All the News That's Fit to Reprint:

Do Investors React to Stale Information?

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Paul C. Tetlock*

Yale University

Abstract

Using news data on S&P 500 firms, I investigate stock market responses to public news stories that may contain stale information. I employ several empirical proxies for news articles with old information, including variables based on past news events, media coverage, analyst coverage, and liquidity. I find that market reactions to stale news stories partially reverse in the next week. By contrast, reactions to stories with more new information reverse to a much smaller extent, or even continue. Return reversals after stale news stories are larger in stocks with a high fraction of small trades. These results and others are consistent with the hypothesis that individual investors overreact to stale information, leading to temporary movements in asset prices.

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“People everywhere confuse what they read in the newspaper with news.” – A.J. Liebling

In an efficient market, firms’ stock prices incorporate all value-relevant signals as soon as they become available, implying that information becomes stale almost instantly. Because financial news releases often occur in groups of closely related stories, investors face a daunting task in sorting out new information from stale information. Based on theory alone, the impact of redundant information on asset prices is unclear. The proliferation of information through multiple media increases the speed and quantity of information dissemination, which could enhance informational efficiency. On the other hand, an increase in information with ambiguous relevance for trading decisions could overload investors’ finite cognitive resources. If they confuse old information already incorporated in market prices with new information, boundedly rational investors could trade on stale information and cause overreaction in prices.

Recent evidence from psychology demonstrates that this latter theory is a plausible account of human behavior. Specifically, a person’s belief in an ambiguous statement increases as he or she encounters the statement more often (Hasher, Goldstein, and Toppino (1977), Bacon (1979), Schwartz (1982), Gigerenzer (1984), Hawkins and Hoch (1992), Arkes, Hackett, and Boehm (1989), Arkes, Boehm, and Xu (1991)). Known as the “truth effect,” this phenomenon occurs regardless of whether the repetition of a statement conveys any new information. Hawkins and Hoch (1992) show that repetition increases one’s familiarity with a claim, which generates a feeling of greater likelihood that the claim is actually true. The truth effect applies to diverse settings, including statements repeated minutes apart or weeks apart, verbal or written statements, and in the context of mostly repeated statements or mostly new statements (Hasher et al. (1977) and Schwartz (1982)). Notably, Hawkins and Hoch (2001) show that the truth effect is especially strong in “cluttered message environments,” which resemble financial markets.

In light of this evidence, I test the hypothesis that investor overreaction to financial news increases with information repetition and redundancy. The central contribution of this paper is to evaluate this hypothesis and explore the mechanism behind such return reversals using an extensive database on public news events. I focus on cross-sectional variation in return reversals because there are many possible explanations for on-average return reversals.

Some recent empirical evidence in Huberman and Regev (2001) may be related to the stale information hypothesis. These authors study the case of a small publicly traded biotechnology firm named EntreMed. In May of 1998, EntreMed’s stock price more than quadrupled after the *New York Times* printed a story about the company’s possible new cure for cancer. Not mentioned in the *Times* article, a very similar story about EntreMed had already appeared five months earlier in *Nature*—a top scientific journal that is not read by most investors—concurrent with a 25% increase in EntreMed’s stock price on the date of the *Nature* story. Curiously, this 25% price increase was dwarfed by a 400% increase that followed the *Times* story. Yet within one month of the *Times* story, more than half of EntreMed’s 400% return had dissipated. At the time of this writing, all of the positive abnormal returns appear to be reversed, but it is difficult to draw inferences based on the ex post performance of a single firm. Indeed, Huberman and Regev’s (2001) compelling EntreMed example warrants a systematic investigation into whether stale information elicits market overreaction.

To measure empirically how markets respond to two or more possibly related news events, I examine public financial news for S&P 500 firms from 1984 to 2004. I characterize a firm’s stock returns on trading days with firm-specific news stories as public news. I assess market responses to these public news events by sorting firms into calendar time portfolios based on their recent public news, and track these portfolios' returns for short time horizons. I find that the portfolios with week-long horizons exhibit partial return reversals of the news-event returns, which is broadly consistent with the evidence in Antweiler and Frank (2006).

I use several empirical proxies to represent the degree to which a news story is stale. Of course, I do not think that the stories identified as stale contain no new information. Although most stories contain both new and old information, some stories contain more old information than others. Because this concept is difficult to capture, I employ many different empirical measures of news stories that are likely to contain a greater proportion of old information. These proxies include the presence of another news story in the prior week, the presence of an extreme abnormal stock return in the prior week, high media coverage in the past month, high analyst coverage in the past month, and high stock liquidity in the past month.[1]

The stale information hypothesis predicts that return reversals after news will be larger when there is more old information about the firm. Consistent with the stale information hypothesis, I find that the return reversals after news events are much stronger when these events contain more old information based on each of the empirical proxies above. By contrast, market reactions to news events with the most new information—as measured by earnings-related news without any news in the prior week—positively predict returns in the next week.[2]

To better understand the mechanism behind the return reversal after old public news, I try to identify the investors who confuse new and old information and, as a result, actively trade on stale information. Barber, Odean, and Zhu (2007) argue that investors trading in small amounts

[1] In unreported analysis, I verify that news stories that are stale based on these proxies elicit smaller initial market reactions than stories that are not stale, supporting the conjecture that stale stories contain less new information.
[2] Pritamani and Singhal (2001) report a similar finding for a sample of 308 earnings news events from 1990 to 1992.

could play the role of noise traders. I measure the presence of these investors as the fraction of dollar volume consisting of trades smaller than $5,000. I show that the impact of staleness on return reversals is much larger in the S&P 500 stocks with a high fraction of small trades.

Finally, I investigate two alternative explanations based on prior evidence of weekly return reversals (Jegadeesh (1990); Lehmann (1990)) and volume-induced return reversals (e.g., Campbell, Grossman, and Wang (1993); Lee and Swaminathan (2000); Llorente, Michaely, Saar, and Wang (2002)). In the set of S&P 500 news events, weekly reversal has some explanatory power, but depends on one measure of stale information. In this sample, there is little evidence for volume-induced return reversal. These results introduce the possibility that overreaction to stale information can help to explain weekly and volume-induced return reversals.

The outline of the paper is as follows. Section I describes the news and financial data used in this study, and documents the short-horizon returns of S&P 500 stocks after public news events. Section II presents the main empirical tests of the stale information hypothesis, showing how the magnitude of the return reversal depends on the features of a stock's information environment. Section III explores the mechanism behind the return reversal and uses alternative measures to scrutinize the stale information hypothesis. Section IV places the results in the context of the related literature. Section V discusses the implications of the stale information hypothesis. The Appendix proposes one possible theoretical framework for stale information.

I. Empirical Data and Methodology

Because this study requires an accurate measure of a firm's information environment, I focus on a set of firms that the financial press follows actively: those in the S&P 500 index. I use the same set of public news stories that is used in Tetlock, Saar-Tsechansky, and Macskassy (2008). These authors construct a database of stories about individual S&P 500 firms that appeared in the *Dow Jones News Service* (*DJNS*) and the *Wall Street Journal* (*WSJ*). Each of the stories in their sample meets certain requirements that they impose to eliminate irrelevant stories and blurbs (see Tetlock et al. (2008) for details). I include a news story in the analysis only if it occurs while the firm is a member of the S&P index. I exclude stories in the first week after a firm has been newly added to the index to prevent the well-known price increase associated with a firm's inclusion in the S&P 500 index from affecting the analysis (e.g., Shleifer (1986)). In total, the data include over 350,000 news stories—over 260,000 from *DJNS* and over 90,000 from *WSJ*—that contain over 100,000,000 words. Over 95% of S&P 500 firms have at least one news story.

The two sources for stories, *DJNS* and *WSJ*, are the two most widely circulated sources of financial news in the United States for institutional and retail investors, respectively, and arguably have the most comprehensive coverage (e.g., Fang and Peress (2007)). Reliable public news data from these two sources are available for a long time period—1984 through 2004. News about S&P 500 firms is also important to study because these firms encompass roughly three-quarters of the total U.S. market capitalization. Of particular relevance for this study, using reliable news data on widely followed firms gives me hope of meaningfully categorizing a firm-specific news event as public. Equally important, nearly all of the public news events coincide with the wide release of information that is stale to at least some degree because journalists are intermediaries between their sources of information and their investing readership.

A. Definitions of Public News and Extreme Return Events

I define a firm-specific public news event (i.e., day 0) as a trading day with at least one news story that meets the above criteria. I convert news publication dates into trading days by matching all news stories occurring after 3:30pm on day -1 and before 3:30pm on day 0 to stock price data on day 0. The 30-minute time lag is designed to allow for some slight delay in the market response to news (e.g., Patell and Wolfson (1984); Chordia, Roll, and Subrahmanyam (2005)).[3] For the main analysis, I merge news stories with stock price data for S&P index constituents from the Center for Research on Security Prices (CRSP), analyst forecast information from the Institutional Brokers' Estimate System (I/B/E/S), and accounting information from Compustat.

Much like Roll (1988), Chan (2003), and Vega (2006), I also examine trading days with extreme abnormal stock returns because these may also represent informative events. For parsimony, I measure a firm's abnormal return as its raw return minus the market return, where the market is the CRSP value-weighted index. Using more sophisticated benchmarks has little impact on the results because the simple market adjustment captures much of firms' systematic volatility, and I adjust for other risk-factors in the calendar time return tests that follow. As cutoffs for large abnormal returns, I use the 5^{th} and 95^{th} percentiles of abnormal returns for S&P 500 firms on each trading day, implying that 10% of firms have extreme return events on each day. I select this percentage so that it is similar to the average percentage of firms with public news events on each day, which is 9.8%. Days with extreme returns overlap but do not perfectly

[3] Using lags between 0 minutes and 60 minutes does not materially change the results in this paper.

coincide with days with newspaper articles: 1.5% of all trading days are both public news and extreme return events.

Figure 1 shows that both public news and extreme return events often occur in close temporal proximity. For each day in which a firm has a public news event, I count the number of trading days that have elapsed since the firm's previous public news event. I repeat this procedure for extreme return events. For both types of events, Figure 1 plots the relative frequency of trading days elapsed since the previous event. Roughly 60% of public news and extreme return events occur within five trading days of the previous event, and roughly 90% occur within 20 trading days. I interpret this as a sign that the themes, topics, and tones of clustered news stories may be related.[4] In this case, the stale information hypothesis has testable implications for the market reactions to these related informational events. Because both distributions in Figure 1 flatten rapidly around five trading days, I use five days as a cutoff time for considering informational events to be potentially related. One week is also a natural time unit for many news sources.[5]

[Insert Figure 1 here.]

Figure 2 depicts the firm-specific return volatility and trading activity that occurs during trading days [-10,10] around public news and extreme return events. The two solid lines represent return volatility, whereas the two dashed lines represent trading activity. The two dark lines display the volatility and trading activity around public news events, and the two lightly colored lines correspond to activity around extreme return events. I measure daily firm-specific

[4] I read a small random sample of news articles to confirm this interpretation.

[5] I find a similar natural cut-off time using more sophisticated tests that account for differences in firms' tendencies to experience informational events. In these tests, for each firm, I analyze how the conditional distribution of the time until the next informational event depends on whether an informational event occurs on day 0.

volatility as the standard deviation of a firm's abnormal return. I measure daily trading activity as a firms' share turnover minus the market turnover for the exchange where the firm is listed.[6]

[Insert Figure 2 here.]

I use the extreme return events as a benchmark for the 10% of events with the highest volatility. The increase in annualized volatility from day -10 to day 0 is 14% for public news events, as compared to 39% for extreme return events. The increase in annualized turnover from day -10 to day 0 is 35% for public news events, as compared to 69% for extreme return events. For both types of informative events, volatility and turnover revert back to their normal levels within about one week of the news. Based on these features of the data, I focus on firms' information environments at the weekly time horizon throughout the paper.

B. Calendar Time Returns after Public News and Extreme Return Events

To see whether the stale information hypothesis could be important, I measure the magnitude of the short-horizon market reactions following news events. I form calendar time portfolios based on sorts of market-adjusted returns on both public news and extreme return event days. In each year, I sort all reactions to public news events (i.e., day-0 returns) into quartiles. I perform the same sort for the day-0 reactions to extreme return events.[7] For all news events of each type in the following year, I use these quartile breakpoints to place firms in portfolios based on their news-event returns on day 0. I form these portfolios on day 2 and hold them until day t, where t = 2, 3, 5, or 10. I skip day 1 because using consecutive returns induces

[6] I divide the volume of Nasdaq firms by a factor of two to adjust for the double-counting of trades. I multiply by 252 to annualize abnormal volume and multiply by $\sqrt{252}$ to annualize abnormal volatility.
[7] I perform the return sorts of public news and extreme return events separately.

bid-ask bounce and because Tetlock et al. (2008) shows that the day-0 market response to firm-specific news stories extends into day 1. I use equal-weighted portfolio returns throughout the analysis because firms in this sample—S&P 500 firms appearing in news stories—are already much larger than the representative publicly traded firm. Value-weighting would weigh the largest firms among this sample of very large firms even more heavily.[8] When $t \geq 2$, this portfolio formation procedure generates a series of $t - 1$ overlapping portfolios. I apply equal weights to each of these portfolios to combine them into an aggregate portfolio as in, for example, Jegadeesh and Titman (1993).

For each type of informative event, this process creates four portfolios ranked by news-event returns. I also define a fifth portfolio that is long on the news events with returns in the bottom quartile and short on the news events with the highest returns. I refer to this as the reversal portfolio because it has positive returns only if news-event returns are subsequently reversed during the portfolio's holding period.

I compute the risk-adjusted returns of each portfolio using a standard time series regression of portfolio returns on several risk factors. I consider six daily risk factors: the market (MKT), size (SMB), and book-to-market (HML) factors proposed in Fama and French (1992 and 1993)), and three factors based on well-known momentum and reversal anomalies. The momentum and reversal factors UMD_ST, UMD_INT, UMD_LT represent long-short portfolios generated by sorts of past returns over the monthly time horizons of [1,1], [2,12], and [13,60], respectively.[9] I measure each news event portfolio's risk-adjusted return as the intercept in the time series regression of the portfolio's raw return on the six risk factors. I compute Newey and

[8] The news-event return reversals are larger with value-weighted returns. This finding is consistent with the stale information hypothesis if firm size is a proxy for the amount of old information available about the firm. I do not emphasize this result because past media coverage is a more direct measure, and is highly correlated with firm size.
[9] I download the daily returns of these factors and the Fama-French factors from Kenneth French's web site.

West (1987) standard errors for the regression coefficients that are robust to heteroskedasticity and serial correlation up to five lags—the *t*-statistics appear in parentheses below the alphas.

For each type of news, Table I presents the daily alphas from the four portfolios based on quartiles of news-event returns and the reversal portfolio. All five portfolios have time horizons of $t = 5$. Panels C and D decompose the set of extreme return events according to whether they appear on the same day as a public news story. The fifth column in Table I displays the daily alphas of the reversal portfolios. The sixth column shows the R^2 statistics for each regression.

[Insert Table I here.]

First, it is noteworthy that 13 of the 16 long-only portfolio alphas in Table I are positive. Because the portfolios in Table I—and the numerous tables yet to come—all contain firms experiencing news events, I infer that returns drift upward slightly in the week after news events. This is consistent with the results in a number of other papers—e.g., Barber and Odean (2007) and Tetlock et al. (2008). To remove the influence of this upward drift, I focus on the difference in portfolio alphas—i.e., the alphas of long-short portfolios—for the rest of the paper.

All of the alphas of the long-short reversal portfolios in column five are positive and nearly all are significant. The most interesting finding is that return reversals are largest when news events receive the least publicity. For example, the fifth column in Panel A shows that stocks with the lowest news-event returns outperform stocks with the highest news-event returns by 5.2 basis points (bps) per day. The fifth column in Panel B shows that the return reversal after extreme return events is much larger at 13.3 bps per day. To test whether these two alphas are different, I form a portfolio long on the extreme return reversal and short on the public reversal. This long-short portfolio's alpha is significantly different from zero at the 1% level.[10]

[10] The return reversal results in Table I are broadly consistent with Table 4 in Antweiler and Frank (2006).

The comparison of the alphas in Panels C and D shows that this difference is not entirely driven by greater return volatility around extreme return events. Within the set of extreme events, greater publicity is associated with much smaller return reversals—3.7 bps versus 16.7 bps per day; this difference is significant at the 1% level. The cumulative alphas, measured over the four-day reversal holding period after the two types of extreme return events, illustrate that the economic difference is also significant: 15 bps versus 67 bps over four days.

I do not view Table I as a test of the stale information hypothesis because there are at least two plausible interpretations: overreaction to uninformative events and uninformative liquidity shocks. Based on the stale information hypothesis, one could argue that extreme return events without publicity are more likely to elicit return reversals because these events contain no new public information. On the other hand, one could also interpret the evidence as showing that an extreme return without publicity is more likely to be a liquidity event than an extreme return with publicity. Particularly for S&P 500 firms that have fairly comprehensive media coverage, extreme return events unaccompanied by public news may be liquidity events. If much of the return reversal after extreme returns is attributable to liquidity shocks, then extreme return events are not ideal for studying whether information elicits overreaction.

To avoid the ambiguous interpretation of extreme return events, I focus on reversals after public news events for the rest of the paper. These public news events are more likely to represent informational events. While I obtain a more reliable measure of the market response to information, I am confined to studying smaller return reversals (21 bps versus 53 bps).

Table II documents how the reversal after public news events varies with the trading strategy's time horizon. The table also reports the estimated risk factor loadings and R^2 statistics from the time series regressions of the long-short public news reversal portfolio on all six risk factors. For ease of comparison across columns, the table converts each daily alpha estimate into a cumulative alpha by multiplying by the number of days in each trading strategy horizon.

[Insert Table II here.]

The table reveals that reversals after public news occur primarily in trading days 2 and 3. The two-day cumulative alpha of 19 bps increases by less than 2 bps if a trader extends her time horizon to day 10. Increasing the time horizon, however, does increase the number of firms in the trader's long-short portfolio, and does reduce the portfolio's volatility. A week-long (days-[2,5]) time horizon nicely balances the two opposing considerations: maximizing the cumulative alpha and having too few firms in the long-short portfolio.

The R^2 statistics in Table I and Table II show that the long-short public news portfolio's volatility is almost entirely idiosyncratic. By design, a long-short portfolio consisting of firms experiencing good and bad firm-specific news events should have little systematic volatility. Consistent with this, the R^2 statistics in all of the risk factor regressions are below 1%. The factor loadings indicate that the reversal portfolio exhibits a slight tilt toward stocks with low betas, high market capitalizations, high short-term momentum, and low intermediate-term momentum. Most of these factor loadings are economically insignificant, however, and do not materially affect the portfolio's risk-adjusted return.

II. Short-Horizon Returns after Public News Events

The predictions of the stale information hypothesis rely on the degree of confusion experienced by investors. The most distinctive implication is that return reversals after public news should be larger when there is more old information for investors to digest. As my primary measures of the amount of extant information, I examine whether public news is preceded by other public news or extreme returns in the recent past. If investors overreact to stale information, reversals should be larger when public news events occur in close proximity to past information. In the second subsection, I explore two indirect measures of old information. In the third subsection, I examine whether new information has the opposite effect of old information.

A. Returns after Stale News Events

As my first proxy for partially redundant public news that may contain stale information, I use the presence of another public news story within the past week—trading days [-5,-1]. Again, I choose this time horizon based on the natural weekly news cycle and the features of the data in Figure 1 and Figure 2. I also separately consider news events without a prior story since days [-15,-6] and since days [-∞,-16], which partitions the rest of the news events into two roughly equal halves. I use fixed ad hoc cutoffs for the time interval between news stories because this measure is designed to capture the degree of information overlap between stories. The nature of informational events and investors' cognitive resources may remain fixed throughout the sample, even as the extent of media coverage and data quality changes.

Table III displays the returns from applying the reversal trading strategy to news events with varying time gaps between news events. The return reversal over days [2,5] is strong in the group of news events with at least one news story in days [-5,-1] (cumulative alpha of 27 bps and *t*-statistic of 4.79 in Panel A) and still exists in news events that occur within 15 days of the previous story (cumulative alpha of 18 bps and *t*-statistic of 2.32 in Panel B). Yet the return reversal is completely gone in the subset of news stories that do not appear soon after other stories (cumulative alpha of -2 bps and statistically insignificant in Panel C). Panel D shows that the 29 bps cumulative difference between the returns on the two portfolios in Panels A and C is significant at the 1% level. This result suggests that the extent of news-event return reversal depends critically on whether a news story contains potentially redundant information.

[Insert Table III here.]

It is difficult to assess the economic importance of these results based on short-horizon evidence. By annualizing the four-day 29 bps difference in reversal, one could infer that the effect is enormous (over 18% per year) or negligible, depending on one's view of trading costs. Because the strategy entails trading contrary to day-0 stock price movements, it is even possible that it could be implemented passively with limit orders, and that realized trading "costs" would actually be negative. The large range of long-run reversal estimates above encompasses the difference between the top and bottom quartile of day-0 reactions to public news events, which is 630 basis points. Although the weekly return reversals are an order of magnitude smaller than the initial market reactions to news events, the longer-term reversal could easily exceed the initial reaction. At longer time horizons, it is harder to disentangle new and old information, and the standard errors on the alphas increase rapidly (e.g., see Table II). In spite of this uncertainty in the long-run economic impact, I can use the short-horizon tests in this paper to confidently assess the statistical importance of stale information, and whether it affects investor behavior. These short horizons have considerable statistical power because I can accurately measure the firm's information environment and reliably estimate return predictability.

Next, I explore a closely related alternative proxy for the redundancy in a public news story: the existence of an extreme return event in days [-5,-1]. I follow the same procedure used to construct Table III, except that I analyze the proximity of a public news story to recent and distant extreme return events rather than other public news events. Table IV shows this analysis.

[Insert Table IV here.]

The most important finding in Table IV is that return reversals after public news are largest when extreme return events immediately precede the public news events. For example, in Panel A the four-day cumulative return reversal for public news occurring within one week of extreme returns is almost 40 bps and is highly statistically significant. The returns of public news events occurring more than 15 days after the previous extreme return event generally do not reverse—i.e., Panel C shows a four-day cumulative alpha of 4 bps and an insignificant *t*-statistic. Panel E confirms that the difference between the reversal portfolios in Panels A and C is economically large and is statistically significant at the 1% level.

As a third proxy for stale public news, I consider the number of public news stories about each stock in the *DJNS* and *WSJ* during the previous calendar month. The underlying idea is that a public news story probably contains more redundant information when there are more prior news stories about the stock. Each month I sort stocks into quartiles according to the number of stories about them in the previous month. I also perform independent sorts on news-event returns using the same methodology as before. In all, this procedure creates 16 portfolios consisting of public news events within four return quartiles for each media coverage quartile. Table V reports the risk-adjusted returns and summary statistics for each of these 16 portfolios. I obtain these results following the same time series regression procedure used earlier.

Consistent with the stale information hypothesis, Panel A in Table V indicates that the return reversal is large and significant within the quartile of news events about stocks with the highest media coverage (cumulative alpha of 28 bps over four days and *t*-statistic of 3.39).

Moreover, Panel D in the table shows that the news-event returns in the lowest quartile of media coverage are not reversed at all—the cumulative alpha is slightly negative and statistically insignificant. Panel E establishes that the difference between the two reversals is 31 bps over four days and is significant at the 1% level. Overall, the evidence in Table I through Table V provides strong preliminary support for the stale information hypothesis.

B. Alternative Measures of Stale News Events

Beyond the three recent news measures in the previous subsection, I propose two alternative measures of extant public information. First, I use a firm's recent analyst coverage as a proxy for the amount of public information about the firm. The empirical prediction is that reversals after public news events should be larger for firms with more analyst coverage. I measure analyst coverage using the number of stock analysts who forecast each firm's quarterly earnings in the previous month. I set the quartile cutoffs for analyst coverage at breakpoints based on coverage before all public news events in the previous month. Then I independently sort (day-0) news-event returns into quartiles using the same sorting methodology as before. This procedure defines 16 (4 x 4) portfolios. I form and hold each of these 16 portfolios using the same trading algorithm discussed earlier for the days-[2,5] time horizon.

Panels A through D in Table VI report the daily alphas for each of the 16 portfolios based on analyst coverage and news-event returns. Each of the 16 alphas represents the intercept from a time series regression of a long-short portfolio return on the six risk factors described in Section II. I label the four quartiles of returns and analyst coverage: highest, above average, below average, and lowest. The reversal portfolio return is equal to the return on the lowest news-event return quartile portfolio minus the return on the highest news-event return quartile portfolio.

[Insert Table VI here.]

Table VI shows that stocks with the highest analyst coverage experience the largest return reversals after public news events (cumulative four-day alpha of 36 bps in Panel A). By contrast, the return reversals for stocks with lower analyst coverage, shown in Panels B through D, are less than half as large (cumulative alphas of 18 bps, 4 bps, and 17 bps). Although the magnitude of the reversal reduction is economically significant, the statistical difference between the reversal portfolio alphas is weaker (e.g., *t*-statistic of 1.81 in column five of Panel E). Nevertheless, these results are consistent with the earlier tests that suggest stale information is related to overreaction to public news events.

As a second alternative measure of the quantity of extant public information, I use Amihud's (2002) notion of stock liquidity. I select this liquidity proxy based on microstructure models of price impact (e.g., Kyle (1985)), and based on Hasbrouck's (2006) finding that Amihud's (2002) liquidity measure is the daily measure most highly correlated with intraday liquidity measures.[11] Higher liquidity may not only reflect an increase in publicly available information (e.g., Glosten and Milgrom (1985)), but also it may encourage the acquisition of information and informed trading (e.g., Kyle (1989)). If there is more extant information about liquid stocks, return reversals after news events will increase with liquidity.

Next, I repeat the same two-way sorting procedure using Amihud's (2002) liquidity measure, instead of analyst coverage and recent news, as a third proxy for the amount of publicly available information. For each stock in each month, I compute the Amihud measure as the daily

[11] Using closing bid-ask spreads produces qualitatively similar, albeit somewhat weaker, results.

average of absolute returns divided by dollar volume. The intuition is that a stock is more illiquid if its price changes considerably without substantial trading volume. For ease of interpretation, I use the reciprocal of this illiquidity measure to obtain a liquidity measure. I form quartiles based on this liquidity measure, and perform the two-way sort on liquidity and public news-event returns exactly as described in Table VI, except I substitute liquidity for analyst coverage.

Table VII reveals that news-event return reversals are large in highly liquid stocks, and are minimal in illiquid stocks. The table presents the risk-adjusted returns of 16 portfolios sorted by liquidity and news-event returns. Panel A shows that the liquid stocks with the lowest news-event returns outperform the liquid stocks with the highest event returns by 10.4 bps per day, or 42 bps over the four-day holding period. The return reversal for the illiquid stocks in Panel D is much smaller—2.1 bps per day, or 8 bps over four days. Panel E shows that the difference between the two reversals of 34 bps is significant at the 1% level. The liquidity evidence agrees with the evidence from the other two proxies for the amount of publicly available information: reversals after public news are larger when old information is abundant. Equally important, these results cast doubt on alternative explanations for the return reversal that predict reversals will be larger in illiquid stocks. For example, most microstructure biases in returns are larger in illiquid stocks, contrary to the evidence in Table VII.

[Insert Table VII here.]

C. Returns after New News Events

If investors cannot judge how much old versus new information a news event contains, they may react to all stories as if they contain some old and some new information. Under this version of the stale information hypothesis, investors will not only overreact to events with predominantly old information, but they will also underreact to events with mostly new information. This idea could reconcile the evidence of overreaction to old information with prior evidence documenting underreaction to information. For example, Hirshleifer, Lim, and Teoh (2007) show that investors underreact more to earnings news when many firms announce their earnings simultaneously. Their evidence is potentially consistent with the stale information hypothesis if earnings announcement events consist of mostly new information. Just as information overload exacerbates overreaction to old information, it may also exacerbate underreaction to new information.

I construct an empirical proxy for new earnings information contained in a news story to test whether underreaction increases with the proportion of new information. I exploit a key result in Tetlock et al. (2008) that news stories mentioning the word stem "earn" are better predictors of firms' quarterly earnings; and these "earn" stories also elicit much stronger market reactions than other news stories. From this evidence, I infer that news stories mentioning "earn" contain more new information than other stories. It is also likely that news stories around earnings announcements contain a considerable amount of new information because much of the variation in quarterly earnings is unexpected. Accordingly, I use news stories either mentioning the word stem "earn" or appearing within one trading day of a quarterly earnings announcement as a proxy for the release of new earnings information.[12]

Table VIII reports the alphas of portfolios formed based on two-way sorts of the release of new earnings information and news-event returns. The main result is that significant return

[12] I could use either the word-based measure or the announcement-based measure as a separate proxy for new earnings information. Because the definitions of these two measures overlap considerably and both measures generate similar results, I combine them into a single proxy.

reversals appear only in the stocks experiencing public news events without much new earnings information. The fifth column in Panels A and B shows that stocks without earnings news experience large cumulative reversals of 36 bps during days [2,5], whereas stocks with new information about earnings experience reversals of just 2 bps. Panel C confirms that the difference in these two return reversals is statistically and economically significant. These results show that the day-0 returns of news events with new earnings information do not reverse.

[Insert Table VIII here.]

An interesting question is whether the above proxy for new information subsumes the explanatory power of the various proxies for old information introduced earlier. To address this issue, I repeat the analysis of stale information in Table III for the subset of news stories that contain new earnings information. That is, I divide the earnings-related news stories according to whether other public news appears before this earnings news in days [-5,-1], days [-15,-6], or days [-∞,-16].[13] I form return reversal portfolios within each group of earnings news stories.

[Insert Table IX here.]

The evidence in Table IX reveals that the magnitude of return reversals after news stories containing earnings news depends heavily on whether another news story immediately precedes the earnings news. The fifth column in Panels A and C shows that cumulative return reversals of 16 bps occur in days [2,5] after the most stale earnings news, whereas return continuations of 36 bps occur after the least stale earnings news. Panel D establishes that the difference in these two reversals is economically and statistically significant (cumulative alpha of 54 bps over four days and a *t*-statistic of 3.30). From these tests, I conclude that return reversals after news events are

[13] Using the other four proxies for stale information produces qualitatively similar results.

larger when news events contain more old information, and are smaller when news events contain more new information.[14]

III. Understanding Return Reversals after Stale News

A skeptical reader could argue that the recent public news, extreme returns, media coverage, analyst coverage, and liquidity proxies all represent asymmetric information. If so, perhaps a rational model could make the same empirical predictions for return reversals after public news events as the stale information hypothesis. To distinguish rational and behavioral stories, the next subsection assesses how the return reversal after stale news depends on the trading activity of a group of potentially irrational investors. The last two subsections explore alternative explanations for the evidence.

A. Behavioral Explanations of Return Reversals after Stale News Events

The stale information hypothesis suggests that the impact of staleness on reversals should increase with trading activity from irrational investors who confuse old and new information. In this subsection, I explore whether traders who conduct small transactions in the TAQ (Trades and Quotes) and Institute for the Study of Security Markets (ISSM) databases could play the role of investors who overreact to stale information.[15] Barber, Odean, and Zhu (2007) show that small

[14] In additional tests, I find that the reversal after stale news is much smaller in news stories without much new information. One interpretation is that investors only fail to distinguish new and old information when news stories contain both types of information. An alternative interpretation is that news stories without new earnings information also contain no old information.

[15] In unreported tests, I explore whether the investors whom Barber and Odean (2000, 2001, and 2002) identified as overconfident could play the role of the irrational investors who overreact to stale information. Using the Barber and

trades correlate strongly with the trades of individual investors whom Barber and Odean (2000, 2001, and 2002) identified as overconfident. I use the TAQ and ISSM data from Barber, Odean, and Zhu (2007) to compute the fraction of dollar volume consisting of small trades, defined as those less than $5,000 in 1991 dollars.

I measure small trading activity for each S&P 500 stock in the calendar month prior to a public news event. I first partition the public news events into stale or not stale, as measured by the proxy based on the presence of another public news story in days [-5,-1].[16] Within both stale and not stale news events, I form portfolios based on an independent two-way sort of small trading activity and news-event returns, just as I did for analyst coverage and news-event returns. The key test is whether the association between staleness and return reversals is stronger within stocks with higher fractions of small trading. Because this test is based on third differences and requires a three-way sort (2 by 4 by 4) of news events, the resulting portfolios contain a median number of just 2 or 3 firms and occasionally contain none. The power of the test also declines slightly because small trade data (prior to decimalization and large-scale algorithmic trading) are only available from 1984 to 2000 rather than from 1984 to 2004, and not all stocks have matching TAQ or ISSM data.

Table X indicates that small trading activity is strongly related to the return reversal after stale news. The key result in the last column of Panel E is that the impact of staleness on return reversals is much larger for stocks in which small trades account for the highest fraction of dollar volume (cumulative alpha of 80 bps over four days and a *t*-statistic of 2.26). Each portfolio return in panel E represents a difference in the differences between the returns in Panels A and B

Odean (2002) data on individual trades from 78,000 accounts at a large discount brokerage during the period January 1991 through November 1996, I find similar results to those reported below.

[16] Using the other four proxies for stale news produces very similar results.

and those in Panels C and D of Table X. In the reversal column (five), Panels A and B establish that staleness increases reversals by 44 bps over four days, whereas Panels C and D provide weak evidence that staleness actually decreases return reversals by 17 bps over four days. In light of prior research by Barber, Odean, and Zhu (2007) and Barber and Odean (2000; 2001; 2002) on small trades and individual investors, I interpret the evidence in Table X as suggestive that the return reversal after stale news stems from the behavioral biases of individual investors.

[Insert Table X here.]

Behavioral anomalies often diminish over time as arbitrageurs seeking high risk-adjusted returns discover these investment opportunities. Next I examine whether the reversal of reactions to public news events decreases in the second half of the sample. For each of two nearly equal subperiods, 1984 to 1994 and 1995 to 2004, I redo the time series regressions in Table II based on the reversal portfolio with a holding period of days [2,5]. Table XI reports the daily alphas of the reversal portfolio and regression summary statistics for both subperiods and the full sample.

[Insert Table XI here.]

I assess how the impact of stale information changes over time by forming two sets of reversal portfolios—based on news likely to be stale and news unlikely to be stale. Table XI presents the subperiod results for both sets of reversal portfolios. To construct each set of reversal portfolios, I divide the sample of public news using the five alternative definitions of stale public news events described earlier: public news and extreme returns within the past week, and top quartiles of media coverage, analyst coverage, and liquidity. I define news events that are not stale as events without a previous public news or extreme return event in the past 15 trading days, and events with media coverage, analyst coverage, and liquidity in the bottom quartile.

A panel-by-panel comparison of the three leftmost and rightmost columns in Table XI reveals that the return reversal after public news events is much larger for the stale news events. This result holds for all five of the stale news proxies in both subperiods—i.e., for all 10 possible comparisons. From this evidence, I infer that the return reversal after stale news events remains robust across subperiods.

A comparison of columns one and two and columns four and five in Table XI indicates that the reversal after public news events is much lower in the second half of the sample. This finding applies to 9 out of 10 possible comparisons in the table. The finding that return reversals after news events decline over time is reminiscent of the evidence in Kaniel, Saar, and Titman (2007) showing that the weekly return reversal effect has fallen sharply in the past 20 years, particularly for large stocks.

Despite the decline of the return reversal phenomenon around general public news, the reversal after stale public news remains economically and statistically large for most of the proxies in Table XI. For example, in column two of Panels C, D, and E which contains stale news events, the four-day cumulative alphas of the return reversal in the 1995 to 2004 subperiod are 34, 26, and 41 bps with *t*-statistics of 2.59, 2.46, and 4.06. These results suggest that arbitrage has not yet eliminated the stale news reversal. By contrast, in four out of five panels in Table XI, the reversals after news that is not stale disappear in the second subperiod. It is possible that trading by rational arbitrageurs has eliminated the reversal after these other news events.

B. Weekly Reversal and Stale Information

This section examines whether stale information is related to the widely known weekly and volume-induced return reversal phenomena. First, I perform an independent two-way sort of weekly past returns and news-event returns to see if these two reversals are distinct. I measure weekly returns as the cumulative market-adjusted return over the week prior to the news event—i.e., days [-5,-1].[17] I use the same two-way sorting methodology as before. Again, I regress each of the 16 portfolio returns for quartiles of news-event returns and the previous week's returns on the six risk factors used earlier. Table XII reports the daily alphas for these portfolios, along with summary statistics for the regressions.

[Insert Table XII here.]

An important result in Table XII is that the news-event return reversal is strong only in the two extreme quartiles of the previous week's returns. Specifically, column five in Panels A and D lists cumulative four-day alphas of 31 bps and 33 bps as compared to 5 bps and 12 bps in Panels B and C. This finding is a direct implication of the stale information hypothesis if one interprets extremes in the prior week's return as prior news. In fact, extreme days-[-5,-1] returns closely resemble the recent extreme returns proxy for stale information shown in Table IV.

Panel E reports the magnitude of the weekly return reversal in each of the quartiles of news-event returns. Each of the four alphas represents the intercept from a regression of the difference in the portfolio returns in Panels A and D on the six risk factors. All four weekly reversal portfolio alphas are positive and marginally significant at the 5% level, indicating that a modest weekly reversal effect exists in this sample even after controlling for news-event returns.

[17] I use market-adjusted returns for consistency with the measure of news-event returns. Using more complicated benchmarks or raw returns instead has no impact on the results.

A closer look at the diagonal alpha entries in Table XII suggests a unified interpretation of both reversals. The previous week's return is only reversed when it is consistent with the current news-event return. Tracking the daily alphas along the diagonal from column one in Panel A to column four in Panel D, one sees a large combined daily-weekly reversal of 13 bps per day, or 52 bps over four days. Conversely, tracking the daily alphas along the diagonal from column one in Panel D to column four in Panel A, one finds a slight continuation of weekly returns of 3 bps per day, or 12 bps over four days. The comparison of the diagonals reinforces the idea that reactions to news events are dependent on prior news: the days-[-5,-1] return is an excellent directional indicator of whether the day-0 response to a news event is an overreaction.

C. Volume-Induced Reversal and Stale Information

Next I explore the possibility that stale information is related to the volume-induced return reversal phenomenon. Theoretical and empirical work in finance suggests high-frequency returns will be reversed when large trading volume accompanies these returns—e.g., Campbell et al. (1993), Lee and Swaminathan (2000), and Llorente et al. (2002). The theory in Llorente et al. (2002) predicts that volume-induced reversals will be large for stocks that have low information asymmetry, which resembles the stale information hypothesis. The intuition in the Llorente et al. (2002) model is that returns associated with risk sharing trades tend to be reversed. This reversal mechanism operates through trading volume on day 0—i.e., the time of the news event.

To distinguish this theory from the stale information hypothesis, I test whether the reversals observed in earlier tests depend on news-event volume. Although the study by Llorente et al. (2002) finds some empirical support for this prediction in a broad sample of NYSE and

AMEX stocks, it does not condition on the type of news, which may be necessary to isolate liquidity events. In the Llorente et al. (2002) theory, news-event returns may actually exhibit momentum when news-event trading volume is low. By contrast, the stale information hypothesis makes no clear prediction for the relationship between a stock's day-0 trading volume and the magnitude of its return reversal. One could argue that high volume in S&P 500 stocks indicates heavy trading by institutions, which may counteract overreactions to stale information. Alternatively, if high volume indicates frequent trading by individuals, reversals after high volume news events should be large.

Following Llorente et al. (2002), I measure volume as a stock's log turnover on the day of the public news event minus its average log turnover over the prior 200 trading days. I perform two-way sorts of day-0 volume and day-0 returns. I assess the risk-adjusted magnitude of the reversals during the days-[2,5] holding period using the same time series regression method applied throughout the paper. Table XIII reports the daily alphas of the reversal portfolios and summary statistics for the time series regressions.

[Insert Table XIII here.]

The primary result in Table XIII is that news-event reversals do not depend on high trading volume on day 0. Column five in Panels A through D shows that economically and statistically significant news-event return reversals occur in all four quartiles of trading volume. In additional unreported tests, I find that return reversals after stale news events also remain robust, regardless of trading volume on day 0. These tests assuage concerns that a public news event is merely a proxy for high volume, which generates a return reversal.

In fact, the evidence suggests that the converse may be true: high trading volume may be a proxy for a news event, which generates a return reversal. Within the sample of public news days, Table XIII shows that volume-induced return reversals are not present. Column four in Panels A through D provides counterevidence against volume-induced reversals: among stocks with the highest day-0 returns, those with the highest day-0 volume actually have higher returns over days [2,5]. Because news events are associated with both high volume and return reversals, it is possible that the general volume-induced return reversal phenomenon is merely a proxy for news events. To address this issue, one would need to examine more than just S&P 500 news events, which comprise roughly 1% of the firm-days in the CRSP database.

Lastly, I investigate whether there is return premium following high-volume news events, much like Conrad, Hameed, and Niden (1994) and Gervais, Kaniel, and Mingelgrin (2001) find. Panel E in Table XIII measures the return premium for news events with high volume in each quartile of day-0 returns. This volume-based return premium is statistically significant in two out of four news-event return quartiles, and the magnitude of its cumulative four-day alpha ranges between 6 bps and 27 bps. This return premium around high-volume news events could be driven by aggressive buying activity from individual investors with limited attention (e.g., Barber and Odean (2007)). Also, net buying activity from individuals could help to explain the general return premium after news events, which is evident in the on-average positive alphas throughout this paper. Future research could investigate these issues more systematically.

D. Linear Regression Estimates of the Effect of Stale Information on Return Reversals

As a final robustness check, I use Fama-MacBeth (1973) regressions to investigate whether each of the proxies for the staleness of the day-0 news story can predict return reversals in the next week, even after simultaneously controlling for other variables that could influence abnormal returns and reversals. These cross-sectional tests complement the non-parametric sorts used in estimating trading strategy returns. The dependent variable in each regression is market-adjusted returns from days 2 through 5. I use monthly cross-sectional regressions because some weekly regressions exhibit signs of small-sample multicollinearity problems. I report the time-series average of the monthly cross-sectional coefficients and R^2 statistics in Table XIV. Only selected regression coefficients appear in the table. I compute Newey-West (1987) standard errors that are robust to heteroskedasticity and autocorrelation up to five months.

Each cross-sectional regression in Table XIV controls for several firm and story characteristics, such as the log of market capitalization (*LnSize*), the log of book-to-market equity (*LnBM*), the log of monthly turnover (*LnTurn*), and abnormal volume on day 0 (*Abvol*[0,0]). I also control for cumulative abnormal returns from day -5 through day -1 (*CAR*[-5,-1])—to account for weekly reversal—and returns in the past calendar month, and from month $t-2$ through month $t-12$. In each regression, I include control variables for the direct effects of the logarithms of each of the five staleness proxies: the number of days since the previous news story (*LnSinceNews*), the number of days since the previous extreme abnormal return (*LnSinceExtreme*), the number of news stories in the previous month (*LnStories*), the number of analysts covering the stock (*LnAnalyst*), and the Amihud liquidity measure (*LnAmihud*). I control for a direct effect of whether a story is earnings-related (*Earn*), using the definition of earnings-related described earlier.

[Insert Table XIV here.]

Importantly, each regression includes an independent variable for the stock's abnormal return on day-0 (*CAR*[0,0]) itself to control for the average extent of return reversal. I measure the dependence of reversal on other variables using interactions with *CAR*[0,0]. All regressions control for size (*LnSize*) and earnings (*Earn*) interactions with *CAR*[0,0]. The five regressions in Table XIV vary according to which of the five staleness variables I interact with *CAR*[0,0]: *LnSinceNews*, *LnSinceExtreme*, *LnStories*, *LnAnalyst*, or *LnAmihud*.

Four of the five staleness proxies work well in predicting the extent to which day-0 returns will be reversed in days 2 through 5. The coefficients on the interactions of CAR[0,0] with *LnSinceNews*, *LnSinceExtreme*, *LnStories,* and *LnAmihud* are economically and statistically similar to the estimates based on trading strategy returns. Although the interaction of *CAR*[0,0] with the proxy for staleness based on analyst coverage *LnAnalyst* has a weak statistically impact, the sign of this coefficient is also consistent with the estimates based on trading strategy returns. I standardize all independent variables in each month to facilitate magnitude comparisons across coefficients. For example, row three in column (2) in Table XIV shows that a one-standard-deviation increase in the *LnSinceExtreme* proxy for staleness decreases reversal from 16.0 bps to 9.2 bps. Extrapolating further, when *LnSinceExtreme* is 2.4 standard deviations above its mean, there is no reversal of day-0 returns.

The positive and significant constant term in each regression confirms that small positive abnormal returns occur after news stories, as observed in the earlier tests. Two interesting control variables are the weekly abnormal return (*CAR*[-5,-1]) and size interaction term (*LnSize* * *CAR*[0,0]). The weekly return reversal effect is strong—*CAR*[-5,-1] coefficient is about -19 bps and statistically significant in all specifications—after controlling for other variables that predict returns. Also, reversals of day-0 returns are larger for big firms—the coefficient on the size interaction is usually negative—perhaps because size is a proxy for a firm's information environment and the extent to which day-0 stories contain old information.

IV. Brief Literature Review

In a broad sense, this study is linked to asset pricing research asking why market prices appear to move more than would be justified by changes in firms' fundamental values. For example, Shiller (1981) looks at whether return volatility corresponds to fluctuations in firms' expected dividend payments. Roll (1988), Cutler, Poterba, and Summers (1989), and Fair (2002) examine whether large price movements coincide with days in which important public news is announced. A general conclusion emerging from this literature is that changes in firms' fundamentals cannot explain some price movements.

More narrowly, this study is related to a rapidly growing area of research on financial news events. Beyond the papers already cited, recent contributions include Barber and Loeffler (1993), Busse and Green (2001), Antweiler and Frank (2004), Das and Chen (2006), and Tetlock (2007). The most closely related studies are Barber and Loeffler (1993), Antweiler and Frank (2006), Tetlock (2007), and Tetlock et al. (2008).

Antweiler and Frank (2006) report evidence that the returns around a broad sample of corporate news events partially reverse at weekly time horizons. They also assess how these return reversals depend on the topic of a news story and the business cycle. Much like Antweiler and Frank (2006), this study investigates the returns around a broad sample of news events at the weekly time horizon. The primary difference is that I test the new empirical implications of a hypothesis that could explain the observed return reversal. In these tests, I examine the relationship between news events, which is not a focus of any of the papers cited above.

Although Tetlock (2007) and Tetlock et al. (2008) examine short-horizon underreaction and overreaction to news, neither study examines firm-specific news at the weekly time horizon.

Equally important, these papers focus on the tone of words contained in news stories, rather than the market reactions to news articles. It is theoretically and empirically possible that the market underreacts to the content of the news, and yet market reactions to news partially reverse. For example, suppose news articles contain both new and old information, and that investors underreact to new information and overreact to old information. This could explain why Tetlock et al. (2008) finds that the tone of a news story, which could capture new information, positively predicts future returns. Yet the evidence here and in Antweiler and Frank (2006) suggests that news-event returns negatively predict future returns, perhaps because news-event returns include market reactions to old information.

The few studies that explicitly consider the links between news events arrive at somewhat different conclusions from each other—e.g., Davies and Canes (1978) versus Barber and Loeffler (1993) in finance, and Hand (1990) versus Ball and Kothari (1991) in accounting. Although the data in these studies can be reconciled with the stale information hypothesis, the limited sample sizes and specific nature of the news events make it difficult to draw general conclusions. Davies and Canes (1978) find that stock market reactions to a set of 785 investment recommendations in one *Wall Street Journal* (*WSJ*) column do not predict future returns at weekly horizons; whereas Barber and Loeffler (1993) show that responses to 94 recommendations that appear in another *WSJ* column negatively predict weekly returns. Both studies emphasize that the public release of an analyst recommendation is second-hand information already known to some investors. Intriguingly, Barber and Loeffler (1993) find that return reversals in their sample occur only when high trading volume accompanies the release of the *WSJ* column—a finding that could be related to the stale information hypothesis.

The stale information hypothesis resembles an idea proposed by Hand (1990) to explain cross-sectional variation in stock market reactions to firms' announcements of gains on swap transactions. Rather than searching for return reversals after news events, Hand (1990) only looks at the returns around the announcements of 230 swap transactions. Hand (1990) interprets the evidence that swap gain announcements elicit significant reactions as implying that unsophisticated investors overreact to irrelevant accounting information. Ball and Kothari (1991), however, argue that the theoretical model in Hand (1990) is incorrect and that the well-known size anomaly discovered by Banz (1981) can explain the stock market reactions to the 230 swap transaction announcements. Hand (1991) acknowledges problems in the theory in Hand (1990), but remains steadfast in the interpretation of the event study data. The evidence in this study sheds some light on this unresolved debate.

V. Concluding Thoughts

This paper presents evidence consistent with the hypothesis that individual investors overreact to information in stale public news stories. News-event returns partially reverse only in stocks with an abundance of old information, based on several alternative measures. The information released during these news events is likely to contain substantial overlap with past information, and hence likely to be stale. By contrast, news events likely to convey more new information elicit much smaller return reversals, or even return continuations. Moreover, the impact of staleness on return reversals is much larger in stocks with a high fraction of small trades, highlighting the important role of individual investors.

Several alternative hypotheses do not account for these findings. Controlling for weekly return reversals and volume-induced return reversals does not explain the news-event return reversals in this sample. Empirical microstructure biases such as bid-ask bounce and nonsynchronous trading make the counterfactual prediction that reversals would be larger in illiquid stocks.

A possible psychological basis for these findings is that investors do not pay sufficient attention to whether the information in news events is old or new (e.g., Hopper et al. (1977)). The Appendix to this paper sketches one mechanism for how this cognitive bias could affect equilibrium asset prices. The model considers the sequential release of two pieces of information: one signal (s_1) consisting of pure new information, followed by a second "impure" signal ($s_1 + s_2$) consisting of new information (s_2) and stale information (s_1).

This simple model initially predicts return momentum as the first signal (s_1) elicits two similar reactions—when it is initially released and when it released again—followed by return reversal that corrects investors' overreaction to stale information.[18] This paper focuses on returns after the market reaction to the follow-up news event ($s_1 + s_2$), which elicits an unambiguous reversal. Yet one could also explore whether there is any positive correlation in the market reactions to successive news events—i.e., s_1 and $s_1 + s_2$. Chan (2003) provides possibly related evidence that return momentum occurs only in firms with public news events, and return reversals occur in firms without news. Future research could test the return momentum implications of the stale information hypothesis by applying the distinction between stale news and other news to the Chan (2003) analysis.

[18] I thank Sheridan Titman for helpful discussions of this point.

Appendix

I outline a model to suggest one possible mechanism for the stale information hypothesis. The model shares features with theories of overreaction and underreaction that are based on investors' individual decision making errors (e.g., Barberis, Shleifer, and Vishny (1998); Daniel, Hirshleifer, and Subrahmanyam (1998); Brunnermeier (2005)), and those that are based on investor heterogeneity (e.g., Hong and Stein (1999)). Most notably, the stale information hypothesis and the theory in Hong and Stein (1999) both emphasize the importance of the information environment. Still, these two theories make two distinct predictions, which I discuss below. Throughout the analysis, I sometimes use the term overreaction to refer to stock return reversals; in the context of stock price levels, however, overreaction refers to an excessive price response to a signal relative to the change in fundamental value.

The main result of the model is that the release of an informative signal elicits overreaction as irrational investors receive both new and old information concurrently. The key assumption is that irrational investors' perceptions of their signal conflate old and new information, implying that they react to old information (e.g., DeMarzo, Vayanos, and Zwiebel (2003)). Because rational investors anticipate that irrational investors will overreact, rational investors trade intensely on the signal that will soon be re-released to irrational investors. This triggers an initial overreaction in prices that occurs even before irrational investors receive the stale signal. Recognizing that the initial release of a signal that will soon be stale is difficult to measure empirically, I emphasize the subsequent overreaction in prices and its relationship to observable variables.

More formally, I suppose there are two types of investors: one is completely rational and the other is imperfectly rational. The investors with bounded rationality are present in measure m, whereas the rational investors are present in measure $1 - m$. Both types of investors have negative exponential utility functions that possess the convenient constant absolute risk aversion (CARA) property. I will look for a rational expectations equilibrium in which all individual traders are atomistic price takers.

There is a single asset that pays a normally distributed liquidating dividend d, where $d = s_1 + s_2 + s_3$ with $s_i \sim N(0, \sigma_i^2)$ for $i = 1,2,3$, and the s_i terms are independent. I assume that the liquidating dividend is gradually revealed to all investors in three periods, so that investors observe the signals s_1 in period 1, $s_1 + s_2$ in period 2, and $s_1 + s_2 + s_3$ in period 3. The two investor types differ only in the way that they process the signal in period 2, which contains both old information (s_1) and new information (s_2). Rational investors perfectly separate the two types of information. They correctly perceive only s_2 as new information, and completely disregard the old signal s_1. By contrast, irrational investors perceive $ks_1 + s_2$ as new information, where $0 < k < 1$, implying that they also partially react to old information. The k parameter captures the extent to which irrational investors overreact to stale information—i.e., $k = 0$ corresponds to a rational investor. A more general model could include an additional parameter that measures the extent of underreaction to new information (s_2).

In each period, including an initial period 0, both types of investors set their asset demands to maximize their CARA utility functions based on all information available to them. To further simplify the exposition of the equilibrium, I make two assumptions to suppress the influence of risk aversion on asset prices. First, the rational and irrational investors' risk aversion parameters are equal. Second, the single asset is available in zero net supply. These assumptions enable me to focus on how traders' expectations affect prices. They do not affect the qualitative results because the fraction of irrational investors remains a free parameter. Also for simplicity, I normalize the market interest rate to zero.

I solve for the equilibrium asset prices using the traditional backward induction approach.[19] The market clearing prices in both periods are:

(1) $$p_2 = (1 + m \cdot k)s_1 + s_2,$$

(2) $$p_1 = [1 + m \cdot (1 - m) \cdot k] \cdot s_1$$

In period 0, prices are equal to zero because zero is the common prior mean for all investors, and all investors have the same background information.

Now I compare the market prices above to the prices that would prevail in the limiting case of $m = 0$ in which all investors are rational Bayesians with unlimited cognitive resources. Equation (1) would become $p_2 = s_1 + s_2$, and Equation (2) would be $p_1 = s_1$ if no irrational investors participated. When $m > 0$, prices in period 1 overreact to the signal s_1 relative to the benchmark $m = 0$ case. This initial overreaction persists in period 2, and is reinforced by the overreaction from irrational investors. Empirically, it is difficult to distinguish these two sources of overreaction, particularly if the signals in periods 1 and 2 arrive at nearly the same time. The root cause of both overreactions is that irrational investors confuse stale and new information.

Researchers commonly interpret return reversals as empirical manifestations of overreaction. Indeed, most price changes in this model are negatively autocorrelated. Two empirically relevant quantities are the covariances between the two news-event returns—around the release of s_1 and $s_1 + s_2$—and subsequent returns. Using Equations (1) and (2), one obtains these expressions for the news-event return reversals after s_1 and $s_1 + s_2$, respectively:

[19] For simplicity and realism, I assume that irrational investors are unaware of their own perceptual errors for simplicity and realism. The main results in the model do not require this assumption.

(3) $$Cov(d - p_2, p_2 - p_1) = -m^3 k^2 \sigma_1^2 \leq 0$$

(4) $$Cov(d - p_2, p_1 - p_0) = -mk[1 + m(1 - m)k]\sigma_1^2 \leq 0$$

Equations (3) and (4) show that both anticipated and unanticipated overreaction to stale information lead to return reversals after stale information is released in period 2. The main implication for the empirical work is that return reversals are likely to be larger when there is abundant recent information (σ_1^2), particularly if this old information resembles new information. The model's second implication is that the return reversal after the second release of s_1 should be greater when more irrational investors are present—i.e., as m increases.

A final interesting implication—not explored in this paper—is that the two price responses to the signals are positively autocorrelated because they represent overreaction to similar underlying information (s_1):

(5) $$Cov(p_2 - p_1, p_1 - p_0) = m^2 k[1 + m(1 - m)k]\sigma_1^2 \geq 0$$

Equation (5) implies that there is return momentum in the two news-event returns. This occurs before the partial return reversal of both news-event returns. In this paper, I focus only on the unambiguous return reversals that occur after the release of stale information, leaving tests of the positive correlation between the news-event returns of successive news releases for future work.

Despite the similarities in the stale information hypothesis and the theory in Hong and Stein (1999), the empirical predictions of the two models are somewhat distinct. Both models feature agents who respond to news events and ignore the information in market prices. A key difference between the two models is the information diffusion process, which Hong and Stein (1999) suppose is a sequence of pure innovations in signals and I model as the arrival of two potentially related signals. This difference generates overreaction in this model and underreaction in Hong and Stein (1999). Nevertheless, many of the comparative statics of the two models are similar if one is willing to consider an increased return reversal as equivalent to reduced return momentum. For example, greater analyst coverage reduces return momentum in Hong and Stein (1999), and increases return reversals in the stale information model.

Fortunately, relative to the predictions made in Hong and Stein (1999), the current model does deliver at least two unique comparative statics. First and foremost, the stale information model draws an explicit link between traders' reactions to successive signals, predicting that return reversals will increase after recent news events. By contrast, the Hong and Stein (1999) model does not make an obvious prediction. Second, an increase in the fraction of irrational traders increases the magnitude of return reversal in the stale information model, whereas it increases return momentum in Hong and Stein (1999). The empirical tests in Sections II and III examine these two unique predictions as well as the predictions that both models make.

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Table I: Return Reversals after Public News and Extreme Return Events

The table displays the daily alphas of several news-event portfolios. Each alpha is the intercept from a standard time series regression of raw portfolio returns on six daily risk factors: the market, size, book-to-market, and three factors based on momentum and reversal anomalies. I compute Newey and West (1987) standard errors for these alphas that are robust to heteroskedasticity and serial correlation up to five lags—the *t*-statistics appear in parentheses below the alphas. For each type of news, Table I presents the daily alphas from the four portfolios sorted by news-event returns and the reversal portfolio held during days [2,5]. Each reversal portfolio is long on firms with news-event returns in the lowest quartile and short on firms with returns in the highest quartile. Panels C and D decompose the set of extreme return events according to whether they appear on the same day as a public news story. Public news events are days with firm-specific newspaper stories, and extreme return events are days in which the absolute value of abnormal returns is high. See text for details.

		Panel A: All Public News			
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.077	0.066	0.040	0.025	0.052
	(3.76)	(3.92)	(2.51)	(1.41)	(4.59)
Observations	5300	5300	5300	5300	5300
R^2	0.004	0.005	0.003	0.004	0.004
		Panel B: All Extreme Return Events			
Day-0 Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.108	0.081	0.001	-0.025	0.133
	(4.09)	(3.57)	(0.03)	(-1.12)	(7.79)
Observations	5296	5091	5175	5300	5296
R^2	0.004	0.004	0.003	0.003	0.004
		Panel C: Extreme Returns without Publicity			
Day-0 Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.127	0.079	-0.019	-0.038	0.168
	(4.94)	(3.50)	(-0.95)	(-1.63)	(10.35)
Observations	5282	5069	5161	5300	5282
R^2	0.005	0.005	0.003	0.003	0.004
		Panel D: Extreme Returns with Publicity			
Day-0 Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.051	0.081	0.031	0.015	0.037
	(1.45)	(2.93)	(1.26)	(0.51)	(1.05)
Observations	5164	5001	5044	5202	5100
R^2	0.001	0.003	0.003	0.002	0.001
		Panel E: Difference Between Extreme Returns without Publicity and with Publicity			
Day-0 Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.073	0.001	-0.055	-0.051	0.127
	(2.38)	(0.04)	(-2.98)	(-2.24)	(3.46)
Observations	5152	4958	5004	5202	5090
R^2	0.002	0.001	0.000	0.001	0.001

Table II: Time Horizons of Return Reversals after Public News

The table displays the risk factor loadings and daily alphas of reversal portfolios formed over different time horizons—days [2,2], [2,3], [2,5], [2,10]—after public news events. Each column in Table II represents a regression for a reversal portfolio with a different time horizon after public news events. Each reversal portfolio is long on firms with news-event returns in the lowest quartile and short on firms with news-event returns in the highest quartile. Each alpha is the intercept from a standard time series regression of raw portfolio returns on six daily risk factors: the market (MKT), size (SMB), and book-to-market (HML) factors proposed in Fama and French (1992 and 1993)), and three factors based on momentum and reversal anomalies. The momentum and reversal factors (UMD_ST, UMD_INT, UMD_LT) are long-short portfolios generated by sorts of past returns over the monthly time horizons of [1,1], [2,12], and [13,60], respectively. I compute Newey and West (1987) standard errors for these alphas that are robust to heteroskedasticity and serial correlation up to five lags—the *t*-statistics appear in parentheses below the alphas. Public news events are days with firm-specific newspaper stories. See text for details.

Time Horizon in Days	[2,2]	[2,3]	[2,5]	[2,10]
MKT	-0.073	-0.063	-0.031	-0.048
	(-1.98)	(-2.10)	(-1.58)	(-2.80)
HML	-0.054	-0.017	0.006	-0.018
	(-0.82)	(-0.36)	(0.18)	(-0.72)
SMB	-0.058	-0.069	-0.051	-0.041
	(-1.28)	(-1.88)	(-1.84)	(-2.11)
UMD_ST	0.051	0.040	0.013	0.038
	(1.40)	(1.55)	(0.68)	(2.33)
UMD_INT	0.050	-0.039	-0.052	-0.043
	(1.40)	(-1.35)	(-2.63)	(-2.74)
UMD_LT	-0.050	-0.023	0.004	0.035
	(-0.70)	(-0.55)	(0.12)	(1.47)
Cumulative Alpha	0.098	0.190	0.208	0.207
	(4.95)	(6.40)	(4.59)	(3.37)
Observations	5279	5299	5300	5300
R^2	0.001	0.002	0.004	0.006

Table III: The Impact of Recent Public News on Return Reversals after Public News

The table displays the daily alphas of several news-event portfolios. Each alpha is the intercept from a standard time series regression of raw portfolio returns on six daily risk factors: the market, size, book-to-market, and three factors based on momentum and reversal anomalies. I compute Newey and West (1987) standard errors for these alphas that are robust to heteroskedasticity and serial correlation up to five lags—the *t*-statistics appear in parentheses below the alphas. Panels A through C decompose the set of public news stories according to whether the most recent public news story appears within three different time intervals: days [-5,-1], days [-15,-6], or days (-∞,-16]. Panel D examines the difference between the returns on portfolios in Panels A and C. For each type of news, Table III presents the daily alphas from the four portfolios sorted by news-event returns and the reversal portfolio held during days [2,5]. Each reversal portfolio in column five is long on firms with news-event returns in the lowest quartile and short on firms with returns in the highest quartile. Public news events are days with firm-specific newspaper stories. See text for details.

Panel A: Public News with Latest Story in Days [-5,-1]					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.083	0.068	0.037	0.015	0.068
	(3.87)	(3.96)	(2.17)	(0.81)	(4.79)
Observations	5300	5300	5300	5299	5299
R^2	0.004	0.005	0.004	0.003	0.003
Panel B: Public News with Latest Story in Days [-15,-6]					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.052	0.063	0.042	0.009	0.044
	(2.29)	(3.31)	(2.30)	(0.45)	(2.32)
Observations	5283	5290	5290	5287	5277
R^2	0.002	0.005	0.001	0.004	0.002
Panel C: Public News with Latest Story in Days (-∞,-16]					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.055	0.056	0.045	0.060	-0.005
	(2.12)	(2.68)	(2.33)	(2.75)	(-0.22)
Observations	5247	5246	5255	5259	5229
R^2	0.005	0.003	0.002	0.001	0.003
Panel D: Difference between Public News with Recent and Distant Public News					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.027	0.011	-0.008	-0.046	0.072
	(1.40)	(0.79)	(0.60)	(-2.68)	(2.94)
Observations	5247	5246	5255	5258	5229
R^2	0.001	0.001	0.001	0.001	0.002

Table IV: The Impact of Recent Extreme Returns on Return Reversals after Public News

The table displays the daily alphas of several news-event portfolios. Each alpha is the intercept from a standard time series regression of raw portfolio returns on six daily risk factors: the market, size, book-to-market, and three factors based on momentum and reversal anomalies. I compute Newey and West (1987) standard errors for these alphas that are robust to heteroskedasticity and serial correlation up to five lags—the *t*-statistics appear in parentheses below the alphas. Panels A through C decompose the set of public news stories according to whether the most recent private news story appears within three different time intervals: days [-5,-1], days [-15,-6], or days (-∞,-16]. Panel D examines the difference between the returns on portfolios in Panels A and C. For each type of news, Table IV presents the daily alphas from the four portfolios sorted by news-event returns and the reversal portfolio held during days [2,5]. Each reversal portfolio in column five is long on firms with news-event returns in the lowest quartile and short on firms with returns in the highest quartile. Public news events are days with firm-specific newspaper stories, and extreme return events are days in which the absolute value of abnormal returns is high. See text for details.

Panel A: Public News with Latest Extreme Return in Days [-5,-1]					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.088	0.067	0.018	-0.010	0.099
	(3.21)	(3.23)	(0.90)	(-0.43)	(4.89)
Observations	5298	5300	5299	5299	5297
R^2	0.002	0.007	0.003	0.003	0.002
Panel B: Public News with Latest Extreme Return in Days [-15,-6]					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.080	0.065	0.045	0.036	0.047
	(3.71)	(3.44)	(2.46)	(1.77)	(2.89)
Observations	5289	5293	5289	5288	5278
R^2	0.004	0.006	0.004	0.003	0.004
Panel C: Public News with Latest Extreme Return in Days (-∞,-16]					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.060	0.065	0.046	0.049	0.011
	(3.34)	(4.13)	(2.92)	(3.02)	(0.93)
Observations	5299	5300	5300	5299	5298
R^2	0.004	0.003	0.003	0.003	0.003
Panel D: Difference Between Public News with Recent and Distant Extreme Returns					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.027	0.002	-0.028	-0.060	0.088
	(1.24)	(0.11)	(-2.00)	(-3.56)	(3.84)
Observations	5297	5300	5299	5298	5295
R^2	0.001	0.004	0.001	0.002	0.001

Table V: The Impact of Media Coverage on News-Event Return Reversals

The table displays the daily alphas of public news-event portfolios sorted by media coverage. Each alpha is the intercept from a standard time series regression of raw portfolio returns on six daily risk factors: the market, size, book-to-market, and three factors based on momentum and reversal anomalies. I compute Newey and West (1987) standard errors for these alphas that are robust to heteroskedasticity and serial correlation up to five lags—the *t*-statistics appear in parentheses below the alphas. I measure media coverage as the number of public news stories about each stock during the previous calendar month. Panels A through D decompose the set of public news stories into four different media coverage quartiles. Panel E examines the difference between the returns on portfolios in Panels A and D. For each media coverage quantile, Table V presents the daily alphas from the four portfolios sorted by news-event returns and the reversal portfolio held during days [2,5]. Each reversal portfolio in column five is long on firms with news-event returns in the lowest quartile and short on firms with returns in the highest quartile. Public news events are days with firm-specific newspaper stories.

Panel A: Stocks with the Highest Media Coverage					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.062	0.058	0.029	0.005	0.069
	(2.19)	(2.88)	(1.49)	(0.24)	(3.39)
Observations	5272	5274	5276	5258	5255
R^2	0.003	0.005	0.004	0.004	0.003
Panel B: Stocks with Above-Median Media Coverage					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.096	0.084	0.031	0.015	0.083
	(4.18)	(4.72)	(1.76)	(0.69)	(4.64)
Observations	5271	5273	5274	5271	5267
R^2	0.002	0.004	0.003	0.003	0.003
Panel C: Stocks with Below-Median Media Coverage					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.069	0.070	0.044	0.020	0.055
	(2.94)	(3.86)	(2.48)	(0.97)	(2.88)
Observations	5237	5240	5243	5241	5228
R^2	0.004	0.004	0.001	0.002	0.003
Panel D: Stocks with the Lowest Media Coverage					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.050	0.036	0.033	0.055	-0.006
	(2.03)	(1.66)	(1.75)	(2.58)	(-0.31)
Observations	5216	5220	5229	5227	5196
R^2	0.002	0.002	0.003	0.003	0.001
Panel E: Highest Minus Lowest Media Coverage					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.015	0.020	-0.006	-0.053	0.077
	(0.57)	(1.12)	(-0.34)	(-2.39)	(2.75)
Observations	5213	5218	5229	5211	5178
R^2	0.001	0.002	0.003	0.002	0.004

Table VI: The Impact of Analyst Coverage on News-Event Return Reversals

The table displays the daily alphas of news-event portfolios sorted by analyst coverage. Each alpha is the intercept from a standard time series regression of raw portfolio returns on six daily risk factors: the market, size, book-to-market, and three factors based on momentum and reversal anomalies. I compute Newey and West (1987) standard errors for these alphas that are robust to heteroskedasticity and serial correlation up to five lags—the *t*-statistics appear in parentheses below the alphas. I measure analyst coverage as the number of analysts covering each stock during the previous calendar month. Panels A through D decompose the set of public news stories into four different analyst coverage quartiles. Panel E examines the difference between the returns on portfolios in Panels A and D. For each analyst coverage quantile, Table VI presents the daily alphas from the four portfolios sorted by news-event returns and the reversal portfolio held during days [2,5]. Each reversal portfolio in column five is long on firms with news-event returns in the lowest quartile and short on firms in the highest quartile. Public news events are days with firm-specific newspaper stories.

Panel A: Stocks with the Highest Analyst Coverage					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.109	0.078	0.034	0.020	0.090
	(4.66)	(3.82)	(1.80)	(0.91)	(5.44)
Observations	5297	5296	5299	5294	5291
R^2	0.002	0.004	0.005	0.003	0.002
Panel B: Stocks with Above-Median Analyst Coverage					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.064	0.057	0.046	0.021	0.044
	(2.76)	(2.93)	(2.48)	(1.02)	(2.47)
Observations	5143	5146	5141	5131	5123
R^2	0.004	0.004	0.002	0.004	0.001
Panel C: Stocks with Below-Median Analyst Coverage					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.047	0.071	0.054	0.037	0.010
	(1.87)	(3.65)	(2.89)	(1.68)	(0.45)
Observations	5141	5146	5140	5134	5129
R^2	0.004	0.004	0.002	0.004	0.004
Panel D: Stocks with the Lowest Analyst Coverage					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.070	0.056	0.031	0.027	0.043
	(2.74)	(2.69)	(1.64)	(1.21)	(2.14)
Observations	5130	5136	5139	5139	5120
R^2	0.003	0.005	0.001	0.004	0.002
Panel E: Highest Minus Lowest Analyst Coverage					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.039	0.026	0.005	-0.009	0.047
	(1.65)	(1.49)	(0.28)	(-0.43)	(1.81)
Observations	5152	5162	5159	5152	5122
R^2	0.003	0.008	0.003	0.004	0.002

Table VII: The Impact of Liquidity on News-Event Return Reversals

The table displays the daily alphas of public news-event portfolios sorted by stock liquidity. Each alpha is the intercept from a standard time series regression of raw portfolio returns on six daily risk factors: the market, size, book-to-market, and three factors based on momentum and reversal anomalies. I compute Newey and West (1987) standard errors for these alphas that are robust to heteroskedasticity and serial correlation up to five lags—the *t*-statistics appear in parentheses below the alphas. I measure stock liquidity using the inverse of Amihud's (2002) illiquidity measure for each stock during the previous calendar month. Panels A through D decompose the set of public news stories into four different liquidity quartiles. Panel E examines the difference between the returns on portfolios in Panels A and D. For each liquidity quantile, Table VII presents the daily alphas from the four portfolios sorted by news-event returns and the reversal portfolio held during days [2,5]. Each reversal portfolio in column five is long on firms with news-event returns in the lowest quartile and short on firms in the highest quartile. Public news events are days with firm-specific newspaper stories.

Panel A: Stocks with the Highest Liquidity					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.098	0.054	0.024	-0.003	0.104
	(4.47)	(2.97)	(1.33)	(-0.15)	(6.44)
Observations	5271	5300	5300	5264	5237
R^2	0.004	0.003	0.004	0.002	0.004
Panel B: Stocks with Above-Median Liquidity					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.074	0.061	0.045	0.008	0.066
	(3.25)	(3.22)	(2.60)	(0.40)	(3.99)
Observations	5287	5292	5298	5296	5284
R^2	0.003	0.005	0.003	0.005	0.002
Panel C: Stocks with Below-Median Liquidity					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.062	0.076	0.047	0.027	0.037
	(2.53)	(4.10)	(2.52)	(1.29)	(1.89)
Observations	5287	5293	5292	5289	5283
R^2	0.004	0.006	0.004	0.005	0.002
Panel D: Stocks with the Lowest Liquidity					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.070	0.046	0.038	0.049	0.021
	(2.73)	(2.05)	(1.81)	(2.21)	(1.02)
Observations	5297	5290	5286	5296	5296
R^2	0.004	0.005	0.003	0.003	0.001
Panel E: Highest Minus Lowest Liquidity					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.029	0.007	-0.013	-0.048	0.085
	(1.23)	(0.38)	(-0.73)	(-2.31)	(3.38)
Observations	5268	5290	5286	5260	5233
R^2	0.005	0.006	0.004	0.003	0.003

Table VIII: Return Reversals after Public News with New Earnings Information

The table displays the daily alphas of public news-event portfolios sorted by whether an event is likely to convey significant earnings information. Each alpha is the intercept from a standard time series regression of raw portfolio returns on six daily risk factors: the market, size, book-to-market, and three factors based on momentum and reversal anomalies. I compute Newey and West (1987) standard errors for these alphas that are robust to heteroskedasticity and serial correlation up to five lags—the *t*-statistics appear in parentheses below the alphas. Public news events are days with firm-specific newspaper stories. Panels A and B decompose the set of public news stories according to whether they convey significant earnings information. I measure earnings information as a public news story that either appears within one trading day of an earnings announcement or contains the word stem "earn." Panel C examines the difference between the returns on portfolios in Panels A and B. For each type of news, Table VIII presents the daily alphas from the four portfolios sorted by news-event returns and the reversal portfolio held during days [2,5]. Each reversal portfolio in column five is long on firms with news-event returns in the lowest quartile and short on firms with returns in the highest quartile.

Panel A: All Public News without New Earnings Information					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.101	0.068	0.031	0.010	0.091
	(4.71)	(3.84)	(1.85)	(0.52)	(7.26)
Observations	5278	5279	5285	5271	5267
R^2	0.004	0.006	0.004	0.003	0.004
Panel B: All Public News with New Earnings Information					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.043	0.067	0.042	0.039	0.005
	(1.88)	(3.78)	(2.51)	(2.04)	(0.29)
Observations	5296	5300	5298	5300	5296
R^2	0.003	0.004	0.002	0.004	0.002
Panel C: Difference between Public News with and without New Earnings Information					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.058	0.002	-0.012	-0.029	0.087
	(3.35)	(0.19)	(-1.06)	(-2.33)	(4.50)
Observations	5274	5279	5283	5271	5263
R^2	0.001	0.002	0.001	0.001	0.001

Table IX: Return Reversals after Stale Earnings News

The table displays the daily alphas of portfolios formed after stocks experience public news events that are likely to convey significant earnings information. Each alpha is the intercept from a standard time series regression of raw portfolio returns on six daily risk factors: the market, size, book-to-market, and three factors based on momentum and reversal anomalies. I compute Newey and West (1987) standard errors for these alphas that are robust to heteroskedasticity and serial correlation up to five lags—the *t*-statistics appear in parentheses below the alphas. Public news events are days with firm-specific newspaper stories. I measure earnings news as public news that either appears within one trading day of an earnings announcement or contains the word stem "earn." Panels A through C decompose the set of earnings news stories according to whether the most recent public news story appears within three different time intervals: days [-5,-1], days [-15,-6], or days (-∞,-16]. Panel D examines the difference between the returns on portfolios in Panels A and C. For each type of news, Table IX presents the daily alphas from the four portfolios sorted by news-event returns and the reversal portfolio held during days [2,5]. Each reversal portfolio in column five is long on firms with news-event returns in the lowest quartile and short on firms with returns in the highest quartile.

Panel A: Earnings News with Latest Story in Days [-5,-1]					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.068	0.046	0.033	0.027	0.041
	(2.50)	(2.33)	(1.76)	(1.22)	(1.79)
Observations	5261	5269	5266	5261	5238
R^2	0.002	0.004	0.003	0.003	0.002
Panel B: Earnings News with Latest Story in Days [-15,-6]					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	-0.011	0.096	0.047	0.028	-0.041
	(-0.38)	(3.62)	(1.84)	(1.03)	(-1.28)
Observations	4709	4691	4709	4694	4452
R^2	0.002	0.001	0.001	0.003	0.003
Panel C: Earnings News with Latest Story in Days (-∞,-16]					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.016	0.063	0.073	0.104	-0.091
	(0.53)	(2.44)	(3.28)	(3.70)	(-2.81)
Observations	4674	4656	4658	4649	4392
R^2	0.006	0.002	0.001	0.002	0.003
Panel D: Difference between Earnings News with Recent and Distant Public News					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.063	-0.013	-0.040	-0.066	0.134
	(2.05)	(-0.57)	(-1.94)	(-2.59)	(3.30)
Observations	4654	4630	4636	4620	4364
R^2	0.002	0.002	0.001	0.001	0.002

Table X: The Effect of Stale News on Reversals Sorted by Small Trading Activity

The table displays the daily alphas of news-event portfolios sorted by stale news, small trading activity, and news-event returns. Each panel presents the daily alphas from four portfolios sorted by news-event returns and the reversal portfolio held during days [2,5]. Each alpha is the intercept from a standard time series regression of raw portfolio returns on six daily risk factors: the market, size, book-to-market, and three factors based on momentum and reversal anomalies. The *t*-statistics based on Newey and West (1987) standard errors appear in parentheses below the alphas. I measure stale public news events based on the presence of another public news story in days [-5,-1]. For each stock during the previous calendar month, I measure small trading activity as fraction of dollar volume consisting of small trades, defined as those less than $5,000 in 1991 dollars. Panels A and B show the alphas for stale and not stale public news stories with a fraction of small trades in the highest quartile. Panels C and D show these alphas for public news stories with small trades in the bottom quartile. Panel E examines the difference in the differences between the returns on portfolios in Panels A and B and those in Panels C and D.

Panel A: Highest Small Trading Activity and Stale News					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.109	0.102	0.049	0.003	0.102
	(2.87)	(2.92)	(1.39)	(0.10)	(2.67)
Observations	4099	3936	3881	4060	3976
R^2	0.002	0.004	0.005	0.002	0.001
Panel B: Highest Small Trading Activity and Not Stale News					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.051	0.025	0.028	0.039	-0.007
	(1.22)	(0.53)	(0.60)	(1.04)	(-0.16)
Observations	3767	3397	3335	3724	3561
R^2	0.006	0.008	0.003	0.002	0.001
Panel C: Lowest Small Trading Activity and Stale News					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.088	0.051	0.036	0.015	0.083
	(2.99)	(2.00)	(1.43)	(0.55)	(2.98)
Observations	3815	3991	4009	3927	3657
R^2	0.005	0.004	0.002	0.006	0.004
Panel D: Lowest Small Trading Activity and Not Stale News					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.117	0.061	0.050	-0.002	0.126
	(3.53)	(2.18)	(2.00)	(-0.06)	(3.58)
Observations	3388	3671	3708	3487	3026
R^2	0.005	0.006	0.003	0.005	0.009
Panel E: Difference in the Impact of Stale News in the Highest and Lowest Small Trading					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.111	0.083	0.023	-0.086	0.200
	(1.90)	(1.42)	(0.36)	(-1.52)	(2.26)
Observations	2747	2660	2651	2821	2342
R^2	0.001	0.002	0.002	0.001	0.001

Table XI: Evaluating Return Reversal after Stale and New Public News in Subperiods

For each of two subperiods, 1984 to 1994 and 1995 to 2004, I redo the time series regressions in Table II that use public news reversal portfolios with a holding period of days [2,5]. Table XI reports the daily alphas and regression summary statistics for both subperiods and the full sample. Each panel reports the subperiod results for reversal portfolios based on stale news and news that is not stale (i.e., new). I divide public news events using the five alternative definitions of stale news events described earlier. The five panels display the results for reversal portfolios within the five different definitions of stale news. Newey and West (1987) *t*-statistics robust to heteroskedasticity and autocorrelation up to five lags appear in parentheses below the alphas.

Panel A: Recent Public News as a Proxy for Stale News						
	Latest Public News in Days [-5,-1]			Latest Public News in Days (-∞,-16]		
	1984-1994	1995-2004	1984-2004	1984-1994	1995-2004	1984-2004
Daily Alpha	0.086	0.046	0.068	0.066	-0.045	0.014
	(5.37)	(1.89)	(4.79)	(3.51)	(-1.93)	(0.95)
Observations	2781	2518	5299	2781	2516	5297
R^2	0.003	0.009	0.003	0.007	0.002	0.002
Panel B: Recent Extreme Return Event as a Proxy for Stale News						
	Latest Extreme Event in Days [-5,-1]			Latest Extreme Event in Days (-∞,-16]		
	1984-1994	1995-2004	1984-2004	1984-1994	1995-2004	1984-2004
Daily Alpha	0.140	0.047	0.099	0.022	0.000	0.011
	(5.36)	(1.44)	(4.89)	(1.27)	(-0.03)	(0.93)
Observations	2780	2517	5297	2779	2519	5298
R^2	0.002	0.004	0.002	0.002	0.005	0.003
Panel C: Media Coverage as a Proxy for Stale News						
	Top Quartile of Media Coverage			Bottom Quartile of Media Coverage		
	1984-1994	1995-2004	1984-2004	1984-1994	1995-2004	1984-2004
Daily Alpha	0.047	0.085	0.069	0.038	-0.056	-0.006
	(1.97)	(2.59)	(3.39)	(1.28)	(-2.07)	(-0.31)
Observations	2767	2488	5255	2724	2472	5196
R^2	0.004	0.007	0.003	0.005	0.006	0.001
Panel D: Analyst Coverage as a Proxy for Stale News						
	Top Quartile of Analyst Coverage			Bottom Quartile of Analyst Coverage		
	1984-1994	1995-2004	1984-2004	1984-1994	1995-2004	1984-2004
Daily Alpha	0.107	0.065	0.090	0.056	0.025	0.042
	(5.27)	(2.46)	(5.44)	(2.18)	(0.83)	(2.18)
Observations	2774	2517	5291	2753	2514	5267
R^2	0.000	0.006	0.002	0.003	0.003	0.002
Panel E: Liquidity as a Proxy for Stale News						
	Top Quartile of Liquidity			Bottom Quartile of Liquidity		
	1984-1994	1995-2004	1984-2004	1984-1994	1995-2004	1984-2004
Daily Alpha	0.110	0.102	0.104	0.070	-0.039	0.021
	(5.45)	(4.06)	(6.44)	(2.45)	(-1.26)	(1.02)
Observations	2750	2487	5237	2778	2518	5296
R^2	0.002	0.011	0.004	0.003	0.002	0.001

Table XII: Reversals after Weekly Returns and News-Event Returns

The table displays the daily alphas of public news event portfolios sorted by the previous week's return. Each alpha is the intercept from a standard time series regression of raw portfolio returns on six daily risk factors: the market, size, book-to-market, and three factors based on momentum and reversal anomalies. I compute Newey and West (1987) standard errors for these alphas that are robust to heteroskedasticity and serial correlation up to five lags—the *t*-statistics appear in parentheses below the alphas. I measure a stock's return in the previous week as the cumulative market-adjusted return in days [-5,-1]. Panels A through D decompose the set of public news stories into four different quartiles of previous week's returns. Panel E examines the difference between the returns on portfolios in Panels A and D. For each weekly return quantile, Table XII presents the daily alphas from the four portfolios sorted by news-event returns and the reversal portfolio held during days [2,5]. Each reversal portfolio in column five is long on firms with news-event returns in the lowest quartile and short on firms in the highest quartile. Public news events are days with firm-specific newspaper stories.

Panel A: Lowest Previous Week's Return					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.105	0.102	0.057	0.028	0.077
	(3.42)	(4.65)	(2.72)	(1.26)	(3.17)
Observations	5286	5287	5290	5286	5277
R^2	0.003	0.007	0.002	0.004	0.002
Panel B: Below-Median Previous Week's Return					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.057	0.056	0.050	0.045	0.012
	(2.58)	(3.07)	(2.83)	(2.22)	(0.65)
Observations	5288	5292	5295	5282	5273
R^2	0.004	0.005	0.003	0.004	0.003
Panel C: Above-Median Previous Week's Return					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.063	0.045	0.034	0.033	0.030
	(3.09)	(2.48)	(1.96)	(1.76)	(1.85)
Observations	5275	5288	5291	5284	5269
R^2	0.004	0.003	0.004	0.003	0.003
Panel D: Highest Previous Week's Return					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.057	0.061	0.019	-0.025	0.082
	(2.44)	(2.95)	(0.97)	(-1.15)	(4.46)
Observations	5295	5290	5283	5287	5287
R^2	0.002	0.004	0.002	0.003	0.001
Panel E: Lowest Minus Highest Previous Week's Return					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.048	0.042	0.038	0.052	-0.003
	(1.86)	(2.16)	(1.93)	(2.68)	(-0.11)
Observations	5281	5277	5273	5273	5264
R^2	0.001	0.003	0.001	0.004	0.001

Table XIII: Reversals after Volume-Induced Returns and News-Event Returns

The table displays the daily alphas of public news event portfolios sorted by news event volume. Each alpha is the intercept from a standard time series regression of raw portfolio returns on six daily risk factors: the market, size, book-to-market, and three factors based on momentum and reversal anomalies. I compute Newey and West (1987) standard errors for these alphas that are robust to heteroskedasticity and serial correlation up to five lags—the *t*-statistics appear in parentheses below the alphas. I measure volume as a stock's log turnover on the day of the public news event minus its average log turnover over the prior 200 trading days. Panels A through D decompose the set of public news stories into four different quartiles of news event volume. Panel E examines the difference between the returns on portfolios in Panels A and D. For each volume quantile, Table XIII presents the daily alphas from the four portfolios sorted by news-event returns and the reversal portfolio held during days [2,5]. Each reversal portfolio in column five is long on firms with news-event returns in the lowest quartile and short on firms in the highest quartile. Public news events are days with firm-specific newspaper stories.

Panel A: Lowest Volume News Events					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.061	0.057	0.021	-0.027	0.078
	(2.32)	(2.96)	(1.09)	(1.10)	(3.46)
Observations	5199	5237	5231	5089	5054
R^2	0.003	0.005	0.004	0.006	0.000
Panel B: Below-Median Volume News Events					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.065	0.063	0.041	0.016	0.048
	(2.86)	(3.42)	(2.27)	(0.74)	(2.73)
Observations	5256	5278	5275	5246	5226
R^2	0.003	0.002	0.003	0.002	0.004
Panel C: Above-Median Volume News Events					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.078	0.078	0.056	0.018	0.062
	(3.47)	(3.98)	(2.91)	(0.91)	(3.56)
Observations	5259	5256	5258	5264	5253
R^2	0.004	0.002	0.003	0.002	0.004
Panel D: Highest Volume News Events					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.076	0.093	0.052	0.051	0.026
	(2.97)	(4.20)	(2.69)	(2.61)	(1.22)
Observations	5260	5184	5206	5260	5257
R^2	0.002	0.004	0.002	0.003	0.001
Panel E: Highest Minus Lowest Volume News Events					
News-Event Return	Lowest	2	3	Highest	Low – High
Daily Alpha	0.016	0.046	0.027	0.068	-0.040
	(0.62)	(2.33)	(1.46)	(3.19)	(-1.31)
Observations	5159	5123	5140	5053	5015
R^2	0.003	0.001	0.001	0.002	0.001

Table XIV: Cross-sectional Regression Estimates of the Effect of Stale News on Reversals

Table XIV displays results from monthly cross-sectional Fama-MacBeth (1973) regressions of market-adjusted returns from days 2 through 5 on each of the proxies for staleness of day-0 news, other controls, and interactions with day-0 returns. I report the time-series average of the coefficients and R^2 statistics in Table XIV. The *t*-statistics in parentheses are based on Newey-West (1987) standard errors that are robust to heteroskedasticity and autocorrelation up to five months. I add an independent variable for the stock's abnormal return on day-0 (*CAR*[0,0]) itself. I include several variable interactions with *CAR*[0,0], including market capitalization (*LnSize*) and earnings (*Earn*) interactions. The five regressions in Table XIV vary according to which of the five staleness variables I interact with *CAR*[0,0]: *LnSinceNews*, *LnSinceExtreme*, *LnStories*, *LnAnalyst*, or *LnAmihud*. All regressions control for the direct effects of all five staleness variables. Each regression controls for many firm and story characteristics, such as the log of market capitalization, the log of book-to-market equity, the log of monthly turnover, abnormal volume on day 0 (*Abvol*[0,0]), and whether a story is earnings-related (*Earn*). I also control for cumulative abnormal returns from day -5 through day -1 (*CAR*[-5,-1]), and returns in the past calendar month, and from month $t – 2$ through month $t – 12$. The regression intercept is the cumulative alpha from days 2 through 5. I standardize all independent variables by month so that coefficient magnitudes are in basis points per one-standard-deviation increase. I depict only selected coefficients below. See text for details.

	(1)	(2)	(3)	(4)	(5)
CAR[0,0]	-18.2	-16.0	-18.1	-18.6	-18.7
	(-8.40)	(-7.26)	(-8.31)	(-8.36)	(-8.80)
LnSinceNews * *CAR*[0,0]	4.1				
	(2.78)				
LnSinceExtreme * *CAR*[0,0]		6.8			
		(4.62)			
LnStories * *CAR*[0,0]			-5.3		
			(-3.56)		
LnAnalyst * *CAR*[0,0]				-1.4	
				(0.93)	
LnAmihud * *CAR*[0,0]					6.0
					(2.00)
LnSize * *CAR*[0,0]	-2.7	-5.8	-2.4	-3.9	1.8
	(-1.62)	(-3.54)	(-1.36)	(-2.16)	(0.46)
Earn * *CAR*[0,0]	9.0	9.3	8.9	9.9	9.3
	(6.26)	(6.68)	(6.31)	(7.15)	(6.78)
CAR[-5,-1]	-18.7	-18.8	-19.0	-18.9	-18.9
	(-7.36)	(-7.45)	(-7.43)	(-7.43)	(7.35)
Abvol[0,0]	4.7	4.6	4.5	4.6	4.8
	(2.34)	(2.15)	(2.15)	(2.18)	(2.25)
Cumulative Alpha	4.7	4.6	4.7	4.6	4.7
	(2.01)	(1.97)	(2.01)	(1.97)	(2.03)
Average R^2	0.065	0.065	0.065	0.065	0.065

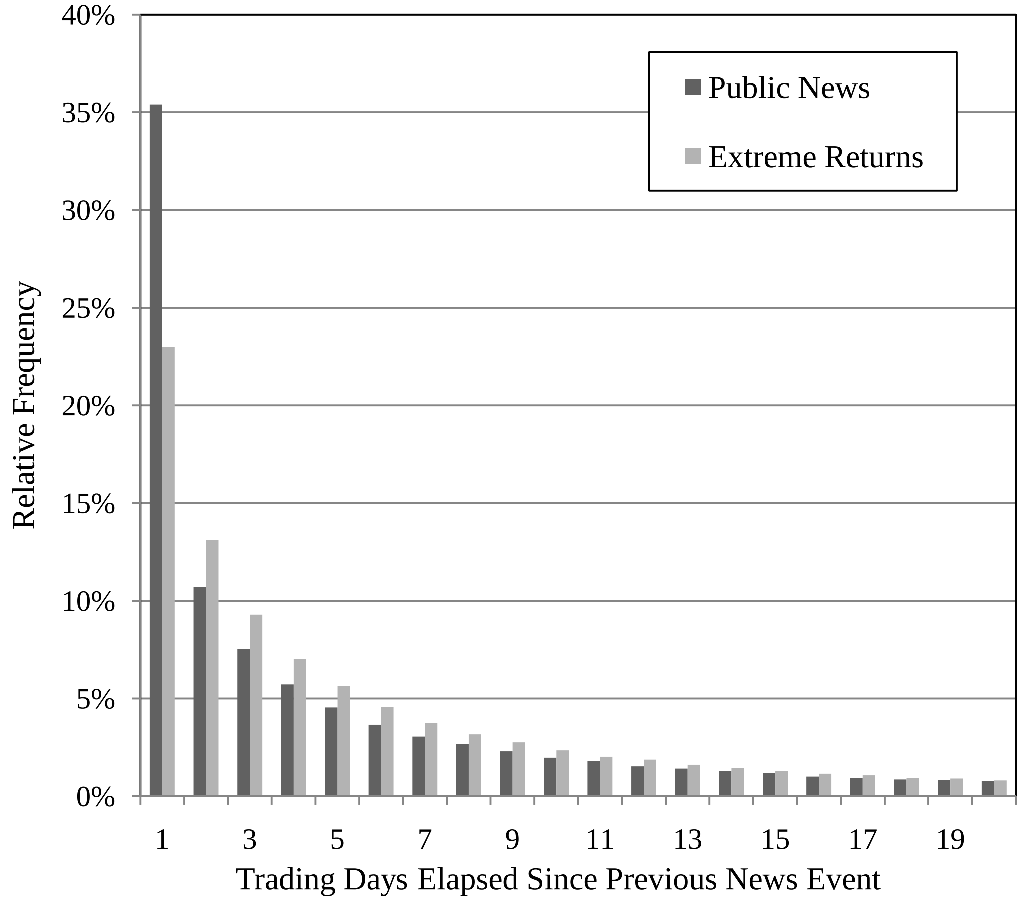

Figure 1: The Clustering of News Events in Time. This figure shows how the relative frequency of firm-specific public news and extreme return events depends on the number of trading days elapsed since the previous news event. I consider the set of S&P 500 firms between the years 1980 and 2004. I define a public news event as a trading day in which at least one news story about the firm appears in either *Dow Jones News Service* or *The Wall Street Journal*. I define an extreme return event as a trading day in which the firm's market-adjusted return is in either the top or bottom 5% of market-adjusted returns of S&P 500 firms. For each day in which a firm has a public news event, I count the number of trading days that have elapsed since the firm's previous public news event. I repeat this procedure for extreme return events.

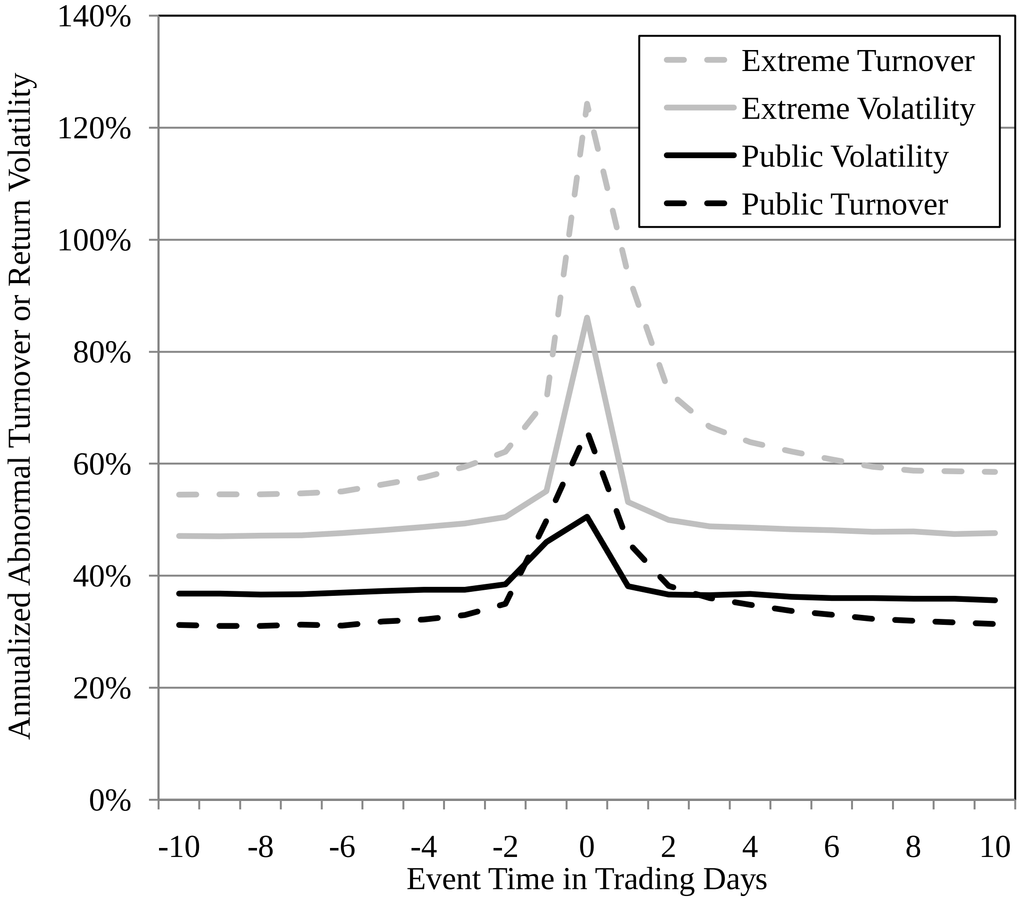

Figure 2: Volatility and Turnover around Public and Extreme Return Events. The figure displays the firm-specific return volatility and trading activity that occurs in a 10-trading-day event window around public news and extreme return events. The two solid lines represent return volatility, whereas the two dashed lines represent trading activity. The two dark lines correspond to the volatility and trading around public news events; and the two lightly colored lines correspond to activity around extreme return events. I measure daily firm-specific return volatility as the standard deviation of a firm's market-adjusted return. I measure daily trading activity as a firms' share turnover minus the market turnover for the exchange where the firm is listed. I divide the volume of Nasdaq firms by a factor of two to adjust for the double-counting of trades. I multiply by 252 to annualize abnormal volume and multiply by $\sqrt{252}$ to annualize abnormal volatility. I consider the set of S&P 500 firms between the years 1980 and 2004. I define a public news event as a trading day in which a news story about the firm appears in either *Dow Jones News Service* or *The Wall Street Journal*. I define an extreme return event as a trading day in which the firm's market-adjusted return is in either the top or bottom 5% of market-adjusted returns of S&P 500 firms.