99%	15.89%	14.68%	18.95%	17.97%
Telecom	1.52%	1.16%	1.36%	1.55%	1.98%
Utils	3.89%	4.16%	4.17%	3.62%	3.69%
Shops	12.49%	12.18%	13.43%	12.63%	11.74%
Health	7.31%	6.04%	8.18%	7.13%	7.88%
Finance	18.83%	18.24%	18.18%	18.42%	20.45%
Other	11.99%	11.12%	11.18%	12.64%	12.84%

Table 2: Returns and Change in Value, Cross-Sectional Evidence

The table presents time series average of monthly cross-sectional regression coefficients used to test the validity of the Grossman Stiglitz hypothesis. The test is conducted for return periods of six months as well as change in value over six months, therefore each subscript indicates a six month period i.e. $R_{i,t-1}$ is the return over the last six months for firm *i* and $R_{i,t-2}$ is the return from t – 12 months to t – 6 months. The means are computed with overlapping observations, therefore t-statistics are computed with Newey-West (1987) standard errors with a lag length of one less than the holding period horizon in months. Panel A presents mean estimates for the regression explaining current return by past returns (momentum). Panel B presents estimates for the regression explaining current return by past change in value, concurrent change in value, past returns and concurrent SIC industry return.

Panel A: $R_{i,t} = \alpha + \gamma_1 R_{i,t-1} + \gamma_2 R_{i,t-2} + \gamma_3 R_{i,t-3} + \varepsilon_{i,t}$

Months	Intercept	$R_{i,t-1}$	$R_{i,t-2}$	$R_{i,t-3}$	Avg # Obs	R^2
251	0.0653	0.0688			1956	0.0140
	4.43	*5.19*				
245	0.0704		0.0053		1764	0.0106
	4.81		*0.44*			
239	0.0744			-0.0368	1615	0.0085
	5.04			*-4.27*		
245	0.0636	0.0623	0.0039		1763	0.0233
	4.44	*4.69*	*0.34*			
239	0.0738		0.0063	-0.0357	1605	0.0185
	5.09		*0.50*	*-4.34*		
239	0.0670	0.0584	0.0047	-0.0340	1604	0.0315
	4.73	*3.95*	*0.39*	*-4.20*		

Panel B: $R_{i,t} = \alpha + \beta_1 R_{v,t-1} + \beta_2 R_{v,t-2} + \beta_3 R_{v,t-3} + \gamma_1 R_{i,t-1} + \gamma_2 R_{i,t-2} + \gamma_3 R_{i,t-3} + \varepsilon_{i,t}$

Months	Intercept	$R_{i,t-1}$	$R_{i,t-2}$	$R_{i,t-3}$	$R_{v,t-1}$	$R_{v,t-2}$	$R_{v,t-3}$	Avg # Obs	R^2
251	0.0653	0.0688						1956	0.0139
	4.43	*5.19*							
251	0.0717				0.0147			1956	0.0046
	4.78				*2.52*				
251	0.0653	0.0659			0.0046			1956	0.0171
	4.45	*5.12*			*0.97*				
245	0.0633	0.0596	0.0066		0.0037	-0.0115		1765	0.0286
	4.48	*4.39*	*0.55*		*0.77*	*-2.38*			
239	0.0668	0.0540	0.0038	-0.0317	0.0087	-0.0058		1616	0.0361
	4.73	*3.65*	*0.31*	*-4.13*	*1.59*	*-1.11*			
239	0.0670	0.0538	0.0032	-0.0332	0.0086	-0.0051	0.0027	1616	0.0389
	4.78	*3.65*	*0.26*	*-4.27*	*1.58*	*-1.00*	*0.52*		

Panel C: $R_{i,t} = \alpha + \beta_0 R_{v,t} + \beta_1 R_{v,t-1} + \beta_2 R_{v,t-2} + \gamma_1 R_{i,t-1} + \gamma_2 R_{i,t-2} + \gamma_3 R_{i,t-3} + \lambda R_{I,t} + \varepsilon_{i,t}$

Months	Intercept	$R_{v,t}$	$R_{v,t-1}$	$R_{v,t-2}$	$R_{i,t-1}$	$R_{i,t-2}$	$R_{i,t-3}$	$R_{I,t}$	Avg # Obs	R^2
251	0.0636	0.2141							1956	0.1074
	4.40	*16.92*								
251	0.0608	0.2137			0.0173				1956	0.1169
	4.36	*16.96*			*1.40*					
251	0.0148	0.2031						0.7043	1956	0.1731
	1.86	*16.91*						*37.48*		
251	0.0135	0.2030			0.0137			0.6906	1956	0.1796
	1.73	*16.97*			*1.38*			*38.23*		
239	0.0167	0.2293			-0.0011		-0.0207	0.6731	1616	0.2030
	2.16	*18.64*			*-0.10*		*-3.79*	*36.28*		
239	0.0163	0.2304	0.0136		-0.0080		-0.0210	0.6707	1616	0.2055
	2.11	*18.55*	*2.73*		*-0.72*		*-3.91*	*36.27*		
239	0.0166	0.2393	0.0149	-0.0034	-0.0096		-0.0203	0.6654	1606	0.2104
	2.15	*17.93*	*2.76*	*-0.93*	*-0.87*		*-3.81*	*35.61*		
245	0.0151	0.2216	0.0134	-0.0051	-0.0008	-0.0149		0.6700	1765	0.1991
	1.96	*17.29*	*2.99*	*-1.63*	*-0.08*	*-1.73*		*35.80*		
239	0.0174	0.2400	0.0193	0.0020	-0.0116	-0.0190	-0.0211	0.6566	1606	0.2153
	2.24	*17.92*	*3.82*	*0.69*	*-1.01*	*-2.16*	*-4.03*	*34.50*		

Table 3: Returns and Change in Value for Momentum Portfolios

The table presents average returns and average change in value (Rv) for ten momentum portfolios. In period 0 stocks are sorted in deciles based on their six month returns. Periods -2 and -1 show the returns and change in value that the portfolios formed in Period 0 had prior to being formed. Period 1 is the six month holding period, which to avoid bid-ask problems and any lags in analysts' earnings changes starts one month after the formation period. Periods 2 and 3 correspond to six months post holding period.

Returns for Momentum Deciles (1985 -2006)

	Period -2 t-18 to t-12	Period -1 t-12 to t-6	Period 0 t-6 to t	Period 1 t+1 to t+7	Period 2 t+7 to t+13	Period 3 t+13 to t+19
Low Mom	14.57%	10.08%	-37.32%	3.23%	7.24%	10.14%
2	11.11%	8.90%	-18.19%	5.09%	6.76%	8.28%
3	9.54%	8.56%	-9.15%	6.26%	6.97%	8.01%
4	9.29%	8.95%	-2.59%	7.03%	7.41%	7.72%
5	9.33%	8.43%	3.07%	7.17%	7.32%	7.47%
6	9.39%	8.63%	8.58%	7.45%	7.35%	7.63%
7	9.68%	8.88%	14.61%	7.86%	7.55%	7.26%
8	10.10%	9.57%	22.19%	8.36%	7.69%	6.98%
9	11.38%	10.85%	33.96%	8.87%	7.03%	7.02%
High Mom	11.74%	14.80%	73.09%	11.33%	7.15%	5.63%
High - Low	-2.82%	4.73%	110.40%	8.10%	-0.09%	-4.51%

Change in Value (R_v) for Momentum Deciles (1985 - 2006)

	Period -2 t-18 to t-12	Period -1 t-12 to t-6	Period 0 t-6 to t	Period 1 t+1 to t+7	Period 2 t+7 to t+13	Period 3 t+13 to t+19
Low Mom	18.56%	14.94%	-12.86%	-5.24%	0.95%	8.42%
2	11.78%	10.91%	-1.17%	0.71%	2.88%	7.54%
3	10.29%	8.30%	2.59%	3.01%	3.50%	6.06%
4	8.97%	8.33%	5.59%	4.32%	4.92%	7.02%
5	8.40%	7.58%	7.52%	6.22%	3.54%	3.99%
6	8.31%	8.38%	10.18%	6.71%	4.40%	4.27%
7	9.31%	8.76%	11.67%	7.72%	6.05%	3.81%
8	9.27%	9.66%	14.80%	9.75%	6.45%	3.77%
9	10.92%	12.30%	22.47%	12.90%	7.24%	3.59%
High Mom	12.02%	17.52%	43.36%	20.21%	9.86%	3.93%
High - Low	-6.55%	2.58%	56.22%	25.46%	8.91%	-4.49%

Excess Returns to Fama French Size & Value Porfolios (1985 -2006)

	Period -2 t-18 to t-12	Period -1 t-12 to t-6	Period 0 t-6 to t	Period 1 t+1 to t+7	Period 2 t+7 to t+13	Period 3 t+13 to t+19
Low Mom	3.29%	1.08%	-42.80%	-2.29%	0.39%	2.76%
2	0.48%	-0.54%	-24.18%	-1.36%	-0.22%	0.50%
3	-0.42%	-0.45%	-15.87%	-0.61%	-0.15%	0.49%
4	-0.54%	-0.13%	-9.80%	-0.02%	-0.19%	0.16%
5	-0.61%	-0.50%	-4.70%	0.05%	-0.08%	-0.02%
6	-0.55%	-0.42%	0.21%	0.30%	-0.02%	0.02%
7	-0.21%	-0.35%	5.70%	0.49%	0.16%	-0.12%
8	-0.22%	0.26%	12.53%	0.99%	0.26%	-0.15%
9	0.62%	1.20%	23.26%	1.58%	-0.24%	-0.18%
High Mom	0.00%	4.09%	60.25%	4.05%	0.02%	-0.76%
High - Low	-3.29%	3.02%	103.05%	6.34%	-0.37%	-3.52%

Table 4: Returns and Change in Value for $R_{v,t-6}$ Value Portfolios

The table presents average returns and average change in value (Rv) for ten value portfolios. In period 0 stocks are sorted in deciles based on their change in value over six months. Periods -2 and -1 show the returns and change in value that the portfolios formed in Period 0 had prior to being formed. Period 1 is the six month holding period, which to avoid bid-ask problems and any lags in analysts' earnings changes starts one month after the formation period. Periods 2 and 3 correspond to six months post holding periods.

Returns for $R_{v,t-6}$ Value Decile (1985 - 2006)

	Period -2 t-18 to t-12	Period -1 t-12 to t-6	Period 0 t-6 to t	Period 1 t+1 to t+7	Period 2 t+7 to t+13	Period 3 t+13 to t+19
Low $R_{v,t-6}$	3.22%	-8.16%	-15.07%	5.42%	8.79%	9.49%
2	5.68%	-1.10%	-5.91%	5.94%	7.49%	8.05%
3	7.03%	2.93%	-0.01%	6.34%	7.32%	7.32%
4	8.00%	5.82%	3.97%	6.79%	6.99%	7.35%
5	9.26%	8.23%	6.85%	7.04%	7.20%	7.28%
6	11.21%	10.71%	9.73%	7.72%	7.20%	7.35%
7	13.56%	13.59%	13.05%	7.63%	6.99%	7.21%
8	16.09%	18.21%	17.05%	7.66%	7.04%	7.28%
9	18.43%	23.70%	23.31%	8.88%	7.09%	7.14%
High $R_{v,t-6}$	13.96%	26.50%	35.15%	9.21%	6.35%	7.56%
High - Low	10.74%	34.66%	50.22%	3.79%	-2.45%	-1.92%

Change in Value (Rv) for $R_{v,t-6}$ Value Decile (1985 - 2006)

	Period -2 t-18 to t-12	Period -1 t-12 to t-6	Period 0 t-6 to t	Period 1 t+1 to t+7	Period 2 t+7 to t+13	Period 3 t+13 to t+19
Low $R_{v,t-6}$	10.21%	10.17%	-43.65%	19.19%	13.45%	16.78%
2	6.79%	6.93%	-15.30%	-0.29%	4.11%	6.75%
3	5.69%	6.63%	-5.29%	0.25%	1.36%	3.69%
4	6.00%	6.46%	0.32%	1.86%	1.97%	2.98%
5	7.10%	7.13%	4.15%	2.83%	2.46%	4.45%
6	8.44%	8.49%	7.48%	4.48%	3.23%	3.51%
7	10.59%	10.09%	11.20%	5.87%	4.23%	3.82%
8	13.08%	13.16%	16.48%	7.29%	4.53%	3.83%
9	18.82%	18.04%	26.64%	10.02%	5.67%	3.87%
High $R_{v,t-6}$	24.22%	21.35%	102.32%	14.73%	10.73%	4.08%
High - Low	14.01%	11.18%	145.96%	-4.46%	-2.72%	-12.70%

Excess Returns to Fama French Size & Value Porfolios (1985 -2006)

	Period -2 t-18 to t-12	Period -1 t-12 to t-6	Period 0 t-6 to t	Period 1 t+1 to t+7	Period 2 t+7 to t+13	Period 3 t+13 to t+19
Low $R_{v,t-6}$	-7.12%	-16.74%	-22.61%	-1.19%	1.12%	1.67%
2	-4.33%	-9.68%	-13.47%	-0.82%	0.08%	0.43%
3	-2.80%	-5.73%	-8.01%	-0.78%	-0.07%	-0.09%
4	-1.63%	-3.14%	-4.07%	-0.38%	-0.43%	-0.27%
5	-0.53%	-0.75%	-1.12%	-0.01%	-0.11%	-0.07%
6	1.21%	1.57%	1.43%	0.45%	0.01%	0.12%
7	3.07%	3.99%	4.64%	0.74%	0.04%	-0.25%
8	5.36%	7.99%	8.22%	0.90%	-0.07%	0.16%
9	6.35%	12.96%	13.93%	1.73%	-0.24%	0.22%
High $R_{v,t-6}$	1.81%	14.96%	25.84%	2.53%	-0.29%	0.51%
High - Low	8.93%	31.70%	48.45%	3.72%	-1.42%	-1.16%

Table 5: How Fundamental Value Evolves When Momentum Works and When it Doesn't

The table presents average change in value (Rv) for a double sort of stocks on past six month returns (Momentum) and realized 1, 3, and 6 month return. The first panel of the table shows that change in value is high for low momentum stocks when these stocks go in the opposite direction (high returns) of what it would had been expected and likewise for high momentum stocks that realize low returns change in value is lower. The second panel shows the average number of firms that get assigned to each of the 100 bins created by the double sort.

Realized Value Rv for t + 1 Month

	Low R_{t+1}	2	3	4	5	6	7	8	9	High R_{t+1}
Low Mom (R_{t-6})	-0.0559	-0.0303	-0.0097	-0.0118	-0.0195	0.0021	-0.0003	-0.0014	0.0149	0.0432
2	-0.0373	-0.0073	0.0079	-0.0010	-0.0018	0.0074	0.0043	0.0079	0.0127	0.0565
3	-0.0111	-0.0067	-0.0042	0.0193	0.0090	0.0046	0.0187	0.0145	0.0256	0.0498
4	-0.0227	0.0025	0.0028	0.0053	0.0069	0.0089	0.0124	0.0196	0.0214	0.0517
5	-0.0096	0.0055	0.0056	0.0095	0.0109	0.0129	0.0118	0.0241	0.0286	0.0666
6	-0.0103	0.0154	0.0090	0.0158	0.0241	0.0144	0.0171	0.0209	0.0369	0.0524
7	0.0001	0.0134	0.0181	0.0173	0.0164	0.0156	0.0200	0.0291	0.0351	0.0565
8	0.0114	0.0199	0.0216	0.0198	0.0205	0.0200	0.0234	0.0417	0.0390	0.0732
9	0.0176	0.0245	0.0331	0.0317	0.0286	0.0272	0.0292	0.0389	0.0515	0.0662
High Mom (R_{t-6})	0.0526	0.0447	0.0434	0.0447	0.0449	0.0487	0.0558	0.0550	0.0707	0.1067

Realized Value Rv for t + 3 Months

	Low R_{t+3}	2	3	4	5	6	7	8	9	High R_{t+3}
Low Mom (R_{t-6})	-0.1811	-0.0907	-0.0765	-0.0667	-0.0254	0.0031	0.0115	0.0343	0.0744	0.1375
2	-0.1318	-0.0543	-0.0263	-0.0239	0.0154	0.0136	0.0236	0.0392	0.0710	0.1256
3	-0.1000	-0.0398	-0.0053	0.0077	0.0112	0.0156	0.0388	0.0451	0.0962	0.1608
4	-0.0949	-0.0066	0.0143	0.0208	0.0179	0.0254	0.0384	0.0504	0.0690	0.1382
5	-0.0653	-0.0067	0.0166	0.0162	0.0243	0.0304	0.0451	0.0614	0.0818	0.1550
6	-0.0543	0.0022	0.0276	0.0304	0.0362	0.0383	0.0619	0.0738	0.0920	0.1615
7	-0.0364	0.0152	0.0257	0.0316	0.0426	0.0542	0.0599	0.0664	0.0919	0.1750
8	-0.0266	0.0247	0.0348	0.0533	0.0699	0.0668	0.0819	0.0808	0.1027	0.1880
9	-0.0091	0.0485	0.0679	0.0634	0.0715	0.0806	0.0905	0.1037	0.1299	0.1974
High Mom (R_{t-6})	0.0535	0.1009	0.1133	0.1066	0.1445	0.1287	0.1298	0.1634	0.1858	0.2787

Realized Value Rv for t + 6 Months

	Low R_{t+6}	2	3	4	5	6	7	8	9	High R_{t+6}
Low Mom (R_{t-6})	-0.2976	-0.1647	-0.1470	-0.0656	0.0154	0.0059	0.0043	0.0325	0.1182	0.3316
2	-0.2384	-0.1238	-0.0680	-0.0372	-0.0035	0.0243	0.0485	0.0782	0.1328	0.3047
3	-0.2185	-0.0920	-0.0260	0.0218	0.0190	0.0450	0.0802	0.1104	0.1458	0.3181
4	-0.1830	-0.0546	0.0121	0.0178	0.0384	0.0449	0.0712	0.1032	0.1439	0.2778
5	-0.1553	-0.0475	-0.0068	0.0309	0.0445	0.0572	0.0926	0.1188	0.1652	0.2919
6	-0.1461	-0.0253	0.0265	0.0453	0.0524	0.0796	0.0992	0.1391	0.1680	0.3311
7	-0.1231	-0.0054	0.0219	0.0503	0.0747	0.0902	0.1038	0.1374	0.1824	0.3357
8	-0.1089	0.0191	0.0608	0.0787	0.0908	0.1198	0.1446	0.1573	0.2056	0.3492
9	-0.0749	0.0539	0.0886	0.1097	0.1211	0.1370	0.1740	0.1836	0.2420	0.3863
High Mom (R_{t-6})	0.0187	0.1485	0.1575	0.1861	0.2485	0.2396	0.2412	0.2797	0.3623	0.5072

Average Number of Firms for t + 1 Months										
	Low R_{t+1}	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High R_{t+1}**
Low Mom (R_{t-6})	31	19	15	13	12	12	13	15	19	31
2	22	18	18	17	16	17	17	17	19	19
3	16	18	18	19	19	19	19	19	18	15
4	14	17	19	20	20	20	20	19	17	13
5	12	17	19	20	21	21	20	19	17	13
6	13	17	19	20	21	21	21	19	17	13
7	13	18	20	20	20	20	20	19	17	13
8	14	18	19	19	19	19	19	19	18	15
9	17	18	18	18	17	17	17	18	19	19
High Mom (R_{t-6})	25	19	16	14	13	13	14	17	20	28

Average Number of Firms for t + 3 Months										
	Low R_{t+3}	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High R_{t+3}**
Low Mom (R_{t-6})	31	20	16	13	13	13	13	15	18	27
2	21	19	17	17	16	17	17	18	18	18
3	16	17	18	19	19	19	19	19	18	15
4	14	17	19	20	20	20	20	19	17	14
5	13	16	19	20	21	21	20	19	17	13
6	13	17	19	20	21	20	20	19	17	13
7	13	18	19	20	20	20	20	19	17	14
8	15	18	19	19	19	19	19	19	18	16
9	18	18	18	17	17	17	17	18	19	20
High Mom (R_{t-6})	25	19	16	14	13	13	13	15	20	30

Average Number of Firms for t + 6 Months										
	Low R_{t+6}	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High R_{t+6}**
Low Mom (R_{t-6})	32	22	17	14	12	12	13	14	17	24
2	22	20	18	17	17	17	17	17	17	17
3	16	18	18	19	19	19	20	18	17	15
4	14	16	18	20	21	21	20	19	17	14
5	12	16	19	21	21	21	20	19	17	13
6	12	16	19	20	21	20	20	19	17	14
7	13	17	18	19	21	20	19	19	18	14
8	14	17	18	19	19	19	19	19	19	17
9	17	18	18	17	16	17	17	19	20	21
High Mom (R_{t-6})	26	19	15	13	12	13	13	15	20	31