# News Momentum*

Hao Jiang[†], Sophia Zhengzi Li[‡], and Hao Wang[§]

This Draft: August 6, 2019

**Abstract**

We decompose daily stock returns into news- and non-news-driven components, using a comprehensive sample of high-frequency firm-level news arrivals. We find that news-driven returns tend to exhibit momentum, different from non-news returns that precede a reversal. A news momentum strategy that buys (sells) stocks with high (low) news returns generates a monthly return of 3.34% in the following week, with a four-factor alpha of 3.37%. The news momentum effect is stronger when investors are distracted. Using analyst earnings forecasts as a proxy, we also find that slow adjustments of market expectations following firm news contribute to news momentum.

**JEL classification**: G02; G10; G14

**Keywords**: News; Momentum; Underreaction; Attention; Expectation.

*We are grateful to Ren-Raw Chen, Charles Hadlock, Claire Yurong Hong, Simon Huang, Xiaomeng Lu, Roni Michaely, Stefan Nagel and Paul Tetlock, along with seminar participants at AQR, Australian National University, Michigan State University, Rutgers University, University of Wisconsin-Madison, Singapore Management University, and conference participants at the Conference on Financial Economics and Accounting, the Mid-Atlantic Research Conference in Finance, the Eleventh Triple Crown Conference, 2018 CICF, the Second UT Dallas Fall Finance Conference, and the 2019 Summer Institute of Finance Conference for their helpful comments.

[†]Eli Broad College of Business, Michigan State University, East Lansing, MI 48824; E-mail: jiangh@broad.msu.edu.

[‡]Rutgers Business School, Piscataway, NJ 08854; E-mail: zhengzi.li@business.rutgers.edu.

[§]Prime Quantitative Research LLC, Piscataway, NJ 08854; E-mail: haowang.zj@gmail.com.

## 1 Introduction

The extensive literature on return predictability has established an interesting array of facts regarding the dynamics of individual stock returns. In particular, whereas short-horizon stock returns within the past month and long-horizon returns in the past 3–5 years exhibit reversals, returns in the period of 3–12 months show a pattern of continuation in the subsequent 3–12 months. This finding on the stock price momentum has received widespread attention, and generated substantial controversy among financial economists regarding its implications for market efficiency (see Jegadeesh and Titman (2011) for a survey).

Underlying this controversy is the joint-hypothesis problem highlighted by Fama (1970), which states that tests of market efficiency are inherently tied to tests of specific asset pricing models. It is therefore difficult to draw a clear inference from apparently anomalous price behavior regarding market efficiency. A powerful solution to this problem, as argued by Fama (1998), is to focus on the behavior of stock prices in a short time window, during which expected returns on individual stocks are small so that the results are not particularly sensitive to the choice of specific asset pricing models. In his influential survey, Fama (1998) examines existing event studies, and concludes that market underreaction is as frequent as market overreaction, thereby supporting the notion of market efficiency.

In this paper, we exploit these insights to contribute to the literature on return predictability. Specifically, we combine a comprehensive sample of time-stamped firm-level public news announcements with high-frequency (e.g., within a 15-minute time interval) price movements of individual stocks, to identify the very short-term response of individual stocks to firm-specific information events. We decompose daily stock returns into news-driven and non-news-driven components, revisiting the issue of short-term return predictability. Our news aggregation approach is related to and inspired by Fama's approach of event study aggregation.

We uncover fresh evidence for systematic underreaction to corporate news. Figure 1 shows our central results: Following an initial response to firm news, stock prices tend to drift in the same direction. The post-news-arrival drift is particularly strong during the first few trading days; it does not reverse even when we extend the event window up to one year. Since long-term stock returns are sensitive to the choice of asset pricing models, we focus on the first few days in most of our empirical analyses. To get a sense of the magnitudes, we construct a trading strategy that exploits the news momentum effect. In particular, we buy (sell) stocks with high (low) news returns in the previous day with a one-week holding period. During the period from 2000 to 2012, this strategy generates an average monthly return of 3.34%, with a four-factor alpha of 3.37%, controlling for the market, size, value, and momentum.[1]

Due to the short investment horizon and the aggregation across a full spectrum of corporate news events, it may not be surprising that the news momentum strategy does not have high loadings on the prominent anomaly variables identified from the prior literature. It is, however, noteworthy that our post-millennium sample covers a period when most of the anomaly variables lose their return forecasting power (McLean and Pontiff (2016); Green et al. (2017)). The high statistical significance of the news momentum profit (with $t$-statistics above 8 in Fama-MacBeth regressions and portfolios sorts) and our simple event study-based methodology give us good reason to address the critique of Harvey et al. (2016) and Harvey (2017). With a stream of robustness tests that further establish the news momentum effect, we turn to its economic understanding.

We start by following Lo and MacKinlay (1990) to decompose the expected news momentum profit into three components: the average autocovariance of individual stock returns, the average cross-autocovariance across stocks, and the cross-sectional variance in expected stock returns. The first component captures the serial correlation in individual stock returns; a positive value would imply positive average returns to a strategy that buys winners and sells losers conditional on news arrivals. The second component reflects the lead-lag effects across stocks; a positive value would imply negative average returns to our news momentum strategy. The third component measures the dispersion in expected returns across stocks; if firms with positive news on average have higher expected returns, the news momentum strategy may be profitable due to the difference in expected individual stock returns. Our decomposition results indicate that the profit of the news momentum strategy comes almost entirely from the positive autocovariance of individual stocks. One limitation of this return decomposition strategy is its requirement that firms must be in existence over our full sample period, which could introduce a certain degree of survivorship bias. To mitigate this bias, we also explore an industry-level news momentum strategy, which generates a similar decomposition

[1] We also use a multifactor model that includes the Fama and French (2015) five-factor model, the momentum factor, and the short-term return reversal factor. The monthly alpha of our news momentum strategy is 3.34%.

result.

What are the economic forces that lead to the systematic market underreaction to firm news? We explore and find supporting evidence for two hypotheses, which are related and not mutually exclusive. The first is inattention hypothesis due to bounded rationality. The second is slow adjustments of market expectations following firm news. As reviewed in Barberis (2018), the inattention hypothesis posits that investors have limited cognitive ability, which prevents them from immediately processing every bit of news to fully understand its implication for firm value. Empirical studies such as Hirshleifer et al. (2009) and DellaVigna and Pollet (2009) use this hypothesis to explain the post-earnings-announcement drift; a series papers by Cohen and Frazzini (2008), Cohen et al. (2013), Cohen et al. (2018) and Cohen and Lou (2012) report useful evidence for inattention to drive investor underreaction to information about a firm's customers, R&D investments, changes in its 10-K filings, and hard-to-process information. We find that the news momentum effect tends to be stronger following a rise in aggregate uncertainty, for Friday and weekend news, and when many firms across different industries experience news events on the same day. These results support inattention as an important driver of the news momentum effect.

Building on this observation, we examine a second hypothesis that features variation in market expectations following firm news arrivals. In particular, we study whether and how analyst expectations of future earnings change after news events. We find that financial analysts tend to revise their earning forecasts in a three-day window after receiving news reports in the direction of the news sentiment. Since analyst earnings forecast revisions tend to associate with abnormal movements in stock prices contemporaneously, the delayed reaction of financial analysts appears to be a driving force of news momentum. We also find that revisions in analyst earnings forecasts tend to positively predict subsequent earnings surprises. This evidence suggests that analysts tend to have sticky beliefs (Coibion and Gorodnichenko (2015); Bouchaud et al. (2019)), which can further contribute to underreaction and news momentum.

It should be noted that our research design focuses on the post-news-arrival return patterns, in contrast to studies that emphasize the anticipation of important economic news as a source of risk, driving stock prices. In particular, that line of research, such as Savor and Wilson (2013, 2016) and Lucca and Moench (2015), documents a large unconditional return premium on days with important news arrivals, which could reflect the compensation for bearing risk associated with the economic news. Our approach instead examines the difference in returns among firms with news stories *following* the initial market reaction, which is less likely to reflect risk premiums for information uncertainty.

Our paper is also related to but different from a large literature that uses linguistic analyses of media articles to extract sentiment and predict stock returns. For instance, Tetlock et al. (2008) use the fraction of negative words in news stories to predict future earnings surprises and stock returns. Tetlock (2011) employs linguistic analyses to identify stale news and reports evidence of overreaction to stale news (initial momentum and subsequent reversal). Our paper uses the stock market reaction to identify good and bad news, with a focus on a high-frequency return decomposition, to understand the nature of short-term return predictability.

## 2 Sample Construction

Our sample consists of all the firms listed on the New York Stock Exchange (NYSE), National Association of Securities Dealers Automated Quotations (NASDAQ), and American Stock Exchange (AMEX) with at least one news story covered by the Dow Jones News Wire. Our intraday price and quote data come from the TAQ database; high-frequency firm news data are from RavenPack; dividends, share splits and other stock market data are from CRSP; accounting data are from Compustat; and analyst forecasts are from I/B/E/S. Our sample period is from March 2000 to October 2012. Following prior literature, we use common stocks with share code of 10 or 11.

To prepare the intraday return data, we gather minute-by-minute observations of intraday prices by applying the cleaning rules of Barndorff-Nielsen et al. (2009) and Bollerslev et al. (2016) to the TAQ database. Using these intraday prices, we then compute intraday returns as every 15-minute return between 9:45 a.m. and 4:00 p.m. and the overnight return as the return between 4:00 p.m. on the previous trading day and 9:45 a.m. on the current trading day.[2] Because the TAQ transaction prices are raw prices without adjustments for share splits, we use the daily "cumulative factor to adjust price" and "dividend cash amount" variables in the CRSP database to adjust for split and dividend.

The RavenPack news database provides a comprehensive sample of firm-specific news stories

[2]We use the price at 9:45 a.m. for overnight returns to ensure that most stocks have traded at least once after the market open, following Patton and Verardo (2012) and Bollerslev et al. (2016). As a robustness test, we use 9:30 a.m. price to compute the overnight return and find qualitatively similar results.

from the Dow Jones News Wire (see, e.g., Jiang and Sun (2015), and Kelley and Tetlock (2017) for recent studies using this data set). To capture a news story specifically about a given firm, we use the "relevance score" that RavenPack provides, which ranges from 0 to 100, capturing how closely the underlying news applies to a particular company, with a score of 0 (100) meaning that the entity is passively (predominantly) mentioned. We require news stories in our sample to have a relevance score of 100. To include only fundamental news, we select acquisitions-mergers, analyst-ratings, assets, bankruptcy, credit, credit-ratings, dividends, earnings, equity-actions, labor-issues, product-services, and revenues from a total of 29 news groups. We exclude repeated news by setting the "event novelty score" (ENS) provided by RavenPack to be 100, which captures only the fresh news about a company. Applying these filters introduces no look-ahead bias because RavenPack assesses all news articles within milliseconds of receipt and immediately sends the resulting data to users. All information is thus available at the time of news release.

To capture the high-frequency market reaction to firm-level news, we combine the intraday return data partitioned at 15-minute intervals and firm-specific news event data time-stamped at the second level. To avoid extremely illiquid stocks, we eliminate stocks that are priced below $1 at the end of the portfolio formation period.[3] Our final sample includes a total of 5,480 firms that have at least one news story over the period of 3,189 days between March 2000 and October 2012. A typical day has an average of 3,781 firms covered by news stories.

Our main innovation is to decompose stock returns into news-driven and non-news-driven returns based on high-frequency market reaction. Specifically, we classify a stock's return according to whether firm-level news is released during the return measurement period. For news occurring within regular trading hours, the news return is simply the 15-minute return over the same period that the news occurs. For news occurring during the weekend, holiday, or overnight, the news return is the nearest subsequent overnight return to reflect that the first reaction to such news stories is incorporated into the stock's price only for the first trade of the following trading day. For example, the return for news events during the weekend is the return over the period of 4:00 p.m. of the surrounding Friday and 9:45 a.m. of the surrounding Monday. After classification, we aggregate all news and non-news returns within each day starting from 4:00 p.m. on day $t-1$ to 4:00 p.m. on day $t$ to form daily news and non-news returns. This essentially decomposes the

[3] Our results are robust to setting an alternative price filter such as $5 per share.

overall daily return into two orthogonal components. More formally, suppose there are $M$ overnight plus intraday returns per day. For example, in the case of 15-minute returns, $M = 26$. Let $r_{i,t}^{j}$ be the $j$th overnight or intraday simple return for firm $i$ on day $t$, where $j = 1, 2, \ldots, M$. We compute the daily news and non-news returns for firm $i$ and day $t$ as follows:

$$R_{i,t,news} = \prod_{j=1}^{M}(1 + r_{i,t,news}^{j}) - 1, \quad R_{i,t,non\text{-}news} = \prod_{j=1}^{M}(1 + r_{i,t,non\text{-}news}^{j}) - 1, \tag{1}$$

where $r_{i,t,news}^{j} = r_{i,t}^{j}$ if there is a news story in the interval $j$ and 0 otherwise, and $r_{i,t,non\text{-}news}^{j} = r_{i,t}^{j}$ if there is no news story in the interval $j$ and 0 otherwise. Clearly, the daily overall return is the product of news and non-news returns, namely,

$$R_{i,t,overall} = (1 + R_{i,t,news}) \times (1 + R_{i,t,non\text{-}news}) - 1.$$

We construct a set of control variables according to standard definitions in the literature. Market value of equity ($Size$) is the product of the closing price and the number of shares outstanding, updated daily from CRSP. Book-to-market ratio ($BM$) in June of year $t$ is computed as the ratio of the book value of common equity in fiscal year $t - 1$ to the market value of equity in December of year $t - 1$ and is updated every year. Momentum ($Mom$) is the cumulative returns from day $t - 252$ to day $t - 21$ for a given day $t$ and is updated daily. Analyst coverage ($Analyst$) is the monthly number of sell-side analysts forecasting annual firm earnings. Realized volatility ($RVOL$) is defined as the square root of the annualized realized variance, which is 252 times the sum of squared 5-minute intraday returns within each trading day. Illiquidity ($ILLQ$) is the Amihud measure of illiquidity (Amihud, 2002), which is the average daily ratio of the absolute stock return to the dollar trading volume over the five-day period preceding each day.

Table 1 provides descriptive statistics for these variables. In Panel A, the mean, standard deviation, and five quantiles are first computed cross-sectionally and then averaged over time. Since our interest is in market reaction to firm-level news, we require at least one news story for a given firm in a given day to be included in the computation of daily news return $R_{news}$. For a firm-day pair without relevant news stories, the entire daily return is non-news return $R_{non-news}$. The results indicate that the average news return is 0.18% per day as compared with the 0.06% per day for the average non-news return. The cross-sectional dispersion of news returns measured by their cross-sectional standard deviation is 4.33%, which is larger than the dispersion of 3.31% for the non-news returns. Panel B shows the average cross-sectional correlations among our key variables. It indicates a moderate correlation between news and non-news returns. Their correlations with firm characteristics are generally low. The correlation structure among firm characteristics is consistent with previous literature. For instance, we find that smaller firms tend to lower analyst coverage, higher volatility, and less liquidity.

# 3 News Momentum

## 3.1 Portfolio Sorts

We start by testing the profitability of a news momentum strategy designed to exploit short-term market reactions to firm-level news. Figure 2 shows the timeline for our strategy. At the 4:00 p.m. market close of each trading day $t$, we sort stocks into decile portfolios based on their news returns on day $t$, $R_{i,t,news}$.[4] We compute the equal-weighted returns for each decile portfolio and a self-financing strategy that buys stocks in the top decile with high news returns and sells stocks in the bottom decile with low news returns with a one-week holding period until market close of day $t+5$. To increase the power of our tests, we follow Jegadeesh and Titman (1993) by using portfolios with overlapping holding periods. That is, we revise the weights on one-fifth of the securities in our news momentum strategy on any given day and carry over the rest from the previous day, resulting in non-overlapping series of portfolio returns throughout calendar days.

Panel A of Table 2 summarizes the portfolio returns, which are converted to monthly returns by multiplying daily returns by 21 for the ease of interpretation. The row labeled "Return" reports average realized returns of each equal-weighted decile portfolio. It shows a monotonically increasing relation between news returns and future stock returns. The average monthly return increases from $-0.78\%$ for the loser portfolio in decile 1 to 2.55% for the winner portfolio in decile 10, yielding a return of 3.34% per month with a $t$-statistic of 11.72. Stated in annual terms, the news momentum strategy generates a return of 40.08% per year and an annualized Sharpe ratio of around 3.29.

To determine whether the return of our news momentum strategy results from their exposures

[4] Only firms with news arrivals on day $t$ enter into portfolio formation. On average, there are approximately 280 firms with news per day.

to other return factors, especially the price momentum factor, we use the popular Fama-French-Carhart four (FFC4) factors (Fama and French, 1993; Carhart, 1997) to control for the risk exposures of news momentum. Specifically, we regress excess returns of each decile portfolio along with the long-short news momentum strategy against the FFC4 factors and compute the regression intercepts, which are named as FFC4 alphas. The row labeled "FFC4" in Panel A of Table 2 shows a similarly strong positive relation between news returns and abnormal future returns in terms of FFC4 alphas. The FFC4 alpha of the news momentum strategy is 3.37% per month and remains highly significant with a $t$-statistic of 11.76.

The similar magnitudes between raw and abnormal returns of the news momentum strategy are explained by the low exposures of the strategy to the four factors, as shown in Panel B of Table 2, which indicates that the news momentum strategy has statistically insignificant loadings on the market, size, and value factors. The only statistically significant exposure of the news momentum strategy is to Jegadeesh and Titman (1993)'s medium-term price momentum factor, with positive sign but a weak magnitude of only 0.06.

A number of studies have emphasized the "crash" in returns of the price momentum strategies, e.g., in early 2009 (Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016). How does our news momentum strategy perform through time? Figure 3 tracks the performance of the news momentum strategy over our sample period. Specifically, we compound the daily returns of the news momentum portfolios over time and measure the cumulative profit $W_t$ on day $t$ as follows:

$$W_t = W_{t-1} \times (1 + R_{winner,t} - R_{loser,t} + R_{rf,t}), \quad t = 1, 2, \ldots,$$

where $R_{winner,t}$, $R_{loser,t}$ and $R_{rf,t}$ are returns of the winner portfolio in decile 10, returns of the loser portfolio in decile 1, and the risk-free rate on day $t$, respectively. In Figure 3, the $y$-axis presents the dollar value given $W_0 = \$1$ initial investment at the start of March 2000. Note that the news momentum strategy generates superior performance throughout our sample period without experiencing major drawdowns. The maximum drawdown is approximately 15.92%, which took place at the start of the sample during a short period between March 8, 2000, and May 04, 2000. Furthermore, our news momentum strategy appears to avoid the severe crash that nearly wiped out the capital of traders on the traditional medium-term price momentum in early 2009.[5]

How long does the news momentum effect persist? We answer this question by computing the cumulative news momentum profits following an event study approach. For each portfolio formation day $t$, we form decile portfolios based on day $t$'s news returns $R_{i,t,news}$ at the end of day $t$, and then compute the cumulative returns from day $t+1$ to day $t+k$ for each decile portfolio. The spread between the cumulative returns in deciles 10 and 1 then forms a time series of cumulative profits of winner-minus-loser portfolios for the event day $k$. To draw inference about these cumulative profits, we aggregate them through time to compute their average and the associated confidence intervals for a given event time $k$. By construction, there are $k-1$ days of overlap between any two consecutive observations of the spread series, so we use Newey-West (1987) robust standard errors with lag $k-1$. For comparison, we perform a similar exercise by forming portfolios based on past non-news returns.

The upper and lower solid curves in Figure 1 plot the average cumulative profits for strategies that buy winners and sell losers using news and non-news returns, respectively, against the event day $k$ for up to 252 days after portfolio formation. The results are striking. The news momentum strategy continues to generate higher returns for up to 252 days after portfolio formation, which is consistent with delayed investor reaction to initial news and a gradual adjustment in prices. In contrast, non-news return experiences a subsequent reversal, which leads the strategy of buying winners and selling losers to generate negative returns. This reversal takes place gradually and remains statistically significant for approximately 75 days after portfolio formation. In our sample period (2000–2012), we do not observe the shift in sign for the short-term reversal to medium-term momentum as Gutierrez and Kelley (2008) observe, most likely due to the momentum crashes that mitigate the medium-term price momentum effect over our sample period.

## 3.2 Fama-MacBeth (1973) Regressions

In this subsection, we examine the news momentum using the method of Fama and MacBeth (1973). Specifically, for each day $t$, we perform the following cross-sectional regressions:

[5] For instance, Daniel and Moskowitz (2016) report that the price momentum strategy lost 42.28% and 45.52% in March and April of 2009, respectively.

$$R_{i,t+1:t+5,overall} = \gamma_{0,t} + \gamma_{news,t} R_{i,t,news} + \gamma_{non\text{-}news,t} R_{i,t,non\text{-}news} + \sum_{j=1}^{p} \gamma_{j,t} Z_{j,i,t} + \epsilon_{i,t}, \quad (2)$$

where $R_{i,t+1:t+5,overall}$ is the cumulative overall return from day $t+1$ to day $t+5$, and the news return $R_{i,t,news}$, the non-news return $R_{i,t,non\text{-}news}$, and the control variables $Z_{j,i,t}$ are all measured at the end of each day $t$ for firm $i$. For each day $t$, we obtain the slope coefficients from these cross-sectional regressions. We compute the time-series average of each slope coefficient to test if the predicting variables are statistically significant in forecasting the five-day-ahead returns. Our control variables include firm size, the book-to-market ratio, stock returns from day $t-252$ to day $t-21$ as a proxy for stock price momentum, analyst coverage, realized volatility, and the prior day illiquidity measure of Amihud (2002). Because the dependent variable has overlapping returns of four days, we use the Newey-West (1987) procedure with four lags to adjust for serial correlation in the time series of the slope coefficients. In these regressions, we use all the 5,480 firms that have at least one news story over the period between March 2000 and October 2012, a universe more comprehensive than that for the portfolio sorts.

Table 3 reports estimated regression coefficients and $t$-statistics under several model specifications. Consistent with portfolio analyses, the results show that news returns have positive predictive power for the five-day-ahead overall returns. The average slope coefficient for news returns in Regression (I) indicates that 4.25% of the prior day's news return carries over into the following week's overall return. The results remain intact after controlling for other predicting variables. The magnitude of news momentum is in the range of 4.25% with a $t$-statistic of 8.28 in Regression (I) and 6.14% with a $t$-statistic of 10.64 in Regression (IV). To get a sense of economic significance, note that Table 1 shows the average cross-sectional standard deviation of daily news return is 4.33%. Therefore, a two-standard-deviation increase in news returns predicts a rise of approximately 27.65% ($2 \times 4.33\% \times 0.0614 \times 52$) per annum in future returns. In contrast, the non-news returns tend to reverse in the subsequent week. Among the control variables, book-to-market ratio, analyst coverage and realized volatility have positive and statistically significant slope coefficients, and firm size is negatively related to future returns, all of which are consistent with previous literature. In summary, the Fama-MacBeth regressions lend further support to the strong news momentum effect in stock returns.

# 4 What Drives News Momentum?

## 4.1 Decomposing News Momentum Profits

The high return to the news momentum strategy can arise from several sources. To better understand its nature, we follow Lo and MacKinlay (1990), decomposing the expected news momentum profit into three components: the average autocovariance of individual stock returns, the average cross-autocovariance across stocks, and the cross-sectional variance in expected stock returns (see also Lehmann (1990); Lewellen (2002); Nagel (2012)). The first component captures the serial correlation in individual stock returns: A positive value is consistent with the market underreaction hypothesis for news momentum (because we have found evidence against the hypothesis of delayed overreaction). The second component reflects the lead-lag effects across stocks: If the average cross-autocovariance among stocks is positive (e.g., returns of large stocks lead those of small stocks due to their higher liquidity), it would reduce the return to the news momentum strategy. The last component reflects the cross-sectional dispersion in expected stock returns: If news momentum strategy systematically picks up more risky stocks with higher expected returns, a high average return could thereby emerge. Clearly, these different components associate with very different interpretations. Examining which source drives the return to the news momentum strategy thus illuminates the nature of the news momentum effect.

Following Lo and MacKinlay (1990), we consider a news momentum strategy with the following portfolio weights:

$$w_{i,t} = \frac{1}{N}(R_{i,t,news} - R_{m,t,news}),$$

where $R_{m,t,news} = (\sum_{i=1}^{N} R_{i,t,news})/N$ is the average news-driven return on day $t$. The portfolio return on day $t+1$ equals:

$$\pi_{t+1} = \sum_{i=1}^{N} w_{i,t} R_{i,t+1,overall} = \frac{1}{N}\sum_{i=1}^{N}(R_{i,t,news} - R_{m,t,news})R_{i,t+1,overall}.$$

We can then show that the expected news momentum profit equals the sum of three components:

$$\mathrm{E}(\pi_{t+1}) \quad = \quad \frac{N-1}{N^2}\mathrm{tr}(\Gamma) - \frac{1}{N^2}[1'\Gamma 1 - \mathrm{tr}(\Gamma)] + \mathrm{Cov}(\mu_{news}, \mu_{overall}), \tag{3}$$

where $\Gamma = \text{Cov}(R_{t,news}, R_{t+1,overall})$ is the covariance matrix between news-driven return $R_{t,news}$ and the overall return $R_{t+1,overall}$, and $\text{Cov}(\mu_{news}, \mu_{overall})$ is the cross-sectional covariance between average news returns and overall returns.

Eq. (3) shows that there are three possible sources of the news momentum profit. The first term, $\frac{N-1}{N^2}\text{tr}(\Gamma)$, is the average autocovariance of individual stocks. It is positive when individual stocks with high past news-driven returns tend to have high overall returns in the future. The second term, $-\frac{1}{N^2}[1'\Gamma 1 - \text{tr}(\Gamma)]$, is the negative of the average cross-autocovariance. It is positive when there is on average a negative cross-autocovariance (e.g., good news for one company leads bad news for another company). The third term, $\text{Cov}(\mu_{news}, \mu_{overall})$, is the cross-sectional covariance of average news returns and average total returns, which captures the dispersion in expected returns associated with news returns. It is positive when firms with high news returns tend to have high expected returns.

Our empirical implementation of this decomposition follows Lehmann (1990) and Nagel (2012), using scaled portfolio weights to ensure that the portfolio is \$1 long and \$1 short, with the magnitude of profits more interpretable:

$$w_{i,t} = \frac{1}{C_t}(R_{i,t,news} - R_{m,t,news}),$$

where $C_t = (\sum_{i=1}^{N} |R_{i,t,news} - R_{m,t,news}|)/2$ is the normalizing constant.

The first row in Panel A of Table 4 shows the decomposition results, which are consistent with the underreaction hypothesis. The total return to the news momentum strategy is 3.79% per month, almost all of which comes from the first, autocovariance component. The total return and the autocovariance component are also highly significant with Newey-West $t$-statistics of 6.03 and 5.29, respectively. In contrast, the second (cross-autocovariance) and third (dispersion in expected returns) components are close to zero. When we compute the four-factor alpha for the total news momentum return and the three components in the first row of Panel B, we obtain similar findings. The result that the positive autocovariance in individual stock returns drives news momentum supports the hypothesis of market underreaction.

One limitation of the decomposition using individual stocks is that it requires complete observations of stocks over the entire sample period. The resulting restriction is that we have only 970 stocks for this analysis. To improve the power of our test and mitigate the concern of potential survivorship bias, we also consider an industry-level news momentum strategy. In particular, we construct news-driven and overall returns of industry portfolios by first classifying stocks into the Fama and French (1997) seventeen sectors.[6] Each day, we calculate the industry news-driven return as the average news-driven returns of all firms within an industry, and the industry overall return as the average return of all firms within the same industry.

The industry news momentum strategy also indicates underreaction as the driving factor for the news momentum. As the second row labeled "Industry Portfolio" in Panel A of Table 4 shows, the industry news momentum earns a total monthly return of 1.09%, to which the first component, autocovariance, contributes a positive monthly return of 2.07%. In contrast, the second component, which captures the lead-lag effect across industries, contributes a return of −0.98% per month, and the third component, dispersion in expected industry returns, contributes a return of 0.01% per month. Panel B of Table 4 shows the results based on the four-factor alpha, which generate a similar pattern.

### 4.2 Inattention Hypothesis

The inattention hypothesis builds on the idea of bounded rationality of investors, who have finite cognitive ability. As a result, it is difficult for them to immediately process every bit of news to fully understand its implication for firm value, which results in underreaction. As discussed in the introduction, there is an extensive empirical literature reporting inattention as a driving force of underreaction to various specific pieces of news. This motivates us to examine how news momentum is related to investor inattention.

We start our empirical tests by testing for time-varying inattention. First, there are periods when aggregate uncertainty spikes, which could drive the scarce investor attention away from firm-specific news. In this scenario, we should observe stronger news momentum following the spike in aggregate uncertainty. To test for this hypothesis, we use the Chicago Board Options Exchange Volatility Index (VIX) to predict returns to the news momentum strategy. Panel A of Table 5 shows that when VIX increases by one standard deviation, the news momentum return increases by 3.36 bps in the following day, which is 21% of the 15.9 bps average daily news momentum return.

[6] We obtain qualitatively similar results using the Fama and French 10 and 12 industry classifications, and the 20 industry portfolios used by Moskowitz and Grinblatt (1999).

This effect is statistically significant and robust to controlling for the four factor model.

Second, we test for the hypothesis that inattention may be stronger to news arriving on Friday and during the weekend (DellaVigna and Pollet, 2009). To have a clean test of this idea, we construct a news momentum strategy that buys (sells) stocks with the highest (lowest) news return in the previous day with a one-day holding period. Then, we regress daily returns to this strategy on (1) five dummy variables that represent each day of the week without an intercept, or (2) a dummy variable of Monday with an intercept. The results in Panel B of Table 5 show supporting evidence. In Column (I), the coefficient for the Monday dummy is 65 bps per day, which is the largest among the five weekdays; it is more than twice as large as the coefficient for Tuesday, which is 28 bps per day. Column (II) presents a formal statistical test on the equality of news momentum returns on Monday and other days. The slope coefficient for the Monday dummy is 23 bps per day, with a $t$-statistic of 2.84. These results suggest stronger market underreaction to Friday and weekend news.

To test for cross-sectional variation in inattention, we use the test design of Hirshleifer et al. (2009). Specifically, we focus on the number of news stories for firms outside the industry of a given firm, i.e., the so-called unrelated firm news. The idea is that a larger number of news stories for unrelated firms tend to distract investor attention to the news story of a given firm on the same day, leading to stronger underreaction. The results of Table 6 provide supporting evidence for this hypothesis. The coefficients of interest are those on $R_{news} \times UnrelatedNews$, which are positive and significant across different return forecasting horizons; they show that firm news that coincides with more news stories about firms in different industries is associated with a larger drift in stock prices. On the other hand, news from other firms in the same industry (i.e., related firm news) does not exhibit such a distraction effect. These results are consistent with those in Hirshleifer et al. (2009). Together, the time-series and cross-sectional evidence supports inattention as an important driver of the news momentum effect.

### 4.3 Slow Adjustments of Market Expectations

We next examine a second hypothesis that features variation in market expectations following firm news arrivals. In particular, we study whether and how analyst expectations of future earnings change after news events. We find that financial analysts tend to revise their earning forecasts after receiving news reports over the past few days in the direction of the news sentiment. Since analyst earnings forecast revisions tend to associate with abnormal movements in stock prices contemporaneously, the delayed reaction of financial analysts appears to be a driving force of news momentum. Interestingly, we also find that revisions in analyst earnings forecasts tend to positively predict subsequent earnings surprises. This evidence suggests that analysts tend to have sticky beliefs, which can further contribute to underreaction and news momentum.

First, to investigate whether analyst expectations of future earnings change after news events, we regress the daily log-transformed number of quarterly earnings forecast revisions on lagged news dummies.[7] Panel A of Table 7 shows that the lagged 1-day and 2-day news dummies positively and significantly predict the number of analysts revising their forecasts over the subsequent day. To distinguish the effects of positive and negative news, in Panel B, we use past positive news dummies to predict the number of analysts revising their forecasts upward, and find similar results as in Panel A. In Panel C, we document a stronger effect of past negative news dummies predicting the number of analysts revising their forecasts downward. Specifically, the lagged 3-day negative news dummy becomes statistically significant in predicting the number of analysts revising their forecasts downward, consistent with the idea that bad news tends to travel slowly.

In Table 8, we examine the determinants of analyst earnings forecast revisions by regressing the revisions over day $t$ on news and non-news returns over the past three days and other firm characteristics. The dependent variable *Forecast Revision* is defined as an analyst's quarterly earnings forecast on day $t$ minus the previous forecast of the same analyst in the same earnings cycle scaled by share price on day $t-2$. The results show that although both past news and non-news returns significantly predict analyst forecast revisions in the same direction, the predictive power of past news returns is nearly three times as strong as that of non-news returns, based on the magnitudes of the regression coefficients. This result is consistent with the idea that non-news returns, albeit noisier than news returns, contain useful information about changes in a firm's fundamentals, which are picked up by financial analysts in revising their earnings expectations.

Panel A of Table 9 further demonstrates that both the abnormal return on the analyst revision date and the three-day cumulative abnormal return around it are positively associated with analyst earnings forecast revisions. In combination with the preceding results, it shows that the delayed

[7] Hoechle et al. (2015) discussed the time stamp errors in I/B/E/S. According to their Table 7, there is not much delay in analyst earnings forecast after 2003 and thus all our analyses in this subsection focus on the post-2003 period.

reaction of financial analysts to past news may be a driving force of news momentum. Interestingly, in Panel B of Table 9, we also find that analyst earnings forecast revisions tend to positively predict subsequent earnings surprises and the cumulative abnormal return surrounding the announcement date, which further corroborates the long-lasting news momentum exhibited in Figure 1.

At first glance, the result that non-news return positively predicts analyst earnings forecast revisions as shown in Table 8 seems to contradict the result in Table 3, in which non-news return negatively predicts future returns. To shed light on this issue, we split the main sample used in Table 3 into two sub-samples: one in which there is no analyst forecast revision during the five-day holding period, and another in which there is at least one analyst earnings forecast revision during the five-day holding period. Because analyst forecast revision date prior to 2003 is less accurate, we use data from January 2003 for this analysis. Table A.1 reports the Fama-MacBeth cross-sectional regressions for these two sub-samples. The results indicate that non-news returns negatively predict future returns when no analysts revise their earnings forecast in the following week; when there is at least one analyst revising her earnings forecast in the next week, non-news returns positively predict future returns.

# 5 The Case of Overnight News

The news momentum strategy uses news returns computed from market close on day $t-1$ to market close on day $t$; the portfolios are formed immediately and held for the next five days. In terms of information usage, it tends to rely more on the relatively fresh intraday news that arrives when market opens on day $t$, but less on the relatively stale overnight news that arrives after market closes on day $t-1$. Is it possible that the market underreacts more to overnight news when it closes? In this section, we focus on overnight news, which has received relatively little attention in the literature. Using an intraday event study approach, we find compelling evidence for delayed reaction to overnight news, which constitutes more than half of our sample. It lends further support to underreaction as the main driver of news momentum.

Specifically, to investigate potential delayed reaction to overnight news, at 10:00 a.m. on each trading day $t$, we sort news returns computed from the close of day $t-1$ to 9:45 a.m. of day $t$ into deciles and then hold the winner-minus-loser portfolio for the subsequent five trading days.[8] We

[8]We skip the return between 9:45 a.m. and 10:00 a.m. to reduce the contamination induced by microstructure

report the cumulative overall returns every 30 minute from 10 a.m. on day $t$ to 4:00 p.m. on day $t + 4$. For comparison, we perform a similar exercise using the overnight non-news returns.

Panel A in Figure 4 plots the time-series averages and 95% confidence intervals against the event time for the two strategies and highlights the difference in post-formation return patterns. Immediately after the portfolio construction at 10:00 a.m., the overnight news momentum gradually increases to 25 bps at 3:30 p.m. and then slightly drops to 17 bps at the 4:00 p.m. close. After the following overnight period, the overnight news momentum sharply rises to 59 bps at 9:45 a.m. after market opens and keeps rising for every overnight period on the subsequent event days. Interestingly, except for event days 1 and 2, the overnight news momentum produces small spreads during the open-to-close periods.[9] The average five-day return in investing in the overnight news has a large spread of 104 bps, substantially larger than the average five-day cumulative return of 88 bps shown in Figure 1, where the impact of the overnight news on the immediate open-to-close period is ignored.

The overnight non-news returns, in contrast, immediately induce a gradual reversal until the 4 p.m. close and then exhibit a momentum pattern during the subsequent overnight periods that offsets some of the intraday reversal. This pattern repeats itself on every subsequent event day. When aggregated, the intraday reversal part dominates the overnight momentum, and the average five-day return in investing in the overnight non-news reversal is 52 bps.

Despite the overall patterns of overnight news momentum and non-news reversal, Panel A of Figure 4 also shows that both types of overnight returns continue during the overnight period in the following days, consistent with the intraday periodicity pattern of Heston et al. (2010).[10] This overnight return periodicity suggests that controlling for it might help tease out the news momentum effect more clearly. To do so, we employ a matched sample procedure as follows. At 10:00 a.m. on every trading day and for every overnight news return, we find one non-news return with the smallest return differences. By using this matched sample, we can compare the predictability of the news- and non-news-driven overnight returns of similar magnitude, reducing the confounding effect

effects such as bid-ask bounce.

[9]Lou et al. (2018) finds that returns of the price momentum strategy based on past 12-month returns tend to accrue overnight. Although a substantial part of our overnight news momentum profits also manifest during the overnight holding period, the intraday component of the overnight news momentum strategy is also statistically and economically significant. For example, Figure 4 suggests that, of the 104 bps of five-day cumulative returns, 17 and 12 bps accrue during the first and second intraday periods, respectively.

[10]Heston et al. (2010) excludes overnight close-to-open price movements from their analysis and documents a striking pattern of return continuation at half-hour intervals that are exact multiples of a trading day.

of the return periodicity. We sort these matched non-news returns for constructing the winner-minus-loser portfolio and then subtract the cumulative return of the winner-minus-loser portfolio based on sorting matched non-news returns from the cumulative return of the winner-minus-loser portfolio based on sorting news returns over the same holding period. These differences constitute the abnormal overnight news momentum adjusted by the return periodicity. For a given event time, we compute the average of the time series of these abnormal returns and its 95% confidence interval in Panel B of Figure 4. Note that the abnormal overnight news momentum based on the adjustment of the matched portfolio remains strong. Overall, the average five-day abnormal news momentum profit is 221 bps, highly statistically significant as indicated by the tight confidence intervals. The abnormal profit is especially prominent during the intraday period when the news-driven returns generate momentum while the matched non-news driven returns generate reversal. The abnormal profit, however, dips during the overnight periods starting at 4:00 p.m. of each day, suggesting that the return periodicity of Heston et al. (2010) absorbs the overnight news momentum profits accrued during the overnight period.

# 6 Robustness Tests

## 6.1 CRSP Data

Our main return sample consists of overnight and 15-minute intraday returns computed from the transaction prices available in the TAQ database. This choice of high-frequency returns is relatively new and differs from the majority of existing literature on either news or momentum, which typically relies on lower-frequency returns at, for example, daily or monthly frequencies. An advantage of the higher-frequency data is that it enables a sharper distinction between news-driven and non-news driven returns, which in turn enhances the ability to separate the different reactions to information and non-information based price changes. However, a possible concern of high-frequency data is that it is noisy in several ways. First, not only do the well-known microstructure issues such as bid-ask bounce and stale price cause the observed returns to be less informative about the real underlying price process, but data recording errors are also likely to appear in the raw intraday data, yielding anomalous returns.[11] Second, it is possible that the news time stamp is imprecise

[11]We implement a set of clearing rules commonly used in high-frequency econometrics literature to eliminate possible errors in the high-frequency data.

about the actual news release time or more importantly the true information event. However, as Tetlock (2010) argues, news and information events usually occur on the same day, so the recorded news event and the true information event might be synchronous at the daily level. Thus, it would be useful to determine if the news momentum discovered from TAQ is sensitive to the sampling frequency and whether high-frequency data enhances or diminishes the findings over the daily return data.

We use the daily CRSP data to repeat the single-sort analysis in Section 3.1. In particular, for the predictor of news returns, we classify the distribution adjusted close-to-close daily returns from CRSP into news and non-news categories based on whether at least one news event occurred during the close-to-close period. In the notation of Equation (1), $M$ becomes 1 because there is only one observation per day, and we define future overall returns to be predicted using the CRSP daily returns. We then sort the five-day-ahead overall returns into decile portfolios using the previous one-day news return. Panel A of Table 10 displays the average monthly returns of portfolios in the same format as Panel A of Table 2.

The news momentum pattern remains in those daily returns. The winner-minus-loser portfolio generates a monthly risk-adjusted average return of 1.98% with a $t$-statistic of 6.05. However, recall that the risk-adjusted spread from sorting news returns constructed from the higher-frequency data is 3.37% per month ($t$-statistic=11.76) in Panel A of Table 2. The spread magnitude and statistical significance constructed from sorting daily or coarser frequency returns are much weaker than those obtained from sorting high-frequency returns. We also replaced the predictor of news returns based on daily data with those based on high-frequency data while keeping the response variable of overall returns based on CRSP data. The same portfolio strategy generates a risk-adjusted monthly spread of 3.48% with a $t$-statistic of 12.15 (untabulated). Our usage of the new measure of news returns purges this component out of the daily news-driven return and is thus crucial in building stronger news momentum strategy.

### 6.2 Mid-Quote Returns

Return data of frequency from 15 minutes to one week computed from transaction data might contain measurement errors arising from microstructure noises. Measurement errors threaten inferences based on transaction return data alone. A stylized example is the spurious reversal pattern due to negative autocorrelation induced by bid-ask bounce at shorter horizons (Roll, 1984), for which, returns of quoted prices are commonly used to address the issue (e.g., Kaul and Nimalendran 1990; Gutierrez and Kelley 2008). However, it is unlikely that the news momentum pattern is driven by microstructure noise such as bid-ask bounce and non-synchronous trading. Indeed, negative autocorrelations due to bid-ask bounce and positive cross-correlations due to non-synchronous trading both contribute to the cross-sectional return reversal pattern rather than the momentum pattern documented here. Nevertheless, it is useful, at least from a practical point of view, to investigate the news momentum patterns using quoted prices. We carry out such analysis by first computing the overnight and 15-minute returns using the mid-quote price and then aggregating them into news and non-news returns according to Equation (1). We repeat the calendar time strategy of Section 3.1 for these returns computed from quoted prices (summarized in Panel B of Table 10). We find that the news momentum pattern remains intact when returns are formed from mid-quote prices. The winner-minus-loser portfolio generates a monthly alpha of 3.42% with a $t$-statistic of 12.75 – remarkably similar to the profitability of 3.37% per month and a $t$-statistic of 11.76 reported in Table 2 from the transaction data.

### 6.3 Open-to-Open Returns

The main results in Section 3 demonstrate the predictability of news returns aggregated over the close-to-close period on the subsequent five-day close-to-close overall returns. Using close-to-close returns make the results more sensitive to the intraday information than the overnight information. An interesting question is to investigate the performance of the news momentum strategy using the open-to-open returns to allow for more overnight effects. To do so, we compute the news returns accumulated over the period from 9:45 a.m. on day $t-1$ to 9:45 a.m. on day $t$ and use them to forecast the five-day ahead overall returns computed from 10:00 a.m. on day $t$ to 10:00 a.m. on day $t+5$. We repeat the same decile portfolio strategies as in Section 3.1 and summarize their returns and FFC4 alphas in Panel C of Table 10. The average winner-minus-loser spread of the decile portfolios based on open-to-open returns is 3.92% per month with a robust $t$-statistic of 12.91. The alpha of the strategy controlling for the four factors is 3.94% per month with a $t$-statistic of 13.03. These performance measures are slightly higher than their counterparts in Table 2, which are based on close-to-close returns.

### 6.4 Firm-Specific News Return

The main results in Section 3 sort stocks by their cumulative news returns, which do not adjust for the riskiness of the stocks. To determine whether doing so would affect our findings, we now identify news momentum based on risk-adjusted news returns. We use the pre-event returns to estimate the regression models as follows:

$$R_{i,t,overall} - R_{rf,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + \epsilon_{i,t},$$

where $R_{i,t,overall}$ is firm $i$'s overall daily return, $R_{m,t}$ is the market return, and $R_{rf,t}$ is the risk-free rate. We fit the model using a rolling OLS approach with a window size of 252 days before the event day. We then compute the market-adjusted high-frequency returns $mr_{i,t}^j$ for firm $i$, interval $j$, and day $t$ as

$$mr_{i,t}^j = r_{i,t}^j - \beta_i r_{m,t}^j, \quad j = 1, 2, ..., M,$$

where $r_{i,t}^j$ and $r_{m,t}^j$ are the $j$th overnight or intraday simple return for firm $i$ and the market, respectively, on day $t$. We use the high-frequency return of the actively traded S&P 500 ETF (ticker SPY) as a proxy for $r_{m,t}^j$. We use the market-risk-adjusted returns $mr_{i,t}^j$ in place of signal construction of Equation (1) and repeat the single-sort analysis. Panel D of Table 10 shows the results of sorting by market-risk-adjusted returns. The effects of news momentum remain largely unchanged after adjusting for market risks. The High-Low spread and its $t$-statistic are close to those in Table 2, in which the market risk is unadjusted when constructing the signal.

### 6.5 Characteristic Adjustment

The single-sort exercise in Section 3.1 uses the Fama-French-Carhart factors for adjusting risks in the news momentum strategy returns. In this section, we implement the characteristic-based benchmark methods of Daniel et al. (1997) and Wermers (2003) as an alternative way to adjust for risks. We use the benchmark portfolio assignments to compute the equal-weighted daily $5\times5\times5$ size, book-to-market ratio, and momentum benchmark returns based on all NYSE/AMEX/NASDAQ data in the CRSP database.[12] A firm's benchmark adjusted return is then a firm's daily overall

[12]The benchmark assignments, updated monthly, are available via `http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm`. To compute daily returns of the benchmark portfolios, we convert this monthly assignment into daily frequency by assuming constant daily assignment within each month.

return minus the daily return of one of the 125 benchmarks to which the firm belongs to on that day. These benchmark-adjusted returns are used in place of the raw overall returns for repeating the single-sort exercise conducted in Section 3.1.

Panel E of Table 10 displays the results of sorting returns in excess of the characteristic-matched benchmark returns. The news momentum effect remains strong. The zero-cost winner-minus-loser portfolio generates a monthly return of 3.06% with a robust $t$-statistic of 11.14. This spread is slightly smaller than the spread of 3.34% for the raw returns in Table 2, suggesting some profits of news momentum might be attributable to portfolio characteristics.

### 6.6 Earnings Announcements

The news momentum pattern we document does not differentiate the types of news stories that could have different impacts on return continuation. It has long been shown that the announcement of earnings news tends to trigger a stock's returns to drift in the same direction of the earnings surprise for several weeks after the announcement (Ball and Brown, 1968; Bernard and Thomas, 1989). One explanation of the short-term news momentum pattern is that it is merely a reconfirmation of the post-earnings-announcement drift pattern and non-announcement observations contribute none to the momentum profits. If so, we should observe small positive return spreads after excluding the firm-trading day observations on the earnings announcement dates. Therefore, we construct news momentum portfolios as before except that we drop all firms that announce their earnings on the same day of the portfolio formation. We identify quarterly earnings announcement using the announcement dates from Compustat. Since the time stamp of the earnings announcement is unavailable in Compustat and earnings announcement can occur before, during, or after the regular trading hours, we are unable to match the returns that immediately reflect the information on earnings announcement. To conservatively remove the effect of earnings announcement, we exclude both the earnings announcement days and the days right after the announcement from our sample.

Panel F in Table 10 displays the resulting profits. The difference in average returns between the High and Low news return decile portfolios is 1.85% per month after adjusting for risks and has a robust $t$-statistic of 5.92. The earnings announcement cannot entirely account for the news momentum pattern. However, the fact that the spread and $t$-statistic are smaller than their counterparts produced by sorting all samples in Table 2 suggests that earnings announcement contributes substantially to the news momentum profits.

### 6.7 Extreme Price Changes

Savor (2012) studies large stock price movements with absolute daily returns exceeding 10%. He groups these extreme price movements to those accompanied with sell-side analyst recommendations and others without, and finds evidence of return drift following extreme price changes with analyst recommendations and reversal following those without analyst recommendations. In this subsection, we assess whether the pervasive news momentum effect we identify is sensitive to this type of extreme price movement.

Specifically, we test the return predictive power of news returns after excluding the firm-trading day observations with extreme price changes. Following Savor (2012), we first identify extreme price movements. We calculate a firm's daily abnormal returns relative to the four-factor model and classify a trading day for this firm into the set of extreme price changes if the daily abnormal return exceeds 10% in magnitude. We then track analyst recommendations from the I/B/E/S. If the price change is accompanied by at least five analyst recommendations issued during the previous 12 months, we consider it information driven. Our computation indicates that the set of information-based extreme price changes represents a small proportion of our sample. We exclude these observations from our sample and then compute the news momentum profits.

Panel G of Table 10 displays the results, which indicate that the news momentum effect remains strong after removing these extreme observations. The last column labeled "High–Low" shows the spread between the average returns of the winner and loser portfolios. The raw return spread is 2.93% per month with a $t$-statistic of 10.75, and the four-factor alpha is 2.97% per month with a $t$-statistic of 10.70.

### 6.8 News Clustering

To examine whether our results may be attributable to news clustering, i.e., positive (negative) news stories tend to be followed by positive (negative) news stories (see, e.g., Wang et al. (2018)), we change the computation of holding period returns to our news momentum strategy by including only non-news returns, which are not driven by news that arrives subsequently. Panel H of Table 10 reports the performance of the news momentum strategy using this metric. The results indicate that the news momentum effect remains strong, even when we consider only non-news-driven returns in the holding period. The column labeled "High–Low" shows the spread in average returns between the winner and loser portfolios, which is 2.85% per month with a $t$-statistic of 10.51; the four-factor alpha is 2.88% per month with a $t$-statistic of 10.53. Thus, news clustering alone could not explain the news momentum.

### 6.9 Drift After Headlines

Chan (2003) studies stock return patterns following the month with headline news. He finds evidence of post-news drift for stocks with headlines and reversal for stocks without identifiable news. In particular, he groups stocks into news and non-news sets based on if they had at least one news headline during a given month $t$, and finds that news stocks experience *less reversal* in month $t+1$ and then drift for most of the subsequent months in the following year. This predictive return profile actually differs from ours, where momentum already exists and is stronger at shorter horizons of hourly to daily holding periods, as evident in Figure 4. To formally illustrate the difference between Chan (2003)'s effect and ours, we replicate Chan (2003)'s strategy in our sample as follows.

At the end of each month, we consider a news group consisting of all stocks that have at least one news story during that month. We then sort them into ten portfolios based on their monthly return and compute the equal-weighted return of a self-financing portfolio that buys stocks in the top decile with high returns and sells stocks in the bottom decile with low returns with $K = 1$, 3, and 6 month holding periods. Following Jegadeesh and Titman (1993), this Chan (2003) strategy includes portfolios with overlapping holding periods. That is, we revise the weights on $\frac{1}{K}$ of the securities in our news momentum strategy in any given month and carry over the rest from the previous month.

Table 11 summarizes the portfolio returns in monthly percentage. The rows labeled "Return" and "FFC4" respectively report the average raw returns and Fama-French-Carhart four-factor alphas for each portfolio. The column labeled "10–1" reports the difference in returns between Portfolio 10 and Portfolio 1, with Newey-West robust $t$-statistics in parentheses. We see that Chan (2003)'s effect does not exist in our sample as returns seem to exhibit weakly reversal rather than momentum for those news stocks. The four-factor alphas are $-0.85\%, -0.44\%$ and $-0.27\%$ per month with $t$-statistics of $-1.74, -1.85$ and $-1.86$ for one-, three- and six-month holding periods, respectively.

## 7 Conclusion

We decompose daily stock returns into news- and non-news-driven components, using a comprehensive sample of high-frequency firm-level news arrivals. We find that news-driven returns tend to exhibit momentum, different from non-news returns that precede a reversal. A news momentum strategy that buys (sells) stocks with high (low) news returns generates a monthly return of 3.34% in the following week, with a four-factor alpha of 3.37%.

To understand the economic forces leading to the pervasive underreaction to firm news, we explore two related mechanisms: investor inattention due to bounded rationality and slow adjustments of market expectations following firm news. For the former hypothesis, we find supporting evidence that the news momentum effect is stronger when investors tend to be distracted. For the latter, we use analyst earnings forecasts and find that analysts are slow and incomplete in updating their earnings forecasts.

One promising avenue for future research is to study investor trading behavior around the arrival of firm news. For instance, it is possible that large institutions may be less willing to trade aggressively in response to firm news, in an attempt to reduce market impact. We plan to examine this issue in our future research.

# References


Amihud, Y. 2002. Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, 5:31–56.

Ball, R. and Brown, P. 1968. An empirical evaluation of accounting income numbers. *Journal of Accounting Research*, pages 159–178.

Barberis, N. C. 2018. Psychology-based models of asset prices and trading volume. Technical report, National Bureau of Economic Research.

Barndorff-Nielsen, O. E., Hansen, P. R., Lunde, A., and Shephard, N. 2009. Realized kernels in practice: trades and quotes. *The Econometrics Journal*, 12(3):1–32.

Barroso, P. and Santa-Clara, P. 2015. Momentum has its moments. *Journal of Financial Economics*, 116(1):111–120.

Bernard, V. L. and Thomas, J. K. 1989. Post-earnings-announcement drift: delayed price response or risk premium? *Journal of Accounting Research*, pages 1–36.

Bollerslev, T., Li, S. Z., and Todorov, V. 2016. Roughing up beta: continuous vs. discontinuous betas, and the cross-section of expected stock returns. *Journal of Financial Economics*, 120(3):464–490.

Bouchaud, J.-P., Krueger, P., Landier, A., and Thesmar, D. 2019. Sticky expectations and the profitability anomaly. *The Journal of Finance*, 74(2):639–674.

Carhart, M. 1997. On persistence in mutual fund performance. *The Journal of Finance*, 52:57–82.

Chan, W. S. 2003. Stock price reaction to news and no-news: drift and reversal after headlines. *Journal of Financial Economics*, 70(2):223–260.

Cohen, L., Diether, K., and Malloy, C. 2013. Misvaluing innovation. *The Review of Financial Studies*, 26(3):635–666.

Cohen, L. and Frazzini, A. 2008. Economic links and predictable returns. *The Journal of Finance*, 63(4):1977–2011.

Cohen, L. and Lou, D. 2012. Complicated firms. *Journal of financial economics*, 104(2):383–400.

Cohen, L., Malloy, C., and Nguyen, Q. 2018. Lazy prices. Technical report, National Bureau of Economic Research.

Coibion, O. and Gorodnichenko, Y. 2015. Information rigidity and the expectations formation process: A simple framework and new facts. *American Economic Review*, 105(8):2644–78.

Daniel, K., Grinblatt, M., Titman, S., and Wermers, R. 1997. Measuring mutual fund performance with characteristic-based benchmarks. *The Journal of Finance*, 52(3):1035–1058.

Daniel, K. D. and Moskowitz, T. J. 2016. Momentum crashes. *Journal of Financial Economics*, 122(2):221–247.

DellaVigna, S. and Pollet, J. M. 2009. Investor inattention and Friday earnings announcements. *The Journal of Finance*, 64(2):709–749.

Fama, E. F. 1970. Efficient capital markets: a review of theory and empirical work. *The Journal of Finance*, 25(2):383–417.

Fama, E. F. 1998. Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics*, 49(3):283–306.

Fama, E. F. and French, K. R. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33:3–56.

Fama, E. F. and French, K. R. 2015. A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22.

Fama, E. F. and MacBeth, J. D. 1973. Risk, return, and equilibrium: empirical tests. *Journal of Political Economy*, 81(3):607–636.

Green, J., Hand, J. R., and Zhang, X. F. 2017. The characteristics that provide independent information about average us monthly stock returns. *The Review of Financial Studies*, 30(12):4389–4436.

Gutierrez, R. C. and Kelley, E. K. 2008. The long-lasting momentum in weekly returns. *The Journal of Finance*, 63(1):415–447.

Harvey, C. R. 2017. Presidential address: The scientific outlook in financial economics. *The Journal of Finance*, 72(4):1399–1440.

Harvey, C. R., Liu, Y., and Zhu, H. 2016. ... and the cross-section of expected returns. *The Review of Financial Studies*, 29(1):5–68.

Heston, S. L., Korajczyk, R. A., and Sadka, R. 2010. Intraday patterns in the cross-section of stock returns. *The Journal of Finance*, 65(4):1369–1407.

Hirshleifer, D., Lim, S. S., and Teoh, S. H. 2009. Driven to distraction: extraneous events and underreaction to earnings news. *The Journal of Finance*, 64(5):2289–2325.

Hoechle, D., Schaub, N., and Schmid, M. 2015. Time stamp errors and the stock price reaction to analyst recommendation and forecast revisions. Working paper, Zurich University of Applied Sciences, and University of St. Gallen.

Jegadeesh, N. and Titman, S. 1993. Returns to buying winners and selling losers: implications for stock market efficiency. *The Journal of Finance*, 48:65–92.

Jegadeesh, N. and Titman, S. 2011. Momentum. *Annual Review of Financial Economics*, 3(1):493–509.

Jiang, H. and Sun, Z. 2015. News and corporate bond liquidity. Working paper, Michigan State University and University of California at Irvine.

Kaul, G. and Nimalendran, M. 1990. Price reversals: bid-ask errors or market overreaction? *Journal of Financial Economics*, 28(1):67–93.

Kelley, E. K. and Tetlock, P. C. 2017. Retail short selling and stock prices. *The Review of Financial Studies*, 30(3):801–834.

Lehmann, B. N. 1990. Fads, Martingales, and Market Efficiency. *Quarterly Journal of Economics*, 105:1–28.

Lewellen, J. 2002. Momentum and autocorrelation in stock returns. *Review of Financial Studies*, 15(2):533–564.

Lo, A. W. and MacKinlay, A. C. 1990. When are contrarian profits due to stock market overreaction? *Review of Financial Studies*, 3(2):175–205.

Lou, D., Polk, C., and Skouras, S. 2018. A tug of war: overnight versus intraday expected returns. *Journal of Financial Economics, forthcoming.*

Lucca, D. O. and Moench, E. 2015. The pre-FOMC announcement drift. *The Journal of Finance*, 70(1):329–371.

McLean, R. D. and Pontiff, J. 2016. Does academic research destroy stock return predictability? *The Journal of Finance*, 71(1):5–32.

Moskowitz, T. J. and Grinblatt, M. 1999. Do industries explain momentum? *The Journal of Finance*, 54(4):1249–1290.

Nagel, S. 2012. Evaporating liquidity. *Review of Financial Studies*, 25(7):2005–2039.

Patton, A. J. and Verardo, M. 2012. Does beta move with news? Firm-specific information flows and learning about profitability. *Review of Financial Studies*, 25(9):2789–2839.

Roll, R. 1984. A simple implicit measure of the effective bid-ask spread in an efficient market. *The Journal of Finance*, 39(4):1127–1139.

Savor, P. 2012. Stock returns after major price shocks: the impact of information. *Journal of Financial Economics*, 106(3):635–659.

Savor, P. and Wilson, M. 2013. How much do investors care about macroeconomic risk? Evidence from scheduled economic announcements. *Journal of Financial and Quantitative Analysis*, 48(2):343–375.

Savor, P. and Wilson, M. 2016. Earnings announcements and systematic risk. *The Journal of Finance*, 71(1):83–138.

Tetlock, P. C. 2010. Does public financial news resolve asymmetric information? *Review of Financial Studies*, 23(9):3520–3557.

Tetlock, P. C. 2011. All the news that's fit to reprint: Do investors react to stale information? *Review of Financial Studies*, 24(5):1481–1512.

Tetlock, P. C., Saar-Tsechansky, M., and Macskassy, S. 2008. More than words: quantifying language to measure firms' fundamentals. *The Journal of Finance*, 63(3):1437–1467.

Wang, Y., Zhang, B., and Zhu, X. 2018. The momentum of news. Working paper, Central University of Finance and Economics, University of New South Wales, and Shanghai University of Finance and Economics.

Wermers, R. 2003. Is money really 'smart'? New evidence on the relation between mutual fund flows, manager behavior, and performance persistence. Working paper, University of Maryland.

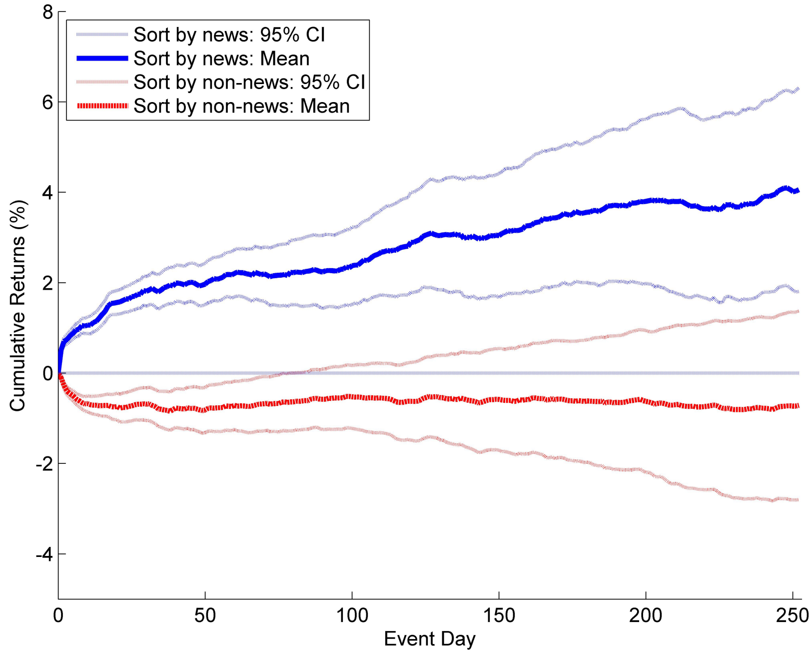


Figure 1: Performance of News Momentum Strategy over Event Time

This figure shows the cumulative returns and their 95% confidence intervals of news momentum and non-news reversal strategies for each event day. Specifically, at the end of each day $t$, we form decile portfolios based on day $t$'s news returns $R_{i,t,news}$ or non-news returns $R_{i,t,non\text{-}news}$ and then compute the cumulative overall returns from day $t+1$ to day $t+k$ for each decile portfolio and event day $k$. The spreads between the cumulative returns in the highest and lowest deciles are the cumulative profits of winner-minus-loser portfolios. Plotted are the average of the cumulative returns and its 95% confidence interval against the event day $k$.

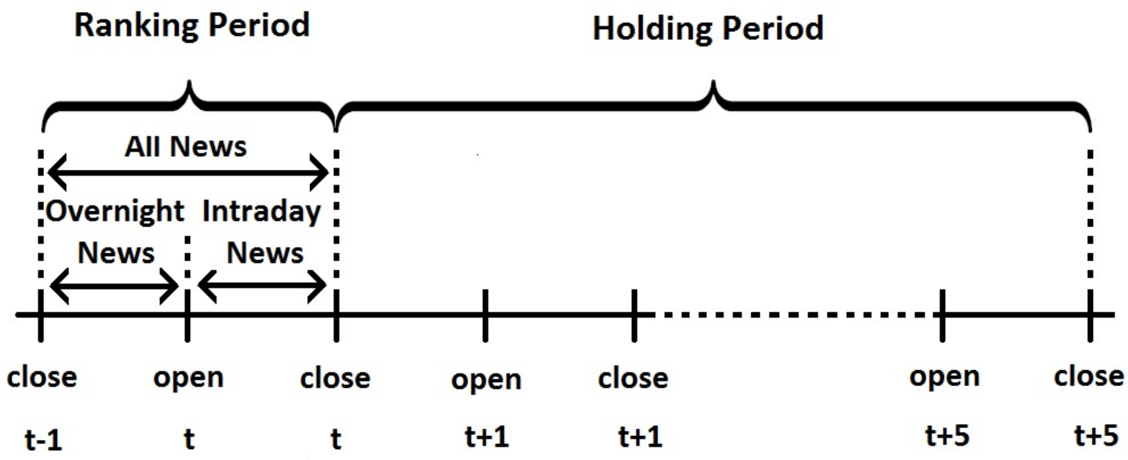


Figure 2: Timeline of News Momentum Strategy

This figure shows the timeline for the news momentum strategy. At the end (market close) of each day $t$, we sort stocks into decile portfolios based on their news returns on day $t$ ($R_{i,t,news}$) and compute the equal-weighted return of a self-financing portfolio that buys stocks in the top decile with high news returns and sells stocks in the bottom decile with low news returns with a one-week holding period until day $t+5$. Following Jegadeesh and Titman (1993), our news momentum strategy includes portfolios with overlapping holding periods. That is, we revise the weights on $\frac{1}{5}$ of the securities in our news momentum strategy on any given day and carry over the rest from the previous day.

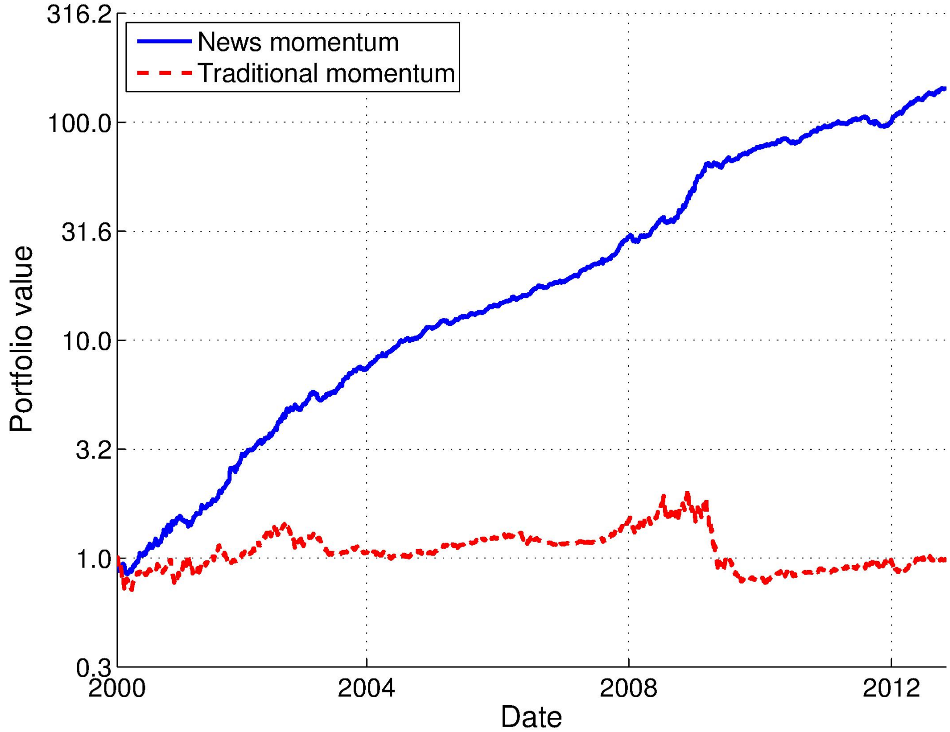


Figure 3: Performance of News Momentum Strategy

This figure shows cumulative gains of the news momentum strategy (the blue solid line) and the performance of the Jegadeesh and Titman (1993) momentum strategy (the red dotted line). At the end (market close) of each day $t$, we sort stocks into decile portfolios based on their news returns on day $t$ ($R_{i,t,news}$) and compute the equal-weighted return of a self-financing portfolio that buys stocks in the top decile with high news returns and sells stocks in the bottom decile with low news returns with a one-week holding period until day $t+5$. Following Jegadeesh and Titman (1993), our news momentum strategy includes portfolios with overlapping holding periods. That is, we revise the weights on $\frac{1}{5}$ of the securities in our news momentum strategy on any given day and carry over the rest from the previous day. Let $R_{winner,t+1}$ and $R_{loser,t+1}$ be the returns of the long and short legs of our news momentum strategy, respectively. The cumulative portfolio value is computed as $W_{t+1} = W_t(1 + R_{winner,t+1} - R_{loser,t+1} + R_{rf,t+1})$ where $R_{rf,t+1}$ is the risk-free rate on day $(t+1)$ and the initial investment is $W_1 = \$1$. Plotted is the time series of $\{W_t\}$. The return to the Jegadeesh and Titman (1993) momentum strategy based on past one year return and one month holding period comes from the data library of Ken French. The scale in the figure is based on the logarithm with base 10.

(a) (b)

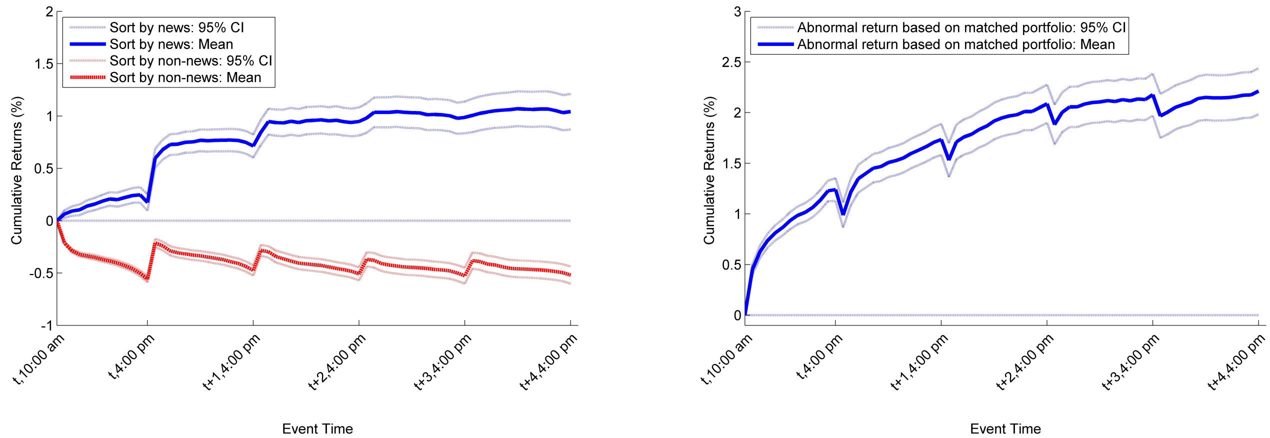


Figure 4: Overnight News Momentum Strategy over Event Time

Panel A shows the average gross cumulative returns to the news momentum strategies using the overnight news and non-news returns and their 95% confidence intervals over event time. Specifically, at 10:00 a.m. on each trading day $t$, we form decile portfolios based on the overnight news or non-news returns from the close of day $t-1$ to 9:45 a.m. of day $t$ and then compute the cumulative overall returns every 30 minute from 10 a.m. on day $t$ to 4:00 p.m. on day $t+4$. The average difference in cumulative returns between the highest and lowest deciles (the average cumulative return to the winner-minus-loser portfolio) is plotted against event time, with the 95% confidence intervals. Panel B uses a return-matching approach to examine the incremental value of news return, taking into account any mechanical return periodicity documented by Heston et al. (2010). Specifically, at 10:00 a.m. on each trading day $t$ and for every overnight news return, we find a stock with a similar magnitude of non-news return (with the smallest absolute value in return difference). Similar to the news momentum strategy, we construct a momentum strategy using this return-matched sample. We plot the difference in average cumulative returns between the two strategies over event time and the 95% confidence intervals.

Table 1: Descriptive Statistics

This table reports the descriptive statistics of our main variables. The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between March 2000 and October 2012 with share code 10 or 11, prices above $1 as of the portfolio formation, and at least one news story covered by the Dow Jones News Wire. Panel A reports the time-series average of the cross-sectional mean, standard deviation, and quantiles of each variable. Panel B reports the time-series average of the cross-sectional correlations of these variables. $R_{news}$ ($R_{non\text{-}news}$) is the daily news (non-news) return aggregated from overnight and intraday 15-minute news (non-news) returns using transaction prices from TAQ and news releases from the RavenPack database. *Size* is the product of the closing price and the number of shares outstanding, updated each day. *BM* is the book-to-market ratio in June of year $t$, which is computed as the ratio of the book value of common equity in fiscal year $t-1$ to the market value of equity in December of year $t-1$. *Mom* is the cumulative returns from prior day 252 to day 21 for a given day $t$. *Analyst* is analyst coverage, which is the number of sell-side analysts forecasting annual firm earnings in each month. $RVOL$ is realized volatility defined as the square root of the annualized realized variance, which is 252 times the sum of squared 5-minute intraday returns within each trading day. *ILLQ* is the illiquidity measure of Amihud (2002), which is the average daily ratio of the absolute stock return to the dollar trading volume over the five-day period preceding each day.

*Panel A: Cross-Sectional Summary Statistics*

| Variable | Mean | Std | P1 | P25 | Median | P75 | P99 |
|---|---|---|---|---|---|---|---|
| $R_{news}$ | 0.18% | 4.33% | -12.69% | -0.79% | 0.05% | 1.00% | 14.11% |
| $R_{non\text{-}news}$ | 0.06% | 3.31% | -8.38% | -1.37% | -0.03% | 1.34% | 9.93% |
| Log(Size) | 19.87 | 1.95 | 15.92 | 18.46 | 19.77 | 21.14 | 24.80 |
| BM | 0.78 | 1.29 | 0.03 | 0.33 | 0.57 | 0.92 | 3.95 |
| Mom | 6.84% | 39.43% | -99.32% | -14.33% | 7.19% | 28.35% | 110.51% |
| Analyst | 6.89 | 6.78 | 0.00 | 1.54 | 4.84 | 10.06 | 28.49 |
| RVOL | 68.29% | 22.37% | 35.17% | 52.74% | 63.82% | 78.74% | 142.26% |
| ILLQ | 0.32 | 3.19 | 0.00 | 0.00 | 0.01 | 0.05 | 6.10 |

*Panel B: Cross-Sectional Correlations*

| | $R_{news}$ | $R_{non\text{-}news}$ | Log(Size) | BM | Mom | Analyst | RVOL | ILLQ |
|---|---|---|---|---|---|---|---|---|
| $R_{news}$ | 1.000 | 0.062 | -0.003 | 0.003 | 0.003 | -0.003 | 0.009 | 0.001 |
| $R_{non\text{-}news}$ | 0.062 | 1.000 | 0.002 | 0.007 | 0.003 | -0.009 | 0.054 | 0.004 |
| Log(Size) | -0.003 | 0.002 | 1.000 | -0.224 | 0.051 | 0.770 | -0.600 | -0.252 |
| BM | 0.003 | 0.007 | -0.224 | 1.000 | 0.041 | -0.211 | 0.054 | 0.133 |
| Mom | 0.003 | 0.003 | 0.051 | 0.041 | 1.000 | -0.063 | -0.045 | -0.037 |
| Analyst | -0.003 | -0.009 | 0.770 | -0.211 | -0.063 | 1.000 | -0.305 | -0.154 |
| RVOL | 0.009 | 0.054 | -0.600 | 0.054 | -0.045 | -0.305 | 1.000 | 0.322 |
| ILLQ | 0.001 | 0.004 | -0.252 | 0.133 | -0.037 | -0.154 | 0.322 | 1.000 |

Table 2: Performance of the News Momentum Strategy

This table reports the performance of the news momentum strategy. The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between March 2000 and October 2012 with share code 10 or 11, prices above \$1 as of the portfolio formation, and at least one news story covered by the Dow Jones News Wire. We aggregate overnight and 15-minute news into daily news returns following Equation 1. At the end (market close) of each day $t$, we sort stocks into ten portfolios based on their news returns on day $t$ ($R_{i,t,news}$) and compute the equal-weighted return of a self-financing portfolio that buys stocks in the top decile with high news returns and sells stocks in the bottom decile with low news returns with a one-week holding period until day $t+5$. Following Jegadeesh and Titman (1993), our news momentum strategy includes portfolios with overlapping holding periods. That is, we revise the weights on $\frac{1}{5}$ of the securities in our news momentum strategy on any given day and carry over the rest from the previous day. We compute daily holding-period returns using transaction prices at 4:00 p.m. from the TAQ database. We multiply daily returns by 21 to get monthly returns in percentage. Panel A summarizes the portfolio returns in monthly percentage. The rows labeled "Return" and 'FFC4" respectively report the average raw returns and Fama-French-Carhart four-factor alphas for each portfolio. The column labeled "10–1" reports the difference in returns between Portfolio 10 and Portfolio 1, with Newey-West robust $t$-statistics in parentheses. Panels B reports the loadings on the four-factor models for the decile and spread portfolios.

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 10–1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Panel A: Portfolio Returns and Alphas | | | | | | |
| Return | -0.78 | 0.40 | 0.87 | 1.07 | 1.10 | 1.31 | 1.37 | 1.45 | 1.67 | 2.55 | 3.34 |
| | (-1.21) | (0.64) | (1.51) | (1.98) | (2.11) | (2.55) | (2.55) | (2.57) | (2.78) | (4.07) | (11.72) |
| FFC4 | -1.11 | 0.05 | 0.50 | 0.70 | 0.73 | 0.91 | 0.98 | 1.06 | 1.32 | 2.26 | 3.37 |
| | (-4.44) | (0.27) | (3.63) | (5.50) | (5.98) | (7.40) | (7.28) | (7.53) | (7.59) | (9.44) | (11.76) |
| | | | | | Panel B: Portfolio Betas from the Fama-French-Carhart Model | | | | | | |
| MKT | 1.00 | 1.03 | 1.00 | 0.96 | 0.94 | 0.92 | 0.96 | 0.99 | 1.01 | 0.99 | -0.01 |
| | (60.62) | (109.88) | (130.01) | (118.03) | (109.04) | (126.18) | (118.71) | (126.85) | (95.72) | (76.04) | (-0.58) |
| SMB | 0.73 | 0.60 | 0.48 | 0.40 | 0.37 | 0.39 | 0.42 | 0.53 | 0.63 | 0.74 | 0.00 |
| | (23.70) | (31.37) | (25.87) | (23.23) | (21.04) | (22.90) | (22.98) | (33.40) | (30.22) | (26.67) | (0.13) |
| HML | 0.05 | 0.11 | 0.16 | 0.18 | 0.20 | 0.24 | 0.20 | 0.17 | 0.09 | -0.01 | -0.06 |
| | (1.56) | (4.72) | (10.12) | (11.00) | (13.20) | (13.32) | (12.99) | (8.45) | (5.08) | (-0.19) | (-1.32) |
| UMD | -0.25 | -0.21 | -0.14 | -0.10 | -0.06 | -0.06 | -0.07 | -0.10 | -0.15 | -0.19 | 0.06 |
| | (-11.20) | (-15.43) | (-13.16) | (-9.34) | (-5.60) | (-5.34) | (-6.42) | (-8.15) | (-12.10) | (-9.97) | (2.44) |

Table 3: Fama-MacBeth (1973) Regressions

This table reports the estimated regression coefficients and Newey-West $t$-statistics (in parentheses) from Fama-MacBeth cross-sectional regressions predicting five-day ahead stock returns using news and non-news returns in the past day. The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between March 2000 and October 2012 with share code 10 or 11, prices above \$1 as of the portfolio formation, and at least one news story covered by the Dow Jones News Wire. $R_{news}$ ($R_{non\text{-}news}$) is the daily news (non-news) returns that are aggregated from overnight and intraday 15-minute news (non-news) returns based on transaction prices computed from merging TAQ and RavenPack news database. *Dummy(No News)* is a dummy variable equal to 1 if there is no news on a given day. *Size* is the product of the closing price and the number of shares outstanding and is updated daily using the daily data of a firm. *BM* is the book-to-market ratio in June of year $t$ which is computed as the ratio of the book value of common equity in fiscal year $t-1$ to the market value of equity (size) in December of year $t-1$ and is updated every July. *Mom* is the cumulative returns from prior day 252 to day 21 for a given day $t$. *Analyst* is the monthly number of sell-side analysts forecasting annual firm earnings from I/B/E/S. $RVOL$ is realized volatility defined as the square root of the annualized realized variance, which is 252 times the sum of squared 5-minute intraday returns within each trading day. $ILLQ$ is the illiquidity measure of Amihud (2002) which is the average daily ratio of the absolute stock return to the dollar trading volume over the five-day period preceding each day.

| | (I) | (II) | (III) | (IV) | (V) |
|---|---|---|---|---|---|
| Intercept | 0.0024 | 0.0023 | 0.0023 | 0.0039 | 0.0063 |
| | (2.27) | (2.20) | (2.17) | (2.77) | (4.95) |
| $R_{news}$ | 0.0425 | | 0.0574 | 0.0614 | 0.0577 |
| | (8.28) | | (11.02) | (10.64) | (11.33) |
| $R_{non\text{-}news}$ | | -0.0792 | -0.0809 | -0.0737 | -0.0488 |
| | | (-24.29) | (-24.80) | (-22.39) | (-13.79) |
| Dummy(No News) | 0.0001 | 0.0000 | 0.0001 | -0.0007 | -0.0007 |
| | (0.50) | (0.01) | (0.33) | (-4.06) | (-4.80) |
| Log(Size) | | | | -0.0003 | -0.0009 |
| | | | | (-2.46) | (-3.83) |
| BM | | | | 0.0007 | 0.0009 |
| | | | | (2.96) | (3.05) |
| Mom | | | | 0.0006 | 0.0000 |
| | | | | (0.86) | (-0.04) |
| Log(1+Analyst) | | | | | 0.0007 |
| | | | | | (3.35) |
| RVOL | | | | | 0.0026 |
| | | | | | (2.91) |
| ILLQ | | | | | 0.0000 |
| | | | | | (0.08) |
| Adj-$R^2$ (%) | 0.11 | 0.66 | 0.75 | 3.06 | 5.81 |
| #Obs | 10,097,270 | 10,097,270 | 10,097,270 | 8,674,126 | 6,174,846 |

Table 4: Decomposing the Profits of the News Momentum Strategy

This table reports the Lo and MacKinlay (1990) decomposition of the news momentum strategy. For the individual stock news momentum, we use the 970 stocks that have complete return observations over the period of March 2000 and October 2012. For the industry news momentum, we form equal-weighted industry portfolios based on the Fama and French (1997) industry classification. The column labeled "Auto" is the first component in Eq. (3), capturing the autocovariance in stock returns; "Cross" is the second component, capturing the cross-autocovariance; "Dispersion" is the third component, representing the dispersion in expected stock returns captured by news returns; and "Total" is the total return to the news momentum strategy. Panel A reports the estimates based on raw returns. Panel B reports the estimates based on alphas from the four-factor model. All return numbers are in monthly percentage, by multiplying daily returns by 21.

| | *Panel A: Raw Return* | | | | *Panel B: FFC4 Adjustment* | | | |
|---|---|---|---|---|---|---|---|---|
| | Auto | Cross | Dispersion | Total | Auto | Cross | Dispersion | Total |
| Individual Stocks | 3.79 | -0.05 | 0.04 | 3.79 | 3.30 | -0.02 | 0.06 | 3.34 |
| | (5.29) | (-0.16) | | (6.03) | (5.35) | (-0.51) | | (5.41) |
| Industry Portfolios | 2.07 | -0.98 | 0.01 | 1.09 | 1.87 | -0.98 | 0.02 | 0.91 |
| | (2.46) | (-1.27) | | (4.92) | (6.49) | (-5.21) | | (4.49) |

Table 5: Time-Varying Inattention

This table shows how news momentum return varies with investor inattention through time between March 2000 and October 2012. In Panel A, we regress daily returns in basis points on news momentum strategy as implemented in Table 2 on the lagged CBOE VIX index standardized to have a mean of zero and standard deviation of one. In Panel B, we examine the seasonality in news momentum returns. To interpret the coefficient on Mondays cleanly as capturing underreaction to Friday and weekend news, we construct a news momentum strategy with daily portfolio rebalancing. Then we regress the resulting daily returns in basis points on five dummy variables that represent each day of the week without an intercept in Regression (I), or a dummy variable of Monday with an intercept in Regression (II).

| *Panel A: Macroeconomic Uncertainty* | (I) | (II) | *Panel B: Friday and Weekend News* | (I) | (II) |
|---|---|---|---|---|---|
| Intercept | 15.90 | 16.00 | Intercept | | 41.69 |
| | (11.72) | (11.87) | | | (12.16) |
| Lagged VIX | 3.36 | 3.56 | Mondays | 64.69 | 23.00 |
| | (2.48) | (2.64) | | (8.82) | (2.84) |
| FFC4 Factors | No | Yes | Tuesdays | 28.23 | |
| | | | | (3.80) | |
| | | | Wednesdays | 45.97 | |
| | | | | (7.09) | |
| | | | Thursdays | 41.99 | |
| | | | | (6.04) | |
| | | | Fridays | 50.61 | |
| | | | | (7.79) | |

Table 6: Distraction Effects of Competing News

In this table, we split competing news from other firms into industry-related and un-related groups, and examine their distraction effects on the news momentum. The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between March 2000 and October 2012 with share code 10 or 11, prices above $1 as of the portfolio formation, and at least one news story covered by the Dow Jones News Wire. Firms are further classified into different industries using the Fama-French 17 industry classification, after excluding firms in industry 17("Others"). $R_{news}$ ($R_{non\text{-}news}$) is the daily news (non-news) returns that are aggregated from overnight and intraday 15-minute news (non-news) returns based on transaction prices computed from merging TAQ and RavenPack news database. *Dummy(No News)* is a dummy variable equal to 1 if there is no news on a given day. *Related News* is the standardized Log(# news from other firms in the same industry) and *Unrelated News* is the standardized Log(# news from firms in other industries), both with zero mean and unit variance. *Size* is the product of the closing price and the number of shares outstanding and is updated daily using the daily data of a firm. *BM* is the book-to-market ratio in June of year $t$ which is computed as the ratio of the book value of common equity in fiscal year $t-1$ to the market value of equity (size) in December of year $t-1$ and is updated every July. *Mom* is the cumulative returns from prior day 252 to day 21 for a given day $t$. *Analyst* is the monthly number of sell-side analysts forecasting annual firm earnings from I/B/E/S. $RVOL$ is realized volatility defined as the square root of the annualized realized variance, which is 252 times the sum of squared 5-minute intraday returns within each trading day. $ILLQ$ is the illiquidity measure of Amihud (2002) which is the average daily ratio of the absolute stock return to the dollar trading volume over the five-day period preceding each day. All regressions include firm characteristics interacted with $R_{news}$ and dummy variables for year, month, day of week, and Fama-French 17 industry classification, with standard errors clustered at stock and date levels.

| | CAR[1,3] (I) | CAR[1,21] (II) | CAR[1,63] (III) |
|---|---|---|---|
| Intercept | 0.0057 | 0.0419 | 0.1435 |
| | (3.80) | (9.99) | (13.78) |
| $R_{news}$ | 0.1210 | 0.1190 | 0.3621 |
| | (4.14) | (1.85) | (4.55) |
| $R_{non-news}$ | -0.0332 | -0.0683 | -0.1096 |
| | (-4.90) | (-4.99) | (-6.32) |
| Dummy(No News) | -0.0001 | -0.0003 | -0.0003 |
| | (-0.88) | (-1.15) | (-0.66) |
| Related News | 0.0001 | -0.0014 | -0.0043 |
| | (0.49) | (-2.89) | (-5.68) |
| Unrelated News | -0.0005 | -0.0011 | 0.0007 |
| | (-2.81) | (-2.43) | (1.03) |
| $R_{news}$ × Related News | -0.0104 | -0.0036 | 0.0209 |
| | (-1.89) | (-0.41) | (1.44) |
| $R_{news}$ × Unrelated News | 0.0111 | 0.0221 | 0.0342 |
| | (2.37) | (2.41) | (2.37) |
| Log(Size) | -0.0004 | -0.0025 | -0.0062 |
| | (-5.37) | (-10.00) | (-9.68) |
| BM | 0.0006 | 0.0037 | 0.0078 |
| | (4.13) | (6.25) | (5.11) |
| Mom | -0.0013 | -0.0101 | -0.0277 |
| | (-2.68) | (-6.99) | (-9.54) |
| Log(1+Analyst) | 0.0002 | 0.0004 | -0.0002 |
| | (1.65) | (1.00) | (-0.21) |
| RVOL | 0.0046 | 0.0121 | 0.0161 |
| | (5.01) | (6.28) | (5.04) |
| ILLQ | 0.0195 | 0.0622 | 0.0929 |
| | (5.58) | (6.68) | (4.59) |
| Characteristics interacted with $R_{news}$ | X | X | X |
| Adj-$R^2$ (%) | 0.36 | 1.27 | 2.64 |
| #Obs | 4,798,380 | 4,765,306 | 4,607,492 |

## Table 7: Firm News Arrival and the Number of Analyst Forecast Revisions

This table reports the estimated regression coefficients and $t$-statistics (in parentheses) from panel regressions by regressing *Log(1+ # Analysts Revise Forecast)* on past news dummies. The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between January 2003 and October 2012 with analyst quarterly earnings forecast coverage from I/B/E/S, share code 10 or 11, prices above $1 as of the portfolio formation, and at least one news story covered by the Dow Jones News Wire. In Panel A, the dependent variable is *Log(1+ # Analysts Revised Forecast on Day t)*, and the regressor *Dummy(News)*$_{t-j}$ is a dummy variable equal to 1 if there is news on day $t-j$. In Panel B (C), the dependent variable is *Log(1+ # Analyst Revised Forecast Upward (Downward) on Day t)*, and the regressor *Dummy(Positive News)*$_{t-j}$ *(Dummy(Negative News)*$_{t-j}$*)* is a dummy variable equal to 1 if there is positive (negative) news on day $t-j$. A news item is classified as positive (negative) if the 15-minute intraday return or the overnight return surrounding the news occurrence is positive (negative). *Size* is the product of the closing price and the number of shares outstanding and is updated daily using the daily data of a firm. *BM* is the book-to-market ratio in June of year $t$ which is computed as the ratio of the book value of common equity in fiscal year $t-1$ to the market value of equity (size) in December of year $t-1$ and is updated every July. *Mom* is the cumulative returns from prior day 252 to day 21 for a given day $t$. *Analyst* is the monthly number of sell-side analysts forecasting annual firm earnings from I/B/E/S. $RVOL$ is realized volatility defined as the square root of the annualized realized variance, which is 252 times the sum of squared 5-minute intraday returns within each trading day. $ILLQ$ is the illiquidity measure of Amihud (2002) which is the average daily ratio of the absolute stock return to the dollar trading volume over the five-day period preceding each day. All regressions include stock and date fixed effects, with standard errors clustered at stock and date levels.

| *Panel A: Predicting Log(1+ # Forecast Revisions on Day t)* | | | | |
|---|---|---|---|---|
| | (I) | (II) | (III) | (IV) |
| Intercept | -0.0616 | -0.0621 | -0.0621 | -0.0616 |
| | (-9.70) | (-9.67) | (-9.66) | (-9.71) |
| Dummy(News)$_{t-1}$ | 0.0225 | | | 0.0225 |
| | (24.87) | | | (24.81) |
| Dummy(News)$_{t-2}$ | | 0.0024 | | 0.0017 |
| | | (6.58) | | (4.77) |
| Dummy(News)$_{t-3}$ | | | 0.0004 | 0.0002 |
| | | | (0.96) | (0.56) |
| Log(Size) | 0.0075 | 0.0077 | 0.0078 | 0.0075 |
| | (8.91) | (9.09) | (9.10) | (8.90) |
| BM | -0.0002 | -0.0002 | -0.0002 | -0.0002 |
| | (-0.53) | (-0.54) | (-0.54) | (-0.54) |
| Mom | -0.0065 | -0.0065 | -0.0065 | -0.0065 |
| | (-10.76) | (-10.84) | (-10.85) | (-10.76) |
| Log(1+Analyst) | 0.0113 | 0.0114 | 0.0114 | 0.0113 |
| | (19.48) | (19.55) | (19.55) | (19.47) |
| RVOL | 0.0421 | 0.0433 | 0.0434 | 0.0420 |
| | (27.11) | (27.21) | (27.22) | (27.08) |
| ILLQ | -0.0698 | -0.0724 | -0.0726 | -0.0696 |
| | (-18.53) | (-19.02) | (-19.06) | (-18.49) |
| Adj-$R^2$ (%) | 8.74 | 8.59 | 8.59 | 8.74 |
| #Obs | 5,930,115 | 5,930,115 | 5,930,115 | 5,930,115 |

| *Panel B: Predicting Log(1+ # Positive Forecast Revisions on Day t)* | (I) | (II) | (III) | (IV) |
|---|---|---|---|---|
| Intercept | -0.0467 | -0.047 | -0.047 | -0.0467 |
| | (-11.85) | (-11.86) | (-11.85) | (-11.86) |
| Dummy(Positive News)$_{t-1}$ | 0.0131 | | | 0.0131 |
| | (16.36) | | | (16.35) |
| Dummy(Positive News)$_{t-2}$ | | 0.0019 | | 0.0017 |
| | | (6.23) | | (5.60) |
| Dummy(Positive News)$_{t-3}$ | | | 0.0005 | 0.0004 |
| | | | (1.75) | (1.48) |
| Log(Size) | 0.0063 | 0.0064 | 0.0064 | 0.0063 |
| | (11.72) | (11.82) | (11.82) | (11.71) |
| BM | 0.0004 | 0.0004 | 0.0004 | 0.0004 |
| | (2.09) | (2.12) | (2.12) | (2.08) |
| Mom | 0.0022 | 0.0022 | 0.0022 | 0.0022 |
| | (5.92) | (5.85) | (5.84) | (5.93) |
| Log(1+Analyst) | 0.0044 | 0.0044 | 0.0044 | 0.0044 |
| | (14.27) | (14.25) | (14.25) | (14.27) |
| RVOL | 0.0158 | 0.0162 | 0.0162 | 0.0158 |
| | (21.72) | (21.78) | (21.79) | (21.70) |
| ILLQ | -0.0092 | -0.01 | -0.01 | -0.0091 |
| | (-5.80) | (-6.24) | (-6.28) | (-5.74) |
| Adj-$R^2$ (%) | 5.46 | 5.40 | 5.40 | 5.47 |
| #Obs | 5,930,115 | 5,930,115 | 5,930,115 | 5,930,115 |

| *Panel C: Predicting Log(1+ # Negative Forecast Revisions on Day t)* | (I) | (II) | (III) | (IV) |
|---|---|---|---|---|
| Intercept | -0.0180 | -0.0180 | -0.0180 | -0.0181 |
| | (-4.49) | (-4.46) | (-4.45) | (-4.53) |
| Dummy(Negative News)$_{t-1}$ | 0.0189 | | | 0.0189 |
| | (25.03) | | | (25.00) |
| Dummy(Negative News)$_{t-2}$ | | 0.0038 | | 0.0035 |
| | | (10.75) | | (9.98) |
| Dummy(Negative News)$_{t-3}$ | | | 0.0022 | 0.0022 |
| | | | (6.05) | (5.89) |
| Log(Size) | 0.0017 | 0.0017 | 0.0017 | 0.0017 |
| | (3.11) | (3.18) | (3.19) | (3.10) |
| BM | -0.0006 | -0.0006 | -0.0006 | -0.0006 |
| | (-2.06) | (-2.10) | (-2.10) | (-2.06) |
| Mom | -0.009 | -0.0091 | -0.0091 | -0.0090 |
| | (-17.30) | (-17.31) | (-17.31) | (-17.30) |
| Log(1+Analyst) | 0.0071 | 0.0071 | 0.0071 | 0.0070 |
| | (16.17) | (16.26) | (16.27) | (16.13) |
| RVOL | 0.0281 | 0.0286 | 0.0286 | 0.0281 |
| | (26.56) | (26.66) | (26.67) | (26.56) |
| ILLQ | -0.0631 | -0.0642 | -0.0642 | -0.0629 |
| | (-19.91) | (-20.10) | (-20.12) | (-19.87) |
| Adj-$R^2$ (%) | 4.99 | 4.89 | 4.89 | 4.99 |
| #Obs | 5,930,115 | 5,930,115 | 5,930,115 | 5,930,115 |

## Table 8: Firm News and Analyst Forecast Revisions

This table reports the estimated regression coefficients and Newey-West $t$-statistics (in parentheses) from panel regressions by regressing analyst quarterly earnings forecast revision on past news and non-news returns. The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between January 2003 and October 2012 with analyst quarterly earnings forecast coverage from I/B/E/S, share code 10 or 11, prices above \$1 as of the portfolio formation, and at least one news story covered by the Dow Jones News Wire. The dependent variable *Forecast Revision* is defined as an analyst's quarterly earnings forecast on day $t$ minus the previous forecast of the same analyst in the same earnings cycle scaled by share price on day $t-2$. $R_{news,t-j}$ ($R_{non-news,t-j}$) is the news (non-news) returns on day $t-j$ ($j$ = 1, 2, or 3) that are aggregated from overnight and intraday 15-minute news (non-news) returns based on transaction prices computed from merging TAQ and RavenPack news database. *Dummy (No News)*$_{t-j}$ is a dummy variable equal to 1 if there is no news on a given day $t-j$ ($j$ = 1, 2, or 3). *Size* is the product of the closing price and the number of shares outstanding and is updated daily using the daily data of a firm. *BM* is the book-to-market ratio in June of year $t$ which is computed as the ratio of the book value of common equity in fiscal year $t-1$ to the market value of equity (size) in December of year $t-1$ and is updated every July. *Mom* is the cumulative returns from prior day 252 to day 21 for a given day $t$. *Analyst* is the monthly number of sell-side analysts forecasting annual firm earnings from I/B/E/S. $RVOL$ is realized volatility defined as the square root of the annualized realized variance, which is 252 times the sum of squared 5-minute intraday returns within each trading day. $ILLQ$ is the illiquidity measure of Amihud (2002) which is the average daily ratio of the absolute stock return to the dollar trading volume over the five-day period preceding each day. All regressions include analyst, stock and date fixed effects, with standard errors clustered at the analyst, stock and date levels.

| | (I) | (II) | (III) | (IV) |
|---|---|---|---|---|
| Intercept | -0.0151 | -0.0155 | -0.0155 | -0.0146 |
| | (-13.02) | (-13.17) | (-13.20) | (-12.75) |
| $R_{news,t-1}$ | 0.0230 | | | 0.0230 |
| | (14.07) | | | (13.95) |
| $R_{non-news,t-1}$ | 0.0094 | | | 0.0094 |
| | (7.25) | | | (7.23) |
| Dummy(No News)$_{t-1}$ | 0.0001 | | | 0.0001 |
| | (2.94) | | | (2.77) |
| $R_{news,t-2}$ | | 0.0253 | | 0.0254 |
| | | (11.05) | | (10.97) |
| $R_{non-news,t-2}$ | | 0.0099 | | 0.0096 |
| | | (7.16) | | (7.03) |
| Dummy(No News)$_{t-2}$ | | 0.0001 | | 0.0001 |
| | | (1.97) | | (1.94) |
| $R_{news,t-3}$ | | | 0.0171 | 0.017 |
| | | | (5.63) | (5.56) |
| $R_{non-news,t-3}$ | | | 0.0087 | 0.0086 |
| | | | (6.10) | (5.84) |
| Dummy(No News)$_{t-3}$ | | | 0.0000 | 0.0001 |
| | | | (0.94) | (1.03) |
| Log(Size) | 0.0018 | 0.0018 | 0.0019 | 0.0017 |
| | (12.36) | (12.74) | (12.74) | (12.06) |
| BM | 0.0002 | 0.0002 | 0.0002 | 0.0001 |
| | (1.06) | (1.15) | (1.20) | (0.80) |
| Mom | 0.0017 | 0.0017 | 0.0017 | 0.0017 |
| | (9.85) | (9.62) | (9.60) | (10.11) |
| Log(1+Analyst) | -0.0001 | -0.0001 | -0.0001 | -0.0000 |
| | (-0.41) | (-0.71) | (-0.76) | (-0.13) |
| RVOL | -0.0029 | -0.0030 | -0.0030 | -0.0029 |
| | (-12.26) | (-12.16) | (-12.17) | (-12.18) |
| ILLQ | 0.0005 | 0.0009 | 0.0012 | 0.0004 |
| | (0.13) | (0.25) | (0.32) | (0.10) |
| Adj-$R^2$ (%) | 18.26 | 17.96 | 17.85 | 18.58 |
| #Obs | 308,744 | 308,687 | 308,658 | 308,658 |

Table 9: Market Reaction to Analyst Forecast Revisions

This table shows how market reacts to analyst quarterly earnings forecast revision surrounding the forecast revision date and the earnings announcement date. The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between January 2003 and October 2012 with analyst quarterly earnings forecast coverage from I/B/E/S, share code 10 or 11, prices above $1 as of the portfolio formation, and at least one news story covered by the Dow Jones News Wire. *Forecast Revision* is defined as an analyst's quarterly earnings forecast on day $t$ minus the previous forecast of the same analyst in the same earnings cycle scaled by share price on day $t-2$. In Panel A, we regress the abnormal return on the revision date ($AR$), or the cumulative abnormal return surrounding the revision date ($CAR$ [0,2]) on analyst forecast revision and firm characteristics. $AR$ is defined as the return on the revision day minus value-weighted return of all CRSP firms listed on the NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 or 11 (value-weighted market portfolio). $CAR$ [0,2] is defined as the difference between the three-day cumulative return surrounding revision day minus the three-day cumulative return of the value-weighted market portfolio, with the accumulation period starting from the revision day and ending two days after the revision. In Panel B, we regress *Earnings Surprise*, or the cumulative abnormal return surrounding the earnings announcement date ($CAR$ [-2, 2]), on analyst forecast revision and firm characteristics. *Earnings Surprise* is the actual earnings per share minus consensus analyst forecast scaled by share price two days before the announcement day. $CAR$ [-2,2] is defined as the difference between the five-day cumulative return surrounding announcement day minus the five-day cumulative return of the value-weighted market portfolio, with the accumulation period starting from two days before the announcement day and ending two days after the announcement. *Size* is the product of the closing price and the number of shares outstanding and is updated daily using the daily data of a firm. *BM* is the book-to-market ratio in June of year $t$ which is computed as the ratio of the book value of common equity in fiscal year $t-1$ to the market value of equity (size) in December of year $t-1$ and is updated every July. *Mom* is the cumulative returns from prior day 252 to day 21 for a given day $t$. *Analyst* is the monthly number of sell-side analysts forecasting annual firm earnings from I/B/E/S. $RVOL$ is realized volatility defined as the square root of the annualized realized variance, which is 252 times the sum of squared 5-minute intraday returns within each trading day. *ILLQ* is the illiquidity measure of Amihud (2002) which is the average daily ratio of the absolute stock return to the dollar trading volume over the five-day period preceding each day. All regressions include analyst, stock and date fixed effects, with standard errors clustered at the analyst, stock and date levels.

| *Panel A: Around Forecast Revision Date* | | | *Panel B: Around Earnings Announcement Date* | | |
|---|---|---|---|---|---|
| | AR | CAR [0,2] | | Earnings Surprise | CAR [-2, 2] |
| | (I) | (II) | | (I) | (II) |
| Intercept | -0.0336 | 0.0095 | Intercept | -0.0088 | -0.1751 |
| | (-5.15) | (1.18) | | (-4.55) | (-10.88) |
| Forecast Revision | 0.6482 | 0.9484 | Forecast Revision | 0.2911 | 0.2249 |
| | (12.53) | (14.76) | | (18.08) | (2.71) |
| Log(Size) | 0.0090 | 0.0036 | Log(Size) | 0.0013 | 0.0276 |
| | (11.33) | (3.71) | | (5.94) | (14.39) |
| BM | 0.0048 | 0.0050 | BM | 0.0005 | 0.0118 |
| | (6.82) | (6.05) | | (1.85) | (5.49) |
| Mom | -0.0061 | -0.0056 | Mom | 0.0006 | -0.0312 |
| | (-7.11) | (-4.87) | | (2.24) | (-12.44) |
| Log(1+Analyst) | -0.0119 | -0.0120 | Log(1+Analyst) | -0.0006 | -0.0186 |
| | (-13.19) | (-11.11) | | (-1.60) | (-8.16) |
| RVOL | -0.0370 | -0.0332 | RVOL | -0.0015 | -0.0164 |
| | (-11.64) | (-9.02) | | (-5.15) | (-4.93) |
| ILLQ | 0.0850 | 0.0597 | ILLQ | -0.0172 | 0.1224 |
| | (3.52) | (2.26) | | (-2.33) | (2.80) |
| Adj-$R^2$(%) | 0.1723 | 0.1443 | Adj-$R^2$(%) | 27.45 | 19.97 |
| #Obs | 308,811 | 308,374 | #Obs | 296,140 | 296,058 |

## Table 10: Robustness Tests

This table reports the performance of the news momentum strategy under different designs. The main sample consists of stocks listed on NYSE/AMEX/NASDAQ over the period between March 2000 and October 2012 with share code 10 or 11, prices above \$1 at the end of the portfolio formation period, and at least one news story covered by the Dow Jones News Wire. The rows labeled "Return" and 'FFC4 alpha" respectively report the average return and Fama-French-Carhart four-factor alpha for each decile portfolio in monthly percentage. The column labeled "High–Low" reports the difference in returns between Portfolio 5 and Portfolio 1, with Newey-West robust $t$-statistics in parentheses. In Panel A, we use the daily returns from the CRSP database to compute both the daily news and overall returns and then repeat the news momentum strategy using these returns. In Panel B, we use the high-frequency mid-quote prices to aggregate overnight and 15-minute returns into the daily news and overall returns and then repeat the news momentum strategy on the basis of these quoted returns. In Panel C, we aggregate 15-minute and overnight news returns over the period of 9:45 a.m. on day $t-1$ to 9:45 a.m. on day $t$ and forecast the five-day ahead overall returns over the period of 10:00 a.m. on day $t$ to 10:00 a.m. on day $t+5$. In Panel D, we use the market-risk-adjusted returns to construct trading signal and repeat the news momentum strategy. In Panel E, we first implement the characteristic-based benchmark methods of Daniel et al. (1997) and Wermers (2003) to adjust risks. We use the benchmark portfolio assignments to compute the daily equal-weighted $5 \times 5 \times 5$ size, book-to-market ratio, and momentum benchmark returns based on all NYSE/AMEX/NASDAQ data in the CRSP database. We then subtract a firm's daily overall return by the daily return of one of the 125 benchmarks to which the firm belongs to on that day. We use these benchmark-adjusted returns in place of the raw overall returns when repeating the news momentum strategy. In Panel F, we first identify quarterly earnings announcements using dates from Compustat. Since the time of the day of the earnings announcement is unavailable in Compustat and earnings announcement can occur before, during, or after the regular trading hours, we are unable to match the returns that immediately reflect the information on earnings announcement. To conservatively remove the effect of earnings announcement, we thus exclude from the samples both the earnings announcement day and the day after the announcement. In Panel G, we first identify events of information-based major price changes by following Savor (2012) and then exclude from firm-date samples those observations corresponding to information-based major price changes. In Panel H, we remove the effect of news clustering by only forecasting the non-news-driven returns.

| | 1 | 2 | 9 | 10 | High–Low |
|---|---|---|---|---|---|
| | *Panel A: CRSP Return* | | | | |
| Return | 0.00 | 0.85 | 1.33 | 1.98 | 1.99 |
| | (-0.00) | (1.35) | (2.27) | (3.15) | (6.01) |
| FFC4 | -0.35 | 0.48 | 0.96 | 1.63 | 1.98 |
| | (-1.20) | (2.66) | (5.73) | (6.92) | (6.05) |
| | *Panel C: Open-to-Open Return* | | | | |
| Return | -0.60 | 0.57 | 1.98 | 3.33 | 3.92 |
| | (-0.90) | (0.95) | (3.37) | (5.33) | (12.91) |
| FFC4 | -0.68 | 0.46 | 1.88 | 3.26 | 3.94 |
| | (-1.09) | (0.82) | (3.39) | (5.48) | (13.03) |
| | *Panel E: DGTW Characteristic Adjustment* | | | | |
| Return | -1.68 | -0.53 | 0.67 | 1.39 | 3.06 |
| | (-6.50) | (-2.79) | (3.67) | (5.53) | (11.14) |
| FFC4 | -1.64 | -0.53 | 0.67 | 1.45 | 3.09 |
| | (-7.42) | (-3.54) | (4.39) | (6.88) | (11.24) |
| | *Panel G: Eliminating Extreme Price Changes* | | | | |
| Return | -0.57 | 0.40 | 1.64 | 2.36 | 2.93 |
| | (-0.91) | (0.65) | (2.77) | (3.89) | (10.75) |
| FFC4 | -0.92 | 0.03 | 1.28 | 2.05 | 2.97 |
| | (-3.92) | (0.16) | (7.63) | (8.90) | (10.70) |

| | 1 | 2 | 9 | 10 | High–Low |
|---|---|---|---|---|---|
| | *Panel B: Mid-Quote Return* | | | | |
| Return | -0.87 | 0.55 | 1.76 | 2.52 | 3.40 |
| | (-1.35) | (0.91) | (2.98) | (4.12) | (12.55) |
| FFC4 | -1.18 | 0.20 | 1.41 | 2.24 | 3.42 |
| | (-4.84) | (1.20) | (8.02) | (9.80) | (12.75) |
| | *Panel D: Market-Risk-Adjusted Returns* | | | | |
| Return | -0.8 | 0.58 | 1.76 | 2.49 | 3.29 |
| | (-1.27) | (0.95) | (2.97) | (4.04) | (12.26) |
| FFC4 | -2.23 | -0.86 | 0.31 | 1.10 | 3.33 |
| | (-10.08) | (-4.70) | (1.75) | (5.20) | (12.30) |
| | *Panel F: Eliminating Earnings Announcements* | | | | |
| Return | 0.20 | 0.71 | 1.45 | 1.99 | 1.79 |
| | (0.29) | (1.13) | (2.35) | (3.03) | (5.76) |
| FFC4 | -0.17 | 0.38 | 1.10 | 1.68 | 1.85 |
| | (-0.65) | (2.23) | (6.05) | (6.62) | (5.92) |
| | *Panel H: Excluding News Clustering* | | | | |
| Return | -0.92 | 0.25 | 1.29 | 1.92 | 2.85 |
| | (-1.49) | (0.43) | (2.24) | (3.17) | (10.51) |
| FFC4 | -1.24 | -0.09 | 0.95 | 1.63 | 2.88 |
| | (-5.26) | (-0.53) | (5.69) | (7.07) | (10.53) |

## Table 11: Performance of Chan (2003)'s Strategy

This table reports the performance of the Chan (2003)'s strategy. At the end of each month, we consider a news group consisting of all stocks that have at least one news story during that month and then sort them into ten portfolios based on their monthly return in order to compute the equal-weighted return of a self-financing portfolio that buys stocks in the top decile with high returns and sells stocks in the bottom decile with low returns with $K = 1$, 3, and 6 month holding periods. Following Jegadeesh and Titman (1993), this Chan (2003)'s strategy includes portfolios with overlapping holding periods. That is, we revise the weights on $\frac{1}{K}$ of the securities in our news momentum strategy in any given month and carry over the rest from the previous month. We compute monthly holding-period returns using transaction prices at 4:00 p.m. from the TAQ database. The rows labeled "Return" and "FFC4" respectively report the average raw returns and Fama-French-Carhart four-factor alphas for each portfolio. The column labeled "10–1" reports the difference in returns between Portfolio 10 and Portfolio 1, with Newey-West robust $t$-statistics in parentheses.

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 10–1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | $K = 1$ | | | | | |
| Return | 2.15 | 1.38 | 1.27 | 1.17 | 1.06 | 1.11 | 1.07 | 1.14 | 0.95 | 1.39 | -0.76 |
| | (3.15) | (2.53) | (2.82) | (2.82) | (2.74) | (2.95) | (2.85) | (2.98) | (2.19) | (2.49) | (-1.43) |
| FFC4 | 1.78 | 0.98 | 0.86 | 0.75 | 0.60 | 0.69 | 0.65 | 0.74 | 0.48 | 0.94 | -0.85 |
| | (5.30) | (4.50) | (5.46) | (5.71) | (5.46) | (6.52) | (6.26) | (6.84) | (3.31) | (4.06) | (-1.74) |
| | | | | | | $K = 3$ | | | | | |
| Return | 1.75 | 1.27 | 1.17 | 1.07 | 1.04 | 1.02 | 0.97 | 0.99 | 1.01 | 1.28 | -0.47 |
| | (2.71) | (2.47) | (2.65) | (2.65) | (2.72) | (2.77) | (2.60) | (2.58) | (2.46) | (2.71) | (-1.52) |
| FFC4 | 1.37 | 0.85 | 0.74 | 0.67 | 0.60 | 0.60 | 0.56 | 0.58 | 0.60 | 0.93 | -0.44 |
| | (6.60) | (7.16) | (8.10) | (7.97) | (7.59) | (8.02) | (7.76) | (7.60) | (5.85) | (6.68) | (-1.85) |
| | | | | | | $K = 6$ | | | | | |
| Return | 1.56 | 1.18 | 1.13 | 1.05 | 1.02 | 1.02 | 1.03 | 1.02 | 1.10 | 1.33 | -0.23 |
| | (2.69) | (2.42) | (2.60) | (2.64) | (2.69) | (2.73) | (2.73) | (2.65) | (2.65) | (2.79) | (-1.11) |
| FFC4 | 1.17 | 0.75 | 0.68 | 0.62 | 0.56 | 0.57 | 0.57 | 0.58 | 0.65 | 0.90 | -0.27 |
| | (7.04) | (7.60) | (8.80) | (8.68) | (8.33) | (8.80) | (9.78) | (8.77) | (8.75) | (8.14) | (-1.86) |

# Supplementary Appendix to:

# News Momentum

Hao Jiang Sophia Zhengzi Li Hao Wang

## Table A.1: News Momentum and Analyst Revisions

This table reports the estimated regression coefficients and Newey-West $t$-statistics (in parentheses) from Fama-MacBeth cross-sectional regressions predicting five-day ahead stock returns using news and non-news returns in the past day. The sample includes stocks listed on NYSE/AMEX/NASDAQ for the period between January 2003 and October 2012 with share code 10 or 11, prices above $1 as of the portfolio formation, and at least one news story covered by the Dow Jones News Wire. Panel A covers observations with five-day ahead stock returns that do not overlap with analyst forecast revisions, and Panel B covers observations with five-day ahead stock returns that overlap with at least one analyst forecast revision. $R_{news}$ ($R_{non\text{-}news}$) is the daily news (non-news) returns that are aggregated from overnight and intraday 15-minute news (non-news) returns based on transaction prices computed from merging TAQ and RavenPack news database. *Dummy (No News)* is a dummy variable equal to 1 if there is no news on a given day. *Size* is the product of the closing price and the number of shares outstanding and is updated daily using the daily data of a firm. *BM* is the book-to-market ratio in June of year $t$ which is computed as the ratio of the book value of common equity in fiscal year $t-1$ to the market value of equity (size) in December of year $t-1$ and is updated every July. *Mom* is the cumulative returns from prior day 252 to day 21 for a given day $t$. *Analyst* is the monthly number of sell-side analysts forecasting annual firm earnings from I/B/E/S. $RVOL$ is realized volatility defined as the square root of the annualized realized variance, which is 252 times the sum of squared 5-minute intraday returns within each trading day. *ILLQ* is the illiquidity measure of Amihud (2002) which is the average daily ratio of the absolute stock return to the dollar trading volume over the five-day period preceding each day.

| | *Panel A: Five-Day Return NonOverlappling with Revisions* | | | | | *Panel B: Five-Day Return Overlapping with Revisions* | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (I) | (II) | (III) | (IV) | (V) | (I) | (II) | (III) | (IV) | (V) |
| Intercept | 0.0033 | 0.0032 | 0.0031 | 0.0051 | 0.0064 | 0.0019 | 0.0018 | 0.0016 | -0.0053 | -0.0046 |
| | (2.83) | (2.81) | (2.71) | (3.87) | (4.98) | (1.61) | (1.54) | (1.42) | (-2.62) | (-2.71) |
| $R_{news}$ | 0.0380 | | 0.0526 | 0.0563 | 0.0535 | 0.0655 | | 0.0598 | 0.0643 | 0.0653 |
| | (6.47) | | (8.66) | (8.06) | (9.17) | (4.32) | | (3.96) | (4.35) | (4.38) |
| $R_{non-news}$ | | -0.0809 | -0.0827 | -0.0751 | -0.0485 | | 0.0204 | 0.0184 | 0.0108 | 0.0154 |
| | | (-23.31) | (-23.78) | (-21.09) | (-12.66) | | (2.62) | (2.34) | (1.43) | (2.14) |
| Dummy(No News) | 0.0001 | -0.0001 | 0.0000 | -0.0006 | -0.0004 | -0.0008 | -0.0010 | -0.0008 | -0.0005 | -0.0002 |
| | (0.46) | (-0.49) | (0.27) | (-3.94) | (-2.57) | (-2.45) | (-3.27) | (-2.54) | (-1.68) | (-0.85) |
| Log(Size) | | | | -0.0004 | -0.0010 | | | | 0.0006 | -0.0007 |
| | | | | (-3.12) | (-4.96) | | | | (4.03) | (-2.11) |
| BM | | | | 0.0002 | 0.0003 | | | | 0.0005 | 0.0007 |
| | | | | (1.06) | (1.28) | | | | (1.10) | (1.41) |
| Mom | | | | -0.0002 | -0.0011 | | | | 0.0067 | 0.0062 |
| | | | | (-0.26) | (-1.60) | | | | (5.64) | (5.67) |
| Log(1+Analyst) | | | | | 0.0005 | | | | | 0.0003 |
| | | | | | (3.30) | | | | | (0.91) |
| RVOL | | | | | 0.0037 | | | | | 0.0042 |
| | | | | | (4.20) | | | | | (2.40) |
| ILLQ | | | | | -0.0002 | | | | | -0.0010 |
| | | | | | (-1.46) | | | | | (-3.43) |
| Adj-$R^2$ (%) | 0.10 | 0.61 | 0.70 | 2.40 | 4.65 | 0.26 | 1.37 | 1.56 | 5.22 | 7.10 |
| #Obs | 7,203,883 | 7,203,883 | 7,203,883 | 6,102,631 | 4,446,466 | 799,829 | 799,829 | 799,829 | 769,413 | 751,887 |