News Momentum *

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Abstract

We decompose daily stock returns into news- and non-news-driven components, using a comprehensive sample of intraday firm-level news arrivals matched with high-frequency movements of their stock prices. We find that, consistent with prior literature, non-news returns precede a reversal. For news-driven returns, however, we find strong evidence of return continuation without subsequent reversals. A strategy of news momentum that buys stocks with high news returns and sells stocks with low news returns generates an annualized return of 40.08% in the following week, with a four-factor alpha of 40.44%, controlling for the market, size, value, and momentum. The strategy's profitability is driven by positive serial correlations in individual stock returns, and is particularly pronounced for overnight and weekend news and among small firms with low analyst coverage, high volatility, and low liquidity. These results suggest that investor under-reaction to news, coupled with limits to arbitrage, drives news momentum.

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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 recent 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 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 (Fama, 1998).

In this paper, we exploit this insight 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. In this way, we decompose daily stock returns into news-driven and non-news-driven components, revisiting the issue of short-term return predictability.

Our results indicate that whereas non-news-driven return precedes a reversal, news-driven return tends to exhibit a strong pattern of continuation. For instance, from 2000 to 2012, a strategy of news momentum that buys stocks with high news returns and sells stocks with low news returns in the previous day with a one-week holding period generates an average annualized return of 40.08%, with a four-factor alpha of 40.44%, controlling for the market, size, value, and momentum.[1]

As implied by the similar magnitudes of average returns and four-factor alpha, the news momentum strategy has small exposures to pervasive factors such as market, size, and value factors: The absolute value of the factor loadings equals to or below 0.06. News momentum exhibits a moderate correlation with the Jegadeesh and Titman (1993) medium-term price momentum: The loading on the momentum factor is 0.06 in the four-factor model and the univariate correlation is 0.11. Unlike the price momentum strategy, which is characterized by high crash risk (a negative skewness of -0.79 and maximum drawdown of 63.66%), news momentum has a positive skewness of 0.51 and maximum drawdown of only 15.92%. Using the Fama-MacBeth (1973) cross-sectional regressions, we find similar evidence of news return continuation and non-news return reversals.

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.

To better understand the source of the news momentum, 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. 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

[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 annualized alpha of our news momentum strategy is 40.03%.

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 result.

What leads to the strong positive serial correlation in individual stock returns after the news arrival? The behavioral finance literature offers two possible interpretations: underreaction and delayed overreaction. When we extend the post-event holding horizon of the news momentum strategy, we find that the news momentum effect appears to persist, even one year after news arrival, without reversals. The evidence therefore tilts toward stock market underreaction as a possible driving force of news momentum.

To shed further light on news momentum, we examine the heterogeneity of its effects across firms. In particular, we find that the news momentum effect tends to be stronger among firms that are smaller, receive less analyst coverage, exhibit more volatile stock prices, and have less liquidity. These results are consistent with attention-based interpretations, according to which less visible firms tend to receive less attention from the investment community, which results in underreaction to public news. These results are also consistent with the argument of Shleifer and Vishny (1997) that mispricing is likely to be more pronounced among stocks with higher limits to arbitrage.

Digging into the pattern of return continuation following news arrival, we examine the high-frequency response of stock prices to overnight news, which constitutes more than half of our sample. To measure the initial response of stock markets to news that arrives anytime after 4:00 p.m. of day $t-1$ and before 9:45 a.m. of day t, we compute overnight returns as the percentage change in prices from market close as of 4:00 p.m. of day $t-1$ to 9:45 a.m. of day t. Then we examine the adjustment of stock prices in every half-hour interval from 10:00 a.m. of day t until market close of day $t+4$, by tracking the cumulative returns of the news momentum strategy over these five trading days. The results indicate a gradual drift in stock prices following the initial response to overnight news. Specifically, the news momentum return on average drifts up to 25 basis points (bps) at 3:30 p.m. and then shows a slight dip to 17 bps at 4:00 p.m. of day t. When the market opens on day $t+1$, the momentum profit jumps to 59 bps. The post-news announcement return drift occurs in a repeated pattern over the subsequent days, and the news momentum return reaches 104 bps at the market close of day $t+4$.[2] This detailed account of the stock market response to overnight news provides further support for investor underreaction to public news.

We perform several robustness tests. First, instead of using transaction prices from the Trade and Quote (TAQ) database to compute intraday returns, we consider daily stock returns from the Center for Research in Security Prices (CRSP) database to compute news-driven returns. This method loses the advantage of finely decomposing daily stock returns and obtains a noisy measure of news-driven returns. We find that a similar news momentum strategy generates an annualized average return of 23.88% and a four-factor alpha of 23.76%. This result illustrates both the gain in precision of measuring news returns using high-frequency data (approximately 68% increase in news momentum profits and 94% increase in Sharpe ratio) and the robustness of the news momentum effect. Second, we consider mid-quote prices instead of transaction prices to compute returns, based on which a news momentum strategy generates similar and slightly stronger performance. Third, instead of computing news returns and holding-period returns using close-to-close transaction prices, we consider returns based on open-to-open prices and observe an even stronger news momentum effect. Fourth, we compute firm-specific news-driven returns by subtracting from the overall

[2]This effect is unlikely to be driven by the periodicity pattern reported by Heston et al. (2010); whereas the overnight non-news returns exhibit a pattern of continuation in the subsequent overnight period, they are followed by an even stronger reversal during the next day, with the net effect of a reversal. Section 5 compares in detail the news momentum and the periodicity pattern of Heston et al. (2010).

stock price change during the short news arrival period, the common component of price changes due to movements in the aggregate stock market. The news momentum effect remains large and statistically significant with this change in experimental design.

Fifth, we use the Daniel et al. (1997) characteristic adjustment to compute the abnormal return of the news momentum strategy and obtain similar results to the four-factor alpha. Sixth, we drop earnings announcements from our news universe to eliminate the effect of the post-earnings announcement drift. With this filtering, our news momentum strategy remains highly profitable. Seventh, we filter out extreme daily price movements (with absolute values exceeding 10%) as Savor (2012) investigates, and the performance of our news momentum strategy is still largely intact. Eighth, to consider whether the news momentum effect results mainly come from news clustering (good news tends to follow good news), we exclude the news-driven returns from the holding period returns to the news momentum strategy. The news momentum effect remains large and statistically significant, suggesting that news clustering is unlikely to drive our results. Ninth, we consider how news momentum return varies over each day of the week and document stronger market reaction to Friday and weekend news. Finally, we consider Chan (2003)'s research design to classify news and non-news returns using monthly stock returns. We find that news return based on that approach does not predict future stock returns in our sample period from 2000 to 2012.

Our study is related to the growing literature that explores the effect of investor attention in financial markets. For instance, Hirshleifer et al. (2009) and DellaVigna and Pollet (2009) explore how investor inattention may exacerbate post-earnings-announcement drift. Cohen and Frazzini (2008) study how insufficient attention to a firm's major customers may lead to return predictability along the value chain. Our evidence of widespread post-news-announcement drift, and the particularly strong news momentum following overnight and weekend news, suggests that investor attention may be an important factor contributing to the pervasive phenomenon of news momentum.

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.

In relation to the voluminous literature on return predictability, we focus on the role of public news announcements. Chan (2003) shares a similar spirit, with methodological differences. In particular, Chan (2003) examines stock return patterns following the month with headline news. He finds evidence of post-news price drift for stocks with headlines and reversal for stocks without identifiable news. Our paper differs in both methodology and empirical results. First, our methodological contribution is to use tick-by-tick data to more accurately capture market reaction to news, thereby increasing the statistical power in identifying investor underreaction to public news. As an illustration, we replicate Chan (2003)'s study in our new sample period. We find that the news return based on his approach has no power to predict subsequent stock returns, but the news return out of our method has strong return forecasting power. Second, in terms of results, we show that there is continued market reaction to firm news after the initial reaction, with much of the further reaction concentrated in the first week following the news. Chan (2003) shows, however, that during the month immediately following the month with headline news, there is no further stock return continuation; rather, the return continuation starts to build up in the subsequent eleven months. These large differences suggest that the underlying phenomenon we capture may be quite different.

We organize the rest of this article as follows. Section 2 introduces the data and variable construction. Section 3 shows evidence of news momentum. Section 4 studies the source of news momentum. Section 5 details the analysis of market reaction to overnight news, and

Section 6 presents the robustness tests. Section 7 concludes.

2 Sample Construction and Variable Definition

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.[3] 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 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

[3]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.

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. 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 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 jth 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. Volatility is defined as the realized variance (RV), which is the sum of squared overnight and 15-minute intraday returns within each trading day. Turnover is the total number of shares traded in the prior five-day period divided by the average number of shares outstanding during the same period. 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. 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.

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 have higher volatilities, less liquidity, and lower analyst coverage.

3 News Momentum

3.1 Univariate Sorts: A Strategy of Buying Winners and Selling Losers

We start by testing the profitability of a news momentum strategy designed to exploit short-term market reactions to firm-level news. Figure 1 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, $R_{i,t,news}$. 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 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 2 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 2, 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.[4]

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

[4]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.

perform a similar exercise by forming portfolios based on past non-news returns.

The upper and lower solid curves in Figure 3 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:

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

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, the daily realized variance, 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.

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 6.41% with a t-statistic of 11.45 in Regression (V). 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 28.87% ($2 \times 4.33\% \times 0.0641 \times 52$) 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 has a positive and statistically significant slope coefficient, and firm size is negatively related to future returns, both 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.

3.3 An Investment Perspective

In this subsection, we examine the incremental investment value of the news momentum strategy. We consider a mean-variance investor whose investment opportunities include five popular trading strategies: holding the market portfolio (MKT), a small firm strategy (SMB) that buys small firms and shorts big firms, a value strategy (HML) that buys value stocks with high book-to-market ratios and shorts growth stocks with low book-to-market ratios, a momentum strategy (UMD) that buys past winners and sells past losers during the past 2 to 12 months, and a short-term return reversal strategy (REV) that buys stocks that have gone down and shorts stocks that have gone up during the prior month.[5]

For each of the five strategies together with our news momentum strategy, we compare the mean, standard deviation, Sharpe ratio, skewness, kurtosis, and maximum drawdown based on the daily returns. Panel A in Table 4 reports these descriptive statistics. The results illustrate the appealing feature of the news momentum strategy: It has the lowest risk as measured by standard deviation, skewness, kurtosis, and maximum drawdown, but has the highest average return. Taking both risk and return into account, a monthly Sharpe ratio of 0.95 suggests the news momentum far outperforms other strategies, among which the highest Sharpe ratio is approximately 0.27 for the short-term return reversal strategy. Panel B in Table 4 displays the time-series correlation matrix among the six strategies. The news momentum has a moderate positive correlation with the price momentum strategy (0.11) and negative correlations with the value and short-term return reversal strategies (-0.07 and -0.07). The low correlations between news momentum and other trading strategies imply large potential gains for a mean-variance investor.

To illustrate these gains, we construct the mean-variance frontiers implied by a set of investment opportunities for the five traditional trading strategies and another set including the news momentum strategy. We then construct optimal portfolios with the highest Sharpe ratio from these two investment opportunity sets. Panel C of Table 4 reports the performance of these two tangency portfolios. The results show substantial gains of tilting the portfolio toward the news momentum strategy: The monthly Sharpe ratio increases from 0.40 to 1.07, with declines in higher-moment risk.

3.4 Exploration of Transaction Cost

From a practical point of view, it is useful to consider whether the strategy of news momentum remains profitable after transaction costs. To shed light on this question, we follow Chordia et al. (2000), using the proportional effective spread (PES) as one measure of trading

[5]We obtain the daily returns of these five strategies from Kenneth French's website.

cost:

$$\text{PES}_{i,t} = \frac{2|Price_{i,t} - 0.5 \times (Bid_{i,t} + Ask_{i,t})|}{Price_{i,t}}, \tag{3}$$

where $Price_{i,t}, Bid_{i,t}$, and $Ask_{i,t}$ are the last transaction, bid and ask prices of stock i on day t. By definition, PES measures the scaled difference between execution price and the midpoint of NBBO (National Best Bid and Offer). We multiply the absolute difference by two to measure the round-trip trading cost. In the literature, effective spread is a widely used measure to estimate the transaction cost (e.g., Hasbrouck 2009; Novy-Marx and Velikov 2016).[6]

To evaluate the trading cost of the news momentum strategy, we compare the gross profit with the average effective spreads associated with the strategy. Because the news momentum strategy in Section 3.1 has a five-day holding period, we assume a 20% daily turnover for each side of the long short portfolio, using one-fifth of PES as a proxy of the trading cost for each of the decile portfolios formed in Section 3.1. The row labeled "PES based on 20% turnover" in Panel A of Table 5 shows the average one-fifth of total PES of each decile portfolio in bps. Interestingly, these decile PESs exhibit a U-shaped pattern, with the highest average PES of $10.5 \times 5 = 52.5$ and $11.3 \times 5 = 56.5$ bps in deciles 1 and 10 and the lowest PES of approximately $4.6 \times 5 = 23$ bps in deciles 5 and 6. This pattern indicates the higher bid-ask spread associated with extreme news-driven returns. A possible explanation is that market markers increase the bid-ask spread to compensate for the greater adverse selection surrounding the arrival of important firm news.

To gauge the profitability of the strategy, we obtain the net return for the news momentum strategy by subtracting the trading costs from the row "Gross Return," which shows the same daily decile portfolio returns in basis points as in Table 2. The results show that

[6]The exact definition of effective spread appears to vary across applications. For example, Chordia et al. (2000) uses the definition as in Eq. (3); Lesmond et al. (2004) replaces the transaction price with mid-quote price in the denominator of Eq. (3); and Hasbrouck (2009) uses the difference between the log transaction price and the log mid-quote price. We find that these variations make little difference to our results.

the return to the equal-weighted news momentum strategy does not survive the erosion of transaction costs. For the long-short news momentum portfolio, the daily average transaction cost associated with the long portfolio in decile 10 and short portfolio in decile 1 adds up to 21.7 bps, which is slightly larger than the average daily return of 15.9 bps to the spread portfolio. This result may not be too surprising in that the equal-weighted portfolio is tilted toward small stocks that are expensive to trade, and is therefore known to be less profitable in practice (Novy-Marx and Velikov, 2016).

The value-weighted news momentum strategy, however, remains profitable after transaction cost. Panel B of Table 5 shows the value-weighted portfolio returns and their average trading costs. While the trading costs exhibit a U-shaped pattern similar to those of the equal-weighted portfolios, their magnitudes are less than one-half of those of the equal-weighted portfolios. Deciles 1 and 10 have an average trading cost of 4.0 and 4.3 bps. Therefore, the trading cost for the long and short portfolio totals only $4.0 + 4.3 = 8.3$ bps. Since the value-weighted news momentum strategy has an average daily return of 11.7 bps, it generates a net profit of $(11.7 - 8.3)/10000 \times 252 = 8.6\%$ per year. These results suggest that the news momentum strategy has the potential to be profitable even after accounting for transaction costs.

4 Source of News Momentum Profits

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:

$$\mathrm{E}(\pi_{t+1}) \quad = \quad \frac{N-1}{N^2}\mathrm{tr}(\Gamma) - \frac{1}{N^2}[1'\Gamma 1 - \mathrm{tr}(\Gamma)] + \mathrm{Cov}(\mu_{news}, \mu_{overall}), \tag{4}$$

where $\Gamma = \mathrm{Cov}(R_{t,news}, R_{t+1,overall})$ is the covariance matrix between news-driven return $R_{t,news} \equiv (R_{1,t,news}, R_{2,t,news}, \ldots, R_{N,t,news})'$ on day t and the overall return $R_{t+1,overall} \equiv (R_{1,t+1,overall}, R_{2,t+1,overall}, \ldots, R_{N,t+1,overall})'$ on day $t+1$, and $\mathrm{Cov}(\mu_{news}, \mu_{overall})$ is the cross-sectional covariance between average news returns and overall returns.

Eq. (4) 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 6 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.[7] 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 6 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 6 shows the results based on the four-factor alpha, which generate a similar pattern.

4.2 News Momentum and Firm Characteristics

In this subsection, we examine the cross-sectional determinants of the news momentum effect to shed further light on its nature. Specifically, we study whether the performance of the news momentum strategy concentrates among stocks with certain characteristics, including firm size, analyst coverage, volatility, illiquidity, and past returns.

Several strands of literature in behavioral finance motivated our choice of these variables. The literature on limited investor attention naturally points to firm size and analyst coverage as proxies for investor attention: Small firms with lower analyst coverage tend to receive less attention from investors. Theoretical works on overconfidence such as Daniel et al. (1998) argue that overconfident investors tend to underreact to public news but overreact to

[7]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).

their private information signals. Smaller firms tend to have fewer information disclosures, firms with lower analyst coverage tend to lack timely financial analyses, and firms with more volatile stock prices tend to have more asymmetric information; therefore, through this theoretical lens, we would expect these companies to have more private information, which results in more underreaction to public news and thus stronger news momentum. From the point of view of limits to arbitrage (Shleifer and Vishny, 1997), illiquid firms with high volatilities are more costly and risky to trade, which could deter arbitrageurs from betting against perceived mispricing. We would expect those firms to exhibit stronger news momentum. Finally, it would be of interest to explore potential interaction between news momentum and the Jegadeesh and Titman (1993) price momentum.

We perform independent double sorts to examine these conjectures.[8] At the end of each day t, we independently sort all stocks into three portfolios along one dimension based on a particular stock characteristic and three portfolios along another dimension based on the news return on day t. We compute equal-weighted returns on the nine portfolios. Similar to the univariate sorts in Subsection 3.1, these portfolios have five-day overlapping holding periods, with one-fifth of the portfolio rebalanced each day. Because volatility and analyst coverage strongly correlate with size, as shown by the large correlation coefficients of 0.5 or higher in Table 1, we compute size-adjusted volatility and analyst coverage to alleviate the confounding effect of firm size.

Table 7 presents the results from the double sorts. Panel A shows that, consistent with our conjecture, the news momentum effect is stronger among small stocks. In particular, the four-factor alphas of winner-minus-loser strategies are 2.19%, 1.45%, and 0.51% per month for small-, medium-, and large-sized firms with the corresponding t-statistics of 9.05, 7.28, and 2.89, respectively. The difference in news momentum profits between small and large firms is 1.68% per month, which is statistically significant with a t-statistic of 5.60. Similarly, we find evidence in Panel B that the news momentum effect tends to be stronger among

[8]We also performed sequential sorts that first sort stocks according to a particular stock characteristic into terciles and then sort stocks within each tercile into terciles based on the daily news returns. The results are qualitatively similar to independent sorts.

stocks with low analyst coverage. For instance, stocks in the bottom tercile with low analyst coverage (adjusted by size) have a news momentum profit that is approximately 60% higher than firms in the top tercile with high analyst coverage. This difference in the four-factor alpha is 0.67% per month, with a t-statistic of 2.50. These results support the notion that stronger underreaction to public news, due to either overconfidence or investor inattention, may be driving the stronger news momentum effect among smaller firms with less analyst coverage.

Panel C of Table 7 shows size-adjusted volatilities. The results indicate a stronger news momentum effect among more volatile stocks. For example, the four-factor alpha for the winner-minus-loser strategy is 1.84% per month in the most volatile tercile, but only 1.01% in the least volatile tercile. The difference in the four-factor alpha between the two groups of stocks is 0.83% per month, with a t-statistic of 2.88. This result is consistent with investor overconfidence as well as higher trading costs deterring the effectiveness of arbitrage against investor underreaction.

In Panel D, we use the Amihud illiquidity measure to explicitly gauge how the news momentum effect interacts with trading costs. Indeed, we find particularly large news momentum profits for stocks most costly to trade. Among the tercile of stocks with the highest illiquidity measure, the four-factor alpha of the news momentum strategy is 1.95% per month, with a t-statistic of 9.67, whereas among the tercile with the lowest illiquidity, the four-factor alpha of a similar news momentum strategy is only 0.27% per month, with a t-statistic of 1.54. This return spread of 1.68% per month has a t-statistic of 6.65.

Before concluding this subsection, we examine the interaction between the news momentum effect and the Jegadeesh and Titman (1993) price momentum. Panel E shows the results. In our sample period of 2000–2012, the price momentum effect is statistically insignificant, but the news momentum effect is strong and significant across the three terciles of stocks based on past returns. Interestingly, we find that the news momentum effect is stronger among loser stocks in the past year.

5 Overnight News

In this section, we perform an in-depth analysis of 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 the 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.[9] We calculate returns of this strategy over the 30-minute interval when the market is open and the interval of overnight return when the market is closed. 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.[10] 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 3, where the impact of the overnight news on the immediate open-to-close period is ignored.

[9]We skip the return between 9:45 a.m. and 10:00 a.m. to reduce the contamination induced by microstructure effects such as bid-ask bounce.

[10]Lou et al. (2017) 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.

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).[11] 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 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

[11] 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.

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.[12] Second, it is possible that the news time stamp is imprecise 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.

[12] We implement a set of clearing rules commonly used in high-frequency econometrics literature to eliminate possible errors in the high-frequency 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 8 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 8). 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 8. 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 jth 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 8 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 $5 \times 5 \times 5$ size, book-to-market ratio, and momentum benchmark returns based on all NYSE/AMEX/NASDAQ data in the CRSP database.[13] A firm's benchmark adjusted return is then a firm's daily overall 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 8 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

[13] 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.

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 8 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 8 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. (2016)), 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 8 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 Weekend News

If investor underreaction drives the news momentum effect, should we observe stronger momentum for news arriving over the weekend? To answer this question, we consider how news momentum return varies over each day of the week. Specifically, 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 coefficient on the Monday dummy is of particular interest, because the return on Monday to the news momentum strategy is based on news arriving over Friday and the weekend. If there is stronger market underreaction to Friday and weekend news, we would expect that (1) in the first regression, the coefficient for the Monday dummy variable would be larger than that for other days of the week; and (2) in the second regression, the coefficient for the Monday dummy variable would be positive.

Results in Table 9 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.

6.10 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 10 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-driven and non-news driven components, by matching a comprehensive sample of intraday firm-level news arrivals with high-frequency price movements of individual stocks. Consistent with prior literature, we find that non-news driven returns precede a reversal. For news-driven returns, however, we find strong evidence of return continuation. A strategy of news momentum that buys stocks with high news returns and sells stocks with low news returns generates an annualized return of 40.08%

in the following week, with a four-factor alpha of 40.44% controlling for the market, size, value, and momentum. We attribute this effect of news momentum to the autocorrelation component and find it is particularly pronounced for overnight news, and among small firms with less analyst coverage, higher volatility, and lower liquidity, which is consistent with imperfect investor reaction to news and limits to arbitrage. We further demonstrate that the news momentum strategy has the potential to be profitable after transaction cost.

The pervasive phenomenon of news momentum that we identify is naturally connected to the stock price momentum observed in stock markets for more than one and a half centuries around the globe (e.g., Chui et al. (2010); Chabot et al. (2014)). Due to the short span of our high-frequency news and price data, we could not fully examine the extent to which underreaction to firm-level information drives the stock price momentum. This line of study would be a fruitful area for future research.

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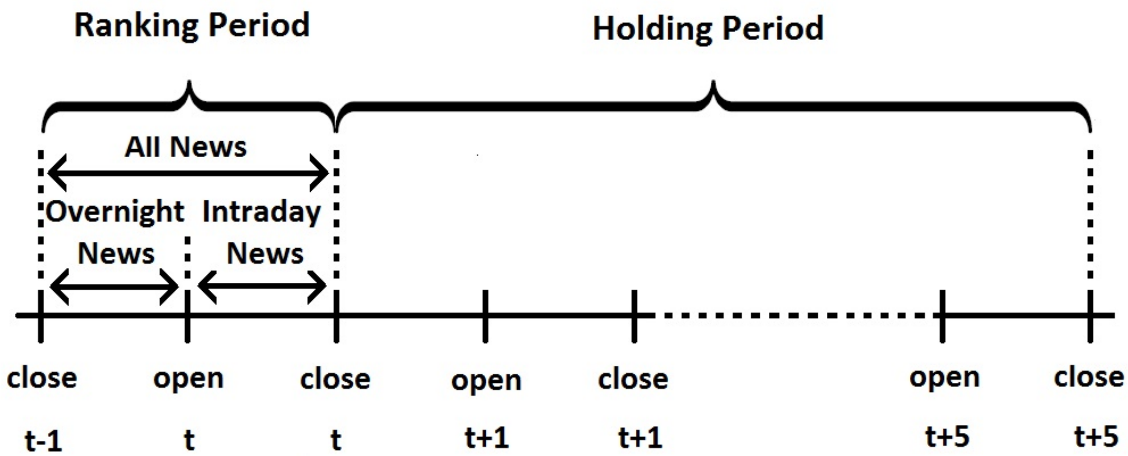

Figure 1: Timeline of News Momentum Strategy

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.

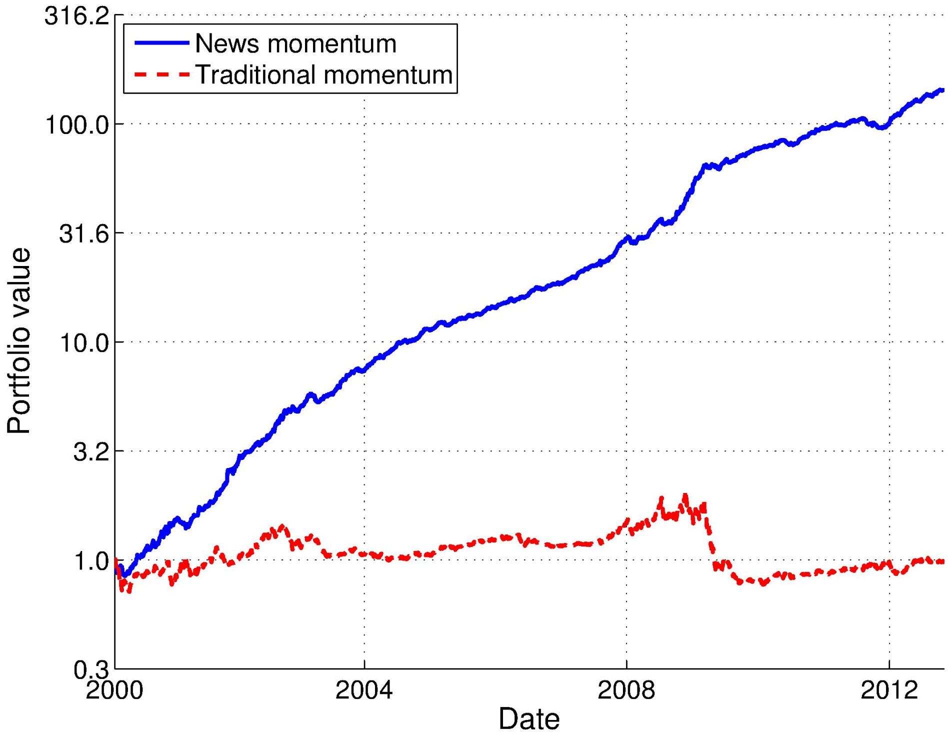

Figure 2: Performance of News Momentum Strategy

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.

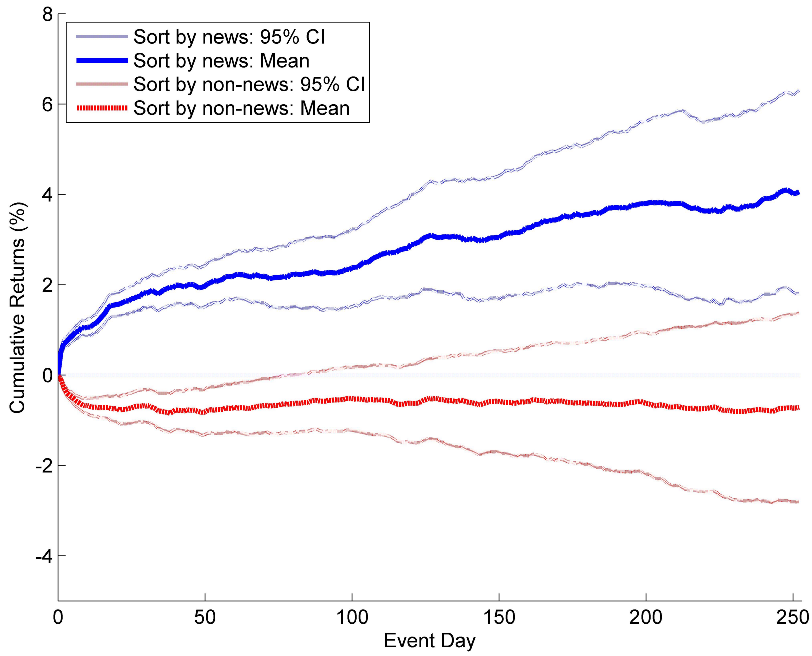

Figure 3: Performance of News Momentum Strategy over Event Time

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.

(a) (b)

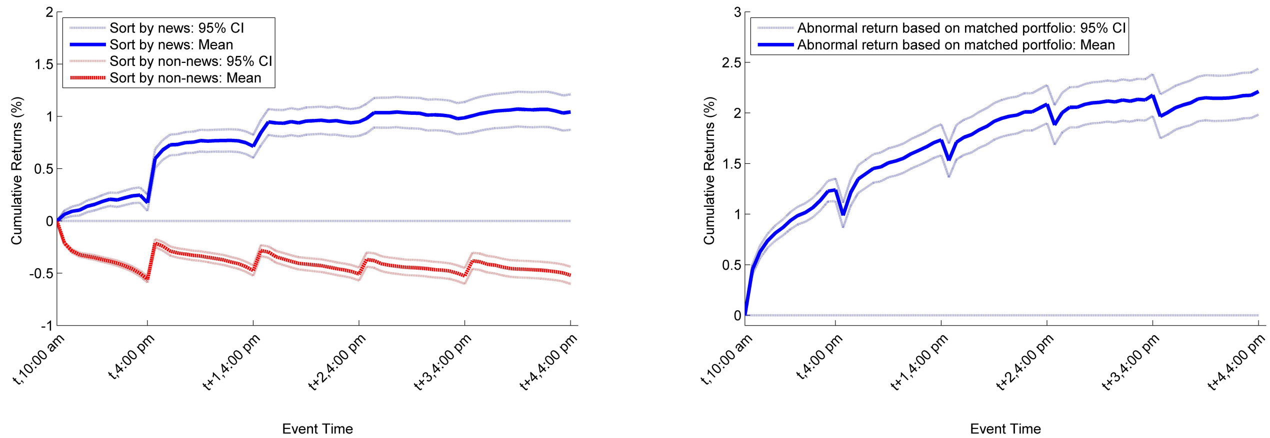

Figure 4: Overnight News Momentum Strategy over Event Time

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 the event day k, 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 with CRSP share code 10 or 11 for the period between March 2000 and October 2012, and with prices above \$1 at the end of the portfolio formation period. 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 $t-1$. *RV* is the daily realized variance, which is the sum of squared overnight and 15-minute intraday returns from 4:00 p.m. on the previous day to 4:00 p.m. on the current day. *Turnover* is the total number of shares traded in the prior five-day period over the average number of shares outstanding for the same period. *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. *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.

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
$\sqrt{\text{RV}}$	3.37%	2.59%	0.81%	1.81%	2.65%	4.06%	13.14%
Turnover	0.01	0.02	0.00	0.00	0.00	0.01	0.06
ILLQ	0.32	3.19	0.00	0.00	0.01	0.05	6.10
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

Panel B: Cross-Sectional Correlations

	R_{news}	$R_{non\text{-}news}$	Log(Size)	BM	$\sqrt{\text{RV}}$	Turnover	ILLQ	Mom	Analyst
R_{news}	1.000	0.062	-0.003	0.003	0.015	0.030	0.001	0.003	-0.003
$R_{non\text{-}news}$	0.062	1.000	0.002	0.007	0.074	0.051	0.004	0.003	-0.009
Log(Size)	-0.003	0.002	1.000	-0.224	-0.538	0.164	-0.252	0.051	0.770
BM	0.003	0.007	-0.224	1.000	0.058	-0.077	0.133	0.041	-0.211
$\sqrt{\text{RV}}$	0.015	0.074	-0.538	0.058	1.000	0.232	0.355	-0.042	-0.285
Turnover	0.030	0.051	0.164	-0.077	0.232	1.000	-0.077	0.034	0.207
ILLQ	0.001	0.004	-0.252	0.133	0.355	-0.077	1.000	-0.037	-0.154
Mom	0.003	0.003	0.051	0.041	-0.042	0.034	-0.037	1.000	-0.063
Analyst	-0.003	-0.009	0.770	-0.211	-0.285	0.207	-0.154	-0.063	1.000

Table 2: Performance of the News Momentum Strategy

This table reports the performance of the news momentum strategy. 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. 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. Our sample includes stocks listed on NYSE/AMEX/NASDAQ over the period between March 2000 and October 2012 with prices above $1 at the end of the portfolio formation period. We multiply daily returns by 21 to get monthly returns in percentage.

	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 prices above $1 as of the portfolio formation. R_{news} ($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. *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. *RV* is the daily realized variance which is the sum of squared overnight and 15-minute intraday returns from 4:00 p.m. on the previous day to 4:00 p.m. on the current 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. *Mom* is the cumulative returns from prior day 252 to day 21 for a given day t and is updated daily.

	(I)	(II)	(III)	(IV)	(V)
Intercept	0.0024	0.0023	0.0023	0.0039	0.0050
	(2.27)	(2.20)	(2.17)	(2.77)	(2.80)
R_{news}	0.0425		0.0574	0.0614	0.0641
	(8.28)		(11.02)	(10.64)	(11.45)
$R_{non\text{-}news}$		-0.0792	-0.0809	-0.0737	-0.0427
		(-24.29)	(-24.80)	(-22.39)	(-11.59)
Dummy(No News)	0.0001	0.0000	0.0001	-0.0007	-0.0006
	(0.50)	(0.01)	(0.33)	(-4.06)	(-4.50)
Log(Size)				-0.0003	-0.0005
				(-2.46)	(-2.02)
BM				0.0007	0.0010
				(2.96)	(2.83)
Mom				0.0006	0.0008
				(0.86)	(1.07)
RV					-0.0481
					(-0.56)
ILLQ					-0.0001
					(-0.65)
Adj-R^2 (%)	0.11	0.66	0.75	3.06	5.20
#Obs	10,097,270	10,097,270	10,097,270	8,674,126	6,245,682

Table 4: Investment Value of News Momentum

This table reports descriptive statistics of daily returns of six investment strategies: the return of the news momentum strategy (NEWS); the excess return on the market (MKT); the average return on small-sized firms minus the average return on big-sized firms (SMB); the average return on high book-to-market ratio firms minus that on low book-to-market ratio firms (HML); the average return on the high prior 2 to 12 month return portfolios minus that on the low prior 2 to 12 month return portfolio (UMD); and the average return on the low prior month return portfolio minus that on the high prior month return portfolio (REV). Daily returns of MKT, SMB and HML, UMD, and REV come from Kenneth French's website. All return numbers are in monthly percentage (multiplying the percentage daily returns by 21). Panel A summarizes the average monthly return (Mean), standard deviation (SD), Sharpe ratio (SR), skewness, kurtosis, and maximum drawdown (MaxDD) of each portfolio. Panel B reports the time-series correlation coefficients among the six strategies. Panel C reports the performance measures of the two tangency (maximum Sharpe ratio) portfolios from the two investment opportunity sets: one with the five traditional strategies and the other with the addition of the news momentum strategy.

Panel A: Strategy Performance

	Mean	SD	SR	Skewness	Kurtosis	MaxDD
NEWS	3.34	3.51	0.95	0.51	12.14	15.92
MKT	0.20	6.26	0.03	0.00	9.54	59.20
SMB	0.16	2.86	0.06	-0.37	7.75	27.11
HML	0.64	3.09	0.21	0.02	8.73	28.63
UMD	0.11	5.08	0.02	-0.79	10.63	63.66
REV	1.31	4.85	0.27	1.44	19.30	24.67

Panel B: Time-Series Correlations

	NEWS	MKT	SMB	HML	UMD	REV
NEWS	1.00	-0.05	0.02	-0.07	0.11	-0.07
MKT	-0.05	1.00	0.12	0.00	-0.38	0.39
SMB	0.02	0.12	1.00	-0.15	0.12	0.03
HML	-0.07	0.00	-0.15	1.00	-0.23	-0.18
UMD	0.11	-0.38	0.12	-0.23	1.00	-0.11
REV	-0.07	0.39	0.03	-0.18	-0.11	1.00

Panel C: Tangency Portfolio Performance

	Mean	SD	SR	Skewness	Kurtosis	MaxDD
Excluding News Momentum	0.73	1.83	0.40	0.71	13.14	11.79
Including News Momentum	2.19	2.05	1.07	0.89	11.77	6.06

Table 5: Gross Return, Transaction Cost and Net Return of the News Momentum Strategy

This table reports the daily gross return, transaction cost, and net return of the news momentum strategy in basis points. Daily news returns are aggregated from overnight and 15-minute news returns computed from matching the transaction prices in the TAQ database and the news stories in the RavenPack news databases. Daily overall returns are computed using the transaction prices at 4:00 p.m. from the TAQ database. 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 average portfolio return and proportional effective spread (PES) 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. Thus, we assume a daily turnover of 20% for estimating the transaction cost. Panels A and B respectively summarize the daily equal- and value-weighted portfolio returns and proportional effective spreads in basis points. The rows labeled "Gross Return", "PES based on 20% turnover" and 'Net Return" respectively report the average unadjusted returns, PES, and net returns for each portfolio. The column labeled "10–1" reports the difference in returns between Portfolio 10 and Portfolio 1. Our sample includes stocks listed on NYSE/AMEX/NASDAQ over the period between March 2000 and October 2012 with prices above $1 at the end of the portfolio formation period.

	1	2	3	4	5	6	7	8	9	10	10–1
				Panel A: Equal-Weighted Portfolios							
Gross Return	-3.7	1.9	4.1	5.1	5.2	6.3	6.5	6.9	7.9	12.2	15.9
PES based on 20% turnover	10.5	7.3	5.7	4.8	4.5	4.7	5.1	6.1	7.8	11.3	21.7
Net Return											-5.8
				Panel B: Value-Weighted Portfolios							
Gross Return	-2.5	2.2	1.6	3.1	1.6	2.5	2.8	2.8	3.8	9.2	11.7
PES based on 20% turnover	4.0	2.6	2.1	1.9	1.8	1.9	1.9	2.2	2.8	4.3	8.3
Net Return											3.5

Table 6: 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. (4), 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 7: Performance of the News Momentum Strategy: Double Sorts

This table reports the performance of portfolios sorted on news momentum and firm characteristics for the period between March 2000 and October 2012. At the end of each day t, we independently sort stocks into 3 portfolios based on news returns and 3 portfolios based on one the firm characteristics. Then we consider the performance of the 9 portfolios from the intersection of the double sorts. Similar to Table 2, we use portfolios with overlapping holding periods. Our set of firm characteristics includes the following. *Size* is the product of the closing price and the number of shares outstanding updated daily using the daily data of a firm. *Analyst Coverage* is analyst coverage which is the monthly number of sell-side analysts forecasting annual firm earnings from I/B/E/S. *Volatility* is the daily realized variance which is the sum of squared overnight and 15-minute intraday returns from 4:00 p.m. on the previous day to 4:00 p.m. on the current 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. *Mom* is the cumulative returns from prior day 252 to day 21 for a given day t and is updated daily. In each panel, the first three rows (columns) represent three levels of the control variable (the news return). The row (column) labeled "Diff" ("High–Low") reports the difference in returns between Portfolio 3 and Portfolio 1 constructed according to the control variable (the news return). The column labeled "FFC4" reports the Fama-French-Carhart four-factor alphas. The corresponding Newey-West t-statistics are reported in parentheses. We report returns in monthly percentage.

	1	2	3	High–Low	FFC4
			Panel A: Size		
Small	0.21	1.87	2.38	2.17	2.19
	(0.36)	(3.39)	(4.20)	(9.12)	(9.05)
2	0.30	1.18	1.75	1.45	1.45
	(0.46)	(2.09)	(2.68)	(7.23)	(7.28)
Large	0.38	0.80	0.92	0.54	0.51
	(0.63)	(1.61)	(1.58)	(3.03)	(2.89)
Diff	0.17	-1.07	-1.46	-1.63	-1.68
	(0.50)	(-3.58)	(-4.71)	(-5.60)	(-5.60)
			Panel C: Size-Adjusted Volatility		
Low	0.85	1.12	1.86	1.01	1.01
	(1.81)	(2.67)	(4.03)	(4.94)	(4.95)
2	0.66	1.04	1.93	1.27	1.28
	(1.13)	(1.84)	(3.37)	(6.85)	(6.75)
High	-0.12	0.82	1.70	1.82	1.84
	(-0.16)	(1.07)	(2.26)	(8.28)	(8.37)
Diff	-0.97	-0.30	-0.16	0.81	0.83
	(-2.23)	(-0.65)	(-0.38)	(2.82)	(2.88)
			Panel E: Mom		
Loser	0.12	1.25	1.83	1.71	1.72
	(0.17)	(1.96)	(2.65)	(7.90)	(8.00)
2	0.26	1.08	2.08	1.82	1.83
	(0.47)	(2.20)	(3.88)	(10.02)	(9.84)
Winner	0.48	1.18	1.60	1.12	1.12
	(0.81)	(2.23)	(2.71)	(5.38)	(5.36)
Diff	0.36	-0.07	-0.23	-0.60	-0.60
	(0.88)	(-0.19)	(-0.58)	(-2.07)	(-2.07)

	1	2	3	High–Low	FFC4
			Panel B: Size-Adjusted Analyst Coverage		
Low	0.55	1.18	2.26	1.71	1.72
	(0.90)	(2.22)	(3.72)	(7.39)	(7.42)
2	1.17	1.47	2.48	1.31	1.32
	(1.98)	(2.84)	(4.28)	(6.77)	(6.86)
High	1.10	1.37	2.16	1.06	1.05
	(1.74)	(2.54)	(3.50)	(6.30)	(6.27)
Diff	0.55	0.18	-0.10	-0.65	-0.67
	(2.09)	(0.90)	(-0.40)	(-2.43)	(-2.50)
			Panel D: ILLQ		
Low	0.50	0.88	0.78	0.28	0.27
	(0.83)	(1.78)	(1.34)	(1.57)	(1.54)
2	0.25	1.19	1.48	1.23	1.21
	(0.38)	(2.16)	(2.32)	(6.06)	(6.08)
High	0.25	1.57	2.20	1.94	1.95
	(0.43)	(2.87)	(3.87)	(9.64)	(9.67)
Diff	-0.25	0.70	1.42	1.66	1.68
	(-0.80)	(2.61)	(5.03)	(6.59)	(6.65)

Table 8: 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 prices above \$1 at the end of the portfolio formation period. 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		1	2	9	10	High–Low
	Panel A: CRSP Return						*Panel B: Mid-Quote Return*				
Return	0.00	0.85	1.33	1.98	1.99	Return	-0.87	0.55	1.76	2.52	3.40
	(-0.00)	(1.35)	(2.27)	(3.15)	(6.01)		(-1.35)	(0.91)	(2.98)	(4.12)	(12.55)
FFC4	-0.35	0.48	0.96	1.63	1.98	FFC4	-1.18	0.20	1.41	2.24	3.42
	(-1.20)	(2.66)	(5.73)	(6.92)	(6.05)		(-4.84)	(1.20)	(8.02)	(9.80)	(12.75)
	Panel C: Open-to-Open Return						*Panel D: Market-Risk-Adjusted Returns*				
Return	-0.60	0.57	1.98	3.33	3.92	Return	-0.8	0.58	1.76	2.49	3.29
	(-0.90)	(0.95)	(3.37)	(5.33)	(12.91)		(-1.27)	(0.95)	(2.97)	(4.04)	(12.26)
FFC4	-0.68	0.46	1.88	3.26	3.94	FFC4	-2.23	-0.86	0.31	1.1	3.33
	(-1.09)	(0.82)	(3.39)	(5.48)	(13.03)		(-10.08)	(-4.70)	(1.75)	(5.20)	(12.30)
	Panel E: DGTW Characteristic Adjustment						*Panel F: Eliminating Earnings Announcements*				
Return	-1.68	-0.53	0.67	1.39	3.06	Return	0.20	0.71	1.45	1.99	1.79
	(-6.50)	(-2.79)	(3.67)	(5.53)	(11.14)		(0.29)	(1.13)	(2.35)	(3.03)	(5.76)
FFC4	-1.64	-0.53	0.67	1.45	3.09	FFC4	-0.17	0.38	1.10	1.68	1.85
	(-7.42)	(-3.54)	(4.39)	(6.88)	(11.24)		(-0.65)	(2.23)	(6.05)	(6.62)	(5.92)
	Panel G: Eliminating Extreme Price Changes						*Panel H: Excluding News Clustering*				
Return	-0.57	0.40	1.64	2.36	2.93	Return	-0.92	0.25	1.29	1.92	2.85
	(-0.91)	(0.65)	(2.77)	(3.89)	(10.75)		(-1.49)	(0.43)	(2.24)	(3.17)	(10.51)
FFC4	-0.92	0.03	1.28	2.05	2.97	FFC4	-1.24	-0.09	0.95	1.63	2.88
	(-3.92)	(0.16)	(7.63)	(8.90)	(10.70)		(-5.26)	(-0.53)	(5.69)	(7.07)	(10.53)

Table 9: Weekend News

This table shows how news momentum return varies over each day of the week. Specifically, we construct a news momentum strategy that buys (sells) stocks with the highest (lowest) 10% news return in the previous day with a one-day holding period. 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). The coefficient on the Monday dummy is of particular interest, because the return on Monday to the news momentum strategy is based on news arriving over Friday and the weekend.

	(I)	(II)
Intercept		41.69
		(12.16)
Mondays	64.69	23.00
	(8.82)	(2.84)
Tuesdays	28.23	
	(3.80)	
Wednesdays	45.97	
	(7.09)	
Thursdays	41.99	
	(6.04)	
Fridays	50.61	
	(7.79)	

Table 10: 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)