

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

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## Abstract

Using a comprehensive database of headlines about individual companies, I examine monthly returns following public news. I compare them to stocks with similar returns, but no identifiable public news. There is a difference between the two sets. I find strong drift after bad news. Investors seem to react slowly to this information. I also find reversal after extreme price movements unaccompanied by public news. The separate patterns appear even after adjustments for risk exposure and other effects. They are, however, mainly seen in smaller, more illiquid stocks. These findings support some integrated theories of investor over- and underreaction.

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# 1 Introduction

There is a large amount of evidence that stock prices are predictable. In the last decade, studies have shown that stock returns exhibit reversal at weekly and three to five year intervals, and drift over 12-month periods.<sup>1</sup> Some research shows that stock prices appear to drift after important corporate events for several months.<sup>2</sup> This suggests that drift is driven by underreaction to information. However, there are many days when financial markets move dramatically, but without any apparent economic news. In other words, there appears to be “excess volatility” in asset prices.<sup>3</sup> This suggests that investors overreact to unobserved stimuli. These two phenomena raise some interesting questions. Do returns after major public news and returns after large price movements (in the absence of public news) differ? And if so, what can this difference tell us about how investors respond to information?

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

I find that stocks with news exhibit momentum, while stocks without news do not. In particular, stocks that had bad public news display negative drift for up to 12 months. Less drift is found for stocks with good news. I interpret this to mean that prices are slow to reflect bad public news. Furthermore, stocks that had no news stories in the event month tend to reverse in the subsequent month. The reversal is statistically significant, even after controlling for size and book-to-market. This is consistent with investor overreaction to spurious price movements. It is also consistent with bid-ask bounce, although I attempt to control for this. I also find that the effects diminish, but are present, when one eliminates low priced stocks, and

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<sup>1</sup>See, for example, [DeBondt and Thaler \(1985\)](#), [Jegadeesh \(1990\)](#), [Lo and MacKinlay \(1990\)](#), and [Jegadeesh and Titman \(1993\)](#).

<sup>2</sup>[Kothari and Warner \(1997\)](#), [Fama \(1998\)](#), and [Daniel, Hirshleifer, and Subrahmanyam \(1998\)](#) review the literature on returns after various corporate events. I describe specific studies below.

<sup>3</sup>For example, [Shiller \(1981\)](#) concludes that stock prices are too volatile to be explained by dividend changes. Excess volatility paper typically look at the link between news stories in the media and stock price movements. Although I deal with longer horizons and do not look at volatility, I share the same sources as two prominent members of the literature, [Roll \(1988\)](#) and [Mitchell and Mulherin \(1994\)](#).

are stronger among smaller, more illiquid stocks than larger ones. A possible explanation is 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 low 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 without earnings announcements.

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, causing 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 (detailed below) that try to explain short-run underreaction and long-run overreaction in terms of investor behavior.

The goal of this paper is to deepen our understanding of how information flows drive anomalies in three 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. 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.<sup>4</sup>

Second, I distinguish between return patterns after news events and after price shocks that do not appear to be news motivated. This adds to our understanding of momentum strategy payoffs. These have not been conditioned on the incidence of news in typical studies, yet are thought to arise because of different investor responses to public and private signals. Specifically, three major theories seek to explain momentum and reversal. [Daniel, Hirshleifer, and Subrahmanyam \(1998\)](#) (hereafter, “DHS”) use overconfidence and biased self-attribution to model investor behavior. The result is that investors hold too strongly to their own information, and discount public signals. [Barberis, Shleifer, and Vishny \(1998\)](#) (“BSV”) rely on conservatism and the representativeness heuristic. They hypothesize that investors change sentiment about future company earnings based on the past stream of realizations. [Hong and Stein \(1999\)](#)

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<sup>4</sup>One paper that takes a similar approach in a different direction is [Pritamani and Singal \(2001\)](#). They collect daily news stories from the *Wall Street Journal* and Dow Jones News Wire for a subset of stocks in 1990-1992 that had extreme returns, and find both positive and negative abnormal return drift for up to 20 days after a news story. Their results are not directly comparable to mine since they use strict filters for trading volume, volatility, size, and price that results in a subset of about 1% of the NYSE/AMEX universe.

(“HS”) present a model not tied to specific psychological biases, with two classes of traders. One group ignores the news, but reacts to prices. The result is initial underreaction and subsequent overreaction. Naturally, all three theories generate momentum and reversal, but they differ in some ways. DHS state that there will be underreaction to public information and overreaction to private information. BSV state that investors will over- or underreact to news depending on the stream of past news. HS state that investors will underreact to news and overreact to pure (non-information based) price movements. Since it is difficult to find price movements that have no component of private signals *ex ante*, the assumptions of DHS and HS are hard to separate empirically. I test the assumption of differential responses to information by separating stocks by news incidence using a headline database. While there are some differences in timing, the results are generally consistent with the DHS idea that investors ignore the balance of the headlines (i.e., they pay attention only to news that supports their prior) while they overreact to private signals embedded in pure price shocks. However, the results are even more supportive of the HS idea that some groups of investors are slow to react to news, while others are feedback traders. This helps us know what sort of information causes investors to change their expectations, and improves our understanding of their behavior.

Third, I examine when post-news drift occurs. In asset markets, arbitrage is a powerful force against non-risk-related predictability. However, in some cases noise trader risk or frictions can limit arbitrage (see, for example, [Shleifer and Vishny \(1997\)](#)). Recent research suggests that various informational or transactional frictions can have a major effect on asset prices. By looking at whether or not the drift occurs when more information is revealed, I provide indirect evidence on frictions. Since most drift happens in the absence of later news, I conclude that frictions slow the diffusion of information.

The paper proceeds as follows. Section 2 outlines previous research into investor reactions, reversal, and drift. Section 3 describes my dataset and testing methodology. I present my results in Section 4 and some extensions in Section 5. Section 6 discusses what my results say about different theories of investor behavior, and how they relate to other findings concerning the effect of information on returns. Finally, Section 7 concludes.

## 2 Literature review

Despite forty years of research by financial economists, the debate continues over how fast information is incorporated into prices. In this section, I describe evidence of predictability in returns.

Most of the research on stock returns after specific news items supports the idea 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<sup>5</sup> and scheduled news releases.<sup>6</sup> Investors also seem to be slow to react to capital structure changes<sup>7</sup> and ignore the personal investments of managers themselves.<sup>8</sup>

Important evidence that contradicts the view that investors underreact include results for acquiring firms in mergers in [Agrawal, Jaffe, and Mandelker \(1992\)](#) and proxy fights in [Ikenberry and Lakonishok \(1993\)](#), apparent reversal for new exchange listings in [Dharan and Ikenberry \(1995\)](#), and a host of different return patterns for IPOs depending on the horizon in [Ritter \(1991\)](#). [Barber and Lyon \(1997\)](#) and [Kothari and Warner \(1997\)](#) question the conclusions of event studies by explaining ways in which some statistical tests used in the above research lack power since the standard errors are understated. [Fama \(1998\)](#) observes that the above patterns present no consensus on investor reactions, and some disappear entirely after accounting for size and book-to-market effects.<sup>9</sup>

Some returns can be predicted without public news. [Jegadeesh and Titman \(1993\)](#) find multi-month momentum and [DeBondt and Thaler \(1985\)](#) find multi-year reversal. The success of technical momentum strategies, in particular, is very puzzling from an efficient markets perspective. Therefore, such strategies have been strongly linked to boundedly rational investor behavior by some researchers. Momentum is robust across subperiods and appears in other

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<sup>5</sup>Dividend initiations and omissions are covered by [Michaely, Thaler, and Womack \(1995\)](#). Stock splits could also fall in this category, examined recently by [Ikenberry and Ramnath \(2002\)](#), with similar conclusions.

<sup>6</sup>[Bernard and Thomas \(1990\)](#) and others show 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. [Womack \(1996\)](#) documents an asymmetric lagged price response after changes in analyst recommendations, for a set of large, liquid stocks.

<sup>7</sup>[Ikenberry, Lakonishok, and Vermaelen \(1995\)](#) find drift after tender offers, and [Loughran and Ritter \(1995\)](#) find it after seasoned equity offerings. [Gompers and Lerner \(1998\)](#) show drift after venture capital distributions.

<sup>8</sup>[Seyhun \(1997\)](#) finds profits to mimicking the large trades of insiders. See also [Lakonishok and Lee \(2001\)](#), who find that predictive power is mostly restricted to buys in smaller stocks.

<sup>9</sup>[Loughran and Ritter \(2000\)](#) have an opposite interpretation based on the same fact.

markets.<sup>10</sup> It is also distinct from post-earnings drift and reversal.<sup>11</sup> Hong, Lim, and Stein (2000) 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.

Finally, there is evidence that investors overreact to price movements and trade more than they should. It appears that the act of trading increases volatility. 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. 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 extreme aggregate price movements. Roll (1988) looks at the R-squared for regressions of daily and monthly stock returns on CAPM and APT factors and finds that much of the variance in returns is unexplained.<sup>12</sup>

In sum, many would describe underreaction to news as a “pervasive regularity”,<sup>13</sup> but others would dispute this claim, noting that the results are inconclusive and the methodology problematic. Furthermore, negative return autocorrelation at very short and long lags confounds the perceived pattern of drift. Some interpret this as evidence of overreaction.

### 3 Methodology

Do drift or reversal patterns occur consistently after news? To summarize my approach, I collect all stocks in a given month that had at least one news story. I rank all such stocks by monthly raw returns and select the top and bottom terciles. I refer to these two sets as “news winners” and “news losers”, respectively. I then examine abnormal returns for up to 36 months after the initial headline month. To determine whether predictable drift or reversal occurs after pure price movements, I repeat the test above for “no-news” stocks, those that had no headline in a given month. In the following sections, I describe each of these steps in more detail.

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<sup>10</sup>Grundy and Martin (2001) show that, after accounting for potential risk factor exposures, momentum exists from the 1920s to the present. Rouwenhorst (1998) shows that momentum occurs in other countries.

<sup>11</sup>Lee and Swaminathan (2000) show momentum is linked to reversal, conditional on trading volume. They also look at it in the context of earnings drift, as do Chan, Jegadeesh, and Lakonishok (1996).

<sup>12</sup>Mitchell and Mulherin (1994) show that while news moves the market, the relationship is not very strong.

<sup>13</sup>See Barberis, Shleifer, and Vishny (1998), abstract.

### 3.1 Portfolio formation

Each month, I separate firms that had one or more news stories from those that did not. I then divide these news stocks by performance. Using the Center for Research in Security Prices (CRSP) monthly data series (with delisting returns), I rank news stocks each month by raw return. 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. Terciles yield diversified portfolios where non-news related characteristics are less important, since there are few sample stocks in the earliest periods. On the other hand, some “bad news” stocks have positive returns when the return breakpoints are positive. I use months for comparison with momentum studies and to reduce microstructure problems that are present in daily or weekly data.

Each month, I also 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 the no-news portfolio as a benchmark for the news portfolio, since they have similar event date returns. This helps us to understand stock behavior after public announcements versus pure price movements. Each month I also sort all subset stocks by returns alone 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 these 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. Again, each stock in the no-news and all groups must trade during the formation month to be included.

The additional analysis of all and no-news stocks will also help me address some problems with long-run event studies identified by [Barber and Lyon \(1997\)](#) and [Kothari and Warner \(1997\)](#). For instance, most cumulative and buy-and-hold abnormal returns appear positive in random samples.<sup>14</sup> This causes the tests to have low power. Also, various data requirements for a sample bias the abnormal returns. Both the news and no-news samples could suffer from

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<sup>14</sup>I mainly test cumulative average abnormal returns (CARs), although I discuss one set of results for buy-and-hold average abnormal returns (BHAARs). Kothari and Warner’s simulation results indicate that BHAARs can be more misleading than CARs. Cumulation bias due to bid-ask spread is mitigated in my CARs, since monthly returns exhibit less bid-ask bounce than weekly returns. [Roll \(1983\)](#) describes this problem.

these problems. 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.

### 3.2 Test procedure

I form monthly equal-weighted portfolios of the winner and loser stocks. Portfolios can be easily interpreted as trading strategies. I calculate overlapping returns using a standard rolling portfolio method as in [Jegadeesh and Titman \(1993\)](#) and [Fama \(1998\)](#). As an example, suppose we want to look at how good news affects returns over four months. At the end of each calendar month, we calculate the abnormal return for all stocks that fell into the news winner category in the last month. We then average the abnormal returns for the calendar month across stocks to get the abnormal return on a portfolio of last month's news winners. For the same calendar month, we also calculate the abnormal return on portfolios of news winners from two, three, and four months ago and average all four resulting portfolio returns. This average tracks the calendar month performance of a news winner strategy that holds a series of portfolios formed in the last month as well as the previous three months. I repeat this process every calendar month to get a time-series of returns. Following Fama (p. 295):

The time-series variation of the monthly abnormal return on this portfolio accurately captures the effects of the correlation of returns across event stocks missed by the model for expected returns. The mean and variance of the time series of abnormal portfolio returns can be used to test the average monthly response of the prices of event stocks for [four months]... following the event.

In this case, the "event" is a high return, conditioned on one or more headlines. I follow the same steps for different horizons (one to 36 months after the event) and for other sets of stocks (winners and losers, all, news and no-news).

Most previous research averages the returns of the component portfolios each month. This average can be interpreted as the payoff to a strategy constructed using overlapping portfolios. For example, in the four-month rolling portfolio strategy, the calendar month  $t$  payoff would be the average of the time  $t$  returns on the four overlapping portfolios formed from months  $t - 1$  to

$t - 4$ . In this paper, I present summed, instead of averaged, returns. This makes it easier to see how a strategy performs over time. However, it makes it harder to frame as a practical trading strategy. Throughout the paper, if one wants to see average monthly returns as in [Jegadeesh and Titman \(1993\)](#), simply divide my average cumulative returns by the post-event horizon over which they are cumulated. The statistical significance will not change, of course.

To summarize the degree of drift or reversal, I also use a long-short strategy where past “good news” stocks are held with positive weights, offset by short positions in “bad news” stocks. This is repeated for all and no-news stocks.

The test statistics are simply the time-series average of calendar month returns divided by the time-series standard error. The test statistic for cumulative abnormal returns (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. How do I calculate CARs? [Daniel and Titman \(1997\)](#) suggest that size and book-to-market characteristics are better predictors of future returns than factor betas. Therefore, I subtract the contemporaneous returns of size and book-to-market matched portfolios. Some stocks are lost due to my matching criteria, described more fully in the next section.<sup>15</sup> Note that I make no adjustment for momentum. I want to test reactions to news, a possible cause of momentum.

### 3.3 Data description

To 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, some sources are only available after being archived in electronic format. To get around the problem of spotty data, I select only those publications with over 500,000 current subscribers, daily publication, and stories available over as much of the 1980-2000 period as

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<sup>15</sup>I have also regressed summed rolling portfolio excess returns on contemporaneous factors (appropriately scaled) according to the CAPM and Fama-French 3-factor models. The constant term is cumulative alpha. The results are very similar to those presented below. The regression method increases the profitability of the news strategy and decreases the losses to the no-news strategy when compared with the portfolio matching approach.

possible.<sup>16</sup> For each company in my set, I hand-collect all dates when the stock was mentioned in the headline or lead paragraph of an article from the sources. To reduce over counting news about the same subject from multiple sources, I note only if there was news on a particular day, not how many stories appeared. I do not include magazines, since it is difficult to say 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.

There are more sources in the later part of the 1980s and 1990s. As a result, I could 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. This source does not suffer from gaps in coverage, and it is the best approximation of public news for traders. Furthermore, a stock only needs a single news story over the month to be selected for the news set, which reduces the chance that later periods (with headlines on many days in a month) dominate the set of news events.

Since data retrieval is time consuming and labor intensive, I focus on a random subset of approximately one-quarter of all CRSP stocks. The result is a set of over 4200 stocks, with 766 in existence at the end of January 1980 and over 1500 at the end of December 2000. Table 1 shows counts of stocks in subsets in December of each year. The all set is roughly the union of the news and no-news sets, for both winners and losers. About 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% have news on more than five 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 news stocks each month also suggests that headlines do not consist solely of previously studied corporate actions.

Panel B presents correlations of news citations with selected firm characteristics. Stocks with headlines are larger and one might expect them to exhibit fewer asset-pricing anomalies than no-news stocks. Cross-sectionally, the correlations of log market value on log citations

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<sup>16</sup>The resulting list of data sources, with their coverage dates, follows: the *Wall Street Journal* (all editions) from 1980-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. The results are virtually unchanged, even in later periods, using only the Dow Jones newswires and *Wall Street Journal*.

per month average 0.37 over time. News citations per month have a weak positive correlation coefficient of 0.01 with returns. The occurrence of headlines is more strongly related to turnover; the average correlation is 0.16. I conclude that headlines do not seem to favor good news (denoted by high returns). Also, depending on the interpretation of turnover, liquid stocks attract more media attention or news causes more trading.

Table 2 presents winner and loser summary statistics for December each year. Winners tend to be larger than losers. News stocks are larger than all momentum stocks, which in turn are larger than no-news stocks. Most selected stocks would be considered small-cap, although some of the winners and news stocks might be classified as mid-caps. 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, but are an appropriate way of viewing the portfolio since I equal-weight observations.

News, no-news and all portfolios have similar event month (time  $t$ ) returns as shown in the last six columns of Table 2. Winner or loser portfolios are not very 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.<sup>17</sup> The monthly Herfindahl averages (not shown) are remarkably uniform across news/no-news and winner/loser categories, at about 16%. Given an average of 18 industries per portfolio each month, this implies that a single industry should not dominate the analysis.

Table 3 shows some details of news stories for a sample midcap firm, Jacobs Engineering (ticker JEC), for 1983-1986. Every news month is displayed. Winner, loser, or “neutral” designations within the set of news months, and the contemporaneous return, are shown in the left columns. This table highlights some features of the data. First, many news “events” are not corporate actions or pre-scheduled earnings releases. These include 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 bad. Since judging the text of stories is subjective, it is wise to rely on the market reaction to filter “good” and “bad” news. Third, the winner and loser categories are broad because I use thirds to divide firms by returns. Fourth, there is potential mixing between news and no-news events, as some

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<sup>17</sup>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.

headlines may not appear to contain any economically relevant information. This will reduce the distinctions between the two sets, but is necessary if we are to avoid picking and choosing important news.

How frequently do stocks have news? Three-quarters of the stocks have news on only 72 months or less. Less than two percent have news on 216 or more months from January 1980 to December 2000. Given that most firms exist for only a few years, however, it is better to ask what percentage of their sample existence in months do they have news. I construct a histogram (not shown) of stocks by percent of months they had headlines out of all months they existed in the sample. Only 14% of the total have news on 90% or more of the months that they existed from 1980-2000. Slightly under half have news about half the time they existed from 1980-2000 (30% to 70% of their sample lifespan). About 8% have news on only 10% or less of the months they existed. Thus, most stocks have fairly frequent periods of both news and no news.

The incidence of news is not autocorrelated. A single stock can switch from being a news winner to a news loser several times in a year. The transition probabilities of stocks in each of the news/no-news winner and loser groups (not shown) confirm this. News losers are slightly more likely to repeat as losers (news or no-news). News stocks have a 60% chance of having more news in subsequent months (be it good, bad, or neutral), and no-news stocks have a 40% chance. However, the average proportion of stocks in the four categories (news winner, news loser, no-news winner, no-news loser) switching into another category over subsequent post-formation months is roughly equal. Therefore any post-news patterns are likely due to reactions to single news events, not the accumulated reaction to multiple related news items.

## 4 Results

I present raw returns first, size and B/M adjusted returns second, and various results for adjusted datasets last. In all cases, rolling portfolios are used.

## 4.1 Raw returns

Panel A of Table 4 shows cumulative returns to the long-short zero investment strategy, out to three years after the event month. Separating stocks on news incidence causes dramatic differences even in first month returns. While there are few statistically significant signs that the long-short strategy is profitable for all and no-news sets, the news set returns nearly 5% in the first twelve months. Returns are negative in the first months, especially for the no-news strategy, which loses 1.83%. This is in line with the results of [Lo and MacKinlay \(1990\)](#), who show 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, news stocks experience less reversal in month  $t + 1$ , and 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 to eliminate the early drift. The difference between news, no-news, and all returns is statistically significant in the first 12 months. <sup>18</sup>

Month-by-month news returns (not shown) are larger three, six, nine, and 12 months after the event month, which suggests that post-earnings drift can be a driver of the long-short returns. My news set contains about 90% of stocks in the CRSP subsample that make earnings announcements (as recorded on IBES and Compustat) in a given month. Therefore, whatever results I find could 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 loses money in the first month, and has es-

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<sup>18</sup>As is generally the case for all of the following subsets, long-run returns seem to exhibit reversal around the two-year mark, so that long-short strategy gains are almost eliminated. However, after 12 months there is virtually no difference between news and no-news monthly returns. I include long-term returns 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, this is less of a 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. Overlapping returns do not necessarily improve the quality of statistical inferences at very long horizons. 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.

entially zero profits thereafter. The 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 procedure is typically used in momentum strategies to reduce influence of short-term microstructure movements on subsequent cumulative returns. The results in Table 4, Panel B, show that waiting a week lessens the magnitude of reversal for no-news stocks, but does not eliminate it. In contrast, the news long-short strategy is even more profitable and has no reversal in the first month.

Undoubtedly, the stronger pattern is that of drift after news events. First month reversal for no-news stocks is economically and statistically less significant. Skipping a week may not eliminate all of the microstructure effects, and one might still have doubts that the reversal is due to overreaction. However, 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). I continue to comment on first month effects since they appear in most later adjustments. The no-news reversal pattern is fairly robust, if not large, but is hard to separate from small stocks.

How is one-month news momentum related to the longer-horizon raw return momentum strategies documented by [Jegadeesh and Titman \(1993\)](#)? One could hypothesize that multi-month raw return momentum simply aggregates news drift and no-news reversal. The no-news stocks in such a strategy obscure the effect of news. One question is how much the firm composition of the standard 6-month strategy overlaps with that of a news or no-news one-month strategy. To address this, I create a six-month rolling portfolio strategy from my subset of CRSP stocks, 1980-2000. Again, I divide winners and losers by thirds. I then split winners and losers into stocks that had news in the last month (and would therefore likely appear in a news long-short strategy) and those that didn't (and would likely appear in a no-news strategy). One month no-news stocks make up about 40-50% of the stocks in the 6-month strategy. However, including these stocks substantially recedes momentum profitability. Excluding no-news stocks generates returns 40-50% higher at six to 12 months horizons. This is consistent with the idea that standard momentum simply reflects news drift and some extra no-news noise.<sup>19</sup>

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<sup>19</sup>As another sign that news and standard momentum reflect the same phenomenon, both the news and standard momentum strategies backfire in January. In contrast, most no-news reversal occurs in January and is long lasting (although it is still statistically significant in non-January months). A blended strategy combining all stocks regardless of news shows January reversal, consistent with previous work.

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. The results for the all set are similar in magnitude and sign to those of the entire CRSP database in the same period for almost all horizons.

## 4.2 Size and book-to-market portfolio matched returns

I next describe the method for adjusting returns for size and book-to-market (B/M). I merge all stocks in the CRSP database with book value<sup>20</sup> using a method outlined by [Fama and French \(1992\)](#). For June of each year  $t$ , all CRSP stocks are formed into 25 portfolios by size at the end of June of year  $t$  and B/M 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 NYSE with positive book values are used to calculate size and B/M breakpoints. The resulting portfolios are then equal weighted, and I calculate 25 sets of monthly returns.<sup>21</sup>

At the end of June every year, I pick only stocks from these 25 portfolios that match those from my subsample of over 4,200 stocks. I lose about 20% of the original sample stocks each month, with slightly more lost in the beginning of the period (23% in January 1980), and less in the later dates (14% in December 2000). This is due to the merging criteria, since I require data from the previous year as well as each June. On average, the resulting stocks are slightly larger than those without the size and B/M requirements. Averaged through time, the result is about 17% fewer news and 23% fewer no-news winners and losers.

I then subtract the size and B/M matched portfolio return from stock returns each month. I cumulate and test the resulting time series of adjusted returns as before. Finally, I skip the first week after portfolio formation before investing. As in Table 4, Panel B, this is meant to mitigate microstructure effects.

I present size and B/M adjusted data in Table 5. In general, the results are the same. Post-news drift is clear from the positive returns to the news long-short strategy. The 12 month cumulated abnormal return for news winners is 1.3% (statistically significant at the 10% level)

<sup>20</sup>Data item 60 on the Compustat tapes. I use the CRSP/Compustat merged database.

<sup>21</sup>I construct my own size and B/M portfolios to be consistent with how I measure size and B/M for individual stocks. My portfolio returns are over 90% correlated with those from Ken French's website.

and news losers is -2.6% (significant at the 1% level). The reversal for the no-news winner group is statistically significant at the 5% level. However, the first month returns are very small relative to the event month run-up, at -0.2% vs. 16.7% for no-news stocks. From Panel C, one can see that no-news losers show the same pattern of reversal followed by zero abnormal returns. They gain back 0.9% following a 13.9% drop. News stocks, however, experience no reversal in the first month. The first month no-news reversal, for both winners and losers, implies that large price swings contain an element of overreaction.

The difference between news and no-news returns is biggest for the losers. There is almost no difference between the two winner sets, except for the first few months. Almost all later adjustments (which tend to lessen the impact of the smallest stocks) confirm that news losers have drift, but news winners do not. In particular, any news winner continuation is due to post earnings drift. These facts support the view that investors primarily underreact to bad news.

In summary, the results of the size and B/M adjustment give further weight to the interpretation of underreaction to news. The evidence suggests an asymmetric response to information. Risk changes are unlikely to explain the entire story. The CAR spreads I have found are around 4% by month 12. [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. Therefore, my results are reasonable when compared to those of other studies.

## 5 Other adjustments

In this section, I adjust the methodology and sample, to explore further the patterns I have found. For comparison, I continue to use size and B/M adjusted returns like those in Table 5, skipping the first week after formation before investing. The results for long-short strategies are shown in Table 6.

## 5.1 Buy and hold average abnormal returns (BHAARs)

CARs are the sum of period-by-period average returns of all stocks in the portfolio. The trading strategy is effectively re-balanced each month, which is economically costly. It also increases the effects of small stocks, particularly after long periods of time. This is because each month, I equal weight all positions, even those that shrank a lot in the previous month. Buy-and-hold average abnormal returns (BHAARs) reflect the profits to a more feasible trading strategy and put more emphasis on relatively larger stocks.

To get BHAARs each month, I calculate the buy-and-hold return to each stock in the portfolio, skipping a week after formation. I then subtract the buy-and-hold return over the same horizon of a matched size and B/M portfolio. In each calendar month, I average these abnormal returns across portfolios. Since the time-series of returns is overlapping, I calculate t-statistics using Newey-West standard errors. Again, the results (Table 6, 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. The no-news strategy loses less over time, but the news strategy profits are a bit larger vs. those of Table 5. Winners and losers for both news and no-news strategies tend to have higher returns at longer horizons. However, 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 three months. Also, both no-news winners and losers reverse and earn increasing compounded negative and positive abnormal returns to the third post-formation month, respectively, while neither news winners nor losers do. The three months it takes for no-news reversal to end makes it more likely that this is not due to a trading shock.

## 5.2 Ranking on event month abnormal returns

Most studies measure the abnormal return around the event for each stock. The interpretation is that the event month idiosyncratic returns reflect firm-specific information, and subsequent abnormal returns show investor under- or overreaction to such news. I repeat the analysis above, ranking on event month size and B/M adjusted returns instead of raw returns. The results (Table 6, 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 -2.4% (t-statistic -2.5) 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 three months.

### 5.3 Weighting stocks by frequency of news within the event month

The impact of an announcement can 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 the effects of multiple headlines would be to weight each stock in a month by the number of days it had a headline when forming news portfolios. If there is less drift, we can 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 6, Panel C) are largely unchanged. Long-short returns show a pattern of drift for news stocks. Almost all of the post-news drift is from news losers, who return -4.0% by month 12 (t-statistic -3.7). News stocks show no reversal in the first month. No-news portfolio returns are of course unchanged from Table 5. 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. Given these findings, it is difficult to say that having more news makes investors less likely to underreact to information. It still seems that there is a delay in price adjustment, regardless of the number of days of coverage a company has.

## 5.4 Liquidity: the effect of low priced stocks

It might not be profitable to attempt to “arbitrage away” apparent underreaction, since much of the drift 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 5, 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.

Dropping low-priced stocks further reduces the sample. In the CRSP database for this period, on average, 32% of observations (stocks in all months) are priced at \$5 or below. The no-news set contains more low priced stocks; 25% of my news winners and losers are low-priced, while 46% and 38% of no-news losers and winners, respectively, fall out of my size and B/M matched subsample. The resulting portfolios of winners and losers have less extreme returns in the event month. Loser returns average about -10% in the event month for news and no-news portfolios. Winner returns average about 13%. Also, my remaining sample consists of larger stocks. Loser news and no-news portfolios average about \$1.02 billion and \$318 million, respectively, while winner news and no-news portfolios average \$1.16 billion and \$425 million. These are much larger averages than those used in the original analysis.<sup>22</sup>

The CARs of the reduced set (shown in Table 6, Panel D) are similar to those of Table 5. News drift is still present, and no-news stock returns are closer to zero. The difference between news and no-news strategy payoffs is smaller, but still statistically significant at all horizons. Again, the news loser drift drives all of the news strategy profitability. News loser 12-month cumulative returns are -3.3% (t-statistic -4.2), which is much different from the no-news loser cumulative return of close to zero. News winners have little drift (at 12 months, they return 1.0%, t-statistic 1.2). Moreover, no-news stocks continue to have reversal. The pattern,

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<sup>22</sup>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.

however, is much weaker and confined to losers. No-news winners return 0.0% in the first month (t-statistic 0.2) and no-news losers return 0.3% (t-statistic 2.8). The difference between news and no-news sets is economically and statistically large only for losers. Therefore, first month no-news reversal is driven by the losers in higher priced stocks.

Even after removing relatively illiquid stocks, news losers continue to show economically and statistically significant negative returns for up to 12 months after formation. This drives the profitability of the news momentum strategy. However, reversal is much weaker, and it is difficult to tell if this is due to liquidity constraints or investor behavior. These probably reinforce one another since individuals, who tend to be less informed, are more dominant shareholders in less liquid small stocks. The fact that news-related patterns diminish when accounting for liquidity (but do not disappear) suggests that frictions may play a role in slowing news. I explore this in more detail below.

## 5.5 A more restrictive definition of news

I count news stocks as all firms that had one or more headlines in a month. This simple definition does not rely on personal judgement to distinguish different forms of public information, which helps us avoid selection bias. Moreover, the news/no-news differences yield interesting results even without adding anything else to the analysis.

However, there are two problems with this division. First, I undoubtedly mix a lot of “no-news” stocks with news stocks, since not all headlines say something that investors would find informative. Second, since the quantity of news increases considerably over time, the number of no-news stocks declines. This weakens any no-news patterns. One way around these problems is to define news stocks by additional criteria, such as abnormally high share turnover. This filter relies on the idea that investors will trade in larger quantities than they usually do when news is truly noteworthy. However, it has some drawbacks. First, we must believe that true public news has been noticed by many traders or a few heavily trading parties. In doing so, however, we rely on the trading behavior of investors to tell us what is noteworthy, when most bounded-rationality hypotheses start from the idea that investors cannot make this distinction. Second, in adopting a more restrictive definition of news, we may overcompensate and force important news events into the no-news category, thus clouding no-news results.

Nevertheless, I reclassify news stocks as those firms that experienced both a headline and abnormally high share turnover. The latter is defined as turnover in the 3 days around headlines that falls in the top third of daily share turnover over the three months prior to the formation month. All other firms are considered no-news stocks. Again, I use formation month returns to differentiate between good news and bad news. This results in many more no-news stocks, and fewer news stocks. For instance, I begin with about 200 no-news winner stocks in January 1980 and end with around 270 in 2000. There are about 100 to 200 no-news losers over the entire period. I have about 30 news stocks in the early 1980s and 350 in the late 1990s, for both winners and losers. The new definition also substantially increases the time-series average size of the news and no-news portfolios, to \$825 million and \$935 million for news losers and winners, and \$248 million and \$416 million for no-news losers and winners. Industry concentration falls a bit for portfolios, with the average Herfindahl index around 13% and the number of industries about the same.

In Table 7, I present news and no-news strategy returns (size and B/M adjusted, skipping the first post-formation week) for the more restrictive definition of news. Not much changes compared to Table 5. The news strategy is slightly more profitable and the no-news strategy is slightly less unprofitable. Losers mostly drive news drift. Both no-news winners and no-news losers reverse in the first month. Overall, the news drift and no-news reversal observed in previous sections are robust to other definitions of news. A tighter filter for news tends to strengthen the news drift results slightly, while weakening the no-news results slightly. However, the same general patterns persist, implying that investors appear to ignore even obvious activity of other traders that highlights important headlines.

## 5.6 The effect of size

Underreaction to news seems stronger in lower priced, more illiquid stocks. Just how small are the stocks that exhibit these patterns? One way to find out is to divide the sample each month into size quintiles. There are problems doing this under the broadest definition of news. If any stock with a headline in a month is part of the news set, then there are not enough no-news stocks in the largest quintiles for comparison. The more restrictive turnover-based news definition mitigates this problem, although there are still a few months with few or zero

no-news stocks in the largest size groupings.

I use the news definition in Table 7 for this analysis. I divide stocks at the end of each June based on month-end market values using NYSE breakpoints. Table 8 shows how the long-short news and no-news strategies perform for different size quintiles of stocks. Time-series average numbers of stocks in the resulting news and no-news groups are also shown in the first columns of each group. One can see that in the smaller quintiles, there are more no-news than news-stocks, while the situation is reversed for larger stocks.

There are several patterns to note. First, news drift is economically and statistically significant into the third quintile. No-news reversal is also present in the two smallest quintiles. It appears that no-news stocks begin to show drift in later months, but this is probably due to the fact that some headline stocks without high share turnover got classified as no-news due to the modified definition. For this reason, it is useful to look at the difference between news and no-news strategies. Note that the third column is not the exact arithmetic difference between news and no-news returns, since some months have zero no-news stocks. These returns clearly show that news drift and no-news reversal are strongest in the two smallest quintiles. This supports the interpretation drift and reversal are related to ease of trading, liquidity, attention, institutional ownership, or other factors related to size.

## 5.7 Subperiod analysis

It is possible that any investor underreaction fell in recent years with the advent of new sources of information. Broadening stock market investment may also have changed any reaction that was present in the 1980s. I split my sample into two subperiods. Table 9 shows size and B/M adjusted returns for 1980-1990 (on the left) and 1991-2000 (on the right). Again, all returns are cumulated after skipping one week between portfolio formation and investment. Long-short, winner, and loser strategy results are in Panels A, B, and C, respectively. Since there are many more headlines in the 1990s, the results will be less clear since some news stocks may in fact have no news under this definition.

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 3% at 12 months for

the news strategy in the 1991-2000 period. Abnormal returns tend to be more negative in the earlier subperiod and more positive for the latter subperiod. In Panel B there is less difference between news and no-news winners for either period, except for the first few months. For losers in Panel C, there is more of a difference between news and no-news in both decades. The difference in cumulative abnormal returns between the two periods could be attributed to the performance of the size and B/M factors. In fact, a 3-factor regression of strategy returns for each subperiod shows that R-square values are smaller in the latter decade. This could mean that the 3-factor model is less well specified in the latter period. However, the patterns of relative magnitudes and signs are more important than the point estimates of abnormal returns. 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. Although underreaction might have diminished in recent years, it remains even in most recent years. There is also evidence of overreaction in the reversals of the first month.

## 5.8 The relationship between trading volume and news

[Lee and Swaminathan \(2000\)](#) find that high trading volume stocks experience more momentum and high volume tends to attenuate drift in winners but strengthens it in losers. They suggest a “momentum life cycle” explanation, which is intended to link drift and reversal over the evolution of stocks. How does this relate to the news findings here? News losers do indeed have higher share turnover than no-news losers, and they drift more, but the hypothesis does not fit exactly for news winners, who show no reversal.

To examine this relationship further, I use a Fama-MacBeth approach in Table 10. Each month from 1980 to 2000, I regress the one, three, six, and 12 month cumulated returns of my subset stocks (skipping the first week) on various past firm characteristics. I then average the coefficients across months, and calculate standard errors from this time series of coefficients. In each case, I wait a week after characteristic calculation before investing. In regressions where the dependent variable is cumulative returns over several months, I use Newey-West standard errors with a lag equal to the number of months over which these cumulative returns overlap. Since I include share turnover among the regressors, I exclude all NASDAQ stocks to

avoid problems with inflated trading volume due to double-counted dealer trades. This is also consistent with how Lee and Swaminathan handle volume.

The top panel of Table 10 shows the results from a baseline regression. The preliminary explanatory variables are log formation month B/M, log market value (from the formation month-end), past month return, an indicator for the occurrence of headlines in the formation month, and an interaction term for news and past return. The size and B/M terms account for other factors that affect the cross-section of returns. The interaction term shows how the incidence of news increases the percent of last month's return that is carried over into future returns. The results confirm what we know about news. First, the positive and significant B/M coefficient confirms the value effect. The past return coefficient is negative, larger in absolute value, and statistically significant. This indicates that unconditional stock returns tend to reverse for up to three subsequent months. The news interaction term, however, shows that this reversal is mostly in no-news stocks, and that firms with news continue to have similar performance in future months relative to other stocks. At longer horizons, the incidence of news creates strong continuation, dwarfing the effects of the return reversal (compare the average coefficient on the news and return interaction term with that for past returns alone).

At the bottom of Table 10, I show the regression coefficients for the same group of explanatory variables, with additional terms for turnover and turnover interacted with past return. The results of Lee and Swaminathan suggest that the coefficient for turnover should be negative, since higher turnover depresses winners and forecasts more bad performance for losers. This is also consistent with a liquidity interpretation of turnover. For example, [Datar, Naik, and Radcliffe \(1998\)](#) use the same turnover measure as a proxy for liquidity, and find that there is a liquidity price premium even after adjustments for other determinants of stock returns. Furthermore, Lee and Swaminathan suggest that turnover should enhance momentum, so we expect the coefficient on the turnover and return interaction term to be positive.

As reported in Table 10, all of these predictions hold. Turnover has a negative coefficient, and the turnover/return interaction term is positive. However, since I measure turnover over the formation month and not over a longer period as in Lee and Swaminathan, my results for trading volume are not directly comparable to theirs and should be treated with caution. More importantly, it appears that the news coefficients are barely changed, suggesting that the news

momentum effect is generally separate from the effects of trading volume.

## 5.9 Risk changes caused by news

As mentioned before, bad news can increase risk and drive 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 abnormal returns, I have already accounted for some changes in known “risk” factors, and still found statistically significant drift for news stocks and reversal for no-news stocks. However, Table 11 shows the evolution of month-by-month 3-factor loadings and alphas for winner and loser portfolios, news and no-news sets. These loadings are from a time series regression of portfolio excess returns each post-formation month on contemporaneous Fama-French factors in calendar time. Specifically, I regress:

$$R_i - r_f = \alpha_i + \beta_i(R_m - r_f) + \gamma_i(SMB) + \delta_i(HML) + \epsilon_i \quad (1)$$

where  $R_i$  is the portfolio return  $i$  months after formation, for  $i = (0, 1, 2, 3, \dots, 36)$ , and  $\beta_i$ ,  $\gamma_i$ , and  $\delta_i$  are the coefficients on the Fama-French market, size, and B/M portfolio returns from the same calendar months. Note that the portfolio returns are unadjusted and non-rolling. To analyze the difference between winners and losers, news and no-news sets, I also conduct the regression on various differenced portfolios (not shown). T-statistics are calculated from robust standard errors.

First, the month-by-month alphas from the regression confirm the general patterns of no-news reversal in month one and news loser drift to month 12. Second, within winner or loser categories, news and no-news portfolios have similar factor loadings at inception and over the course of the strategy. A 3-factor regression on the difference between news and no-news loser portfolios at  $t = 0$  (not displayed) shows no statistically significant differences between the two groupings for all factor loadings. Furthermore, the difference is statistically indistinguishable from zero in almost all subsequent months, except that news stocks achieve higher betas than no-news ones. The same holds for news and no-news winners, except that the size coefficient of the news minus no-news portfolio is 0.17 (t-statistic 2.06) at formation.

However, this differenced portfolio SMB coefficient becomes negative in most post-formation months. Overall, there are no consistent differences in factor loadings aside from market beta. One might say that news stocks gain market risk over time. This makes the similarity in their post-formation returns more unusual.

Are factor loadings for winners much different from those for losers, within news or no-news categories? No. For the news group, only the formation month market beta on the portfolio of winners minus losers (not shown) is statistically different from zero (0.29, t-statistic 2.24). However, any differences disappear in months after formation. For no-news stocks, winners have higher betas than losers at formation (the beta of the no-news winner-loser portfolio is 0.37, t-statistic 3.14), but all other winner and loser factor loadings are indistinguishable. Even the difference in beta quickly dwindles until the portfolio of no-news winners minus losers attains nearly zero factor loadings across the board. In summary, loser and winner stocks are similar over time for news and no-news groups. If anything, they tend to become more and less risky, respectively, which is the opposite of what one would expect from observing the drift patterns. Therefore, the abnormal returns are unlikely to be caused by changes in risk.

Finally, the 3-factor model does a good job of describing returns. R-square statistics for my portfolios are around 0.7 to 0.8, similar to other diversified portfolios like mutual funds that have R-squares of about 0.8 or more.<sup>23</sup>

## 5.10 When does drift occur?

The results above indicate that smaller stocks seem to underreact (mostly to bad news). Why might this be the case? There are two potentially overlapping explanations. The first is that investors simply have different attitudes to good and bad news. They form incorrect expectations about future performance, and consistently underreact to bad news. Another

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<sup>23</sup>One could add the “momentum factor” to the regression. As mentioned before, news drift is a possible cause of momentum. Therefore, it is reasonable that it could be strongly related, but not completely explained by, an unconditional momentum portfolio that includes no-news stocks. Using the additional momentum “factor portfolio” from Ken French’s website (UMD), I repeat the month-by-month time-series regressions above. Almost all of the loadings on Market-RF, SMB and HML are the same. As expected, the news strategy has a statistically significant positive loading on UMD (around 0.5 in post-formation months), and the strategy alphas are cut in half, but are still statistically different from zero. The no-news set also has a smaller, but statistically significant loading on the UMD factor. R-squares for the regression rise only slightly when compared to those in Table 10. Therefore, while the news long-short strategy is related to traditional momentum, it is not entirely explained by it, which is consistent with unconditional momentum reflecting both news drift and noise.

explanation would be that frictions of some sort prevent some information, particularly bad news, from being impounded into the stock price. The frictions would likely include short sales constraints, since other costs such as bid-ask spreads or noise trader risk cannot explain an asymmetric drift pattern. Note that short sales constraints might explain the persistence of drift, but not why it exists in the first place. For most holders of stocks, it makes more sense to sell shortly after negative headlines are public, rather than wait for a predictable 4% loss.

One way to examine these stories would be to look at how much of the news drift occurs on months with subsequent news. This approach 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 of value stocks and often disappointed by the earnings of growth stocks (i.e. post earnings drift is stronger in value stocks). If investors form systematically incorrect expectations about performance, they will be serially surprised. One might expect to see that most post-bad-news drift comes in months with major news. Alternatively, if investors face difficulty in selling their stock or other frictions, one might expect to see proportionally more post-bad-news drift in months without major news. Investors could liquidate positions over an extended period of time to reduce transactions costs. If the main cost is short-selling, there will be less extended drift for news winners than for news losers in non-news months.

Earnings announcements are times when we know that major news was released. One way to see if the profitability of a news strategy comes when information is made public is to see how much of the return occurs during earnings announcements. However, we know from other research that stocks making earnings announcements tend to show drift on subsequent earnings announcement days. Before proceeding, we must first account for this phenomenon.

Earnings announcement stocks constitute about a third of all news stocks each month. Do the responses to earnings announcements drive my results? To answer this question, I repeat the size and B/M adjusted analysis of Table 5, but exclude all stocks that had a known earnings announcement in the event month from my set of observations.<sup>24</sup> A few no-news stocks (not

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<sup>24</sup>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 size and B/M adjusted analysis of section 4.2. Similar studies usually use deciles instead of thirds. I find large and statistically significant abnormal returns of 0.9%, 0.3%, 0.3%, and 0.7% in the third, sixth, ninth, and twelfth month after the announcement, respectively. The cumulative twelve month abnormal return is over 3.8%. Therefore my sample does seem to exhibit earnings momentum.

shown) with apparently unpublicized earnings announcements are dropped.

Even after excluding earnings months, the results are comparable to those in Table 5. I show only the non-earnings-announcement-related news strategy returns in the first group of columns in Table 12. Long-short adjusted profits to a news strategy are smaller (around 3% twelve months after formation vs. nearly 4% 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 and statistically significant at 12 months when compared to Table 5. News winners experience a reversal (-0.2% vs. 0% for Table 5 news winner returns in the first month) and have an adjusted cumulative return of -0.2% 12 months after formation (vs. 1.3%). No-news winners show little change (unsurprising, since they contain few earnings announcement stocks), and the difference between news and no-news winners is generally smaller. News losers excluding earnings announcement stocks have lower returns than those in Table 5, Panel C. They reach a cumulative 12-month return of -3.3% (t-statistic -2.8). No-news losers are largely unchanged. The difference between news and no-news returns is larger for losers, reaching nearly -6.4% in month 12 vs. the -5.5% found in Table 5 (t-statistics of -5.4 vs. -5.3). In conclusion, post earnings announcement drift is important but does not drive all of the underreaction I have found. Excluding stocks that had earnings announcements eliminates any trace of post-news-winner drift. Investors do not appear to underreact to good news, aside from positive earnings announcements.

Having first accounted for post-earnings drift, we can now explore if there is “post-news” drift for non-earnings-announcement-related stocks. Mechanically, for each post-formation month, I take the strategy returns from above and zero out all of the positions for stocks that did not have an earnings announcement. I preserve the weights in all other stocks. I also repeat the zeroing procedure for stocks in subsequent months that did have earnings announcements to get the cumulative returns attributable to stocks without news. The sum of the two sets of cumulative returns will equal the results above.

The second and third groups of columns in Table 12 presents results for this decomposition. Most of the drift comes from non-earnings announcement months. Panel C shows that almost all of the news loser drift comes from months without major news, supporting the frictional story. The subsequent CARs from counting only those news loser stocks with earnings announcements

are indistinguishable from zero. It seems that investors are not particularly responsive to subsequent news about 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 when they announce earnings. Yet “news surprise” is almost entirely cancelled out by the negative returns in non-announcement months. The result is the small CARs for news winners that we observed earlier. However, the magnitudes of the winner movements are small when compared to those of the loser drift.

In summary, I find some signs that frictions increase bad news drift by slowing the incorporation of information into prices. The decomposition of returns for news winners implies a more complicated story, however.<sup>25</sup> Hong, Lim, and Stein (2000) find that smaller stocks with little size-adjusted analyst coverage experience the most momentum, driven mostly by losers. They propose that investors are slow to react to bad news (defined as an unconditional negative return) unless they have “help” from Wall Street analysts. My conclusions support this idea. One crucial difference, however, is that I find that investors are slow to respond to public news. In other words, the underreaction appears to result not from barriers to “knowing” news, but barriers to “understanding” it. One possibility is that analysts may not give investors private information, but may help them digest public news.

## 6 Discussion of results and implications

This paper has documented that stocks with public news in a given month experience momentum. Those that do not have public news show no momentum; if anything, they tend to reverse if they had a large price movement. What do these findings add to our understanding of momentum and reversal?

Although the strategy here uses a one-month horizon to distinguish winners from losers, it overlaps with longer-horizon momentum strategies used in previous research. First, the general patterns of momentum are the same: winners beat losers for up to 12 months, the patterns are

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<sup>25</sup>News returns decomposed by news and non-news (not just earnings or non-earnings) months yields similar findings.

robust to risk adjustments, the strategy backfires in January, it is stronger in smaller stocks, and holds in different time periods. It is harder to extend the one-month news results to longer horizons because one would need to decide how to weight news over six or 12 months (and no-news stocks are rare over long periods), but there is considerable overlap in stocks selected by both strategies.

More importantly, there is a theoretical link between news motivated drift and momentum. One goal of this paper is to test if there is underreaction to public news. This is an assumption of most behavioral theories, and is supported here. The fact that the “control” set of no-news stocks tends to reverse also supports the view that investors overreact to signals that are not informative. This evidence of differential responses to news and no-news is broadly consistent with all three models (DHS, BSV, HS) mentioned in the introduction. The general point that they make is supported: both underreaction and overreaction feature in investor responses to stimuli. There are some distinctions and qualifications, however. One difficulty in relating my results to the DHS, BSV, and HS theories lies in mapping “news” and “no-news” shocks to the signals featured in their models. However, the general point that they make is supported: both underreaction and overreaction feature in investor responses to stimuli.

Delayed overreaction drives the DHS model.<sup>26</sup> A central theme of the DHS paper is that “stock prices overreact to private information signals and underreact to public signals” (see DHS, p. 1841). Specifically, momentum results when investors overreact to certain signals for a period of time and ignore others, which inevitably leads to reversal. The question is: what is considered private and public information? If private information includes things investors read in the newspaper, then the growth and shrinkage of news drift supports their view. However, the fact that most drift occurs in the absence of subsequent confirmatory signals (see Table 11) is at odds with one feature of their model, that overreaction gets worse as more information confirms initial beliefs. If private information is captured by no-news, then the one-month no-news reversal would reflect a correction of overreaction. DHS, however, model much longer horizon reversal. Instead, I find very short horizon reversal. Again, while this feature of their model is not supported, there is a difference in responses that is broadly in line with the

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<sup>26</sup>Strictly speaking, in the DHS model, drift reflects “continuing overreaction”. I use the term “underreaction” to denote that prices move only partly to the level they eventually reach at a future date; after that date the price may fall again. The only difference between the terms is the horizon on which an investor should condition.

assumptions of their theory.

The news/no-news split, combined with evidence on frictions in the previous section, fits the HS model relatively well. Interestingly, this is the framework that has the least grounding of the three in specific aspects of psychology. The empirical results show that people do not appear to read the news headlines, while some people seem to over-react to price movements. Also, it seems to take a long time for news in headlines to affect prices. These are all features of the HS model. The distinction between public news and no-news seems to be tailored to test the HS “news-watchers” and “momentum traders” assumptions. One apparent difference is that in the HS model, newswatchers receive (and act on) private signals, not public ones. They are private in the sense that newswatchers only act on a fraction of information at any given time, and ignore the rest. This gives the model a long-lasting drift because information diffuses slowly. However, the definition of “private signals” is not necessarily at odds with drift after public news. The model is really meant to “capture the idea that information moves gradually across the newswatcher population” (HS, p. 2148). Like DHS, HS never really define what these perceived private signals are in real life. It could be several pieces of related news, released sequentially. It could also be a single story, which somehow is revealed across investor groups slowly. My finding that news is not autocorrelated supports the latter interpretation. Therefore, public news and private signals are not necessarily different.<sup>27</sup> Furthermore, the fact that post-news drift occurs in the absence of other news supports the idea that information diffuses slowly. The HS interpretation of overreaction also fits the horizons of no-news reversal. Depending on the calibration of various aspects of their model, reversal could take place over many horizons, but most plausible values show that overreaction is very short term (within a few months), and the correction of the overreaction much more gradual (see their Figures 1-3).

In the BSV model, the sequence of signals is important to determining the amount of over- or under-reaction. Since I do not form portfolios beyond one month of returns, I cannot directly test this assumption. BSV argue that momentum is stronger after a period of contradictory headlines, and reversal more prevalent after a run of reinforcing news stories. Therefore, both momentum and reversal could result from the same type of signals, in a different order. While this may be true, the strong news and no-news return difference suggests that one does not need

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<sup>27</sup>For example, [Hong, Lim, and Stein \(2000\)](#) effectively assume that analysts (who can be fairly public figures) produce “private information” in their test of the slow diffusion assumption of HS.

a time-series pattern of signals to predict returns. Furthermore, the BSV model is extremely difficult to test given all the unspecified parameters such as an appropriate horizon and what constitutes a particular sequence. However, in the context of news headlines, one could look at returns around headlines over the past quarter or year, and classify them as good or bad relative to some benchmark. One could classify the chain of news returns by some pre-determined algorithms, and analyze momentum profits. These are tasks that require more thought and theoretical guidance.

Finally, none of the three models makes any provision for asymmetry in returns, nor do they explicitly say why the patterns should be stronger in smaller stocks than larger ones. This clearly suggests that new versions of behavioral theories should be richer, perhaps by incorporating specific frictions and heterogeneous investors.

Recent work by [Daniel and Titman \(2001\)](#) and [Cohen, Gompers, and Vuolteenaho \(2001\)](#) also enrich our understanding of momentum and reversal as responses to different types of information. They focus on the specific meaning of information rather than how people hear it. Daniel and Titman decompose accounting and market variables into expectations about “tangible” and “intangible” growth rates, and provide evidence that investors overreact in the long run to the second. Unlike me, they find no evidence of underreaction. This is because their “tangible” news and my “public” news are not exactly the same. The tangible/intangible differentiation relies on valuation levels and longer horizons instead of changes in expectations over a single month, and the results are not directly comparable to the findings here. Cohen et al. use vector autoregressions (also based, in part, on accounting variables) to show that individual investors underreact to that part of returns that predicts cash flows. Their “cash flow news” is conceptually similar to my public news and their conclusions are almost the same. Since I measure information directly from its source, however, the test presented here is arguably more direct. On the other hand, it is also less specific than theirs about the nature of the information. They go a step further and show that most underreaction is due to non-institutions (those with less than \$100 million in assets), which helps us understand who might react to news (and prevent drift from occurring) and who might not.

## 7 Conclusion

I have examined various views of investor reaction to news in an integrated framework. Using a comprehensive sample of headlines for a large, randomly selected group of firms, I test the hypothesis that stocks exhibit no abnormal return after public news. This is not the case. Stocks that experienced negative returns concurrent with the incidence of a news story continued to underperform their size, B/M, 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 can drive the reversal of returns. However, the reversal continues to appear after waiting a week to pursue a no-news long-short strategy. Ranking by idiosyncratic risk by adjusting for size and B/M characteristics does not eliminate these results. Neither does weighting by number of news stories or excluding earnings announcements. Buy-and-hold abnormal returns display the same pattern of news drift and first month no-news reversal. Drift patterns become less evident as one moves up size quintiles, 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 evidence that the relations are weaker, 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. This noteworthy result is more understandable if one considers the possibility of different types of investors. Most of the drift is on the downside among smaller, probably illiquid stocks. Furthermore, most negative drift happens over many months even without new information in the press. This supports the idea that more sophisticated investors might not be able to arbitrage away the pattern, since shorting is more expensive than buying. Thus, it appears that both bounded rationality and frictions, far from being minor factors in asset pricing, interact to create relatively long-lasting anomalies.

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**Table 1: Summary of News Observations in Analysis, Selected Months, 1980-2000**

This table shows the number of observations in the randomly selected sample of CRSP stocks, for each December. The subset covers approximately one quarter of all CRSP stocks that existed from 1980-2000. Panel A shows numbers of stocks by days of headlines for three groups: "all", "news", and "no-news", which denote all stocks in the sample, those that had a headline, and those that did not. Each group is further divided into "winner" and "loser" sets, based on returns. Winners and losers for news and no-news stocks are determined by news stock return breakpoints, while the "all" set is determined by returns for all stocks in the sample. Panel B shows the time-series averages of monthly Pearson cross-sectional correlations between number of days with news and month-end market values, returns, and turnover.

Year	Total stocks	stocks with			stocks with News, By Days:			Losers, Number of stocks			Winners, Number of stocks		
		No News	4 or Fewer		5 or More	All		News	No-News		All	News	No-News
			4 or Fewer	5 or More		All	News		No-News				
1980	766	407	340	19	253	119	172	252	118	130			
1981	874	492	358	24	289	127	184	288	126	156			
1982	1039	597	420	22	343	146	202	342	145	156			
1983	1259	781	460	18	416	159	278	415	157	203			
1984	1348	840	460	48	447	168	350	443	167	209			
1985	1334	796	479	59	441	185	380	440	177	198			
1986	1368	789	505	74	452	192	280	350	174	176			
1987	1448	922	466	60	481	198	509	477	173	198			
1988	1406	875	477	54	466	176	324	463	175	234			
1989	1385	808	518	59	459	191	277	456	190	215			
1990	1391	784	545	62	460	201	299	459	198	227			
1991	1408	723	616	69	465	260	349	464	226	172			
1992	1454	668	676	110	480	260	237	479	258	214			
1993	1617	733	748	136	534	292	296	533	291	188			
1994	1747	722	871	154	578	339	262	576	338	201			
1995	1805	736	885	184	598	353	245	594	352	205			
1996	1933	703	1030	200	639	406	209	637	405	206			
1997	1891	621	1037	233	625	420	196	624	419	170			
1998	1743	516	923	304	576	406	210	575	404	121			
1999	1600	486	830	284	528	368	205	528	367	88			
2000	1531	491	791	249	506	344	160	505	343	134			
Average	1421	575	712	135	476	282	209	464	277	160			

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

Time Series	Market Value	Returns	Turnover
Average	0.37	0.01	0.16
Standard deviation	0.07	0.05	0.07

**Table 2: Summary Statistics of Winner and Loser Portfolios, Selected Months, 1980-2000**

This table shows average month-end market values and returns for "winner" and "loser" stocks, for three subsamples: "all", "news", and "no-news". Only year-end values are shown. "Winners" have formation-month returns in the top third of all stocks in the subsample, and "losers" in the bottom third. "All" sets rank on all sample stocks, news stocks are selected from among those with 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, while "all" breakpoints use the entire sample. The time series averages are for the entire set of months (not shown).

Year	Average Market Value, Millions						Average Monthly Returns					
	Losers			Winners			Losers			Winners		
	All	News	No-News	All	News	No-News	All	News	No-News	All	News	No-News
1980	162	336	71	301	359	249	-0.15	-0.13	-0.14	0.09	0.10	0.08
1981	161	277	72	242	409	103	-0.14	-0.13	-0.13	0.10	0.10	0.10
1982	99	144	75	356	715	68	-0.13	-0.12	-0.13	0.18	0.17	0.22
1983	120	185	79	433	891	97	-0.15	-0.14	-0.15	0.10	0.10	0.12
1984	73	177	38	241	322	129	-0.13	-0.11	-0.12	0.14	0.14	0.16
1985	127	243	56	466	880	99	-0.12	-0.09	-0.09	0.19	0.22	0.21
1986	119	221	67	345	487	205	-0.17	-0.16	-0.17	0.11	0.12	0.10
1987	116	267	109	332	518	165	-0.17	-0.12	-0.12	0.22	0.24	0.27
1988	164	352	70	235	380	119	-0.11	-0.11	-0.11	0.17	0.17	0.20
1989	127	218	66	608	984	219	-0.15	-0.15	-0.14	0.13	0.14	0.15
1990	66	128	27	428	532	189	-0.20	-0.20	-0.18	0.17	0.18	0.17
1991	202	353	38	892	1286	339	-0.14	-0.11	-0.11	0.25	0.29	0.25
1992	481	779	178	320	460	145	-0.12	-0.11	-0.11	0.22	0.23	0.22
1993	252	482	113	614	769	257	-0.13	-0.13	-0.12	0.15	0.16	0.17
1994	193	316	60	581	664	218	-0.16	-0.16	-0.15	0.13	0.14	0.13
1995	358	531	109	872	1242	238	-0.14	-0.14	-0.15	0.17	0.18	0.16
1996	855	1238	131	533	686	221	-0.15	-0.16	-0.15	0.14	0.16	0.13
1997	247	322	76	1923	2521	590	-0.22	-0.22	-0.22	0.14	0.15	0.13
1998	427	1056	90	2116	2681	695	-0.17	-0.17	-0.16	0.24	0.26	0.24
1999	1557	2163	272	2298	2649	1024	-0.14	-0.14	-0.12	0.41	0.48	0.37
2000	1393	1993	121	2067	2288	1161	-0.26	-0.27	-0.25	0.23	0.24	0.21
Time Series Average	387	548	137	666	825	245	-0.14	-0.13	-0.13	0.18	0.18	0.18

**Table 3: News Details for Sample Stock JEC, 1983-1986**

This table shows details of headlines for a stock in various months (Jacobs Engineering from 1983-1986). All news set stocks are sorted by returns each month. Winners (in the top third of by return) and losers (in the bottom third) are held with positive and negative weight in the strategy, respectively. Neutral months are those in which the stock had news, but did not fall into either the winner or loser category. Jacobs Engineering is only displayed if it had a headline in a month from the news sources. Portfolio status is shown in the first column, followed by dates, returns, and news summaries.

Portfolio	Year	Month	Return (%)	News summary
loser	1983	January	-4.90	Buys 7.8% of Raymond International; in \$12 million dispute; sells headquarters
loser	1983	February	-5.16	Lower yr. on yr. net; boosts stake in Raymond International
neutral	1983	April	8.24	Raymond International buys back all its shares from firm.
neutral	1983	May	7.61	Loss, Raymond International approves anti-takeover measures vs. firm
neutral	1983	July	-1.08	Larger loss vs. year ago
neutral	1983	August	-5.44	Gets contract from Shell Oil
loser	1983	November	-6.25	Loss, but less than year ago
loser	1984	February	-16.67	Loss; omits dividend
winner	1984	March	20.00	President resigns
loser	1984	April	-8.97	Loss, but less than year ago
loser	1984	June	-3.18	New executive vice president appointed
neutral	1984	July	-8.20	Third quarter loss
neutral	1984	September	-1.85	Buys equipment for chemical plant from Ingersoll-Rand
loser	1984	December	-22.41	Larger loss vs. year ago
winner	1985	January	31.11	First quarter net gain
neutral	1985	April	0.00	Second Quarter gain vs. loss in previous year
loser	1985	July	-3.70	Third Quarter net profit vs. loss in previous year
loser	1985	November	-2.08	Fourth Quarter net profit vs. loss in previous year
winner	1985	December	36.17	Chairman proposes management buyout
loser	1986	January	-6.25	Higher net profit vs. previous year
loser	1986	February	-6.67	Chairman withdraws buyout proposal
winner	1986	April	20.00	Wilshire Oil holds 6.5% stake in firm
winner	1986	May	15.15	Wilshire Oil buys more of firm
neutral	1986	July	-12.00	Lower yr. on yr. net
loser	1986	August	-3.03	Agrees to buy Payne & Keller
winner	1986	October	16.67	Gets EPA contract
winner	1986	November	8.57	Loss; Wilshire Oil raises stake to 10.3%

**Table 4: Cumulative Long-Short Returns (%), 1980-2000, at Different Horizons.**

This table shows the summed raw returns for rolling portfolios over several holding periods. Each month, all stocks within a subsample are ranked by their performance. Stocks in the top and bottom thirds are held in the same portfolio with positive and negative weights, 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. Overlapping portfolio returns are summed to get cumulative returns. Panel A shows the average cumulative returns and t-statistics to immediately investing after portfolio formation, and Panel B shows the results to waiting a week after formation before investing. All months are weighted equally in the time-series average. Only returns from January 1980 to December 2000 are used in performance calculations.

Months after Portfolio Formation	All Stocks		News Stocks		No-News Stocks	
	Average	t-statistic	Average	t-statistic	Average	t-statistic
<b>Panel A: Immediate Investment After portfolio Formation</b>						
1	-0.98 %	-4.18	-0.33 %	-1.34	-1.83 %	-6.92
3	-0.37	-0.74	0.86	1.67	-1.98	-3.74
6	0.45	0.59	2.11	2.80	-1.82	-2.26
9	1.74	1.68	3.78	3.63	-0.96	-0.91
12	2.48	2.18	4.65	4.15	-0.53	-0.45
24	0.88	0.43	3.49	1.78	-2.74	-1.36
36	-1.15	-0.38	0.90	0.31	-3.94	-1.43
<b>Panel B: Waiting 1 Week After Portfolio Formation Before Investment</b>						
1	-0.15 %	-0.73	0.35 %	1.71	-0.80 %	-3.71
3	0.44	1.00	1.49	3.32	-0.80	-1.67
6	1.21	1.72	2.76	3.92	-0.74	-0.95
9	2.44	2.50	4.36	4.38	0.18	0.18
12	3.18	2.99	5.39	4.96	0.58	0.51
24	2.06	1.07	4.72	2.41	-1.07	-0.54
36	0.05	0.02	2.31	0.76	-2.57	-0.90

**Table 5: Cumulative Size & B/M Adjusted Returns (%), 1980-2000, Skipping 1st Week**

This table shows the summed size and B/M adjusted returns for rolling portfolios at various horizons. Portfolios are formed for two subsamples of stocks: 1) a "news" set consisting of all stocks that had at least one news headline during the month, and 2) a "no-news" set of all stocks without a headline for the month. Each month, 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 weights, respectively. One week is skipped between portfolio formation and investment. The resulting long-short portfolios are then aggregated into larger portfolios with overlapping positions, to accurately calculate standard errors. Panel A shows the average cumulative returns and t-statistics to the long-short strategy for both sets, Panel B shows the results for winners (top third), and Panel C shows the results for losers (bottom third). All months are weighted equally in the time-series average. Only returns from January 1980 to December 2000 are used in performance calculations.

Months After Portfolio Formation	News Stocks		No-News Stocks		Difference	
	Average	t-statistic	Average	t-statistic	Average	t-statistic
<b>Panel A: Long-Short Strategy</b>						
1	0.03 %	0.20	-1.14 %	-5.75	1.18 %	7.01
3	0.91	2.44	-1.60	-3.78	2.51	7.37
6	1.70	2.94	-1.58	-2.34	3.28	6.01
9	3.12	3.99	-1.09	-1.23	4.21	6.10
12	3.93	4.43	-0.70	-0.69	4.62	5.62
24	3.42	2.38	-2.33	-1.44	5.75	4.59
36	0.97	0.48	-3.63	-1.70	4.60	3.03
<b>Panel B: Winner Portfolio</b>						
formation date	16.60 %	57.83	16.67 %	63.70	-0.07 %	-0.36
1	0.00	0.00	-0.24	-1.98	0.24	2.00
3	0.32	1.26	-0.12	-0.39	0.43	1.66
6	0.42	0.94	0.44	0.92	-0.01	-0.03
9	0.99	1.59	1.42	2.24	-0.43	-0.63
12	1.32	1.69	2.23	2.90	-0.91	-1.01
24	1.84	1.44	4.24	3.25	-2.40	-1.57
36	2.28	1.26	6.35	3.35	-4.07	-1.77
<b>Panel C: Loser Portfolio</b>						
formation date	-13.89 %	-83.37	-13.90 %	-86.73	0.01 %	0.14
1	-0.03	-0.28	0.91	7.17	-0.94	-6.83
3	-0.60	-2.09	1.48	5.01	-2.08	-6.23
6	-1.28	-2.45	2.02	3.68	-3.29	-5.45
9	-2.13	-2.77	2.52	3.22	-4.64	-5.59
12	-2.60	-2.65	2.93	2.94	-5.53	-5.25
24	-1.58	-0.80	6.57	3.50	-8.15	-4.07
36	1.31	0.43	9.98	3.79	-8.67	-3.04

**Table 6: Cumulative Long-Short Size and B/M Adjusted Returns (%), Skipping 1st Week, for Various Adjusted Sets 1980-2000**

This table shows cumulative size and B/M adjusted returns for rolling portfolios of various groups of stocks. Portfolios are formed for two subsamples within a group: 1) a "news" set of all stocks with at least one headline during a month, and 2) a "no-news" set of all stocks without a headline. 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. One week is skipped between portfolio formation and investment. The resulting long-short portfolios are then aggregated into larger portfolios with overlapping positions. Panel A shows buy-and-hold average abnormal returns and t-statistics. Panel B ranks on event-month abnormal returns. Panel C weights stocks by days of news. Panel D excludes stocks with prices less than \$5. Months are weighted equally in the time-series averages. Only returns from January 1980 to December 2000 are used in calculations. All results except those in Panel A are summed rolling portfolio returns.

Months after Formation	News Set		No-News Set		Difference	
	Avg.	t-statistic	Avg.	t-statistic	Avg.	t-statistic
1	0.03 %	0.20	-1.14 %	-5.75	1.18 %	7.01
3	1.15	3.37	-1.43	-3.71	2.58	7.52
6	2.10	5.78	-1.27	-2.17	3.37	6.67
9	4.22	8.25	-0.48	-0.64	4.71	6.72
12	5.35	8.24	-0.24	-0.22	5.59	5.37
24	5.03	2.89	-0.83	-0.41	5.86	4.42
36	4.08	1.85	-0.67	-0.22	4.75	2.50

  

Months after Formation	News Set		No-News Set		Difference	
	Avg.	t-statistic	Avg.	t-statistic	Avg.	t-statistic
1	0.01 %	0.00	-1.15 %	-5.45	1.16 %	6.88
3	0.90	2.38	-1.74	-3.92	2.65	7.90
6	1.59	2.72	-1.73	-2.50	3.31	6.20
9	2.91	3.66	-1.19	-1.32	4.09	5.95
12	3.76	4.22	-0.82	-0.84	4.58	5.69
24	3.20	2.27	-2.41	-1.56	5.61	4.66
36	0.94	0.49	-3.62	-1.80	4.56	3.07

  

Panel B: Using Event Month Size and B/M Adjusted Returns						
Months after Formation	News Set		No-News Set		Difference	
	Avg.	t-statistic	Avg.	t-statistic	Avg.	t-statistic
1	0.17 %	0.93	-1.14 %	-5.75	1.31 %	7.32
3	0.93	2.37	-1.60	-3.78	2.53	6.88
6	1.86	3.18	-1.58	-2.34	3.44	5.99
9	3.43	4.38	-1.09	-1.23	4.52	6.19
12	4.23	4.78	-0.70	-0.69	4.92	5.74
24	4.55	3.48	-2.33	-1.44	6.87	5.26
36	2.70	1.60	-3.63	-1.70	6.33	3.86

  

Panel C: Weighted by Days of Headlines						
Months after Formation	News Set		No-News Set		Difference	
	Avg.	t-statistic	Avg.	t-statistic	Avg.	t-statistic
1	0.01 %	0.00	-0.27 %	-1.54	0.28 %	1.78
3	0.87	2.57	0.06	0.16	0.81	2.70
6	1.83	3.68	0.83	1.58	1.00	2.42
9	3.40	5.25	1.99	3.09	1.41	2.78
12	4.36	5.54	2.50	3.18	1.86	2.95
24	4.79	4.53	3.37	3.12	1.42	1.45
36	3.64	2.95	3.29	2.61	0.35	0.28

  

Panel D: >\$5 Stocks						
Months after Formation	News Set		No-News Set		Difference	
	Avg.	t-statistic	Avg.	t-statistic	Avg.	t-statistic
1	0.01 %	0.00	-0.27 %	-1.54	0.28 %	1.78
3	0.87	2.57	0.06	0.16	0.81	2.70
6	1.83	3.68	0.83	1.58	1.00	2.42
9	3.40	5.25	1.99	3.09	1.41	2.78
12	4.36	5.54	2.50	3.18	1.86	2.95
24	4.79	4.53	3.37	3.12	1.42	1.45
36	3.64	2.95	3.29	2.61	0.35	0.28

**Table 7: Cumulative Size & B/M Adjusted Returns (%), 1980-2000, Skipping 1st Week Using a More Restrictive Definition of News**

This table shows the summed size and B/M adjusted returns for rolling portfolios at various horizons. Portfolios are formed for two subsamples of stocks each month: 1) a "news" set consisting of all stocks that had at least one headline with high share turnover in the three days around the headline, and 2) a "no-news" set of all other stocks. Each month, 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 weights, respectively. One week is skipped between portfolio formation and investment. The resulting long-short portfolios are then aggregated into larger portfolios with overlapping positions. Panel A shows the average cumulative returns and t-statistics to the long-short strategy for both sets, Panel B shows the results for winners (top third), and Panel C shows the results for losers (bottom third). Months are equal-weighted in the time-series average. Only returns from January 1980 to December 2000 are used in performance calculations.

Months After Portfolio Formation	News Stocks		No-News Stocks		Difference	
	Average	t-statistic	Average	t-statistic	Average	t-statistic
<b>Panel A: Long-Short Strategy</b>						
1	0.21 %	1.09	-0.93 %	-5.08	1.14 %	6.88
3	1.18	2.73	-1.26	-3.28	2.44	6.85
6	2.05	3.12	-0.91	-1.53	2.96	5.28
9	3.63	4.19	-0.19	-0.23	3.81	5.25
12	3.93	3.93	0.61	0.70	3.32	3.78
24	4.18	3.00	-0.47	-0.34	4.65	3.62
36	2.28	1.31	-1.95	-1.04	4.23	2.61
<b>Panel B: Winner Portfolio</b>						
formation date	19.84 %	53.33	17.50 %	62.51	2.34 %	9.57
1	0.12	1.00	-0.37	-3.23	0.50	4.07
3	0.54	1.70	-0.42	-1.63	0.95	3.58
6	0.53	0.94	0.25	0.57	0.28	0.59
9	1.18	1.52	0.96	1.64	0.22	0.32
12	1.25	1.29	1.82	2.59	-0.56	-0.66
24	2.23	1.40	3.64	3.04	-1.41	-0.95
36	3.11	1.44	5.46	3.28	-2.35	-1.13
<b>Panel C: Loser Portfolio</b>						
formation date	-13.83 %	-68.15	-12.99 %	-78.33	-0.85 %	-7.49
1	-0.09	-0.66	0.56	5.24	-0.64	-5.27
3	-0.64	-2.08	0.85	3.26	-1.48	-4.98
6	-1.52	-2.85	1.16	2.49	-2.68	-5.39
9	-2.45	-3.13	1.15	1.70	-3.60	-5.24
12	-2.68	-2.73	1.21	1.44	-3.89	-4.68
24	-1.95	-1.02	4.11	2.55	-6.07	-4.11
36	0.82	0.29	7.41	3.14	-6.58	-3.17

**Table 8: Size-Split Cumulative Size & B/M Adjusted Returns (%),1980-2000, Skipping 1st Week, Using a More Restrictive Definition of News**

This table shows the summed size and B/M adjusted returns for rolling portfolios at various horizons, for five size quintiles. Portfolios are formed for two subsamples of stocks: 1) a "news" set consisting of all stocks that had at least one headline with high share turnover during the month, and 2) a "no-news" set of all other stocks. Stocks in the top and bottom thirds (by news return breakpoints) are held in an equal-weighted portfolio with positive and negative weights, respectively. One week is skipped between portfolio formation and investment. The resulting long-short portfolios are then aggregated into larger portfolios with overlapping positions, to accurately calculate standard errors. News and no-news long-short portfolio returns are displayed for all five size quintiles, arranged in descending order from largest stocks to smallest. All months are weighted equally in the time-series average. Only returns from January 1980 to December 2000 are used in performance calculations. Time-series average counts of stocks in the modified news and no-news groups are shown in the first columns of each set.

Size Quintile	Months After Formation	News Stocks			No-News Stocks			Difference	
		Count	Average	t-statistic	Count	Average	t-statistic	Average	t-statistic
5 (Large)	1	38	0.02 %	0.06	20	-0.44 %	-0.87	0.69 %	1.25
	3		0.21	0.29		-0.51	-0.47	1.04	0.91
	6		-0.46	-0.40		-0.38	-0.24	0.17	0.11
	9		0.16	0.12		0.69	0.31	-0.24	-0.13
	12		0.58	0.39		1.42	0.54	-1.07	-0.47
	24		1.04	0.41		5.51	1.28	-4.40	-0.97
	36		2.03	0.64		4.84	0.76	-3.16	-0.46
4	1	41	0.59	1.70	31	-0.46	-0.95	0.95	1.83
	3		-0.05	-0.08		-0.44	-0.59	0.28	0.32
	6		0.90	0.87		0.67	0.62	-0.10	-0.09
	9		3.17	2.44		1.34	0.97	1.51	1.06
	12		2.41	1.59		2.93	1.72	-0.60	-0.34
	24		2.15	0.81		2.01	0.67	0.13	0.04
	36		3.88	1.20		3.10	0.77	0.54	0.13
3	1	49	-0.26	-0.75	49	-0.41	-1.16	0.13	0.31
	3		1.01	1.42		0.22	0.37	0.76	0.86
	6		2.18	1.91		1.28	1.46	0.89	0.64
	9		3.61	2.56		2.32	2.08	1.38	0.80
	12		4.05	2.42		4.04	2.83	-0.06	-0.03
	24		3.95	1.74		2.86	1.32	1.04	0.38
	36		3.06	1.10		5.19	1.88	-2.12	-0.59
2	1	74	0.05	0.18	90	-0.55	-2.16	0.59	1.69
	3		1.57	2.56		-0.01	-0.03	1.54	2.36
	6		3.67	4.00		1.11	1.48	2.51	2.91
	9		5.26	4.10		2.61	2.55	2.73	2.32
	12		7.63	5.20		3.71	3.32	3.82	2.92
	24		8.39	3.88		5.17	3.13	3.28	1.70
	36		5.93	2.19		4.18	1.86	1.82	0.67
1 (Small)	1	244	0.21	0.76	501	-1.06	-5.20	1.26	4.82
	3		1.31	2.45		-1.64	-3.90	2.94	6.13
	6		1.98	2.41		-1.40	-2.10	3.38	4.34
	9		3.47	3.34		-0.78	-0.86	4.35	4.36
	12		4.01	3.28		-0.01	-0.01	3.96	3.16
	24		4.11	2.32		-1.62	-0.99	5.66	3.21
	36		1.87	0.81		-3.50	-1.57	4.75	2.23

**Table 9: Cumulative Size and B/M Adjusted Returns (%), for Subperiods 1980-1990 and 1991-2000**

This table shows the summed abnormal returns for rolling portfolios at various horizons. Results for 1980-1990 and 1991-2000 are on the left and right, respectively. Portfolios are formed for two subsamples of stocks: 1) a "news" set consisting of stocks with at least one news headline during the month, and 2) a "no-news" set of stocks without a headline. All stocks within the subsample are ranked by returns each month. Stocks in the top and bottom thirds ("winners" and "losers") are held in an equal-weighted portfolio with positive and negative weight, respectively. One week is skipped between portfolio formation and investment. The resulting long-short portfolios are then aggregated into larger portfolios with overlapping positions. Panel A shows the average cumulative returns and t-statistics to the winner-loser strategy, Panel B shows winner results, and Panel C shows losers results. All months are weighted equally in the time-series average. Only returns from January 1980 to December 2000 are used in calculations.

Months after Formation	1980-1990				1991-2000							
	News Set		No-News Set		News Set		No-News Set					
	Avg.	t-statistic	Avg.	t-statistic	Avg.	t-statistic	Avg.	t-statistic				
1	-0.18 %	-0.99	-1.57 %	-7.09	1.39 %	6.13	0.24 %	0.82	-0.71 %	-2.12	0.95 %	3.77
3	0.93	2.25	-2.03	-4.62	2.96	6.34	0.89	1.37	-1.13	-1.49	2.02	3.97
6	1.93	3.00	-1.93	-2.55	3.86	5.18	1.89	1.93	-0.70	-0.61	2.60	3.33
9	3.61	4.36	-1.19	-2.55	3.86	5.18	2.85	2.06	-0.09	-0.61	2.60	3.33
12	4.51	4.30	-0.58	-0.44	5.09	4.59	3.33	2.22	-0.02	-0.01	3.35	2.69
24	5.84	3.36	-0.83	-0.36	6.67	3.58	2.71	1.13	-2.52	-0.99	5.23	2.90
36	5.26	2.22	-0.56	-0.18	5.81	2.45	-0.10	-0.03	-3.52	-0.98	3.42	1.47

  

Panel A: Long-Short Cumulative Size and B/M Adjusted Returns												
Months after Formation	News Set		No-News Set		Difference		News Set		No-News Set		Difference	
	Avg.	t-statistic	Avg.	t-statistic	Avg.	t-statistic	Avg.	t-statistic	Avg.	t-statistic	Avg.	t-statistic
	1	-0.17 %	-1.41	-0.63 %	-4.58	0.46 %	2.84	0.16 %	1.01	0.17 %	0.84	-0.01 %
3	0.03	0.09	-0.68	-2.40	0.71	2.26	0.51	1.18	0.51	0.94	0.01	0.01
6	-0.23	-0.47	-0.12	-0.23	-0.12	-0.21	1.23	1.62	1.24	1.49	-0.02	-0.02
9	0.02	0.03	0.68	1.03	-0.65	-0.88	1.74	1.63	2.37	2.09	-0.63	-0.53
12	-0.12	-0.14	1.25	1.51	-1.36	-1.42	2.08	1.60	2.98	2.22	-0.90	-0.57
24	-0.75	-0.49	2.92	1.86	-3.68	-2.13	3.90	1.90	4.48	2.06	-0.57	-0.22
36	-0.93	-0.40	4.76	2.11	-5.70	-2.13	5.45	1.85	5.80	1.71	-0.35	-0.08

  

Panel B: Winner Cumulative Size and B/M Adjusted Returns												
Months after Formation	News Set		No-News Set		Difference		News Set		No-News Set		Difference	
	Avg.	t-statistic	Avg.	t-statistic	Avg.	t-statistic	Avg.	t-statistic	Avg.	t-statistic	Avg.	t-statistic
	1	0.01 %	0.08	0.94 %	6.16	-0.93 %	-5.15	-0.08 %	-0.38	0.88 %	4.26	-0.96 %
3	-0.91	-2.61	1.34	3.60	-2.25	-5.32	-0.38	-0.82	1.63	3.43	-2.01	-3.80
6	-2.16	-3.46	1.81	2.64	-3.98	-5.59	-0.66	-0.81	1.95	2.25	-2.61	-2.79
9	-3.59	-3.92	1.87	1.82	-5.46	-5.24	-1.11	-0.90	2.46	2.08	-3.57	-2.93
12	-4.62	-3.77	1.83	1.36	-6.45	-4.81	-1.25	-0.82	2.99	2.01	-4.25	-2.73
24	-6.60	-2.71	3.75	1.46	-10.35	-4.02	1.19	0.38	7.00	2.39	-5.80	-1.90
36	-6.19	-1.66	5.32	1.52	-11.51	-3.15	5.55	1.07	9.32	2.31	-3.77	-0.79

  

Panel C: Losers Cumulative Size and B/M Adjusted Returns												
Months after Formation	News Set		No-News Set		Difference		News Set		No-News Set		Difference	
	Avg.	t-statistic	Avg.	t-statistic	Avg.	t-statistic	Avg.	t-statistic	Avg.	t-statistic	Avg.	t-statistic
	1	0.01 %	0.08	0.94 %	6.16	-0.93 %	-5.15	-0.08 %	-0.38	0.88 %	4.26	-0.96 %
3	-0.91	-2.61	1.34	3.60	-2.25	-5.32	-0.38	-0.82	1.63	3.43	-2.01	-3.80
6	-2.16	-3.46	1.81	2.64	-3.98	-5.59	-0.66	-0.81	1.95	2.25	-2.61	-2.79
9	-3.59	-3.92	1.87	1.82	-5.46	-5.24	-1.11	-0.90	2.46	2.08	-3.57	-2.93
12	-4.62	-3.77	1.83	1.36	-6.45	-4.81	-1.25	-0.82	2.99	2.01	-4.25	-2.73
24	-6.60	-2.71	3.75	1.46	-10.35	-4.02	1.19	0.38	7.00	2.39	-5.80	-1.90
36	-6.19	-1.66	5.32	1.52	-11.51	-3.15	5.55	1.07	9.32	2.31	-3.77	-0.79

**Table 10: Returns over 1, 3, 6 and 12 Months Regressed on News, Past Returns, Turnover, and Other Variables**

This table shows the average coefficients over months from a cross-sectional regression of returns over 1, 3, 6, and 12 month horizons (skipping the first week) on various past firm characteristics. Time-series t-statistics are in italics, below each average coefficient. Newey-West standard errors are used in calculations for all 3, 6, and 12 month return regressions. Market Value is measured at the end of the past month "B/M" refers to the book-to-market ratio for each firm-month observation, calculated using past data as in Fama and French (1992). "Turnover" refers to shares traded during the past month divided by shares outstanding. "I\_news" refers to an indicator variable for whether or not the firm-month had any headlines. "Ret\_0" refers to the past month's return. All NASDAQ stocks are excluded.

Dependent Variable is Returns Over:	intercept	ln(market value)	ln(B/M)	Ret_0 (formation month return)	turnover	turnover* Ret_0	I_news	I_news* Ret_0	average R-square
<b>News Effects</b>									
1 month	0.008 <i>1.77</i>	0.000 <i>0.54</i>	0.002 <i>2.65</i>	-0.033 <i>-3.04</i>			-0.002 <i>-1.61</i>	0.025 <i>2.07</i>	4.4%
3 month	0.024 <i>1.88</i>	0.002 <i>0.91</i>	0.010 <i>3.90</i>	-0.023 <i>-1.22</i>			-0.007 <i>-3.35</i>	0.041 <i>1.86</i>	5.7%
6 month	0.074 <i>2.23</i>	0.001 <i>0.37</i>	0.019 <i>3.26</i>	-0.003 <i>-0.09</i>			-0.013 <i>-2.64</i>	0.067 <i>2.19</i>	5.8%
12 month	0.179 <i>2.59</i>	-0.001 <i>-0.08</i>	0.039 <i>2.79</i>	0.019 <i>0.35</i>			-0.031 <i>-4.77</i>	0.147 <i>2.71</i>	5.5%
<b>News and Turnover Effects</b>									
1 month	0.009 <i>2.07</i>	0.000 <i>0.48</i>	0.002 <i>2.67</i>	-0.031 <i>-2.57</i>	-0.026 <i>-1.68</i>	0.099 <i>1.44</i>	-0.001 <i>-1.07</i>	0.019 <i>1.54</i>	5.8%
3 month	0.032 <i>2.10</i>	0.002 <i>1.00</i>	0.009 <i>3.80</i>	-0.020 <i>-1.01</i>	-0.115 <i>-3.02</i>	0.202 <i>1.58</i>	-0.005 <i>-2.46</i>	0.033 <i>1.58</i>	7.1%
6 month	0.078 <i>2.41</i>	0.002 <i>0.45</i>	0.018 <i>3.16</i>	-0.003 <i>-0.08</i>	-0.194 <i>-2.58</i>	0.280 <i>1.45</i>	-0.010 <i>-1.99</i>	0.068 <i>2.19</i>	7.2%
12 month	0.189 <i>2.76</i>	0.000 <i>0.05</i>	0.037 <i>2.75</i>	0.031 <i>0.49</i>	-0.439 <i>-2.89</i>	0.296 <i>0.82</i>	-0.025 <i>-4.07</i>	0.144 <i>2.77</i>	7.0%

**Table 11: Month-by-month 3-Factor Exposures for News/No-News Winner and Loser Portfolios, 1980-2000, at Various Horizons after Formation**

Portfolios are formed for two subsamples of stocks: 1) a "news" set consisting of all stocks with at least one news headline during the month, and 2) a "no-news" set of all stocks without a headline for the month. In each month from January 1980 to December 2000, all stocks within the subsample are ranked by returns. Stocks in the top and bottom thirds are called "winners" and "losers", respectively. This table shows month-by-month alphas, coefficients, t-statistics, and R-square values from a monthly time series regression of winner and loser portfolio excess returns on contemporaneous Fama-French 3 factor returns. The model is:

$$R_i - r_f = a_i + b_1(R_m - r_f) + b_2SMB + b_3HML + e_i$$

where the right hand side variable is monthly excess returns for a portfolio formed 1, 3, ..., 36 months ago and the left hand side variables are Fama-French market, size and B/M factor-mimicking portfolio returns. Winners and losers are in the upper and lower sections, respectively. T-statistics are based on heteroskedasticity robust standard errors.

Months after Formation	Monthly Alpha (%)	t-stat	Market-Rf		SMB		HML		Monthly Alpha (%)	t-stat	Market-Rf		SMB		HML		
			Coef.	t-stat	Coef.	t-stat	Coef.	t-stat			Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	
<b>Winners</b>																	
<b>News</b>																	
0	17.01	58.7	1.23	12.4	1.30	6.2	0.07	0.4	0.72	16.71	56.6	1.32	13.5	1.12	6.2	0.20	1.2
1	-0.46	-3.4	0.97	30.2	0.92	11.6	0.13	2.0	0.88	-0.75	-3.8	0.86	16.9	0.98	10.1	0.22	2.5
3	0.04	0.3	1.05	28.1	0.96	11.2	0.11	1.6	0.89	0.14	0.8	0.87	18.9	1.09	10.2	0.23	2.4
6	0.13	1.1	1.03	25.5	0.88	12.2	0.11	1.5	0.89	0.07	0.4	0.95	16.9	0.95	9.6	0.30	2.8
9	0.05	0.4	1.04	32.4	0.83	11.2	0.10	1.2	0.88	0.16	0.8	1.00	20.0	0.90	10.0	0.30	2.7
12	0.04	0.3	1.10	19.9	0.80	6.9	0.14	1.4	0.83	0.12	0.6	0.99	16.8	0.79	6.5	0.28	2.3
24	0.09	0.5	1.07	24.7	0.78	7.4	0.31	2.9	0.82	0.05	0.3	0.92	18.8	0.85	8.6	0.35	3.4
36	0.15	0.9	1.06	21.2	0.74	8.1	0.40	5.6	0.84	0.00	0.0	0.94	17.3	0.73	5.7	0.40	3.4
<b>No-News</b>																	
<b>Losers</b>																	
<b>News</b>																	
0	-14.73	-65.5	0.94	16.5	0.73	5.0	0.16	1.1	0.68	-14.51	-75.3	0.95	18.9	0.70	0.6	0.17	1.5
1	-0.27	-1.3	1.15	17.2	0.87	5.6	0.11	0.9	0.78	0.93	3.8	1.03	15.7	0.90	5.9	0.27	1.7
3	-0.75	-3.9	1.07	18.0	0.87	5.9	0.16	1.3	0.77	0.02	0.1	0.97	14.3	0.99	7.1	0.36	2.5
6	-0.71	-3.9	1.07	18.5	0.91	7.7	0.20	1.7	0.78	-0.15	-0.6	0.99	15.4	0.89	6.8	0.30	2.2
9	-0.64	-3.3	1.04	15.4	0.97	7.2	0.29	2.3	0.76	-0.22	-1.0	0.92	14.2	0.91	6.8	0.29	2.3
12	-0.55	-3.4	1.01	23.1	0.93	9.8	0.24	2.7	0.81	-0.33	-1.7	0.87	18.5	0.93	10.1	0.24	2.4
24	-0.24	-1.3	1.03	21.2	0.94	9.7	0.21	2.0	0.81	-0.28	-1.5	0.92	17.4	0.96	8.3	0.30	2.4
36	-0.11	-0.6	1.06	21.0	0.98	8.3	0.21	1.6	0.81	0.01	0.1	0.84	13.4	1.07	9.2	0.22	1.6

**Table 12: Non-Earnings-Announcement-Related News Stock Returns  
Decomposed by EA and non-EA Months, 1980-2000, 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. I exclude all stocks that had an earnings announcement in the formation month. The returns to this strategy are shown in the first set of columns. The cumulative payoffs to the non-earnings-announcement-related news strategy are divided into returns that 1) would accrue had only those strategy stocks with earnings announcements in a subsequent month been held, and 2) returns from holding only those strategy stocks which had no earnings announcement in a given month. For the long-short strategy, stocks in the top and bottom thirds are held in an equal-weighted portfolio with positive and negative weights, respectively. The resulting portfolios consist of overlapping positions. Panel A shows the average cumulative 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 Formation	Non-EA-Related News Stocks		Decomposition of Subsequent Returns: in EA Months			
	Avg.	t-stat	Avg.	t-stat	Avg.	t-stat
<b>Panel A: Long-Short Strategy</b>						
1	-0.07 %	-0.37	0.01 %	0.05	-0.08 %	-0.52
3	0.51	1.18	0.13	0.83	0.38	1.11
6	1.22	1.76	-0.01	-0.03	1.23	2.24
9	2.67	2.94	0.12	0.37	2.55	3.43
12	3.13	2.96	-0.03	-0.08	3.17	3.77
24	2.88	1.85	-0.54	-0.86	3.42	2.76
36	0.84	0.39	-1.55	-1.73	2.39	1.41
<b>Panel B: Winner Portfolio</b>						
1	-0.15 %	-1.30	0.07 %	1.28	-0.23 %	-2.48
3	-0.17	-0.55	0.18	1.51	-0.35	-1.49
6	-0.34	-0.63	0.36	1.77	-0.69	-1.66
9	-0.11	-0.15	0.52	1.82	-0.63	-1.09
12	-0.16	-0.16	0.70	1.92	-0.85	-1.18
24	-0.34	-0.23	1.61	2.54	-1.95	-1.64
36	-0.33	-0.16	2.40	2.55	-2.73	-1.60
<b>Panel C: Loser Portfolio</b>						
1	-0.08 %	-0.52	0.07 %	0.85	-0.15 %	-1.32
3	-0.68	-2.05	0.05	0.37	-0.73	-2.71
6	-1.56	-2.55	0.37	1.47	-1.92	-3.91
9	-2.78	-3.14	0.40	1.16	-3.19	-4.47
12	-3.29	-2.80	0.73	1.38	-4.02	-4.47
24	-3.22	-1.43	2.15	2.33	-5.37	-3.05
36	-1.17	-0.34	3.94	2.83	-5.12	-1.91