MISPRICING FOLLOWING PUBLIC NEWS:

OVERREACTION FOR LOSERS, UNDERREACTION FOR WINNERS

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March 17, 2008

ABSTRACT

We document an important relation between two well-established anomalies: momentum and short-term reversal. Only stocks with negative momentum experience short-term reversal. Using Chan's (2003) news database, we show that the market appears to overreact to public news following bad past performance and underreact following strong past performance. The results are robust to using alternative methodologies. Stocks with current good news and negative momentum earn on average –9.3% annual *raw* returns during the subsequent month, while stocks with current good news and positive momentum earn +32.2%. The large, negative raw returns point to cognitive biases, rather than risk-based explanations, as the source of abnormal returns.

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ABSTRACT

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The weak-form Efficient Market Hypothesis holds that stock returns cannot be predicted based on past price behavior (Fama, 1970). Therefore, any study that attempts to present the existence of abnormal returns based on information obtained from past prices is at odds with even the weakest form of the Efficient Market Hypothesis. However, during the past three decades, the literature documented three types of return predictability anomalies, all based on historical price patterns. In the cross-section, stock returns present with reversal (or overreaction) at long-term intervals of three to five years, momentum (or underreaction) at medium-term intervals of six to twelve months, and again reversal (or overreaction) at short-term intervals of one or four weeks.[1]

In response to Fama's (1998) call for a unified theory of behavioral finance that can simultaneously explain over- and underreaction, the literature responded with several behavioral models that link long-term reversal and medium-term momentum patterns. For example, Daniel, Hirshleifer and Subrahmanyam (1998) propose a model which incorporates investor's overconfidence about private signals leading to medium-term underreaction to public news and long-term overreaction to private signals. Barberis , Shleifer and Vishny (1998) presents a model in which investors are misinformed about the statistical properties of earnings and therefore believe in either contrarian or trend-following forecasting, which results in medium-term continuation and long-term reversal. And Hong and Stein (1999) derive similar implications through a model with news-watchers and trend followers.

[1] See, e.g. DeBondt and Thaler (1985) who document reversal at three- to five-year intervals; Jegadeesh and Titman (1993) who document momentum at three- to twelve-month intervals. Short term reversal is documented by Lehmann (1990) for weekly returns and by Jegadeesh (1990) for monthly returns.

By contrast, little is known about the relation between (medium-term) momentum and short-term reversal.

We examine the interaction of momentum and short-term reversal and show that reversal occurs only in stocks with negative momentum. Using Chan's (2003) public news data we explain reversal as a short-term overreaction to public news for stocks with negative momentum. At the same time, we document a short-term underreaction to public news for stocks with positive momentum.

To our knowledge, the magnitude of the abnormal returns resulting from this anomaly is one of the largest ever documented in the literature. A hedge portfolio that is long in stocks with good news and positive momentum, and short in stocks with good news and negative momentum, earns a remarkable 46.3% per year after controlling for the Fama-French factors, even after excluding stocks priced at less than $5 a share.

A possible explanation for this anomaly is that it represents a priced, unknown risk factor. Risk-based explanations suggest that any abnormal returns are fair compensation for risk, and do not necessarily contradict the Efficient Market Hypothesis. For example, Chan (1988), Ball and Kothari (1989), and Zarowin (1990) all propose risk-based explanations for the DeBont and Thaler (1985) long-term reversal anomaly.

We believe that risk-based explanations are not consistent with the results presented in our study, simply because stocks with negative momentum and good news earn *negative raw returns* of approximately -9.3% per year, during more than two decades. To justify a negative risk premium of this magnitude, these stocks' dividend payoffs would have to be highest in those states of the world for which the aggregate output is low (and which carry high Arrow-Debreu state prices). Yet, these stocks are shown to load positively on all three Fama-French risk factors, suggesting that their expected rate of return should be positive.

In the absence of a reasonable risk-based explanation, we believe that the anomaly is driven primarily by cognitive biases. In the discussion section we propose an explanation which draws from the psychology literature in the areas of cognitive dissonance and overconfidence. In doing so, our goal is not to identify the precise cognitive bias that is at the origin of this new anomaly, but rather to suggest a plausible explanation and to initiate an academic dialogue that would enhance our understanding of price formation under non-Bayesian updating.

The next section presents data sources and descriptive statistics. Section II shows that short-term reversal occurs only in stocks with negative momentum. Section III explores the role of public news, and Section IV presents an explanation based on the literature in psychology. Section V concludes.

I. DATA SOURCES AND DESCRIPTIVE STATISTICS

Our main dataset include all stocks traded on NYSE, AMEX and NASDAQ during the period from 1980 to 2006. Stock returns are obtained from the Center for Research in Security Prices (CRSP) at University of Chicago. All returns are corrected for de-listing to avoid survivorship bias. Following Jegadeesh and Titman (2001), we exclude stocks with a share price below $5 at the portfolio formation date to make sure that the results are not driven by small, illiquid stocks or by bid–ask bounces.

Momentum is measured as the cumulative raw return from month *t-6* to *t-1*. To measure reversal we compare stock returns between months *t* and *t+1*. We define "reversal" as a situation where returns at month *t+1* are of the opposite sign of those at month *t*. If the two returns are of the same sign, we refer to it as "continuation."

To examine stock price responses to public news, we employ a news dataset assembled by Chan (2003), which covers a random sample of approximately one-quarter of all CRSP stocks over the period from 1980 to 2000.[2] Chan (2003) maintains a count of news items obtained from Dow Jones Interactive Publications Library of past newspapers, looking at only publications with over 500,000 current subscribers. For each

[2] We are grateful to Wesley S. Chan for sharing his dataset.

stock covered, the dataset collects the dates at which the stock was mentioned in the headline or lead paragraph of an article of one of the publications covered.[3]

II. RELATION BETWEEN MOMENTUM AND SHORT-TERM REVERSAL

A. Univariate Analysis

We begin with a univariate analysis of the momentum and reversal effects. At this point our goal is only to replicate the findings of Jegadeesh (1990), and of Jegadeesh and Titman (1993) with our new sample. Table II presents the results.

Panel A of Table II presents the momentum effect. Stocks are sorted into deciles based on their cumulative returns during months [t-6, t-1], and the returns of each decile are measured at month t+1. Consistent with Jegadeesh and Titman (1993), we observe a near-monotonic positive relation between past and future returns. Moreover, this relation is significant at high levels (t=6.14) as evidenced by the return of the hedge portfolio that is long past winners and short past losers.

Panel B of Table II presents the reversal effect. Stocks are sorted into deciles based on their returns during month t, and the returns of each decile are measured at month t+1. Here, the best performers in any month are the losers from the previous month, and vice-versa. And the returns on the hedge portfolio show that this effect is statistically

[3] For a more detailed description of the dataset see Chan (2003)

significant (t=-2.59). We thus confirm Jegadeesh's (1990) finding of stock price reversal for the one-month horizon.

B. Interaction between Momentum and Reversal.

We now seek to understand the relation between momentum and reversal. We do so by relating returns at month t+1 to the interaction of returns measured during [t-6, t-1] (momentum), and those measured during month t (reversal). As is common with this type of studies (Jegadeesh and Titman, 1993; Avramov et al., 2006; Jegadeesh, 1990; Chan, 2003), we use two econometric approaches: calendar-time portfolios and Fama-MacBeth regressions.

B.1. Calendar Time Portfolios

We assign stocks to quintiles based on momentum measured during [t-6, t-1]. We also independently sort each quintile into five portfolios based on stock returns measured during month t. The returns of the resulting 25 portfolios are measured during month t+1. The monthly mean returns are then averaged intertemporally and the results are presented in Table III. The last two lines of Table III show the performance of a hedge portfolio that is long past month's losers and short past month's winners. A separate hedge portfolio is constructed for each momentum quintile.

A reversal effect occurs when there is a monotonically decreasing relation between returns at month t (denoted R1, R2 … R5) and returns at month t+1. The statistical significance of any reversal relation is measured with the hedge portfolio at the bottom of the table.

Surprisingly, we find that reversal only occurs for stocks with negative momentum (M1 and M2). Moreover, this reversal is strongest in the lowest (M1) momentum category. In that case, the hedge portfolio earns a mean monthly return of 1.76%, with a high level of statistical significance (t=7.89). By contrast, there is no evidence of reversal among high-momentum stocks (M5). In that case, the hedge portfolio earns an insignificant 0.48% return per month, during the same period.

B.2. Fama-MacBeth Regressions

We repeat the analysis from Table III using Fama-MacBeth regressions. Each month *t*, we sort stocks into five quintiles based on their momentum measured during [t-6, t-1]. We then run cross-sectional regressions of the return at month t+1 on the return at month t, for each of the five momentum portfolios. As in Fama and MacBeth (1973), we compute the final coefficients from the inter-temporal average of month-specific regression estimates.

The results are presented in Table IV. We observe a striking difference between the monthly serial correlation within the low (M1) and high momentum (M5) portfolios. As before, reversal occurs only in the lowest two momentum portfolios. For M1, reversal is highest with a coefficient of -0.0491 (t=-9.93). These results are consistent with those reported in Table III.

C. Robustness Tests

We now reexamine our results with the goal of assessing their robustness. We repeat our tests with plausible changes in asset pricing models and econometric approaches.

C.1. Illiquidity

Avramov et al. (2006), suggest that short-run contrarian profits are driven by illiquidity, consistent to the rational equilibrium framework of Campbell et al. (1993). They show that weekly reversal is stronger for stocks with high illiquidity, and implicitly argue that illiquidity is also a driver of monthly return reversals. If the low momentum stocks are also the most illiquid, our results could be driven by liquidity effect. We now introduce a liquidity control in our analysis.

Our proxy for illiquidity is the Amihud (2002) measure, which is computed as the absolute price change per dollar of daily trading volume. To control for illiquidity, we first sort stocks into four momentum quartiles, and also independently sort stocks into four illiquidity quartiles. In each of the resulting 16 portfolios, we perform cross-sectional Fama-Macbeth (1973) regressions, and compute the intertemporal mean of the beta coefficients:

$$R_{it+1} = \alpha_t + \beta_t R_{it} + \varepsilon_{it} \qquad (1)$$

If our results are driven by illiquidity rather than momentum, then we should not observe any significant difference among β coefficients within the same illiquidity quartiles. Moreover, the β coefficients should be significantly negative only among the high illiquidity stocks. By contrast, if the momentum effect persists independent of illiquidity, we should observe significantly negative beta coefficients for *all* low momentum stocks.

Table V presents the results. Each cell in Table V shows the intertemporal average of Fama-MacBeth beta coefficients obtained from Equation (1). The data show a clear illiquidity effect, in that reversal is stronger (betas are more negative) for stocks with higher illiquidity.

However, our results *are not* driven by illiquidity. The momentum effect is always significant regardless of the illiquidity level. Among low illiquidity stocks (IL1), the average β from equation (1) increases monotonically with momentum, from -0.02509 (t= -3.18) to 0.00387 (t=0.46). A similar increase is noticed among high illiquidity stocks (IL5): the average β from equation (1) increases monotonically from -0.056 (t=-9.5) to -0.00427 (t=-0.68).[4] Moreover, among stocks with low momentum (M1), the reversal effect is always statistically significant, regardless of the level of liquidity. We conclude that while illiquidity moderates the relation between momentum and reversal, it does not explain it.

[4] In all illiquidity quartiles, the momentum effect is found to be statistically significant at the 1% level (not shown).

C.2. Turnover

Campbell, Grossman, and Wang (1993) propose a rational expectations explanation for the reversal effect. They argue that non-informed trading causes price movements that, when absorbed by liquidity suppliers, cause prices to revert. This suggests that non-informed trading is accompanied by high trading volume, while low volume reflects informed trading. If our results are entirely explained by the rational expectations model of Campbell et al., the reversion effect should be affected *only* by trading volume, not momentum. Conrad, Hameed, and Niden (1994) find support for the Campbell et al. model, at weekly frequencies.

We control for trading volume using monthly turnover measures computed as the monthly dollar trading volume divided by market capitalization. We use the same method as in the previous sub-section where we controlled for illiquidity. However, as suggested in Lee and Swaminathan (2000), we exclude all NASDAQ stocks to avoid problems with inflated trading volume caused by double counting dealer trades.

The results are presented in Table VI. The interaction of momentum and reversal remains persistent even after controlling for turnover. The effect of momentum is always significant regardless of the illiquidity level. Among low turnover stocks (T1), the average β from equation (1) increases with momentum from -0.05007 (t=-6.20) to -0.03234 (t=-5.19). Similarly, among high turnover stocks (T5) the average β increases with momentum from -0.01918 (t=-1.85) to 0.01713 (t=2.76). The differences are always significant at 1% level. Most importantly, for low momentum stocks, the reversal effect is always significant regardless of turnover. As with the case of illiquidity, we conclude that while turnover is an important moderator of the relation between momentum and reversal, it does not explain it.

C.3. Multiple Controls

Until now we have shown that the momentum-reversal relation survives controlling for illiquidity and, independently, turnover. But will the relation remain significant if we control for both effects simultaneously? To answer this question we conduct Fama-Macbeth regressions on the entire sample. We also include other firm characteristics that are known to be associated with the cross-section of stock returns: book-to-market, dispersion of analyst forecast, institutional ownership, and number of analysts covering the firm.

The results are presented in Table VII. Our focus is on the interaction coefficient of momentum and current monthly returns (*MOM*RET*). The interaction coefficients are always positive and highly significant, suggesting that the reversal effect diminishes as momentum increases, regardless of which control variables are used in the statistical specification. This is again consistent with our previous findings.

C.4. Dependent Sorts

All calendar time portfolio results that depend on two variables are derived from independent sorts on the two variables. For example, in Table III, stocks are sorted independently on momentum and current returns. We re-do all tests with *dependent* sorts, sorting first by momentum then by the other variable within each momentum group. The results (not shown) are almost identical in terms of magnitudes and statistical inferences.

C.5. Small Cap Screen

We repeat our tests after excluding all small cap stocks from the analysis. Industry professionals place the boundary between small- and mid-cap stocks anywhere from one to two billion dollars. In the absence of a clear consensus, we use a threshold of $1.5 billion for stocks traded in December 2006. For months prior to December 2006, we deflate the $1.5 billion value with the CRSP value-weighted return index (including dividends). We then eliminate all stocks whose market value falls below the $1.5 billion threshold (or the deflated value thereof). The results (not shown) are almost identical in all respects.

C.6. Different Momentum Definitions

Jegadeesh and Titman (1993) show that the momentum effect is robust to measurement periods ranging from three to months. As a result, we repeat our analysis with momentum redefined as cumulative returns measured alternatively over months [t-3, t-1], [t-9, t-1], and [t-12, t-1]. Our results (not shown) are not affected by these alternative measurement horizons.

III. THE ROLE OF PUBLIC NEWS

In the previous section we document that reversal occurs exclusively among low momentum stocks. We now show that this result is driven by the differential response of low- and high-momentum stocks to public news.

We obtain a count of public news from Chan's (2003) dataset. His is the first paper to document the importance of public news for monthly mean reversals.[5] Every month, Chan (2003) separates his data into two groups: stocks that were mentioned in the headline or lead paragraph of an article from a publication with more than 500,000 current subscribers (news stocks) and other stocks (no news stocks). He then looks at monthly serial correlation patterns for these two different groups. He finds reversal only for the "no news" sub-sample. By contrast, monthly serial correlation is not significant for the "news" sample. Chan's analysis, however, does not explore the role of momentum, mainly because his paper focuses primarily on explaining long term anomalies as opposed to the interaction between momentum and short-term (monthly) reversal.

A. "News" and "No News" Samples

We examine the effect of momentum on the reversal effect separately for the "news" and "no news" sub-samples. Our focus is on the "news" sub-sample where Chan found no significant monthly serial correlation of any sign. We will show that Chan's zero-serial-

[5] Pritamani and Singal (2001) collected daily news stories from the Wall Street Journal and Dow Jones News Wire for a subset of less than 1% of CRSP stocks, during only the period from 1990 to 1992.

correlation result is in fact the average of two distinct economic realities: reversal for low-momentum stocks, and continuation for high-momentum stocks. Our analysis uses the same news dataset collected by Chan (2003), which spans a time period from 1980 to 2000. Following Jegadeesh and Titman (2001), we again exclude stocks with a share price below $5 at the portfolio formation date, to ensure that the results are not driven by small, illiquid stocks or by bid–ask bounces.

Following Chan, we divide stocks into two groups: Stocks that were mentioned in the headlines (the news group) based on Chan's dataset, and stocks that were not (the no-news group). We repeat our previous analysis with these two sub-samples. For conciseness, we present only the results obtained with portfolio sorts; the results based on the Fama-MacBeth method are very similar. Within each sub-sample (news and no-news), every month we sort stocks into five groups according to momentum month t-6 to t-1. We then independently sort stocks into five groups according to the rate of return observed that particular month, t.

The results are presented in Table VIII. Panel A of Table VIII replicates Chan's finding. We show that stocks with no public news present with reversal for all momentum portfolios. By contrast, the results form the "news" sub-sample, shown in Panel B are new and intriguing. Recall that Chan had found zero serial correlation for this sub-sample *without* conditioning on momentum. Once we condition on momentum, we find strong negative serial correlation (reversal) among stocks with low momentum, and strong *positive* serial correlation (continuation) among stocks with high momentum.

B. Economic Significance

The results from Table VIII, especially those in Panel B suggest that there is significant mispricing among stocks with public news, high current return, and extreme (high or low) momentum. Stocks with high current returns and high momentum [M5, R5] earn an average monthly raw return of 2.35% during the subsequent month. At the other extreme the average monthly *raw* return for stocks with low momentum and high current returns [M1, R5] is -0.76%. The differential performance between these two groups (3.29% per month) suggests a mispricing of a remarkable magnitude. To our knowledge, no other study finds hedge portfolio returns even close to 3% per month, especially after eliminating small stocks.

To understand the full economic significance of this mispricing, we compute annual returns for the long, short, and hedge portfolios for each year during the sample period. We also inquire if the mispricing is due to the well-known January effect. The results are presented in Table IX. The large, top section of the table shows annual percentage returns for the three portfolios and for two popular benchmarks: the SP500 and the CRSP value-weighted return including dividends. The third line from the bottom shows the average annual return computed during the months of January only. The second line from the bottom shows average annual returns computed each year from the months of February to December. The last row in Table IX shows the average annual returns for all stocks, for the entire sample period.

We observe that the hedge (long minus short) portfolio produces positive raw returns in every single year in our sample. Moreover, this portfolio beats the SP500 in all but three years. Other performance statistics are also favorable. For example, the volatility of the hedge portfolio is 21.3% per year and its Sharpe ratio is a remarkable 2.1 (not shown in the table). This compares favorably to a volatility of 15.1% and a Sharpe ratio of 0.92 for the SP500 portfolio.

Although a mild January effect is present, it cannot be the source of this anomaly. The hedge portfolio earns 59.0% per year during January and 44.1% per year during the months of February to December. The average annual performance of the hedge portfolio is 45.3% over the twenty-one-year sample period. To our knowledge, this is the largest magnitude for equity long-short strategies that has been documented in the literature.

Figure 1 provides a visual depiction of the economic importance of our findings. All four lines show the cumulative value of a one-dollar investment made during the month of January 1980. The top line in the figure depicts the performance of the hedge portfolio based on the news-momentum-reversal strategy. The second line from the top shows the performance of only the long leg of that hedge portfolio. The bottom line shows the short leg of the hedge portfolio, except that the performance is shown from the buyer's perspective and not that of the short-seller.[6] The remaining (thin) line shows the performance of the value-weighted market index.

It is immediately apparent that the performance of the hedge portfolio is clearly superior to that of the benchmark. One dollar invested in January 1980 grows to $1,425 with the actively managed strategy, compared to only $24 in the market index. Also remarkable is that our strategy can identify a set of stocks with negative *raw* returns of a significant magnitude. If an inadvertent investor would take a long position in stocks belonging to the short portfolio, that investor would lose more than 90% of its initial investment. The dollar invested in 1980 would be worth less than 8 cents at the end of 2000. To our knowledge, we are the first to identify an anomaly that produces negative *raw* returns of this magnitude. Most other anomalies document negative *abnormal* returns.

This particular finding has a very important implication in light of the popularity of risk-based explanations of financial anomalies. When an anomaly produces negative *abnormal* but positive *raw* returns, it could be consistent with either mispricing or lower risk premium. A good example is Johnson (2004) who observes that stocks with high dispersion of opinion have negative abnormal returns (which are nonetheless positive on a raw basis). He proposes an option-theoretic, rational expectations model to explain this result. However, when an anomaly produces negative *raw* returns equal to -9.3% per year for over 20 years, there is little that risk-based explanations can do to make it consistent with rational expectations. Indeed, any such explanation is held to the high

[6] Thus, the negative performance depicted in the graph implies positive profits for the short-seller.

standard of providing direct evidence that such stocks could have a *negative expected rate of return* in equilibrium.[7] In short, we believe that the results of our short portfolio present what is perhaps the most unambiguous evidence of mispricing ever documented in the literature.

In Table X we re-examine the performance of the long, short, and long-short portfolios after controlling for the Fama-French factors. Not surprisingly, the long portfolio (Panel A) presents with a significantly positive abnormal return. In Panel B, we observe a negative abnormal return for the short portfolio. More interesting however are the loadings on the Fama-French factors for the short portfolio. These loadings are all positive, suggesting that the risk premium should also be positive, at least as captured by the Fama-French factors. The positive risk loadings from Panel B present *prima-facie* evidence that the negative raw returns from Table IX represent true mispricing as opposed to a (negative) risk premium.

The results of the long-short portfolio (Panel C) show a remarkable 3.22% monthly abnormal return for a strategy that is essentially market-neutral (β=-0.02, t=-0.21). Since the theoretical return of any market neutral strategy is the risk-free rate, the size of the long-short abnormal returns is clearly indicative of significant mispricing.

[7] We recognize that negative expected returns are possible in equilibrium, but only in the case of assets whose cashflows are negatively correlated with the aggregate output. Thus, a risk-based explanation can only be convincing if it presents clear evidence of such negative correlation.

IV. DISCUSSION

We have documented significant mispricing for stocks with good news and extreme momentum. The magnitude of the mispricing, as well as the large, *negative raw returns* obtained for stocks with low momentum and good current news, point to behavioral, rather than risk-based explanations for this anomaly.

Specifically, we observe that stock prices *overreact* – at the one-month horizon – to public news when the momentum is negative. For this group of stocks we see a strong *reversal* in returns between month t (when the news arrives) and month t+1 (when, presumably, prices begin to return towards equilibrium).

By contrast, for stocks with positive momentum prices *underreact* to public news at the one-month horizon. In this case, returns from month t continue unto month t+1 in the same direction.

The price response pattern we document here is new to the finance literature. We are the first to document an anomaly where separate stock groups simultaneously overreact and underreact to news, depending upon each group's price history. Moreover, this differential reaction occurs for the same, short term, horizon. We refer to this type of anomaly as *cross-sectional differential reaction.* It contrasts with *time-series differential reaction* documented in prior literature, where the same group of stocks presents with both over- and under- reaction at different time horizons (such as 3-12 months momentum and 3-5 years reversal).

The cross-sectional differential reaction anomaly cannot be readily explained by the prominent theoretical models from the behavioral finance literature, mainly because such models focus primarily on explaining the existing evidence of *time-series* differential reactions (e.g. Daniel, Hirshleifer, and Subrahmanyam, 1998). As a result, we turn to the literature in cognitive psychology in search of an explanation. We look for factors that link information processing (reaction to news) to past history (momentum).

We draw from the work done in the areas of *cognitive dissonance* and *overconfidence*, and believe that our results are consistent with their key predictions. We present below a conceptual behavioral framework that could produce the type of anomaly reported in this paper. We hasten to add, however, that we view this framework as exploratory in nature. Our main objective is to show that psychology theory *could* explain differential reaction not only in time series but also in the cross-section. That is, depending upon investors' ex-ante cognition, stock prices could either underreact or overreact to public news for the same (short-term) time horizon. This is an important contribution in view of Fama's (1998) critique that behavioral theories fail to produce a unified theoretical body of knowledge that can explain a large class of anomalies. Of course, we also hope that our discussion here will stimulate additional research related to the effect of cognitive dissonance and overconfidence on the price formation mechanism.

We should also add that we are at this point concerned only with the differential price reaction among stocks *with public news*. Recall that this reaction is documented in Panel B of Table VIII, as well as in Tables IX, X and Figure 1. This is because for this group of stocks we can confidently attribute (at least part of) month *t* return to information conveyed by public news that month.[8] We do not attempt to explain the apparently homogeneous under-reaction of stocks with no public news (Panel A of Table VIII), because we are not sure to what causes we should attribute the returns observed at month *t* for this other group of stocks.

A. Cognitive Dissonance

Pioneered by Festinger (1957), the concept of cognitive dissonance is the mental conflict people experience when presented with evidence that is inconsistent with their prior beliefs (Shiller, 1999). Festinger argues that faced with cognitive dissonance people will take actions to minimize it, even if such actions appear irrational. Indeed, eliminating dissonance appears to be one of humans' most basic psychological needs.

In a classic experiment, subjects were asked to work on some tasks that were inherently boring. Some of the subjects were manipulated by the experimenter into believing that the tasks were in fact exciting. This created a state of cognitive dissonance for this group of subjects. Seeking to reduce dissonance, those same subjects eventually changed their beliefs and agreed that the tasks were exciting. The results suggest that people are

[8] This follows Chan (2003).

uncomfortable to be in a dissonant state, and that one way to reduce dissonance is to abandon one's prior set of beliefs in favor of an alternative set that is more consistent with public evidence (i.e. seeing a boring task as interesting, because the experimenter claims it is interesting). Most importantly, this paradigm change occurs even in the absence of any rational basis to embrace the alternative set of beliefs (the experimenter's opinion about the task does not change the fact that an intrinsically boring task remains boring).

B. Overconfidence.

Langer and Roth (1975) are the first to document overconfidence as a cognitive bias. In their experiment, subjects who are manipulated into believing to have superior skill sets are confident that they can not only predict coin tosses but also affect their outcome. Their finding has been repeatedly replicated, and it is now generally accepted among psychologists that people show excessive confidence about their own judgments. Overconfidence has also been extensively studied in the behavioral finance literature.[9] As Shiller (1999) observes, overconfidence *does not* in itself predict whether prices will respond to news with an over- or underreaction pattern. Rather, it simply predicts that overconfident people will make errors, but not in any well-specified direction. By contrast, we believe that when overconfidence is analyzed together with cognitive dissonance, it has the potential to explicate cross-sectional differential reactions such as the ones documented in our study.

[9] See, Shiller (1999) for a review of the behavioral finance literature on overconfidence.

C. Relation to Empirical Results.

To relate our findings with cognitive dissonance we begin with the observation that investors are net long in the stock market, and by a wide margin.[10] We also assume that investors are overconfident in their own judgment. Moreover, we assume that this overconfidence plays a key role at the time of stock purchase: investors select only those stocks for which they have favorable private beliefs that indicate expected positive returns. In short, we assume that investors only purchase stocks on which they expect to make money, and feel quite confident with their choices.

We then take the view that in the cross-section of stock returns, among stocks with low momentum (i.e. negative past returns), the investor base is more likely to include people in a state of severe cognitive dissonance – those who purchased the stock moths ago with the expectation that it would *increase* in value, but nevertheless faced the obvious reality of a severe price depreciation.

By contrast, the investor base for high-momentum stocks (those with positive past returns) will not likely face any cognitive dissonance. These investors probably feel good about their choices and attribute the stock's performance to their own stock picking

[10] This is substantiated by the fact that the average ratio of short interest to total shares outstanding is quite low. For example, this ratio was approximately 0.7% in the 1980s and 1.2% in the 1990s.

abilities.[11] When faced with this type of *cognitive consonance*, investors remain overconfident about their own private signals of firm quality and are thus likely to overweigh them when compared to public signals.[12] Public news will therefore be underweighed as investors adjust their expectations in a non-Bayesian manner and continue place excessive weight on their own private signal, as they did at the time of the initial stock purchase. This results in underreaction to public news (both good and bad) for high-momentum stocks, consistent with the evidence presented in this paper.

Returning now to negative-momentum stocks, if the investor base is significantly affected by cognitive dissonance, a paradigm shift will occur with the arrival of public news. Similar to the shift documented by Festinger (1957) in his classic experiment, these investors will now abandon their previous paradigm of relying primarily on private signals and instead adopt the alternative paradigm that public signals are more informative about firm quality. Due to overconfidence, they will place a higher-than-normal weight on the public signal. This causes stock prices to overreact to public news (both good and bad) for stocks with negative momentum.

At this point, an important observation is warranted. One could also interpret our empirical results to imply that investors are overconfident in the case of low momentum stocks (where prices overreact), and underconfident for high momentum stocks (where

[11] This relates to the "self attribution bias" proposed by Daniel, Hirshleifer and Subrahmanyam (1998), and also to the psychological concept of "illusion of control" and "magical thinking." Shiller (1999) provides an excellent review of studies in these two latter areas.

[12] The concept of *cognitive consonance* is the opposite of *cognitive dissonance* and refers to situations when people are presented with evidence that conforms to their prior beliefs.

prices underreact). Indeed, the concepts of *overreaction* and *underreaction* are often taken as synonymous to *overconfidence* and *underconfidence* (respectively), but this need not be the case (Shiller, 1999). This alternative explanation is less than satisfactory because it does not meet Fama's (1997) test of forming a unified theory. Why would investors, in the cross-section, be underconfident in some cases and overconfident in other?

By contrast, our proposed explanation has the unique advantage of treating overconfidence and cognitive dissonance as universal phenomena that are present among *all* groups of investors. In the cross-section of stock returns, overconfidence can manifest in either overreaction or underreaction depending upon investor's cognition (dissonant or consonant), which is itself predictable.

V. SUMMARY AND CONCLUSION

We examine the interaction of momentum and short-term reversal. Although each of these two effects is well documented in the finance literature, the relation between the two is not well understood. We show that reversal occurs only for stocks with negative momentum. Moreover, using Chan's (2003) news database we find that the reversal effect suggests overreaction to public news for stocks with negative momentum. By contrast, for stocks with large, positive momentum, we find underreaction to public news.

These findings present opportunities for earning abnormal returns of a magnitude never before documented in the literature. A market-neutral hedge portfolio long on stocks with good news and positive momentum and short on stocks with good news and negative momentum earns well over 40% per year, even after accounting for the Fama-French factors. Even more remarkable is that the raw returns of stocks in the short leg of the hedge portfolio are actually negative and large in magnitude (-9.3% per year). These stocks load positively on the Fama-French factors, suggesting that their negative returns are unlikely caused by negative risk premia or another type of rational explanation.

Our paper is also the first to document a case where overreaction and underreaction do coexist in the cross-section of stock returns. This contrasts to prior behavioral finance literature where these two phenomena are often viewed as affecting stock returns in the time series, at different time intervals.

We propose a behavioral explanation to explain the link between momentum and the differential reaction to public news. Our explanation draws from the behavioral concepts of cognitive dissonance and overconfidence. Overconfident investors who hold stocks with negative momentum are more likely to face cognitive dissonance when compared to those who hold positive-momentum stocks. As a result, the former place excessive weight on public news, leading to overreaction, while the latter place excessive weigh on their private signals, leading to underreaction.

We hope that our study provides the impetus for more researchers to rely on theory from cognitive psychology in explaining anomalous findings in the asset pricing literature. Investors and analysts are, above all, humans, and as such are subject to the same biases that have been thoroughly studied in the psychology literature. Five decades of research in cognitive psychology provide rich insights to help us build a unified framework that explains the menu of anomalies documented in the empirical asset pricing literature.

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Table I: Descriptive Statistics

Monthly returns, Stock Price, Market Capitalization and Trading Volume are from CRSP. Illiquidity is the Amihud (2002) measure using daily return and volume obtained from CRSP. Number of News is from Chan (2003). The sample period is from 1980 to 2006, except for the Chan (2003) news sample, which extends from 1980 to 2000. Stocks are included in the database if they have valid returns over the previous six months, as well as a share price higher than five dollars.

Variable	Number of Observations	Monthly Mean	Monthly Standard Deviation	Minimum	Maximum
Monthly Return (t)	1569457	0.02	0.13	-0.84836	12.67
Stock Price	1569457	29.30	657.36	5.0001	109990
Market Capitalization (In Billion $)	1569457	1.50	8.90	0	602.43
Trading Volume (In Billion $)	859991	0.20	1.42	0	275.51
Illiquidity	1447409	0.66	3.15	0	774.65
Number of News	231818	1.40	1.55	0	11

Table II: Univariate Momentum and Reversal Effects

In Panel A, we sort stocks each month into deciles based on the compounded returns from month *t*-6 to *t*-1. In Panel B we sort stocks into deciles based on the raw returns at month t. In each case, we measure the return of each decile portfolio during month *t*+1. The table shows the intertemporal average of the month *t*+1 returns. The sample contains common stocks listed on the NYSE, AMEX, and NASDAQ during the period from January 1980 to December 2006. We require each stock to have a valid return during months *t-6* to *t*, and a minimum price of $5 per share. The last column of each panel presents the returns of a hedge portfolio that is long decile 10 stocks and short decile 1. The hedge portfolio's t-statistic is shown in italics and is based on robust standard errors.

Panel A: Returns at month *t*+1 as a function of returns from *t*-6 to *t*-1 (Momentum)

Momentum Decile (measured from month *t*-6 to month *t*-1)										**Long-Short (10-1)**	
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Mean**	***t-stat***
0.0006	0.0089	0.0118	0.0123	0.0126	0.0122	0.0127	0.0137	0.0154	0.0199	+0.0193	*6.14*

Panel B: Returns at month *t*+1 as a function of month *t* returns (Reversal)

Current Return Decile (measured at month *t*)										**Long-Short (10-1)**	
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Mean**	***t-stat***
0.0139	0.0135	0.0134	0.0131	0.0124	0.0127	0.0124	0.0119	0.0100	0.0071	-0.0069	*-2.59*

Table III: Interaction between Momentum and Reversal:
A Calendar-Time Portfolio Approach

At the end of each month t, we sort stocks into five quintiles based on their momentum measured during [t-6, t-1]. M1 denotes low (negative) momentum and M5 denotes high (positive) momentum. We also independently sort stocks into quintiles based on their performance during month t. Stocks in the bottom 20% in terms of month-t performance are labeled R1, while those in the top 20% are labeled R5. Returns reported in each cell are the equally-weighted monthly intertemporal averages of each portfolio during month (t+1). The last two lines show the returns of a hedge portfolio that is long R1 and short R5, for each momentum quintile. T-statistics for the hedge portfolio are shown in italics and are based on robust standard errors. We require each stock to have a valid return during months [*t-6, t*] and a minimum price of $5 per share. The sample period is 1980-2006.

Month t Return Quintile	**Momentum Quintile [t-6, t-1]**				
	M1 (low)	**M2**	**M3**	**M4**	**M5 (high)**
R1 (low)	0.01133	0.01374	0.01243	0.01259	0.01891
R2	0.01051	0.01368	0.01321	0.01357	0.01749
R3	0.00791	0.01195	0.01255	0.01343	0.01671
R4	0.00483	0.01157	0.01285	0.01344	0.01634
R5 (high)	-0.00623	0.00823	0.01078	0.01403	0.01843
R1-R5	0.01756	0.00551	0.00166	-0.00145	0.00048
t value	*7.89*	*2.90*	*0.85*	*-0.72*	*0.22*

Table IV: Interaction between Momentum and Reversal:
A Fama-MacBeth Approach

Each month stocks are sorted into five quintiles based on their momentum. Stocks which are at the bottom 20% of the market based on their compounded return for months t-6 through t-1 are labeled M1. Stocks which are at the top 20% of the market based on their compounded return for months t-6 through t-1 are labeled M5. Every month return at month t+1 is cross-sectionally regressed on the return at month t within each of the five momentum portfolios. The table reports time series averages of the coefficients as in Fama and MacBeth (1973). T-statistics are shown in parentheses below each point estimate. The R-Square reported is the average of R-Squares from the monthly cross-sectional regressions. The sample period is 1980-2006.

Momentum Quintile	intercept	RET(t)	R^2
M1 (low)	0.0065	-0.0491	1.15%
	(1.7000)	*(-9.9300)*	
M2	0.0123	-0.0133	0.94%
	(4.7700)	*(-2.4600)*	
M3	0.0126	0.0020	1.02%
	(5.4500)	*(0.3600)*	
M4	0.0130	0.0050	0.92%
	(5.1600)	*(0.9100)*	
M5 (high)	0.0168	-0.0027	0.87%
	(4.86)	*(-0.5300)*	

Table V: Illiquidity Control

This table shows the average β coefficients for the following monthly cross-sectional Fama and Macbeth (1973) type regressions:

$$R_{i,t+1} = \alpha_t + \beta_t R_{i,t} + \varepsilon_{i,t}$$

Stocks are grouped into 16 portfolios according to independent sorts on momentum (M1 to M4) and illiquidity (IL1 to IL4). The table shows the intertemporal average β coefficient for each portfolio. Momentum is the compounded raw returns from month t-6 to t-1. M1 represents the lowest momentum quartile and M4 is the highest. Illiquidity is measured using the Amihud method (ratio of absolute returns to dollar volume). IL1 represents the lowest illiquidity quartile and IL4 is the highest. The sample period is from 1980 to 2006. T-statistics are shown in parenthesis and are based on robust standard errors.

Momentum Quartile [t-6, t-1]	**Illiquidity Quartile**			
	IL1 (low)	**IL2**	**IL3**	**IL4 (high)**
M1 (low)	-0.02309	-0.04064	-0.04428	-0.06364
	(-2.63)	*(-5.97)*	*(-6.77)*	*(-11.07)*
M2	-0.01091	-0.00659	-0.00246	-0.01361
	(-1.46)	*(-0.86)*	*(-0.35)*	*(-2.02)*
M3	0.006545	0.00511	0.001863	-0.00833
	(0.86)	*(0.69)*	*(0.28)*	*(-1.31)*
M4 (high)	0.003658	-0.00466	0.00387	-0.00503
	(0.44)	*(-0.66)*	*(0.55)*	*(-0.86)*

Table VI: Turnover Control

This table shows the average β coefficients for the following monthly cross-sectional Fama and Macbeth (1973) type regressions:

$$R_{i,t+1} = \alpha_t + \beta_t R_{i,t} + \varepsilon_{i,t}$$

Stocks are grouped into 16 portfolios according to independent sorts on momentum (M1 to M4) and turnover (TO1 to TO4). The table shows the intertemporal average β coefficient for each portfolio. Momentum is the compounded raw returns from month t-6 to t-1. M1 represents the lowest momentum quartile and M4 is the highest. Turnover is computed as monthly dollar trading volume divided by market capitalization. T1 represents the lowest turnover quartile and T4 is the highest. The sample period is from 1980 to 2006. NASDAQ stocks are excluded due to difficulties in interpreting turnover measures. T-statistics are shown in parenthesis and are based on robust standard errors.

Momentum Quartile [t-6, t-1]	**Turnover Quartile**			
	T1 (low)	**T2**	**T3**	**T4 (high)**
M1 (low)	-0.05004	-0.06539	-0.05179	-0.03149
	(-5.92)	*(-7.27)*	*(-5.88)*	*(-4.85)*
M2	-0.03552	-0.04403	-0.02191	0.004411
	(-3.86)	*(-4.67)*	*(-2.54)*	*(0.63)*
M3	-0.02982	-0.03519	-0.01562	0.013858
	(-3.48)	*(-3.83)*	*(-1.86)*	*(1.93)*
M4 (high)	-0.02094	-0.01221	-0.02281	0.016033
	(-2.11)	*(-1.39)*	*(-2.72)*	*(2.50)*

Table VII: Controlling for Illiquidity, Turnover, and Other Firm Characteristics

Returns at month t+1 are crosssectionally regressed on firm characteristics that are known at month t. The table reports the intertemporal averages of coefficients as in Fama and MacBeth (1973). SIZE is the log of market capitalization at month t, BM is the log of book-to-market equity at month t, RET is the return at month t, TURN is the turnover at month t, ILL is the illiquidity measure at month t, DISP is the dispersion in analyst forecasts at month t, INSTOWN is the number of shares held by institutional investors divided by the total number of shares at month t, NANALYST is the total number of analysts covering the stock at month t, and VOL is the total number of shares traded at month t. The dataset contains all stocks traded on NYSE, AMEX and NASDAQ, except for models (1), (2) and (3) where NASDAQ stocks are excluded due to problems in measuring turnover. The sample period is from 1980 to 2006, except for regressions which include DISP (model (6)), where the sample period is 1983 to 2006. The Adjusted R-Square is the intertemporal average of adjusted R-Squares from monthly cross-sectional regressions. Robust t statistics are given in parenthesis.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
INTERCEPT	0.012027	0.026216	0.013242	0.024096	0.011454	0.016314
	(5.24)	*(4.18)*	*(5.53)*	*(4.07)*	*(4.31)*	*(2.02)*
RET	-0.03059	-0.03678	-0.02971	-0.02108	-0.01361	-0.01937
	(-5.61)	*(-6.76)*	*(-5.44)*	*(-5.23)*	*(-3.01)*	*(-4.3)*
MOM	0.007535	0.007837		0.009945	0.008688	0.00875
	(3.26)	*(3.49)*		*(5.38)*	*(4.15)*	*(3.71)*
MOM*RET	0.039146	0.042346		0.035616	0.03382	0.054937
	(4.57)	*(5.52)*		*(5.73)*	*(4.9)*	*(6.12)*
TURN	-0.0004	-0.00057	0.00002			
	(-0.81)	*(-1.14)*	*(0.03)*			
TURN*RET	0.010551	0.01264	0.008962			
	(6.31)	*(7.01)*	*(5.21)*			
ILL	-0.00023	-0.00114	-0.00044		-0.00018	
	(-0.7)	*(-2.79)*	*(-1.31)*		*(-1.01)*	
ILL*RET	-0.00351	-0.00229	-0.00396		-0.00302	
	(-1.36)	*(-0.81)*	*(-1.7)*		*(-3.79)*	
DISP						-0.00086
						(-2.3)
SIZE		-0.00131		-0.00166		-0.00097
		(-2.43)		*(-2.67)*		*(-1.53)*
BM		0.000718		0.001631		0.001306
		(1.02)		*(1.93)*		*(1.48)*
INSTOWN						0.001365
						(1.14)
NANALYST						0.000013
						(0.15)
VOL						-1.51E-08
						(-1.28)
R^2	3.44%	5.05%	2.04%	3.50%	2.40%	5.26%

Table VIII
Momentum and Reversal for Stocks with and without Public News

At the end of each month t, we sort stocks from Chan's dataset into "no-news" (Panel A) and "news" (Panel B) groups. Stocks with share prices lower than $5 are excluded. Within each news group we sort stocks into five momentum quintiles based on returns during [t-6, t-1], denoted M1 to M5. We also independently sort stocks into quintiles based on returns during month t, denoted R1 to R5. The table shows intertemporal averages of returns measured during month (t+1) for each of the resulting 25 equally-weighted portfolios. The sample period is 1980-2000. T-statistics for the long-short portfolio are shown in parenthesis and are based on robust standard errors.

Panel A: Stocks with No Public News

Month t Return Quintiles	**Momentum Quintiles [t-6, t-1]**				
	M1 (low)	**M2**	**M3**	**M4**	**M5 (high)**
R1 (low)	0.015407	0.013279	0.013008	0.019375	0.023735
R2	0.010089	0.012192	0.012207	0.017071	0.021467
R3	0.005987	0.013686	0.013923	0.013716	0.019601
R4	0.005097	0.01045	0.014323	0.014396	0.015037
R5 (high)	-0.006420	0.008459	0.006432	0.014793	0.015518
R1-R5	0.021832	0.00482	0.006577	0.004582	0.008216
t value	*(5.98)*	*(1.22)*	*(1.81)*	*(1.24)*	*(2.21)*

Panel B: Stocks with Public News

Month t Return Quintiles	**Momentum Quintiles [t-6, t-1]**				
	M1 (low)	**M2**	**M3**	**M4**	**M5 (high)**
R1 (low)	0.010881	0.014256	0.007324	0.0135	0.015896
R2	0.008162	0.012685	0.012878	0.010513	0.019207
R3	0.009706	0.012553	0.012926	0.013839	0.017001
R4	0.005051	0.011098	0.015592	0.01268	0.019523
R5 (high)	-0.007610	0.010593	0.015302	0.012884	0.023513
R1-R5	0.018486	0.003663	-0.00798	0.000615	-0.00762
t value	*(4.63)*	*(0.96)*	*(-2.21)*	*(0.16)*	*(-2.00)*

Table IX:
Raw Returns of a News-Momentum-Reversal Trading Strategy

At the end of each month t, we select from Chan's dataset only firms that had one or more public news item during the current month. Stocks with share prices lower than $5 are excluded. Within each news group we sort stocks into five momentum quintiles based on returns during [t-6, t-1]. We also independently sort stocks into quintiles based on their returns during current month t. A long portfolio is formed of stocks lying at the intersection of the highest momentum *and* highest current return quintiles. Stocks that belong to the lowest momentum *and* highest current return quintiles are placed in a short portfolio. The table shows intertemporal averages of returns measured during month (t+1) for each of the long, short, and hedge (long minus short) portfolios, and also for the SP500 and value-weighted return with dividends from CRSP (VWRETD). Returns are annualized by compounding monthly returns and shown in percentage. The sample period is 1980-2000.

Sample period	**Raw Returns of the Trading Strategy (% per year)**			**Benchmark (% per year)**	
	Long leg *high momentum, high current returns*	**Short leg** *low momentum, high current returns*	**Long** *minus* **Short**	**SP500**	**CRSP VWRETD**
1980	87.6%	51.0%	25.2%	22.7%	29.5%
1981	15.5%	-18.8%	41.4%	-9.0%	-4.1%
1982	63.4%	-9.2%	79.1%	16.6%	24.1%
1983	35.4%	-5.7%	43.4%	17.8%	22.8%
1984	2.8%	-37.5%	61.4%	2.3%	7.6%
1985	77.6%	6.1%	67.8%	27.1%	32.9%
1986	-0.5%	-8.5%	8.7%	16.3%	19.8%
1987	6.2%	-24.4%	39.5%	6.9%	10.1%
1988	11.4%	2.5%	8.8%	12.9%	17.5%
1989	41.9%	-3.3%	46.5%	28.1%	32.3%
1990	-2.3%	-23.2%	26.7%	-5.1%	-1.7%
1991	99.3%	13.4%	76.8%	27.7%	32.1%
1992	20.8%	3.4%	16.8%	4.7%	8.0%
1993	33.3%	-8.1%	44.7%	7.2%	10.1%
1994	11.5%	-27.5%	52.1%	-1.0%	1.9%
1995	59.5%	2.1%	56.4%	34.3%	37.8%
1996	41.2%	-9.7%	55.7%	20.9%	23.9%
1997	18.1%	-2.9%	21.6%	32.5%	35.1%
1998	3.5%	-28.2%	42.7%	29.5%	32.1%
1999	138.6%	9.5%	119.1%	20.5%	22.3%
2000	2.0%	-34.9%	54.3%	-8.9%	-7.1%
January months only	70.9%	7.8%	59.0%	26.2%	29.3%
No January months	29.3%	-10.6%	44.1%	12.7%	16.7%
Entire period: 1980-2000	32.2%	-9.3%	45.3%	13.7%	17.6%

Table X:
Adjustment for Fama-French Factors

At the end of each month t, we select from Chan's dataset only firms that had one or more public news item during the current month. Stocks with share prices lower than $5 are excluded. Within each news group we sort stocks into five momentum quintiles based on returns during [t-6, t-1]. We also independently sort stocks into quintiles based on their returns during current month t. A long portfolio is formed of stocks lying at the intersection of the highest momentum *and* highest current return quintiles. Stocks that belong to the lowest momentum *and* highest current return quintiles are placed in a short portfolio. Each portfolio's return series is regressed on the three Fama-French factors. The table shows the estimates from the time series Fama-French regressions. Panel A shows the results for the long portfolio. Panel B shows the results for the short portfolio. Panel C shows the results for the hedge (long minus short) portfolio. The sample period is 1980-2000.

<u>Panel A: Long Leg (High Momentum and High Current Returns)</u>

Parameter	Estimate	t value	p value
INTERCEPT	0.01095	*3.92*	0.0001
Rm-Rf	1.04853	*15.18*	<.0001
SMB	1.26880	*8.45*	<.0001
HML	-0.16937	*-1.09*	0.2758

<u>Panel B: Short Leg (Low Momentum and High Current Returns)</u>

Parameter	Estimate	t value	p value
INTERCEPT	-0.02128	*-7.86*	<.0001
Rm-Rf	1.06756	*14.13*	<.0001
SMB	0.75898	*6.87*	<.0001
HML	0.13240	*1.07*	0.2865

<u>Panel C: Long-Short Portfolio</u>

Parameter	Estimate	t value	p value
INTERCEPT	0.03223	*8.34*	<.0001
Rm-Rf	-0.01903	*-0.21*	0.8356
SMB	0.50983	*3.23*	0.0014
HML	-0.30177	*-1.67*	0.0956

Figure 1
Performance of momentum-reversal strategies for firms with public news: 1980 – 2000