Stock Price Reaction to News and No-News: Drift and Reversal after Headlines

Article *in* Journal of Financial Economics · February 2003

DOI: 10.1016/S0304-405X(03)00146-6

1 author:

Wesley Chan
Massachusetts Institute of Technology

Stock Price Reaction to News and No-News: Drift and Reversal After Headlines

Wesley S. Chan*
M.I.T.

First Draft: 8/28/2000
This Draft: 4/24/2001

Abstract

I examine returns to a subset of stocks after public news about them is released. I compare them to other stocks with similar monthly returns, but no identifiable public news. There is a major difference between return patterns for the two sets. I find evidence of post-news drift, which supports the idea that investors underreact to information. This is strongest after bad news. I also find some evidence of reversal after extreme price movements that are unaccompanied by public news. The patterns are seen even after excluding earnings announcements, controlling for potential risk exposure, and other adjustments. They appear, however, to apply mainly to smaller stocks. I also find evidence that trading frictions, such as short-sale constraints, may play a role in the post-bad-news drift pattern.

*I wish to thank Kent Daniel, Ken French, Li Jin, S. P. Kothari, Jon Lewellen, Sendhil Mullainathan, Dimitri Vayanos, and Geoffrey Verter for many stimulating discussions, and the members of the MIT PhD Finance seminar for their helpful comments. Please address all correspondence to me at wschan@mit.edu.

1 Introduction

There is a large amount of evidence that stock prices are predictable. In the last decade, various studies have shown that stock returns exhibit reversal at weekly and 3-5 year intervals, and drift over 12-month periods.[1] Some research shows that stock prices appear to drift after important corporate events for up to several months.[2] This suggests that some of the drift is driven by underreaction to information. However, there are also numerous days when financial markets move dramatically, but without any apparent economic news or stimulus. In other words, there appears to be "excess volatility" in asset prices.[3] This suggests that investors may react (or overreact) to unobserved stimuli. These two phenomena raise an interesting question. Is there a predictable difference between stock returns after public news announcements and returns after large price movements, but no public news?

Using a database of news stories about companies from major news sources, I look at stock returns after two sources of information. The first is major public announcements, which are identifiable from headlines and extreme concurrent returns. The second source is large price movements unaccompanied by any identifiable news.[4] Each month, I form portfolios of stocks by each information source, and construct trading strategies. I examine if there is subsequent drift or reversal, against the alternative of no abnormal returns.

[1]Major examples of predictability in asset prices based on past returns include DeBondt and Thaler (1985), who find that losers outperform winners at 5 year horizons. Lo and MacKinlay (1990) also find cross-serial correlation at weekly lags as an explanation for portfolio momentum and individual stock reversal. Jegadeesh and Titman (1993) discover return momentum up to 12 months. I will describe papers that deal with momentum in more detail below.

[2]Kothari and Warner (1997), Fama (1998), and Daniel, Hirshleifer, and Subrahmanyam (1998) all have excellent synopses of the literature on stock price reactions to various corporate events. I will describe some specific studies in more detail below.

[3]A classic documentation of a mismatch between fundamental news and stock prices is Shiller (1981), who concludes that stock prices are too volatile to be explained by changes in dividends.

[4]One feature of the "excess volatility" literature is that it looks at the link between news stories in the media and stock price movements. Although I deal with longer horizons and do not look specifically at volatility, I share the same sources. I detail a few of these studies in the next section.

I have two major results. First, stocks that had bad public news also display negative drift. Less drift is found for stocks with good news. I interpret this to mean that prices are slow to reflect bad public news. Second, stocks that had no news stories in the event month tend to reverse in the subsequent month. This reversal is statistically significant, even after controlling for size, book-to-market, and liquidity influences. This is consistent with the view that investors overreact to spurious price movements. However, it is also consistent with bid-ask bounce, although I attempt to control for this. I also find that the effects are present, but diminish when one eliminates low priced stocks, and are stronger among smaller stocks than larger ones. This is not surprising if one believes that some investors are slow to react to information, and transaction costs prevent arbitrageurs from eliminating the lag. The fact that most drift occurs after negative returns reinforces this view, since shorting stocks is more expensive than buying them. I also show that most bad news drift occurs in subsequent months that did not have headlines. This implies that it takes some time to see the full impact of a single news item on a stock, due to frictions.

My results fit two old strains of thought among investment practitioners, which have gained an academic following. First, investors are slow to respond to valid information, which causes drift. Second, investors overreact to price shocks, causing "excess" trading volume and volatility and leading to reversal. The results are also consistent with a richer set of theories that try to explain short-run underreaction and long-run overreaction in terms of investor behavior.

My methodology extends the previous literature in two ways. First, I sample all forms of news. Fama (1998) suspects that the abnormal reaction literature focuses only on events that show interesting results. Other events that are similar but have no unusual patterns are unreported, which gives the impression that underreaction is prevalent when it is not. My dataset is free of selection bias. I am able to see if underreaction or overreaction remains a feature of the data by looking at a wider class of events than has been previously examined. Furthermore, the dataset is not restricted to events whose timing is "endogenously" determined by corporate insiders. Those who argue that post-event patterns are explained by risk and those who believe that securities are mispriced debate the impact of these types of announcements. For example, post IPO or SEO underperformance could be explained by risk factors captured by size and B/M. Or managers who see an opportunity to sell overpriced securities (which have low B/M ratios and large size) might initiate IPOs.[5] It is hard to distinguish between the two explanations. However, the mispricing story implies that investors are slow to respond to signals. This is not the case in the risk story. I look at this possibility for all news.

Second, I distinguish between return patterns after news events and after price shocks that do not appear to be news motivated. I look at the difference between the two. This adds an important dimension to our understanding of momentum strategy payoffs. By construction, these are not conditioned upon the incidence of news, but are hypothesized to arise because of reactions to information. In addition, recent behavioral theories feature different reactions to public and private signals. These two types of signals can be approximated by the two "events" I have separated. This lets me test some implications of those models (namely, that investors underreact to some signals and overreact to others) by looking at stock returns after public news and periods of no news, but extreme price movements.

The paper proceeds as follows. Previous research into investor reactions, reversal, and drift is outlined in section 2. In section 3 I describe my dataset and present the methodology used to construct portfolios and conduct tests in section 4. I present my results in section 5,

[5] See Loughran and Ritter (2000) for a discussion of this question.

with some extensions, and conclude in section 6.

2 Previous Related Research

Despite forty years of research by financial economists, the debate continues over how fast information about a security's value is incorporated into prices. In this section, I describe empirical evidence of predictability in stock prices and sketch existing theories of investor behavior. As is the case with most ideas that challenge previous paradigms, new theories came after new evidence.

Most of the results of stock returns after specific news items seem to fall on the side of underreaction, which is defined as average post-event abnormal returns of the same sign as event date returns (abnormal or raw). The main examples include signaling events such as dividend initiations and omissions, which are covered by Michaely, Thaler, and Womack (1995). Stock splits could also fall in this category, examined recently by Ikenberry and Ramnath (2000), with similar conclusions. Bernard and Thomas (1990) and others document drift after earnings surprises for up to 12 months after the initial surprise. Michaely and Womack (1999) find a lag in response to changes in analyst recommendations. Investors also seem to be slow to react to capital structure changes. Ikenberry, Lakonishok, and Vermaelen (1995) find drift after tender offers, and Loughran and Ritter (1995) find it after seasoned equity offerings. Gompers and Lerner (1998) also document drift after venture capital share distributions. Seyhun (1997) finds profits to mimicking the large trades of insiders. La Porta, Lakonishok, Shleifer, and Vishny (1997) explicitly link earnings surprise and valuation levels, showing that high book-to-market stocks experience more positive surprises than low book-to-market stocks.

Important evidence that contradicts the view that investors underreact include results for acquiring firms in mergers (see Agrawal, Jaffe, and Mandelker (1992)) and proxy fights (Ikenberry and Lakonishok (1993)), apparent reversal for new exchange listings (Dharan and Ikenberry (1995)), and a host of different observed return patterns for IPOs, depending on the horizon (Ritter (1991)).[6] Barber and Lyon (1997) and Kothari and Warner (1997) cast doubt on the conclusions of event studies by explaining ways in which the statistical tests used in the above research are biased. I discuss some of their findings below. Fama (1998) vigorously challenges the conclusion that investors have abnormal reactions to events. He observes that the above patterns present no consensus on investor reactions, and some disappear entirely after accounting for size and book-to-market effects.[7] Also, apparent post-event drift need not be inconsistent with market efficiency, as various shifts in risk-factor returns and changing betas can explain some return patterns. Brown, Harlow, and Tinic (1993) examine risk changes in response to large price swings for a group of large stocks, and find evidence that stocks' risk exposure can explain post-event return differences.

Next, I describe work on price movements not clearly motivated by news. The studies that describe short-term momentum (see Jegadeesh and Titman (1993)) and long-term reversal (see DeBondt and Thaler (1985)) motivate the theories described below. However, the success of technical momentum strategies, in particular, is the most puzzling from an efficient markets perspective. Therefore, such strategies have been linked more strongly to behavioral patterns by some researchers. Grundy and Martin (1998) show that, after accounting for potential risk factor exposures, multi-month momentum exists in almost all periods from the 1920s to the present. Rouwenhorst (1998) shows that momentum occurs in other countries, while Grinblatt and Moskowitz (1999) show that it is strongest in industries. Lee and Swaminathan (2000) show

[6]However, some argue that one can not truly know the response of stock prices to IPO announcements since the stock does not trade when an IPO is announced.

[7]Loughran and Ritter (2000) have an opposite interpretation based on the same fact.

momentum is linked to reversal, conditional on trading volume, and look at it in the context of earnings drift, as do Chan, Jegadeesh, and Lakonishok (1996). One view is that momentum arises because of investors ignore news, just as they appear to do in the case of the some event studies. Hong, Lim, and Stein (2000) show evidence to support this assumption. They find that momentum is strongest in stocks that have no analyst coverage. They interpret this to mean that research analysts play an important role in disseminating information. However, Lewellen (2000) has challenged the interpretation that underreaction drives momentum. He finds no autocorrelation for portfolios, but instead a strong cross-relation across groups of winners and losers.

Finally, there is some evidence that investors overreact to price movements and trade more than they should. French and Roll (1986) find that the variance of stock returns is larger when the market is open than when it is closed, even when similar amounts of information are released. This implies that the act of trading increases volatility. Cutler, Poterba, and Summers (1989) look at the relations between extreme market-wide returns and major business stories from the New York Times. They conclude that neither economic variables nor news stories can fully explain aggregate price movements. Roll (1988) looks at the R^2 for regressions of daily and monthly stock returns on CAPM and APT factors and finds that much of the variance in returns is unexplained. Mitchell and Mulherin (1994) document that while news moves aggregate market returns, the relationship is not very strong. Also, Brad Barber and Terrance Odean find that individual investors trade too much and perform poorly relative to buy and hold strategies. They tend to sell winners and avoid selling losers, which might slow the incorporation of information into prices; see Barber and Odean (2000) in particular. In contrast, institutional investors seem to herd (see Grinblatt, Titman, and Wermers (1995) and Nofsinger and Sias

(1999)), although it is unclear whether or not this affects prices. The literature indicates that they suffer no future losses from herding.

In sum, many would describe underreaction to news as a "pervasive regularity"[8], but others would dispute that, noting that the results are inconclusive and the methodology problematic. Furthermore, negative return autocorrelation at very short and long lags confounds this perceived pattern of drift. Some interpret this as evidence of overreaction.

There are three major theories that seek to explain the patterns described above. Daniel, Hirshleifer, and Subrahmanyam (1998) (hereafter, "DHS") use two well-documented psychological characteristics, overconfidence and biased self-attribution, to model investor behavior. This results in investors holding too strongly to their own information, and discounting public signals. Barberis, Shleifer, and Vishny (1998) ("BSV") rely on two other patterns, conservatism and the representativeness heuristic. They hypothesize that investors change sentiment about future company earnings based on the past stream of realizations, and discount recent information. Hong and Stein (1999) ("HS") present a model, not tied to specific psychological biases, with two classes of traders. One group ignores the news, but reacts to prices. This causes underreaction initially and subsequent overreaction. Naturally, all three theories generate the observed patterns. However, they differ in their specific assumptions. DHS state that there will be underreaction to public information, and overreaction to private information.[9] BSV assume that investors will overreact or underreact to news depending on the stream of past news. HS assume that investors will underreact to news and overreact to pure (that is, non-information based) price movements. Since it is difficult to find price movements that have no component

[8] See Barberis, Shleifer, and Vishny (1998), abstract.

[9] Their model splits signals into two groups: personal (used by informed investors only) and external (available to all). Public information is not strictly defined; for instance, informed investors could read the newspaper and interpret the information in a headline as a "personal" signal. However, it seems reasonable to equate public news with external signals.

of private signals ex-ante, the assumptions of DHS and HS will be hard to separate empirically. I will look at these assumptions by separating stocks by news incidence using a headline database, as detailed below.

3 Data Description

Since I examine stock price reactions to public news, I need to know when information was released. I use the Dow Jones Interactive Publications Library of past newspapers, periodicals, and newswires. This database has abstracts and articles from many sources, going back to before 1980. However, the inception dates for coverage of different sources vary. Some are included for the entire period in which they published, and others are only available after being archived in electronic format. To get around the problem of spotty data, I select only those publications with most recent circulations over 500,000, daily publication, and stories available over as much of the 1980-1999 period as possible.[10] For each company in my set, I select all dates when the stock was mentioned in the headline or lead paragraph of an article from the sources. In order to reduce the over counting of news about the same subject from multiple sources, I note only if there was news on a particular day, not how many stories appeared. While my data filter does pull the text of headlines that give the content of the news, I choose to focus on the simple occurrence of news stories. I do not include magazines, since it is slightly more difficult to pinpoint on which day or week they became publicly available. Also not covered are investment newsletters, analyst reports, and other sources not available to the broadest audience. My focus is not on the forecasting performance of various information sources, but

[10] The resulting list of data sources, with their coverage dates, follows: The Wall Street Journal (all editions) from 1977-present, Associated Press Newswire from 1985, the Chicago Tribune from 1989, the Globe and Mail (for coverage of a few Canadian companies) from 1977, Gannett New Service from 1987, the Los Angeles Times from 1985, the New York Times from 1980, the Washington Post from 1984, USA Today from 1987, and all Dow Jones newswires from 1979.

on how investors react to public news.

The sources are weighted by coverage towards the later part of the 1980s and 1990s. As a result, I may miss a larger fraction of news events early in my sample period. However, by far the sources with the most complete coverage across time and stocks are the Dow Jones newswires. Wall Street professionals see these newswire stories as they are released, and thus they are the best approximation of public news for traders. This source does not suffer from gaps in coverage. Furthermore, I group news events over days and also a month-long window as detailed below. This reduces the chance that later periods, which usually have multiple news items on a single day, are over weighted.[11]

Since data retrieval is time consuming and labor intensive, I focus on a subset of CRSP stocks. I randomly select approximately 1/10th of all stocks that existed at any time between January 1980 and December 1999.[12] This results in a set of 1557 stocks, with 280 in existence at the end of January 1980 and almost 600 at the end of December 1999. I then collect all available news for these stocks. Table 1 shows counts of stocks in subsets for some months. As can be seen from the first few columns of Panel A, roughly half of my subset of stocks has some news in each month. The proportion ranges from 40% at the start of the period to 60% at the end of the period. On average less than 5%, however, have news on more than 5 days in a month, although that percentage increases through time. The increasing number of days with news is consistent with improving media coverage. The numerous stocks for which there was news each month also suggests that my dataset of headlines do not consist solely of previously studied corporate actions.

[11] I exclude all sources other than the Dow Jones newswire and Wall Street Journal and redo the analysis. The results are virtually unchanged, even in later periods.

[12] I sort all stocks that existed at any time from 1980 to 1999 by CRSP permno and pick every 10th number. This method accounts for the fact that companies that were listed around the same time have CRSP permnos that tend to cluster together.

Panel B presents correlations of news citations with a few firm characteristics.[13] Stocks with headlines are not small stocks for which one might expect to find more asset-pricing anomalies. Cross-sectionally, the correlations of log market value on log citations per month (logs for rescaling since both market value and citation incidence are positively skewed) range from 0.2 to 0.6, with the time series average across months at 0.4. For the vast majority of months the correlation is above 0.3. The positive relationship between size and coverage is reasonable, given the costs reporters face finding information for smaller stocks (and the limited market for such news).

News citations per month have weak positive correlation coefficients of 0.01 with returns. There is large dispersion over time in the cross sectional correlation, although the relation is still statistically significant. The occurrence of headlines is more strongly related to turnover. The correlations range from -0.1 to 0.6, and average about 0.15. I conclude that headlines do not seem to favor good news (denoted by high returns). Also, depending on one's interpretation of turnover, one could infer that highly liquid and/or more controversial stocks attract more media attention. Alternatively, one might believe that news causes more trading for risk sharing purposes when it is released.[14]

4 Methodology of Investor Reaction Analysis

A major question I attempt to answer is: Is there a consistent pattern drift or reversal after news? I use event study methodology that has been widely applied to earnings drift, corporate

[13] Rank correlations are almost identical.

[14] The preliminary analysis suggests some potentially interesting research tangents. One could see if there is a difference between stocks that experience more trading and numerous headlines, vs. stocks that experience more trading without news. One could also look at aggregate market returns and volatility when many stocks have news, vs. when there is little news; see Mitchell and Mulherin (1994). However, the current data set may be too small for such detailed analysis.

action, and momentum research. To summarize, I collect all stocks in a given month that had an event of interest (in this case, at least one news story). I rank all such stocks by raw returns and select the top and bottom thirds.[15] I shall refer to these two sets as "news winners" and "news losers". I then examine cumulative raw and abnormal returns for up to 36 months after the initial headline month. I also do the same for no-news stocks, as described below.

The details of my procedure are as follows. As mentioned previously, I mark the incidence of headlines in a month instead of each headline, to mitigate the overweighting of later periods that have more news. Having first divided my sample by news incidence, I then divide by performance. Using the CRSP monthly stock data series (with delisting returns), I rank all stocks with headlines in each month by raw return. In order to be included in the ranking, the stock must have traded during the month. I pick the top and bottom thirds as my "good news" and "bad news" groups, respectively. I use thirds because there are few stocks in the sample in the earliest periods. Thirds will give me a portfolio that is more diversified so that non-news related characteristics should be less important. On the other hand, some of the "bad news" events will in fact have positive returns, simply because the breakpoints may be positive. This may dilute the results.

I then form monthly equal-weighted portfolios of the selected stocks. Portfolios can be easily interpreted as trading strategies. I calculate overlapping returns for the "good news" equal-weighted portfolio as in Jegadeesh and Titman (1993), which mitigates non-independence in successive observations of long horizon cumulative returns. For a J month cumulative return horizon, I sum the time t return for a portfolio formed at $t-1$ with the time t return for a

[15] For comparison with other event studies, I also rank on idiosyncratic returns. These are the event month residuals after subtracting returns on size and book to market (B/M) matched portfolios. The results, discussed below, are very similar.

portfolio formed at $t-2$, a portfolio formed at $t-3$, etc. all the way to a portfolio formed at $t-J$. This sum contains the calendar time t returns for portfolios formed up to J months in the past. Doing this for each month t in the dataset gives me a time series of cumulative returns, none of whose observations is dependent on another. I do this for J between 1 and 36.[16] To summarize the degree of drift or reversal, I present the returns from a long-short strategy whereby past "good news" stocks are held with positive weights, and offset short positions in "bad news" stocks.

The various sets of cumulated returns for overlapping portfolios can be averaged across time. The test statistic for returns for J cumulative months is:

$$\frac{Avg(P_J)}{\sigma(P_J)/\sqrt{T-J}} \tag{1}$$

where the time series average cumulative return on the overlapping portfolios is $Avg(P_J)$, and the time series standard deviation of the cumulative returns is $\sigma(OP_J)$. T is the number of dates in my data, 240. For example, for the 2 month cumulative return, I start collecting two-month cumulative returns from March 1980 all the way to December 1999. Therefore $J = 2$, and $T - J = 238$ is the number of months in the sample.[17] I use three methods to calculate CARs:[18]

Abnormal returns are the residual once a proxy for expected returns is subtracted from each month's return. Only cumulative abnormal returns (CARs) are expected to be mean zero. Nonetheless, I also present raw return results for comparison of magnitudes. The statistic

[16]Following standard practice in similar empirical papers, I focus on cumulative returns here, although I comment on month-by-month returns when they are illuminating.

[17]As an alternative, I have cumulated J month forward returns and averaged over calendar months for most portfolios in my analysis. I then calculated statistical significance using Newey-West autocorrelation consistent standard errors. In every case the results are little changed.

[18]I make no explicit adjustment for momentum. I want to test reactions to news, and therefore I indirectly seek to test a possible cause of momentum.

for CARs should be distributed unit normal if there is no systematic abnormal performance. For good news, positive CARs indicate post event drift (consistent with underreaction), and negative CARs indicate reversal (consistent with overreaction); vice versa for bad news.

1. **CAPM:** For each portfolio, each month's abnormal return is $\hat{\alpha}_{it}$, from the model

$$R_{it} - r_{ft} = \alpha_{it} + \beta_i(R_{mt} - r_{ft}) + \epsilon_{it} \tag{2}$$

and R_{it}, R_{mt}, and r_{ft} are the return on portfolio i (winner, loser, or long-short winner-loser), the return of the CRSP value-weighted index of all stocks, and the 1 month T-bill return at time t, respectively. The cumulative alpha for each month J after the event month t can be derived by summing up successive returns:

$$\sum_{j=1}^{J}(R_{i,t+j} - r_{f,t+j}) = \sum_{j=1}^{J}\alpha_{i,t+j} + \sum_{j=1}^{J}[\beta_i(R_{m,t+j} - r_{f,t+j})] + \sum_{j=1}^{J}\epsilon_{i,t+j} \tag{3}$$

My method of cumulating returns using overlapping portfolios allows me to estimate $\sum_{j=1}^{J}\alpha_{i,t+j}$ by simply regression. This can be seen by slightly modifying the above expression (and dropping the i portfolio identifier) to produce:

$$\sum_{j=1}^{J}R_{t,t-j} = Jr_{f,t} + \sum_{j=1}^{J}\alpha_{t,t-j} + \sum_{j=1}^{J}(\beta_{t-j})\left[(R_{m,t} - r_{f,t})\right] + \sum_{j=1}^{J}\epsilon_{t,t-j} \tag{4}$$

where $R_{t,t-j}$ now denotes the time t return of a portfolio created at month $t-j$, β_{t-j} is the beta of the portfolio, and $\epsilon_{t,t-j}$ is the time t error term for the portfolio. Thus I can calculate $\sum_{j=0}^{J}\alpha_{t,t-j}$ as the constant term in a regression of time t summed overlapping portfolio returns minus J times the time t riskfree rate on time t market excess returns. This time-series regression allows me to use all observations.

2. **Fama French 3-Factor Model:** Monthly abnormal return is $\hat{\alpha}_{it}$, from the model

$$R_{it} - r_{ft} = \alpha_{it} + \beta_{i1}(R_{mt} - r_{ft}) + \beta_{i2}SMB_t + \beta_{i3}HML_t + \epsilon_{it} \tag{5}$$

and SMB_t and HML_t are the Fama-French size and book-to-market factor mimicking portfolio returns at time t, respectively. I estimate the cumulative 3-factor "alpha" by using the same time series regression of summed time t overlapping portfolio excess returns on time t factor returns.[19]

3. **Size and Book-to-Market (2 index) Model:** I include this because work by Daniel and Titman (1997) suggests that the size and book-to-market characteristics of stocks may be better predictors of future returns than factor betas. Instead of using regressions to calculate alphas for each time period, I subtract the contemporaneous returns of size and book-to-market matched portfolios.[20] Some stocks will be lost due to matching criteria.

Another question I attempt to answer is: Is there predictable drift or reversal after pure price movements? I conduct the analysis on two other portfolios. One has past returns that are similar to those of the "news" group but that are chosen solely based on past performance. Each month I sort all subset stocks by returns and pick the top and bottom thirds as winners and losers, respectively. This is the "all" set. I use a different set of return breakpoints to separate winners and losers because I want to see how a pure 1-month momentum strategy would do. I continue to use thirds, however, to make the "all" results roughly comparable to the news and no-news returns.[21] Another has stocks with no news headlines (the "no-news" portfolio). Each month, I use the news return breakpoints to select a group of winner and loser stocks from among the monthly no-news set. No-news stock returns could reflect reactions to private signals, news not covered by my sources, or supply and demand shocks. One can also think of no-news as a benchmark for the news portfolio return, since they have similar event

[19]SMB, HML, and market data are obtained from Ken French via his website.

[20]I describe the matching methodology more fully in the next section.

[21]The breakpoints are not very different, although on average news stocks have slightly higher event month returns than "all" stocks. I have compared the results of my "all" set with those for the entire CRSP database in the same period. The results are similar in magnitude and sign for almost all horizons.

date returns. Again, in order to be included in the analysis, each stock in the two other groups must have traded during the month. I repeat the computation of CARs and long-short portfolio payoffs as above for both sets. This helps us to understand stock behavior after signals from different sources, namely public announcements vs. price movements.

The additional analysis of all and no-news stocks will also help me to address some problems with long-run event studies that are identified by Barber and Lyon (1997) and Kothari and Warner (1997). For instance, most cumulative and buy-and-hold abnormal returns appear positive, regardless of the sample.[22] Also, various data requirements for a sample bias the abnormal returns. This causes the tests to have low power. Both the "news" and "no-news" samples may suffer from the problems mentioned in these papers. However, the difference between the two sets of returns should still tell us something definitive about how news affects stocks, under the hypothesis that misspecification affects both samples in more or less the same way.

Table 2 presents summary statistics for my winner and loser groups, and shows December values in detail. One can see that winners tend to be larger than losers (with exceptions in the early 1980s). News stocks are usually larger than unconditionally selected momentum stocks, which in turn are larger than no-news stocks. This is about what one would expect, given that smaller stocks are more volatile, and larger stocks have more news. Losers grow over time. In December 1980, the average market capitalization of all losers was \$89 million, vs. \$214 million for news losers, and \$51 million for no-news losers. By December 1999, all, news, and no-news loser portfolios averaged \$770 million, \$2,064 million, and \$155 million, respectively.

[22] In this paper, I mainly test cumulative abnormal returns (CARs), although I discuss one set of results for buy-and-hold abnormal returns (BHARs). The results of the Kothari and Warner study motivate me to do this because their simulation results indicate that, if anything, the latter are more misleading than the former. My CARs have less cumulation bias due to bid-ask spread, since I cumulate monthly returns, which exhibit less bid-ask bounce than weekly returns. Roll (1983) describes this problem.

Winners also show a dramatic shift in size. In December 1980, all winners averaged \$483 million, news winners average \$403 million, and no-news winners average \$236 million. The figures for winners in December 1999 are \$1,252 million, \$1,326 million, and \$413 million for all, news, and no-news winners, respectively. Therefore, most selected stocks would be considered small-cap, although some of the news stocks at later dates and winners might be classified as mid-caps, since they average over \$1 billion in a few months. One should note that no-news stocks might be more subject to microstructure movements since they are typically very small. These averages conceal large variations in market valuations, but are an appropriate way of viewing the portfolio since I equal-weight observations.

How much overlap is there between all the sets? The all set is simply the union of the news and no-news sets, for both winners and losers. Both news and no-news stocks are present in roughly equal proportion, although in later periods the news group accounts for more (see Table 1). The proportion of news stocks rises rapidly from about 40% in the early 1980s to about 60% during the 1990s. While I have 20 news losers/winners in January 1980, I have 121 news losers/winners in December 1999. In contrast, no-news losers increase less dramatically over the 20-year sample period even though the number of stocks under consideration rises. The number of no-news winners is almost always less than no-news losers. This means that proportionately more of the no-news shocks are negative. Note from the last six columns of Table 1, Panel A that the number of no-news stocks fluctuates more than the number of news stocks.

The all and news breakpoints are roughly equal. News, no-news and all portfolios have similar event month (time t) returns as shown in the last six columns of Table 2. However, no-news returns are more extreme in the tails. Finally, none of the winner or loser portfolios are extremely concentrated by industry. I classify all portfolio stocks by the 20 industries used by Grinblatt and Moskowitz (1999), and calculate the cross sectional Herfindahl index for each month.[23] The monthly Herfindahl averages (not shown) are remarkably uniform across news/no-news and winner/loser categories, at about 16%. Given an average of 15 industries per portfolio each month, this implies that a single industry could account for at most about a third of the portfolio. Even this is unlikely given the numerous stocks with headlines in the month, especially in later periods (e.g. over 100 in the 1990s).

Table 3 shows some details of news stories for two companies in the news strategy. Summaries for Jacobs Engineering (ticker JEC) are shown for 1983-1987 in the top panel, and news for Super Valu Stores (ticker SVU) from 1993-1997 is shown in the bottom panel. I selected these stocks since they were among the issues that existed for the full 1980-1999 period; however, only some months are displayed to save space. Super Valu has been a component of the S&P500 over the 1985-2000 period and would be considered a large-cap stock. Jacobs Engineering has been a component of the S&P400 since the index was created and would be considered a mid-cap. "Winner" or "loser" designation within the news strategy, and the contemporaneous return, are shown in the left columns. This table highlights some features of the data.

First, the news includes many corporate actions such as mergers and tender offers, as well as earnings announcements. These are also often accompanied by other news. However, my news set misses some earnings announcements. Furthermore, many news "events" are not corporate actions or pre-scheduled earnings releases. These include analyst ratings changes, capital spending announcements, blockholder sales and purchases, and new contracts. Second, there are some months when a reading of the headline does not reveal if the news was good or

[23]My Herfindahl index is $\sum_{i=1}^{20} P_{it}^2$, where P_{it} is the percentage of stocks in industry i in month t. This is a measure of the industry concentration of the portfolio each month.

bad. For example, acquisitions and ratings changes are accompanied by positive or negative returns. This suggests that it may be wise to rely on the market reaction to filter "good" and "bad" news. Third, the "winner" and "loser" categories are broad and potentially imprecise because I use thirds to divide firms by returns. For instance, some stocks display zero or slightly positive returns in some months, but may be classified as "losers", based on relative performance. Finally, news does not appear autocorrelated, since a single stock can switch from being a news winner to a news loser several times in a year. This implies that any post-news patterns are due to reactions to single news events, and not the accumulated reaction to multiple news events over an extended period.[24]

It is important to examine this last point further. Learning more about the typical pattern of drift or reversal will tell us more about what drives it. Are people "serially surprised" by news? Do they face frictions that would explain any patterns? I turn to this issue in the last part of the paper.

5 Results

5.1 Raw Returns

I first present the long-short strategy raw returns to news, no-news and all portfolios in Table 4. Panel A of Table 4 shows cumulative returns to the long-short zero investment strategy, out to 3 years after the event month. Separating stocks on news incidence causes dramatic differences even in first month returns. While there are no statistically significant signs that the long-short

[24]This is confirmed by looking at the transition probabilities of stocks in each of the news/no-news winner and loser groups. The average proportion of stocks in the 4 categories (news winner, news loser, no-news winner, no-news loser) switching into another category (news winner, news loser, no-news winner, no-news loser, news middle third, or no-news middle third) over subsequent post-formation months is roughly equal. The only thing that can be said is that news stocks tend to have news in subsequent months, and no-news stocks do not.

strategy is profitable for all and no-news sets, it is for the news set, which returns nearly 6% in the first twelve months.[25] For the first month, returns are negative, especially for the no-news strategy, which loses almost 2%. This is in line with the results of Lo and MacKinlay (1990), who document positive returns to a short-term contrarian strategy up to one month. It takes the all strategy almost half a year to recover from the effects of the $t+1$ reversal. In contrast, not only do the news stocks experience less reversal in month $t+1$, they also have more drift than all stocks for most of the following year. There are also some large negative returns beyond the 12-month horizon for news stocks, although they are not enough eliminate the early drift. The difference between news and all returns is statistically significant in the first 12 months.

Month-by-month returns (not shown) are particularly large 3, 6, 9, and 12 months after $t0$, approaching 1 percent a month for the news subset, which suggests that earnings drift may be a driver of the long-short returns I observe. Chan, Jegadeesh, and Lakonishok (1996) and Bernard and Thomas (1990) explicitly look at profits to long-short strategies based on abnormal returns around 1-4 quarters past earnings announcements, and find strong momentum. My news set contains about 80% of stocks in the CRSP subsample that make earnings announcements (as recorded on IBES) in a given month. This is important because whatever results I find may be largely driven by the earnings drift phenomenon. Later, I eliminate earnings announcements from my sample and redo the analysis. As discussed below, earnings announcement returns are important, but the news drift remains economically and statistically significant even after excluding them.

A long-short strategy using no-news stocks experiences a loss in the first month, followed

[25] One would expect that winners selected in month t would outperform losers on average through months $t0+1$ to $t0+36$, because winners more often than not have higher expected returns than losers. This point is made by Conrad and Kaul (1998). Lewellen (2000), however, notes that 1-12 month returns are too noisy to accurately estimate mean returns of stocks. Therefore, this motivation for the success of momentum-like strategies is not extremely compelling.

by essentially zero profits thereafter. This pattern of returns is consistent with an interpretation of no-news shocks as having a temporary component, due to overreaction. It is also consistent with microstructure effects like bid-ask bounce. To examine this possibility, I wait one week after forming portfolios before investing in the strategy. This is the procedure typically used in momentum strategy calculations. It reduces the chance that short-term microstructure movements influence the subsequent cumulative returns. The results in Table 4, Panel B, indicated that no-news stocks continue to have strong reversal in the first month, whereas the news set has none. While waiting a week cuts the negative cumulative return for no-news stocks roughly in half by month 6 and month 9, it does not eliminate it. In contrast, the news long-short strategy is even more profitable and has no reversal in the first month.

Without a doubt, the stronger pattern is that of drift after new events, while the first month reversal effect for no-news stocks is economically and statistically less significant. Skipping a week may not eliminate all of the microstructure effects, and therefore one might still have doubts that the reversal effect is due to overreaction. This is certainly valid, but skipping an entire month would make it impossible for me to study any short term effects (although doing so strengthens my post-news drift findings considerably). I continue to comment on first month effects since they appear in all of my later adjustments. The no-news reversal pattern is fairly robust, if not large.

In subsequent tables and charts, I do not refer to the "all" stock strategy since its component stocks are an even mix of news and no-news stocks. In a breakdown of winners and losers, I find that almost all of the difference in returns between news and no-news sets is due to the losers. They do markedly worse in the news set than in the no-news set. The only difference between winners lies in the first month, when no-news winners reverse and news winners do not (as is the case for losers).

This preliminary, unadjusted evidence suggests an asymmetric response to information. A news long-short strategy earns money and a no-news strategy loses money. Risk changes are unlikely to explain the entire story. Since no-news winners do not outperform losers over the rest of the 3-year period, they do not seem to have higher expected returns. Therefore we can discount differences in risk characteristics as an explanation for the reversal pattern. Furthermore, bad news would have to make stocks less risky, and good news would have to increase risk, in order to explain the drift in actual returns.

5.2 3-Factor and CAPM Abnormal Returns

Without modeling systematic risk of stock returns, one cannot say if stock prices depart from rationality. In the following sections I discuss cumulative abnormal returns.

CAPM and Fama French 3-factor adjusted returns tell essentially the same story as was seen in the raw returns of Table 4. I display 3-factor cumulative alphas in Table 5, with long short, winner, and loser performance in Panels A, B, and C, respectively. First, $t0$ 3-factor adjusted returns are similar for news and no-news sets, whether one looks at winners or losers. Again, the news long-short strategy is steadily profitable, whereas the no-news long-short strategy loses money. No-news losses are driven by month 1 reversal, for both winners and losers, as can be seen in Panels B and C. Subsequent no-news performance is largely flat. News stocks exhibit no reversal in the first months, and news losers have persistent and large negative alphas, far below those of no-news losers.

CAPM results (not shown) are very similar to those for the 3-factor model. News losers exhibit the same pattern of persistent negative abnormal returns, and no-news stocks experience month 1 reversal. Also, $t0$ abnormal returns are very similar for news and no-news portfolios, within performance groups. For example, news losers return a cumulative CAPM alpha of -7.8% after 12 months (t-statistic 2.5), vs. a cumulative 3-factor alpha of -6.9%. long-short strategy profits are largely unchanged, at about 5.8% after twelve months (t-statistic 4.7) vs. 6.2% for 3-factor the adjustment.

In summary, the following patterns stand out: even after making some adjustments no-news stocks experience short term reversal, and news losers show substantial drift. These results are not surprising, given that the CAPM and 3-factor model have had difficulty explaining momentum strategy returns in previous studies.[26]

At this point I should comment on long-run abnormal returns. As is generally the case for all the following subsets, they seem to exhibit reversal around the two-year mark or beyond, so that any gains from the long-short strategy are almost eliminated. This is true for sorts in the next sections. However, the difference between news and no-news long-term performance on a month-by-month basis is rarely statistically significant. I include long-term returns mainly to see if short-term effects are transitory, and I cannot rule that out. However, I am reluctant to draw further inferences from them, for several reasons. First, there is the chance that the expected returns models I use are misspecified. Barber and Lyon (1997) and Kothari and Warner (1997) show that this becomes more of a problem as time goes on. However, I believe that misspecification is not a crippling problem in the short term, and I generally find zero abnormal returns in most months beyond the first few. Second, in my 19 year sample period there are only six completely non-overlapping 3-year returns, a very small sample. Many authors show that overlapping returns do not necessarily improve the quality of statistical inferences

[26] In fact, Grundy and Martin (1998) show that 3-factor adjustments make momentum strategy returns larger and more stable. This appears to be the case here, at least to the twelve-month horizon.

at very long horizons (see, in particular, Richardson and Stock (1989) on the poor asymptotic properties of a particular test of predictability). Third, it is conceptually harder to justify long-run movements in stock returns as a response to publicly available news than it is to explain short-term movements, especially when intervening periods show no particular abnormal return pattern. I present cumulative returns out to the third year, however, for the interested reader.

5.3 Size and Book-to-Market Portfolio Matched Returns

I next describe the method for adjusting returns for size and book-to-market. I merge all stocks in the CRSP database with book value[27] using a method outlined by Fama and French (1992) and duplicated by La Porta, Lakonishok, Shleifer, and Vishny (1997), and Daniel and Titman (1997), among others. For June of each year t, all stocks are formed into 25 portfolios by size at the end of June of year t and book-to-market at the end of December of year $t-1$. I use market value from December and accounting book value for the fiscal year ending in year $t-1$ for B/M. Only stocks on the New York Stock Exchange having positive book values are used to calculate the 5 size and 5 B/M breakpoints. The resulting portfolios are then equal weighted, and I calculate 25 sets of monthly returns.[28]

At the end of June of every year, each stock in my subsample of over 1500 stocks is assigned to one of these 25 portfolios. If it cannot be found within one of the 25 portfolios, it is not used. I lose about 25% of the original sample stocks each month, with slightly less lost in the beginning of the period (18% in January 1980), and more in the later dates (37% in December 1999). This is due to the merging criteria, since I require data from the previous year

[27] Data item 60 on the Compustat tapes. I merge using the CRSP/Compustat merged database.

[28] I construct my own size and B/M portfolios to be consistent with how I measure size and B/M for individual stocks. My portfolios are over 90% correlated with those from Ken French's website, but are not as comprehensive.

as well as each June. On average, the resulting stocks are slightly larger than those without the size and book-to-market requirements. Averaged through time, about 20% fewer news and 25% fewer no-news winners and losers survive.

I then subtract the size and book-to-market matched portfolio return from each stock's return each month. This gives me a time series of adjusted returns, which I cumulate and test as before. Finally, I skip the first week after portfolio formation before investing. As in Table 4, Panel B, this is meant to exclude microstructure effects from contaminating the profitability of the strategy.

I present size and B/M adjusted data in Table 6. In general, the results are the same. The portfolio matching method lessens the profitability of the news strategy and increases the losses to the no-news strategy when compared with the regression approach (compare Table 6 with Tables 3 and 4). News winners display little discernible pattern. The reversal for the no-news winner group is statistically significant at the 1% level. However, the $t0+1$ returns are very small relative to the $t0$ run-up, at -0.6% vs. 16.3% for no-news stocks. More strikingly, there is almost no difference between the two winner sets, except for the first few months. From Panel C, one can see that the same pattern of reversal followed by zero abnormal returns is present for no-news losers. They gain back over 8% of the return they had lost in the previous month (0.7% following a 13.7% drop), a larger reversal than seen in the winners. News losers, however, experience no reversal in the first month. The first month no-news reversal results, for both winners and losers, are consistent with the hypothesis that large price swings contain an element of overreaction.

Post-news drift is clear from the positive returns to the news long-short strategy. One difference between the results of Table 6 and those of Table 4 and the 3-factor regressions in Table 5 is that now the post-news drift is somewhat driven by news winners in addition to the news losers. The cumulated abnormal return at twelve months for news winners is 1.7% (significant at the 10% level) and for news losers is -3.3% (significant at the 5% level). However, several facts reinforce the original finding that losers drive post-news drift. First, the news strategy long-short profit is economically and statistically large at twelve months, while the no-news strategy loses money. Second, the difference between news and no-news returns is biggest for the losers. Third, almost all of my later adjustments (most of which lessen the impact of the smallest stocks) confirm that news losers have drift, but news winners do not. In particular, I find that all of the "news winner drift" is due to post earnings drift. These facts, combined with the 3-factor and raw results, support the view that investors primarily underreact to bad news.

In summary, the results of the size and book-to-market adjustment give further weight to the interpretation of underreaction to news. The CAR spreads I have found average around 4% to 6% by month 12, depending on the model of expected returns. While these may seem large, they are reasonable when compared to the results of other studies. Abarbanell and Bernard (1992) find size adjusted CARs of 8% for a strategy of longing positive and shorting negative earnings surprise stocks from 1976-1986, and Bernard and Thomas (1990) find long-short CARs of between 4% and 10%. The studies use quintiles and deciles, respectively, while I use thirds. Various horizon momentum strategies also return anywhere from 8% to 12% a year. Grundy and Martin (1998) show that a 6-month past momentum strategy that skips a month before investment earns a 3-factor adjusted return of 1% a month. Therefore, my results are well within the boundaries of those for previous event and momentum studies.

On a final note, the fact that all long-short news strategies appear to earn some abnormal returns may mean that the models are misspecified. Another view might be that the models are fairly good for describing expected returns for stocks without news catalysts. For example, size and book-to-market adjustment may work for no-news stocks, and may not for news stocks. Underreaction could be pervasive enough that a randomly selected benchmark group of stocks will seem to underreact. In this way, a model that generates abnormal returns may not be misspecified. Also, while Kothari and Warner (1997) and Barber and Lyon (1997) find that CARs calculated by various models tend to be positive, I find little evidence of sustained positive abnormal returns for any subset of stocks. Instead, the strongest pattern is of negative CARs for bad news events, as will be reinforced below.

5.4 Other Adjustments

In this section, I adjust the methodology and sample, to account for previously discovered effects and explore further the drift for bad news stocks I have found. For comparison, I continue to use size and B/M adjusted returns like those in Table 6. Again, in all cases, I skip the first week after formation before investing. The results for long-short strategies are shown in the various panels of Table 7.

5.4.1 Buy and Hold Abnormal Returns (BHARs)

Cumulative Abnormal Returns (CARs) are the sum of period-by-period average returns of all stocks in the portfolio. This means that the strategy is effectively re-balanced each month, which is economically costly as a trading strategy. Re-balancing to get CARs also tends to overstate the effects of small stocks, particularly after long periods of time. Buy-and-hold Abnormal Returns (BHARs) reflect the profits to a more feasible trading strategy. Furthermore, if most of the abnormal returns are from losers that become smaller and smaller, a few tiny stocks could drive the entire effect. BHARs would address this by putting more emphasis on relatively larger stocks.

I repeat the size and B/M adjusted analysis, but maintain the weightings over months so that the event-time portfolio performance shows the time $t0 + J$ value of investing \$1 in each stock at time $t0$. Again, the results (Table 7, Panel A) are little changed. The news long-short strategy is profitable, while the no-news long-short strategy is unprofitable. The difference is statistically significant in all months but the first. The no-news strategy loses less, and the news strategy profits are a bit smaller using BHARs than with CARs (compare the numbers above with Table 6). Losers are the major reason for the difference between news and no-news strategy returns. They return -3.5% (t-statistic -5.4) at 12 months. The difference in news and no-news loser cumulative returns is statistically significant at the 1% level for all months, while the difference for winners is not beyond the first 3 months. Also, both no-news winners and losers reverse, while neither news winners or losers do.

5.4.2 Ranking on Event Month Abnormal Returns

Most studies measure the abnormal return around the event for each stock. The interpretation is that the $t0$ idiosyncratic returns reflect firm specific information, and subsequent abnormal returns show investor under or over-reaction to this type of news. I repeat the analysis above, ranking on event month size and B/M adjusted returns instead of raw returns. Note that the estimated $t0$ abnormal returns will be noisy. The results (Table 7, Panel B) are essentially unchanged. Idiosyncratic news drift is less pronounced. Again, news losers play a larger role in the difference between news and no-news portfolios. They return -3.2% (t-statistic -2.4) at twelve months. Stocks ranked by no-news idiosyncratic returns also show strong reversal in the first month, while news stocks do not reverse. Both no-news winners and losers contribute to this. The cumulative return difference between news and no-news losers is statistically significant at the 1% level for all months, but not for winners beyond the first 3 months.

5.4.3 Weighting Stocks by Frequency of News within the Event Month

Investors may give less weight to news from only one or two days, and more to news that is repeated over several days. The impact of an announcement may be complex and professional investment analysts and reporters might need time to discover the full story. Therefore, stocks with news over several days should show less drift. One way to observe this would be to weight each stock in a month by the number of days on which it had a headline when forming news portfolios. If there is less drift, we may conclude that investors underreact less to many headlines than to a few news stories. An alternative view might be that investors' underreaction is proportional to the amount of information they receive, which would mean that more headlines implies more underreaction.

I repeat the size and B/M adjusted analysis, weighting news stocks in the portfolios by the number of days of headlines within the event month. Again, the results (Table 7, Panel C) are largely unchanged. Long-short returns show a pattern of drift for news stocks and early reversal of no-news stocks. Almost all of the post-news drift is from news losers, who return -4.5% by month 12 (t-statistic -3.0). News stocks show no reversal in the first month. No-news portfolio returns are of course unchanged from Table 6. The differences between news and no-news strategy returns are large and statistically significant at the 1% level in the first month, and beyond for losers. It is not surprising that there is little change from previous results, since extreme return stocks probably have more news. Weighting by number of headlines, however, does reduce the influence of the smallest stocks, since headline incidence and size are correlated.

5.4.4 Excluding Earnings Announcement Months

As noted before, some of my set of news headlines includes earnings announcements, and therefore my findings undoubtedly incorporate previously discovered post-earnings drift.[29] Do the responses to earnings announcements drive my results? To answer this question, I repeat the size and B/M adjusted analysis (using raw returns to rank $t0$ stocks), but exclude all stocks that had a known earnings announcement in the event month from my set of observations.[30] A few no-news stocks are dropped, since they apparently had earnings announcements that were not publicized in my headline database.

Even after excluding earnings months, the results (Table 7, Panel D) are comparable to those in Table 5. Long-short adjusted profits to a news strategy are smaller (around 4% twelve months after formation vs.nearly 5% with earnings announcement stocks included) but still large and statistically significant at the 1% level. The difference between news and no-news long-short strategy is still economically large at 12 months and statistically significant when compared to Table 6. For winners, the news set experiences a reversal (-0.6% vs. 0.1% for Table 6 news winner returns in the first month) and has an adjusted cumulative return of 0.5% 12 months after formation (vs. 1.7%). No-news winners show little change (unsurprising, since they contain few earnings announcement stocks), and the difference between news and no-news winners is smaller in all months. News losers excluding earnings announcement stocks have

[29] Earnings announcement stocks make up on average about a third of all news stocks each month.

[30] I first check to see if my sample exhibits earnings momentum. I select all stocks that had an earnings announcement in each month, and repeat the idiosyncratic return analysis adjusting for size and book-to-market and skipping the first week. Similar studies usually use deciles instead of thirds. I find large and statistically significant abnormal returns of 0.9%, 1.0%, 0.4%, and 0.5% in the third, sixth, ninth, and twelfth month after the announcement, respectively. The cumulative twelve month abnormal return is nearly 4.6%. Therefore my sample does seem to exhibit earnings momentum.

lower returns than those in Table 5, Panel C. They reach a cumulative 12-month return of -4.4% (t-statistic 2.9). No-news losers are largely unchanged. The difference between news and no-news returns is larger for losers, reaching nearly -7.3% in month 12 vs. the -5.6% found in Table 5 (t-statistics of -4.5 vs. -3.6). I conclude that post earnings announcement drift, while important, does not drive all of the results of underreaction I have found. One important thing to note is that excluding stocks that had earnings announcements eliminates any trace of post-news-winner drift. This implies that investors do not appear to underreact to good news, aside from positive earnings announcements.

5.4.5 The Effects of Size: Value Weighting

Fama (1998) has noted that in many studies, abnormal returns shrink or disappear altogether when the observations are weighted by market value. I explore that conclusion in Table 7, Panel E. The object is to find if the observed first month reversal and loser drift are stronger in small stocks. If so, such patterns would be economically less important, although still a matter of concern for some corporate managers and their investors. One should note that value weighting results in very high weight given to a few such behemoths as Disney. Very small weights are assigned to the multitudes of smaller stocks that make up the majority of observations in my winner and loser portfolios, since market valuations are highly right skewed.

Size and B/M adjusted long-short strategy returns show much less drift, although the news long-short portfolio returns over 1.6% at twelve months. However, the no-news strategy earns more money over 12 months. The $t0$ news returns are also less extreme than those of the no-news set. The CARs for news winner stocks are very small in absolute terms and statistically indistinguishable from zero. However, no-news winner reversal is still present.

There is a pattern of negative adjusted returns over the subsequent twelve months for news loser stocks (-2.6% after 12 months), which is not statistically significant at the 5% confidence level. However, a similar pattern is also observed among the no-news loser set, which continues to display reversal in the first month. In every month, the difference between news and no-news winner and loser returns is virtually zero. I conclude that any bad news underreaction found for news stocks are more prevalent for smaller stocks than for larger stocks. In this respect, my results are no different from those found in most other studies of post-event reactions. Some reversal for no-news stocks seems to remain, however, even when giving much more weight to large companies.

5.4.6 Excluding Low-Priced Stocks

It may not be profitable to attempt to "arbitrage away" apparent underreaction, since much of the drift effect seems to be driven by smaller stocks. These tend to be more illiquid, and have higher direct transactions costs as a percentage of any position. Large transactions would probably have a large price impact. This might explain why the drift effect seems to persist, although not why it arises in the first place. One way to see how liquidity affects the drift pattern is to exclude those stocks that have high direct transactions costs. I repeat the size and B/M adjusted analysis of Table 6, but eliminate all stocks with prices of $5 or less from my sample. My remaining sample should consist of more liquid stocks, since price is related to ease of buying or selling. I could also examine trading volume and bid-ask spread, but these too are imperfect measures of liquidity.[31]

[31] Weighting portfolio stocks by event month turnover gives similar results. Month $t0+1$ no-news losers return 0.3% (t-statistic 1.0) and no-news winners return -0.8% (t-statistic -3.0). News stocks show no reversal, and news long-short returns are 7.3% at month 12 (t-statistic 4.6). Losers drive news drift. Weighting portfolio stocks by absolute volume in the event month is problematic, given that shares traded have little relation to value traded. However, no-news reversal and news drift are still present, if less strong. News long-short 12-month returns are 4.6% (t-statistic 2.9) and news stocks show no $t0 + 1$ reversal, while no-news stocks return

Dropping low-priced stocks further reduces the sample. In the CRSP database for this period, on average, 28% of observations (stocks in all months) are priced at $5 or below. The no-news stocks in my size and B/M matched subsample contain more low priced stocks; 24% of my news winners and losers are low-priced, while many more no-news stocks fall out of the analysis (44% and 40% of no-news losers and winners, respectively). The resulting portfolios of winners and losers have much less extreme returns in the event month. Loser returns average about -10% in the event month for "all", news and no-news portfolios. Winner returns average about 13% (compare these with the average returns in the last 6 columns of Table 2). Also, my remaining sample consists of larger stocks. Loser news and no-news portfolios average about $785 million and $251 million, respectively, while winner news and no-news portfolios average $851 million and $303 million. These are much larger averages than those used in the original analysis.[32]

The CARs of the reduced set (shown in Table 7, Panel F) are similar to those of Table 6. News drift is still present, and no-news stock returns are closer to zero, although first month returns still shows reversal. The difference between news and no-news strategy payoffs is smaller, but still statistically significant. Again, the news loser drift drives all of the news strategy profitability. News loser 12-month cumulative returns are -3.9% (t-statistic -3.8), which is much different from the no-news loser cumulative return of close to zero. News winners have no drift. Moreover, both no-news losers and winners continue to have reversal. This pattern, however, is much weaker and not statistically significant. At two and three years after portfolio formation, there is no noticeable change in patterns for any set.

-1.2% (t-statistic -3.2) in month $t0 + 1$ and almost nothing thereafter.

[32]The summary statistics shown in Table 2 are not exactly comparable to those I describe here. Table 2 shows statistics for all of my stocks, not for the subset that can be matched with size and B/M portfolios. However, the characteristics of the size and B/M matched group (regardless of price) are not very different from those of Table 2, except that they are somewhat larger in size.

The news loser drift pattern is still economically and statistically significant. This may be because my price filter is an imperfect screen for easily tradable stocks. However, it also suggests that post bad-news-drift is a robust phenomenon.

5.4.7 Subperiod Analysis

It is possible that any investor underreaction has been reduced in recent years with the advent of new and diverse sources of financial information. It is also possible that broadening stock market investment has changed any reaction that was present in the 1980s. I split my sample into two subperiods. Table 8 shows 3-factor alphas for 1980-1989 (on the left) and 1990-1999 (on the right). Long-short, winner, and loser strategy results are in Panels A, B, and C, respectively. Few stocks survive for two or more years within each ten-year period. Long-run statistical inference is therefore difficult, so I do not show returns beyond 12 months. I also use 3-factor regressions rather than size and B/M adjusted returns because the matching criteria for CRSP and Compustat data may eliminate too many stocks from each subperiod.[33]

One can see that the drift after news is much larger in the earlier period, although there are still statistically significant and economically sizeable returns of over 5% at 12 months for the news strategy in the 1990-1999 period. Alphas tend to be more negative in 1980-1989, and more positive for 1990-1999. In Panel B, one can also see that there is not much difference between news and no-news winners, for either period, except for the first few months. For losers, in Panel C, there is some difference between the two decades. There seems to be less drift in the more recent years for the news set. The difference in cumulative alphas between the two periods may be attributed to the 3-factor regression, which fits the returns better in the

[33] This also means, however, that I cannot skip a week before investment to control for microstructure effects, since I do not have weekly Fama-French 3-factor data.

1980s. The R-squareds for the month-by-month regressions average about 0.8 for 1980-1989, and 0.6 for 1990-1999. This may mean that the 3-factor model is less well specified in the latter period. However, the general patterns of relative magnitudes and signs are more important than the point estimates of alphas. The difference between news and no-news set returns is consistent for both periods. For both winner and losers, in both decades, the same general patterns hold. There is pronounced reversal for no-news stocks, and evidence of drift in news stocks, mostly for the losers. I conclude that although underreaction may have diminished in recent years, it is still present. There is also some evidence of overreaction in the reversals of the first month.

5.5 Risk Changes Caused by News

As mentioned before, researchers have examined the possibility that risk changes are responsible for predictable patterns in stock prices. Brown, Harlow, and Tinic (1993) look at how volatility and beta change after large daily price movements. They conclude that stocks with negative shocks, which they interpret as experiencing bad news, become riskier than those with positive shocks. Thus bad news drives up expected future returns. However, this does not explain multi-month drift patterns. Losers continue to underperform, even though a risk explanation would say that they should have higher post-event returns since they become riskier. The same paradox, in reverse, holds for winners.

In my analysis of cumulative alphas, I have already accounted for changes in known "risk" factors, and still found statistically significant drift for news stocks and reversal for no-news stocks. However, it is interesting to see if news changes a stock's risk. Table 9 shows the evolution of month-by-month 3-factor loadings for winner and loser portfolios, news and no-news sets. These loadings are from the time series regressions described in the previous section. At $t = 0$, news and no-news sets are similar. All losers are small, and winners even smaller.[34] Winners also have higher betas than losers. One can see that news losers do become more risky in some sense. Betas rise, and they move more in tandem with smaller stocks. No-news losers also become more exposed to SMB. The opposite pattern is evident for the winners, which by and large are growth stocks (negative exposure to HML) that attain lower betas and exposure to SMB over time.

Finally, one can see that the 3-factor model does a good job of describing returns. R-squared statistics for my portfolios are around 0.7 to 0.8, although other diversified portfolios like mutual funds average R-squareds of about 0.8 or more. This reinforces the impression that the abnormal returns I have found are not due to changes in risk. Loser and winner stocks tend to become more and less risky, respectively, which is the opposite of what one would expect from observing the drift patterns.

5.6 When Does Drift Occur?

The results shown above indicate that smaller stocks seem to underreact to bad news. Why might this be the case? Researchers have offered two explanations, which are not necessarily mutually exclusive. The first is that investors simply have differential attitudes to good and bad news. They may consistently underreact to bad news, but have a different response for positive signals. Another explanation would be that transactional frictions prevent some information, particularly bad news, from being impounded into the stock price. Arbitrageurs would have more difficulty in taking positions and forcing stock price movements. The frictions would most

[34] SMB weightings for winners and losers correspond to those for Fama and French's smallest and next smallest size quintile portfolios, respectively. See Fama and French (1993), Table 6.

likely take the form of short sales constraints, since other costs such as bid-ask spreads or noise trader risk and "limits of arbitrage" arguments cannot explain an asymmetric drift pattern (although they may provide justification for the existence of anomalies in general). Note that short sales constraints may explain the persistence of drift, but probably not why it exists in the first place. Few investors would wait several months to achieve a predictable 4-7% loss. For most holders of stocks with bad news, it makes more sense to sell sooner, during shortly after the headlines are public.

One way to examine these stories would be to look at how much of the news drift occurs on months with subsequent news. This is similar to the analysis of La Porta, Lakonishok, Shleifer, and Vishny (1997) (LLSV), who show that the market appears to be positively surprised by the earnings or value stocks, and often disappointed by the earnings of growth stocks (i.e. post earnings drift is stronger in value stocks). If investors systematically underreact to news (as the post-earnings drift literature would suggest), then one might expect to see that most post-bad-news drift comes in months with headlines. The news in those months would tend to confirm the information released in the event month. Alternatively, if investors face difficulty in selling their stock, one might expect to see proportionally more post-bad-news drift in months without headlines. In this case, investors must liquidate positions over an extended period of time to reduce transactions costs. If the main cost makes it difficult to short-sell, there will be less extended drift for news winners than for news losers in non-headline months.

There are numerous other possibilities, but these two simple alternatives seem to be the most likely, given the patterns documented above. I observe the size and B/M adjusted returns to the news long-short strategy over the subsequent 12 months that are solely attributed to stocks that had headlines. Mechanically, I take the strategy returns from Table 6 and zero out all of the returns for stocks in any month after $t0$ that did not have a headline. I repeat the procedure for stocks in subsequent months that did have headlines to get the cumulative returns attributable to stocks without news. Of course, the sum of the two sets of cumulative returns will equal the results of Table 6. Note that this methodology decomposes a trading strategy, but the resulting cumulative returns are not profits to two separate trading strategies themselves. It is impossible to tell which months will have a headline ahead of time.[35]

Table 10 presents results for the set of news stocks only. Panel A shows long-short returns. It would appear that roughly half of the drift comes from news months. However, Panel C shows that almost all of the news loser drift, which drives news long-short returns, comes from months without news. This supports the frictional story. The subsequent CARs from counting only those news loser stocks with headlines are indistinguishable from zero. It seems that investors are not particularly responsive to subsequent news for stocks that fell into the news loser category. However, there is continued price pressure in other months, suggesting that someone is selling shares after bad news, even in the absence of more bad news.

The results for the winner leg of the long-short strategy (Panel B) are harder to interpret. News winners continue to rise in subsequent months that had news. Yet this "news surprise" is almost entirely cancelled out by the negative returns in no-news months. This results in the small magnitude CARs for news winners that we observed earlier. One could tell many stories to explain this pattern. For instance, investors may expect subsequent confirmatory news after a positive headline, but are disappointed when none occurs. Or some investors react strongly to good news when it is announced, but others sell after run-ups (implying some sort of overreaction). However, none of these is as simple as the underreaction to trading frictions

[35] Earnings announcements, however, are an exception since the are planned in advance.

hypothesis, so it is difficult to characterize the news winner pattern.[36]

In sum, I find some signs that frictions play a role in bad news drift by slowing the incorporation of information into prices. The pattern of returns on headline and no-headline months for news winners implies a more complicated story, however. Finally, note that stocks tend to go up when there is news, and go down when there is none. This seems logical given that uncertainty causes prices to be discounted, and the resolution of uncertainty would reduce this.

6 Conclusion

I have examined various views of investor reaction to news in an integrated framework. I have used a comprehensive sample of headlines for a large, randomly selected group of firms to test the hypothesis that stocks exhibit no abnormal return after public news. I find that this is not the case. Instead stocks that experienced negative returns concurrent with the incidence of a news story continued to underperform their size, book-to-market, and event return matched peers. Stocks that experienced good news show less drift. On the other hand, extreme return stocks that had no news headlines for a given month experienced reversal in the subsequent month and little abnormal performance after that. The post-event drift is mainly after bad news and is very robust. The conclusion of overreaction is somewhat weaker, since liquidity effects may drive the reversal of returns. However, the reversal continues to appear when one waits a week to pursue a no-news long-short strategy. One could argue that one week is enough

[36] Repeating the LLSV earnings drift analysis on my news strategy shows that about 20% of the post-news drift comes from earnings surprise. Again, most loser drift comes during months without earnings announcements, and most winner drift comes from months with earnings announcements. Therefore earnings surprise drives whatever news winner drift exists. This reinforces the earlier finding that investors do not underreact to good news, except for positive earnings surprises. But this does not resolve the question of why investors would be "serially surprised" by good (earnings) news, and sell stocks with good news in later months that had no headlines.

time for prices to return to equilibrium after a large, non-news motivated trade. Any pattern after that is more likely to be caused by something else. Ranking by idiosyncratic risk does not eliminate these results. Neither does weighting by number of news stories or excluding earnings announcements (which had previously shown drift). Buy-and-hold abnormal returns display the same pattern of news drift and first month no-news reversal. Drift patterns do become less evident when weighting by $t0$ market valuation, implying that underreaction is mostly confined to small stocks. They also seem stronger for low-priced stocks, although the results hold for higher-priced stocks, too. There is also evidence that the relations are less strong, but still economically significant, in more recent years.

These results seem to confirm some assumptions of the DHS model of investor behavior or the HS model of two classes of investors. Investors appear to underreact to public signals and overreact to perceived private signals. The stronger finding is for the news stocks. Very negative returns coupled with headlines seem to predict continued underperformance for up to twelve months. This result is more understandable if one considers the existence of different classes of investors. Most of the drift is on the downside among smaller, probably illiquid stocks. More sophisticated investors may not be able to arbitrage away the pattern, since shorting is more expensive than buying. This is supported by the fact that most negative drift happens over many months without new information in the press. Perhaps individual investors are more likely own more illiquid stocks. If individual investors exhibit psychological biases (which they seem to), then the drift pattern might naturally arise because of their behavior.

My empirical conclusions are probably closest in spirit to those of Hong, Lim, and Stein (2000), who find that smaller stocks with little analyst coverage experience the most momentum, driven mostly by losers. The main thrust of their paper is to link empirical patterns with information. They find evidence to support the view that investors are slow to react to bad news (defined as an unconditional negative return) unless they have "help" in the form of additional research coverage by Wall Street analysts. One crucial difference, however, is that I find signs that investors in smaller stocks are slow to respond to public news. No such slowness is evident among stocks with no public news. In contrast with Hong, Lim, and Stein (2000), stocks with public news in my set tend to be larger and probably have more analyst coverage. In other words, the underreaction appears to result not from barriers to "knowing" news, but barriers to "understanding" it. This is a distinction between information dissemination and information interpretation that may be worth exploring more in the future.

There are other areas of potential future research. First, how correlated is news across winner and loser sets? Grinblatt and Moskowitz (1999) find that most momentum is industry related. They hypothesize that 1-month industry momentum is due to an intra-industry lead-lag effect. While it is possible that my results include some lead-lag effects, I condition on public news, a signal that is more direct than a cross-correlation. However, it is probable that news is related across firms. The interaction of cross-firm correlations with news is another avenue of research. Second, who invests in stocks with drift? Investor segmentation may explain some of my results. It seems likely that more sophisticated investors would avoid the news loser stocks, and therefore information reaction would be muted. Are the remaining stockholders individuals, who exhibit psychological biases in their investing strategies? Third, it seems that short sales are very important. How critical are transactions costs in eliminating some behavioral or clientele effects, and promoting others? Answering these questions, and exploring other anomalies through the news/no-news lens, should sharpen our understanding of the critical function of asset prices in transmitting information.

References

Abarbanell, Jeffery S., and Victor Bernard, 1992, Tests of analysts' overreaction / underreaction to earnings information as an explanation for anomalous stock price behavior, *Journal of Finance* 47, 1181–1207.

Agrawal, Anup, Jeffery F. Jaffe, and Gershon Mandelker, 1992, The post-merger performance of acquiring firms in acquisitions: A re-examination of an anomaly, *Journal of Finance* 47, 1605–1621.

Barber, Brad, and Terrance Odean, 2000, Trading is hazardous to your wealth: The common stock investment performance of individual investors, *Journal of Finance* 55, 773–806.

Barber, Brad M., and John D. Lyon, 1997, Detecting long-run abnormal stocks returns: The empirical power and specification of test statistics, *Journal of Financial Economics* 43, 341–72.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307–43.

Bernard, Victor L., and Jacob K. Thomas, 1990, Evidence that stock prices do not fully reflect the implications of current earnings for future earnings, *Journal of Accounting and Economics* 13, 305–340.

Brown, Keith C., W. V. Harlow, and Seha M. Tinic, 1993, The risk and required return of common stock following major price innovations, *Journal of Financial and Quantitative Analysis* 28, 101–16.

Chan, Louis K.C., Narasimhan Jegadeesh, and Josef Lakonishok, 1996, Momentum strategies, *Journal of Finance* 51, 1681–1714.

Conrad, Jennifer, and Gautham Kaul, 1998, An anatomy of trading strategies, *Review of Financial Studies* 11, 489–519.

Cutler, David M., James M. Poterba, and Lawrence H. Summers, 1989, What moves stock prices?, *Journal of Portfolio Management* 15, 4–12.

Daniel, Kent D., David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor psychology and security market under- and over-reactions, *Journal of Finance* 53, 1839–85.

Daniel, Kent D., and Sheridan Titman, 1997, Evidence on the characteristics of cross-sectional variation in common stock returns, *Journal of Finance* 52, 1–33.

DeBondt, Werner F. M., and Richard H. Thaler, 1985, Does the stock market overreact?, *Journal of Finance* 40, 793–808.

Dharan, Bala G., and David Ikenberry, 1995, The long-run negative drift of post-listing stock returns, *Journal of Finance* 50, 1547–1574.

Fama, Eugene F., 1998, Market efficiency, long-term returns and behavioral finance, *Journal of Financial Economics* 49, 56–63.

——— , and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.

——— , 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

French, Kenneth R., and Richard W. Roll, 1986, Stock return variance: The arrival of information and the reaction of traders, *Journal of Financial Economics* 19, 3–30.

Gompers, Paul, and Josh Lerner, 1998, Venture capital distributions: Short-run and long-run reactions, *Journal of Finance* 53, 2161–83.

Grinblatt, Mark, and Tobias J. Moskowitz, 1999, Do industries explain momentum?, *Journal of Finance* 54, 1249–90.

Grinblatt, Mark, Sheridan Titman, and Russ Wermers, 1995, Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior, *American Economic Review* 85, 1088–1105.

Grundy, Bruce D., and Spencer J. Martin, 1998, Understanding the nature of the risks and the source of the rewards to momentum investing, Wharton Working Paper, May 1998.

Hong, Harrison, Terence Lim, and Jeremy Stein, 2000, Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies, *Journal of Finance* 55, 265–95.

Hong, Harrison, and Jeremy Stein, 1999, A unified theory of underreaction, momentum trading and overreaction in asset markets, *Journal of Finance* 54, 2143–84.

Ikenberry, David, and Josef Lakonishok, 1993, Corporate governance through the proxy contest: Evidence and implications, *Journal of Business* 66, 405–35.

——— , and Theo Vermaelen, 1995, Market underreaction to open market share repurchases, *Journal of Financial Economics* 39, 181–208.

Ikenberry, David L., and Sundaresh Ramnath, 2000, Underreaction, Rice University Working Paper.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65–91.

Kothari, S.P., Jay Shanken, and Richard Sloan, 1995, Another look at the cross-section of expected returns, *Journal of Finance* 50, 185–224.

Kothari, S. P., and Jerold B. Warner, 1997, Measuring long-horizon security price performance, *Journal of Financial Economics* 43, 301–39.

La Porta, Rafael, Josef Lakonishok, Andrei Shleifer, and Robert W. Vishny, 1997, Good news for value stocks: Further evidence on market efficiency, *Journal of Finance* 52, 859–874.

Lee, Charles M. C., and Bhaskaran Swaminathan, 2000, Price momentum and trading volume, *Journal of Finance,* forthcoming.

Lewellen, Jonathan, 2000, Momentum profits and the autocorrelation of returns, MIT Working paper.

Lo, Andrew W., and A. Craig MacKinlay, 1990, When are contrarian profits due to stock market overreaction?, *Review of Financial Studies* 3, 175–205.

Loughran, Tim, and Jay Ritter, 1995, The new issues puzzle, *The Journal of Finance* 50, 23–52.

Loughran, Tim, and Jay R. Ritter, 2000, Uniformly least powerful tests of market efficiency, *Journal of Financial Economics* 55, 361–89.

Michaely, Roni, Richard H. Thaler, and Kent L. Womack, 1995, Price reactions to dividend initiations and omissions: Overreaction or drift?, *Journal of Finance* 50, 573–608.

Michaely, Roni, and Kent Womack, 1999, Conflict of interest and the credibility of underwriter analyst recommendations, *Review of Financial Studies* 12, 653–86.

Mitchell, Mark L., and J. Harold Mulherin, 1994, The impact of public information on the stock market, *Journla of Finance* 49, 923–950.

Nofsinger, John R., and Richard W. Sias, 1999, Herding and feedback trading by institutional and individual investors, *Journal of Finance* 54, 2263–95.

Richardson, Matthew, and James H. Stock, 1989, Drawing inferences from statistics based on multiyear asset returns, *Journal of Financial Economics* 25, 323–348.

Ritter, Jay R., 1991, The long-run performance of initial public offerings, *Journal of Finance* 46, 3–27.

Roll, Richard W., 1983, On computing mean returns and the small firm premium, *Journal of Financial Economics* 12, 371–86.

——— , 1988, R^2, *Journal of Finance* 43, 541–566.

Rouwenhorst, K. Geert, 1998, International momentum strategies, *Journal of Finance* 53, 267–284.

Seyhun, H. Nejat, 1997, *Investment Intelligence: Tips from Insider Trading* (MIT Press: Cambridge).

Shiller, Robert J., 1981, Do stock prices move too much to be justified by subsequent changes in dividends?, *American Economic Review* 71, 421–498.

Table 1: Summary of News Observations in Analysis, Selected Months

This table shows the number of observations in my subsample of CRSP stocks, for each December. Panel A shows numbers of stocks by days of headlines, and for "winner" and "loser" portfolios for three groups: "all", "news", and "no-news", which denote all stocks in the subset, those that had a headline, and those that did not in the event month. Panel B shows the time-series averages of monthly Pearson cross-sectional correlations between number of days with news and ending market values, returns, and turnover.

Panel A: Counts of Stocks in Various Subsets

	Total	Stocks with	Stocks with News, By Days:		Losers, Number of Stocks			Winners, Number of Stocks		
Year	Stocks	No News	4 or Less	5 or More	All	News	No-News	All	News	No-News
1980	314	203	109	2	39	20	28	39	20	10
1981	368	261	103	4	41	20	19	41	20	24
1982	382	254	126	2	110	40	92	110	40	52
1983	471	308	161	2	151	54	103	151	54	89
1984	494	334	151	9	159	52	116	159	52	78
1985	510	330	166	14	165	60	145	165	59	68
1986	550	347	181	22	177	66	125	183	76	107
1987	565	383	170	12	184	62	204	184	60	75
1988	558	383	166	9	179	76	196	181	57	116
1989	545	361	174	10	177	61	106	177	61	81
1990	537	334	195	8	177	67	119	176	67	95
1991	535	286	234	15	175	83	107	175	83	76
1992	546	289	233	24	177	97	133	177	84	86
1993	594	315	253	26	195	92	129	195	92	91
1994	635	532	92	11	206	33	231	206	33	148
1995	646	300	312	34	213	114	108	213	114	87
1996	690	319	341	30	227	122	106	227	122	87
1997	690	267	366	57	225	138	88	225	138	85
1998	647	232	344	71	211	135	87	211	135	54
1999	598	225	313	60	195	121	99	195	121	38

Panel B: Cross-Sectional Correlations of Number of Headline Days/Month with:

Time Series	**Market Value**	**Returns**	**Turnover**
Average	0.42	0.01	0.15
Standard deviation	0.07	0.01	0.11
Maximum	0.57	0.24	0.55
Minimum	0.18	-0.26	-0.11

Table 2: Summary Statistics of Winner and Loser Portfolios, Selected Months

This table shows average month end market values and returns for "winner" and "loser" stocks. Only December values are shown in detail. "Winners" have returns within the month in the top third of all stocks in the subsample, and "losers" in the bottom third. "All" sets rank on all stocks, "news" stocks are selected from among those which had at least one headline in the given month, and "no-news" stocks are drawn from those with no headlines. I divide stocks by news and no-news incidence first, then by performance, to form portfolios. News and No-news winner and loser breakpoints are the same, based on the performance of the news set.

	Average Market Value, Millions						Average Returns					
	Losers			Winners			Losers			Winners		
Year	All	News	No-News	All	News	No-News	All	News	No-News	All	News	No-News
1980	89	214	51	483	403	236	-0.12	-0.10	-0.12	0.07	0.09	0.09
1981	308	473	144	139	298	130	-0.13	-0.13	-0.14	0.09	0.06	0.09
1982	102	255	72	220	438	53	-0.14	-0.10	-0.13	0.16	0.18	0.19
1983	136	254	67	231	440	108	-0.15	-0.15	-0.15	0.08	0.09	0.08
1984	61	138	25	208	232	94	-0.13	-0.10	-0.13	0.13	0.15	0.15
1985	101	145	61	259	260	99	-0.10	-0.07	-0.08	0.21	0.24	0.25
1986	93	185	53	225	364	125	-0.16	-0.16	-0.15	0.09	0.12	0.06
1987	78	315	47	291	438	105	-0.17	-0.11	-0.13	0.23	0.27	0.29
1988	118	335	78	193	320	125	-0.12	-0.07	-0.08	0.17	0.16	0.18
1989	189	342	91	549	1,060	201	-0.14	-0.16	-0.13	0.13	0.16	0.14
1990	65	145	32	310	412	148	-0.20	-0.20	-0.19	0.17	0.17	0.18
1991	47	92	33	457	695	228	-0.15	-0.13	-0.14	0.28	0.31	0.28
1992	214	293	200	372	583	175	-0.12	-0.09	-0.09	0.21	0.23	0.21
1993	205	510	101	602	944	323	-0.13	-0.12	-0.12	0.14	0.14	0.16
1994	108	521	100	540	2,132	241	-0.16	-0.13	-0.14	0.13	0.14	0.14
1995	214	325	142	745	925	290	-0.14	-0.12	-0.15	0.16	0.17	0.16
1996	732	1,315	175	539	629	156	-0.16	-0.16	-0.16	0.14	0.17	0.13
1997	167	225	84	1,563	2,309	382	-0.22	-0.22	-0.21	0.13	0.13	0.12
1998	577	830	131	1,028	1,323	417	-0.20	-0.20	-0.18	0.27	0.30	0.27
1999	770	2,064	155	1,252	1,326	413	-0.14	-0.14	-0.12	0.41	0.48	0.46
Time Series Average	269	442	117	438	630	177	-0.13	-0.13	-0.13	0.17	0.18	0.18

Table 3: News Details for Selected Stocks and Dates

This table shows some news details for Jacobs Engineering (from 1983-1987) and Super Valu Stores (from 1993-1997). All news stocks are sorted by returns each month. Winners (in the top third of sorted stocks by return) and losers (in the bottom third) are held with positive and negative weight in the strategy, respectively. Each stock below is only displayed if it had a headline and was selected for a winner or loser portfolio. Both stocks existed in the database for the entire 1980-1999 sample period. Portfolio status is shown in the first column, followed by dates, returns, and news summaries.

Portfolio	Year	Month	Return	News summary
				Jacobs Engineering
loser	*1983*	*1*	*-4.90 %*	*Buys 7.8% of Raymond International; in $12 million dispute; sells headquarters*
loser	*1983*	*2*	*-5.16*	*Lower yr. on yr. net; boosts stake in Raymond International*
loser	*1984*	*2*	*-16.67*	*Loss; omits dividend*
winner	1984	3	20.00	President resigns
winner	1985	12	36.17	Chairman proposes management buyout
loser	*1986*	*2*	*-6.67*	*Chairman withdraws buyout proposal*
winner	1986	4	20.00	Wilshire Oil holds 6.5% stake in firm
loser	*1986*	*8*	*-3.03*	*Agrees to buy Payne & Keller*
winner	1986	10	16.67	Gets EPA contract
winner	1986	11	8.57	Loss; Wilshire Oil raises stake to 10.3%
loser	*1987*	*1*	*0.00*	*Higher yr. on yr. net; names new President; signs Wyle Labs contract*
winner	1987	7	58.03	Higher yr. on yr. net; to buy Santa Fe Southern Pacific construction unit
winner	1987	10	-6.14	Completes purchase of Santa Fe Southern Pacific unit
				Super Valu Stores
loser	*1993*	*8*	*-0.76*	*Merrill Cuts To Neutral*
loser	*1993*	*9*	*-9.93*	*Says ShopKo net declined, plans cost cuts; starts new membership club*
winner	1993	12	8.61	Higher yr. on yr. net; Vice Chmn. retires; to buy Sweet Life; Painwebber upgrades
loser	*1994*	*7*	*-5.37*	*Sweet Life unit helps sales, hurts net; issues debt; buys Hyper Shoppes for cash*
winner	1994	11	2.00	Buys MD Food distribution facility
loser	*1995*	*1*	*-2.56*	*Restructuring; Smith Barney starts at neutral; in supply pact w/ John B. Sanfilippo*
winner	1995	2	9.41	Reveals capital spending/expansion plans; names new directors
loser	*1995*	*4*	*-1.40*	*Reports year-end net*
winner	1995	5	8.47	Unit opens first Irish Store; selects ACR as POS supplier
loser	*1995*	*8*	*-2.86*	*Opens midwest regional office*
loser	*1996*	*9*	*-2.22*	*Higher yr. on yr. net; Goldman upgrades; ShopKo to merge with Phar-Mor*
winner	1996	10	8.18	Phar-Mor/ShopKo gives shares; retains shares in related cos.; debt downgraded
winner	1997	4	2.94	Beats earnings expectations; ShopKo to halt merger, buy Super Valu stake; competitor leaves Columbus
winner	1997	7	17.39	Financial Chief resigns; ShopKo stake nets $350m; Lukoil to supply gas at stores
loser	*1997*	*9*	*0.00*	*Higher yr. on yr. net; shareholder rights plan amended*
winner	1997	12	6.52	Beats earnings expectations

Table 4: Cumulative Long-Short Returns (%), at Different Horizons.

This table shows the cumulative raw returns to buying 1 month past winners and shorting 1 month past losers over several holding periods. In each month from 1/1980-12/1999, all stocks within a subsample are ranked by their performance. Stocks in the top third and stocks in the bottom third are held in the same portfolio with positive and negative weight, respectively. This portfolio formation process is conducted on three sets of stocks: 1) an "All" subset of randomly selected CRSP database stocks, 2) a "News" group consisting of all stocks that had at least 1 news headline during the month, and 3) a "No-News" group of all stocks without a news headline for the month. The resulting long-short portfolios are then aggregated into larger portfolios with overlapping positions, to accurately calculate standard errors. Panel A shows the average returns and t-statistics after immediately investing after portfolio formation, and Panel B shows the results to waiting 1 week after formation before investing.

Months after Portfolio	All Stocks		News Stocks		No-News Stocks	
Formation	Average	T-stat	Average	T-stat	Average	T-stat
Panel A: Immediate Investment After portfolio Formation						
1	-1.14 %	-4.83	-0.33 %	-1.25	-1.91 %	-6.11
3	-0.49	-1.05	1.03	2.08	-1.94	7.00
6	0.30	0.37	2.92	3.72	-2.21	-2.38
9	1.12	1.05	4.16	3.92	-1.90	-1.62
12	2.16	1.74	5.55	4.50	-1.34	-0.98
24	0.61	0.28	4.41	2.06	-3.64	-1.59
36	-2.49	-0.81	0.59	0.19	-6.43	-2.16
Panel B: Waiting 1 Week After Portfolio Formation Before Investment						
1	-0.18 %	-0.96	0.43 %	2.07	-0.77 %	-2.94
3	0.47	1.16	1.78	3.98	-0.81	-1.52
6	1.28	1.74	3.69	5.10	-1.05	-1.21
9	2.12	2.13	4.93	4.91	-0.70	-0.63
12	3.18	2.71	6.32	5.39	-0.12	-0.09
24	1.59	0.74	5.15	2.47	-2.56	-1.15
36	-1.41	-0.47	1.40	0.45	-5.22	-1.79

Table 5: Cumulative 3-Factor Alphas (%)

This table shows the cumulative 3-factor adjusted returns to buying 1 month past winners and shorting 1 month past losers over several holding periods. In each month from 1/1980-12/1999, all stocks within the subsample are ranked by their performance. Stocks in the top and bottom thirds are held in an equal-weighted portfolio with positive and negative weight, respectively. This portfolio formation process is conducted on two sets of stocks: 1) a "News" subset consisting of all subset stocks that had at least 1 news headline during the month, and 2) a "No-News" subset of all stocks without a news headline for the month. The resulting long-short portfolios are then aggregated into larger portfolios with overlapping positions, for purposes of accurately calculating standard errors. Panel A shows the average returns and t-statistics to the long-short strategy for both sets, Panel B shows the results for winners, and Panel C shows the results for losers.

Months After Portfolio	News Stocks		No-News Stocks		Difference	
Formation	Alpha	T-stat	Alpha	T-stat	Alpha	T-stat
Panel A: Long-Short Strategy						
1	-0.22 %	-0.79	-1.79 %	-5.52	1.48 %	4.26
3	1.42	2.79	-1.65	-2.71	2.94	4.92
6	3.31	4.12	-1.93	-2.02	5.47	6.85
9	4.63	4.27	-1.86	-1.53	6.20	6.37
12	6.16	4.89	-1.52	-1.07	7.22	6.15
24	5.10	2.44	-4.13	-1.76	8.39	4.61
36	0.65	0.22	-7.12	-2.37	7.32	3.00
Panel B: Winner Portfolio						
formation date	16.54 %	44.42	16.20 %	44.87	0.34 %	2.02
1	-0.41	-2.50	-0.98	-4.72	0.67	6.23
3	-0.29	-0.75	-1.13	-2.43	1.22	6.72
6	-0.69	-1.01	-1.46	-1.71	1.62	7.50
9	-0.80	-0.82	-1.54	-1.22	1.72	6.52
12	-0.69	-0.52	-1.19	-0.68	0.74	5.71
24	-3.45	-1.33	0.04	0.01	-2.77	3.41
36	-5.82	-1.47	1.22	0.23	-5.18	1.90
Panel C: Loser Portfolio						
formation date	-14.24 %	-68.43	-14.07 %	-75.53	-0.17 %	-1.58
1	-0.19	-0.75	0.81	2.79	-1.00	-3.72
3	-1.72	-2.97	0.52	0.66	-2.24	-3.83
6	-4.00	-3.67	0.47	0.32	-4.47	-4.72
9	-5.43	-3.36	0.32	0.15	-5.75	-4.62
12	-6.85	-3.27	0.33	0.12	-7.18	-4.60
24	-8.55	-2.05	4.17	0.80	-12.72	-4.50
36	-6.47	-1.03	8.34	1.11	-14.81	-3.64

Table 6: Cumulative Size & B/M Adjusted Returns (%), skipping 1st. Week

This table shows the cumulative size and B/M adjusted returns to buying 1 month past winners and shorting 1 month past losers. In each month from 1/1980-12/1999, all stocks within the subsample are ranked by returns. Stocks in the top and bottom thirds are held in an equal-weighted portfolio with positive and negative weight, respectively. Portfolios are formed for two sets of stocks: 1) a "News" subset consisting of all stocks that had at least 1 news headline during the month, and 2) a "No-News" subset of all stocks without a headline for the month. The resulting long-short portfolios are then aggregated into larger portfolios with overlapping positions, for purposes of accurately calculating standard errors. Panel A shows the average returns and t-statistics to the long-short strategy for both sets, Panel B shows the results for winners, and Panel C shows the results for losers.

Months After Portfolio	News Stocks		No-News Stocks		Difference	
Formation	Alpha	T-stat	Alpha	T-stat	Alpha	T-stat
Panel A: Long-Short Strategy						
1	0.12 %	0.59	-1.25 %	-4.47	1.36 %	4.32
3	1.09	2.58	-1.78	-3.42	2.87	5.14
6	2.62	4.02	-1.82	-2.17	4.44	5.46
9	3.95	4.53	-1.89	-1.78	5.84	5.99
12	4.95	4.70	-1.59	-1.28	6.54	5.43
24	4.54	2.51	-2.95	-1.54	7.49	3.89
36	1.15	0.42	-4.90	-1.91	6.06	2.29
Panel B: Winner Portfolio						
formation date	16.14 %	46.21	16.34 %	44.35	-0.19 %	-0.72
1	0.09	0.78	-0.60	-3.29	0.69	3.25
3	0.34	1.13	-0.87	-2.48	1.21	2.89
6	0.64	1.18	-0.55	-0.91	1.19	1.69
9	1.08	1.47	-0.22	-0.25	1.30	1.43
12	1.70	1.74	0.73	0.65	0.97	0.82
24	1.92	1.07	3.45	1.52	-1.53	-0.69
36	4.88	1.52	9.19	2.58	-4.30	-1.32
Panel C: Loser Portfolio						
formation date	-13.53 %	-68.98	-13.72 %	-76.05	0.19 %	1.56
1	-0.02	-0.13	0.65	3.53	-0.67	-2.81
3	-0.76	-1.95	0.91	1.84	-1.66	-3.17
6	-1.98	-2.88	1.27	1.39	-3.26	-3.67
9	-2.86	-2.80	1.68	1.31	-4.54	-3.80
12	-3.25	-2.45	2.32	1.41	-5.57	-3.62
24	-2.62	-0.96	6.40	2.10	-9.02	-3.12
36	3.73	0.76	14.09	2.91	-10.36	-2.42

Table 7: Cumulative Long-Short Size and B/M Adjusted Returns (%), Skipping 1st Week, for Various Adjusted Sets

This table shows cumulative size and B/M adjusted returns from buying 1 month past winners and shorting 1 month past losers, for various sets of stocks. In each month, the stocks in the set are ranked by their returns. Stocks in the top and bottom thirds ("winners" and "losers") are held in a portfolio with positive and negative weight, respectively. Portfolios are formed for: 1) a "News" subset consisting of all stocks that had at least 1 news headline during the month, and 2) a "No-News" subset of all stocks without a headline in the month. The resulting long-short portfolios are then aggregated into larger portfolios with overlapping positions, to accurately calculate standard errors. The first week of returns is excluded from calculations. Panel A shows average returns and t-statistics for a Buy and Hold strategy. Panel B shows results using event-month abnormal returns to rank stocks. Panel C shows results after weighting observations by days of headlines. Panel D shows strategy returns after excluding earnings announcement stocks. Panel E shows strategy returns after value weighting portfolio stocks. Panel F shows strategy returns after excluding low priced ($5 and under) stocks.

Months after Portfolio	News Set		No-News Set		Difference		News Set		No-News Set		Difference	
Formation	Alpha	T-stat	Alpha	T-stat	Alpha	T-stat	Alpha	T-stat	Alpha	T-stat	Alpha	T-stat
	Panel A: Buy and Hold Returns (BHARS)						**Panel B: Using Event Month Size and B/M Adjusted Returns**					
1	0.12 %	0.59	-1.25 %	-4.47	1.36 %	1.36	0.13 %	0.65	-1.37 %	-4.97	1.60 %	4.64
3	1.20	2.87	-1.34	-2.87	2.55	4.35	1.21	2.81	-1.94	-3.66	3.54	5.69
6	2.87	4.92	-0.86	-1.20	3.74	4.41	2.73	4.14	-1.99	-2.35	5.01	5.57
9	4.38	6.03	-0.74	-0.80	5.13	4.64	3.86	4.42	-2.27	-2.12	6.55	5.84
12	5.16	5.71	-1.37	-1.22	6.52	4.73	4.79	4.57	-1.77	-1.43	7.01	5.13
	Panel C: Weighted by Days of Headlines						**Panel D: Excluding Earnings Announcement Stocks**					
1	0.35 %	1.75	-1.25 %	-4.47	1.60 %	4.87	-0.20 %	-0.72	-1.37 %	-4.70	1.17 %	3.35
3	1.37	3.01	-1.78	-3.42	3.14	5.48	0.46	0.80	-1.93	-3.51	2.39	3.54
6	3.33	4.53	-1.82	-2.17	5.15	6.03	1.49	1.85	-2.25	-2.53	3.75	4.11
9	4.36	4.49	-1.89	-1.78	6.25	6.00	2.96	2.82	-2.79	-2.55	5.75	5.10
12	5.40	4.65	-1.59	-1.28	6.99	5.43	3.95	3.13	-2.70	-2.13	6.65	4.68
	Panel E: Value Weighting Stocks						**Panel F: >$5 Stocks**					
1	-0.11 %	-0.44	-0.47 %	-1.64	0.37 %	1.02	0.09 %	0.52	-0.21 %	-0.94	0.30 %	1.16
3	-0.25	-0.51	0.27	0.51	-0.52	-0.79	0.68	1.78	-0.19	-0.46	0.87	1.67
6	0.87	1.11	1.45	1.76	-0.58	-0.64	2.25	4.17	0.55	0.92	1.70	2.49
9	1.25	1.30	1.74	1.63	-0.49	-0.44	3.31	4.93	1.32	1.67	1.99	2.53
12	1.60	1.39	2.18	1.64	-0.58	-0.43	4.24	4.95	1.22	1.26	3.03	3.22

Table 8: Cumulative 3 Factor Alphas (%), for Subperiods 1980-1989 and 1990-1999

This table shows the cumulative 3-factor alphas from buying 1 month past winners and shorting 1 month past losers. On the left are results from 1980-1989, and on the right side are results from 1990-1999. In each month of both subperiods, all stocks within the subsample are ranked by their performance. Stocks in the top and bottom thirds ("winners" and "losers") are held in an equal-weighted portfolio with positive and negative weight, respectively. Portfolios are formed for: 1) a "News" subset consisting of all stocks that had at least 1 news headline during the month, and 2) a "No-News" subset of all stocks without a headline for the month. The resulting long-short portfolios are then aggregated into larger portfolios with overlapping positions, for purposes of accurately calculating standard errors. Panel A shows the average returns and t-statistics for the long-short strategy, Panel B shows the results for the winners, and Panel C shows the results for the losers.

	1980-1989						1990-1999					
Months after Portfolio	News Set		No-News Set		Difference		News Set		No-News Set		Difference	
Formation	Alpha	T-stat	Alpha	T-stat	Alpha	T-stat	Alpha	T-stat	Alpha	T-stat	Alpha	T-stat
Panel A: Long-Short Cumulative 3 Factor Alphas												
1	0.24 %	0.65	-1.33 %	-3.66	1.26 %	2.56	-0.63 %	-1.56	-2.13 %	-3.92	1.64 %	3.24
3	2.52	3.58	-0.73	-1.00	3.29	3.77	0.60	0.78	-2.55	-2.52	2.95	3.44
6	5.20	4.52	0.40	0.34	4.20	3.62	1.79	1.48	-3.68	-2.29	6.15	5.15
9	7.33	4.80	2.15	1.38	3.75	2.69	3.26	1.91	-4.81	-2.39	7.13	5.17
12	8.14	4.43	2.30	1.21	4.47	2.58	5.28	2.64	-4.51	-1.94	9.01	5.52
Panel B: Winner Cumulative 3 Factor Alphas												
1	-0.59 %	-2.35	-1.14 %	-3.88	0.49 %	1.38	-0.24 %	-1.11	-0.68 %	-2.31	0.83 %	2.54
3	-0.94	-1.83	-1.63	-2.42	1.16	1.97	0.54	0.90	-0.46	-0.68	1.57	2.33
6	-2.03	-2.19	-2.60	-2.15	1.18	1.18	0.77	0.74	0.10	0.08	2.21	1.94
9	-2.55	-2.00	-2.91	-1.64	0.75	0.58	1.23	0.77	0.58	0.29	2.60	1.80
12	-3.59	-2.20	-3.35	-1.40	0.02	0.01	2.68	1.21	2.32	0.81	1.28	0.64
Panel C: Losers Cumulative 3 Factor Alphas												
1	-0.83 %	-2.75	0.19 %	0.60	-1.02 %	-3.01	0.39 %	0.97	1.44 %	2.95	-1.05 %	-2.50
3	-3.46	-5.01	-0.89	-0.92	-2.57	-3.25	-0.02	-0.02	2.14	1.63	-2.16	-2.43
6	-7.23	-5.30	-3.00	-1.66	-4.23	-3.22	-0.99	-0.56	3.83	1.56	-4.82	-3.38
9	-9.88	-4.93	-5.06	-1.91	-4.82	-2.67	-2.07	-0.75	5.38	1.49	-7.45	-3.96
12	-11.72	-4.44	-5.65	-1.61	-6.08	-2.65	-2.71	-0.76	6.78	1.48	-9.49	-3.99

Table 9: 3-Factor Exposures for News/No-News Winner and Loser Portfolios, Selected Months after Formation

This table shows month-by-month Coefficients, T-statistics, and R-squared values from a regression of winner and loser portfolios on the Fama-French 3 factor returns. Regressions are conducted by matching each portfolio's returns at certain months after formation with contemporaneous factor returns. This is repeated for both News and No-News sets.

Months after	Market-Rf		SMB		HML			Market-Rf		SMB		HML		
Formation	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat	R-squared	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat	R-squared
Losers														
	News							No-News						
0	0.98	18.24	0.95	12.08	0.38	4.43	0.72	0.93	19.31	0.96	13.52	0.33	4.25	0.75
1	1.13	17.26	1.16	12.06	0.16	1.47	0.73	0.98	13.03	1.22	11.04	0.20	1.64	0.63
3	1.09	18.37	1.07	12.65	0.17	1.83	0.75	0.94	12.04	1.25	11.20	0.31	2.50	0.60
6	1.04	17.30	1.19	13.73	0.30	3.18	0.73	1.02	12.91	1.19	10.54	0.32	2.55	0.61
9	1.03	18.53	1.15	14.33	0.17	1.87	0.77	0.92	11.88	1.34	12.09	0.30	2.41	0.61
12	1.00	17.63	1.13	13.78	0.08	0.88	0.76	0.89	13.41	1.10	11.35	0.21	1.91	0.65
24	1.08	18.78	1.22	14.43	0.29	3.09	0.77	0.92	14.46	1.08	11.62	0.18	1.73	0.68
36	1.05	16.64	1.20	13.22	0.22	2.10	0.75	0.87	13.37	1.21	12.95	0.20	1.93	0.69
Winners														
	News							No-News						
0	1.16	12.05	1.47	10.38	-0.25	-1.61	0.65	1.30	13.92	1.30	9.52	-0.07	-0.44	0.66
1	1.00	23.65	1.04	16.81	0.10	1.45	0.84	0.83	15.47	1.09	13.78	0.14	1.62	0.72
3	1.02	22.21	1.07	16.09	0.05	0.63	0.83	0.89	16.40	1.18	15.02	0.16	1.86	0.74
6	1.06	25.46	0.95	15.88	0.00	0.01	0.86	0.88	16.96	1.09	14.71	0.09	1.15	0.76
9	1.04	22.64	1.00	15.13	0.19	2.63	0.82	1.00	18.54	0.97	12.43	0.24	2.76	0.74
12	1.05	22.28	0.97	14.16	0.07	0.92	0.82	0.94	16.77	1.10	13.50	0.32	3.51	0.72
24	1.08	20.52	0.86	11.16	0.25	2.83	0.77	0.90	13.47	1.23	12.54	0.33	3.00	0.66
36	1.11	20.72	0.91	11.70	0.29	3.28	0.78	0.87	14.46	0.91	10.54	0.23	2.40	0.67

Table 10: Breakdown of News Stock Returns in post-Event Months by News Month or No-News Month returns, skipping 1st Week

This table shows the cumulative size and B/M adjusted returns to buying 1 month past "news" winners and shorting 1 month past "news" losers. The cumulative payoffs to the news strategy are divided into returns that 1) would accrue had only stocks with news in each subsequent month been held, and 2) returns from holding only those strategy stocks which had no news in each subsequent month. The resulting portfolios consist of overlapping positions, for purposes of accurately calculating standard errors. For the long-short strategy, stocks in the top and bottom thirds are held in an equal-weighted portfolio with positive and negative weight, respectively. Panel A shows the average returns and t-statistics to the long-short strategy for both sets, Panel B shows the results for winners, and Panel C shows the results for losers.

	Counting only stocks with:			
Months After Portfolio	News in Month		No News in Month	
Formation	Alpha	T-stat	Alpha	T-stat
		Panel A: Long-Short Strategy		
1	-0.01 %	-0.09	0.13 %	1.24
3	0.55	1.65	0.55	2.46
6	1.61	3.02	1.01	2.89
9	2.09	3.02	1.86	3.95
12	2.86	3.42	2.10	3.61
		Panel B: Winner Portfolio		
1	0.22 %	2.19	-0.12 %	-1.69
3	0.84	3.25	-0.50	-3.18
6	1.77	3.91	-1.14	-4.28
9	2.69	4.20	-1.61	-4.27
12	3.89	4.45	-2.18	-4.57
		Panel C: Loser Portfolio		
1	0.23 %	1.72	-0.25 %	-2.86
3	0.30	0.96	-1.05	-5.46
6	0.16	0.28	-2.14	-6.12
9	0.60	0.69	-3.46	-6.86
12	1.03	0.91	-4.28	-6.55