The Momentum of News

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Abstract

Relying on a comprehensive data set of news releases, we construct monthly firm-level news scores during the 2000–2014 period and document a news momentum phenomenon that stocks with more positive news in the past generate more positive news in future. We propose two hypotheses to explain this phenomenon and find that news momentum is driven by the persistence of firms' fundamentals instead of firms' information environments. A trading strategy, which combines a long position in a good-news quintile portfolio with a short position in a bad-news portfolio, generates 8.352 percent risk-adjusted return annually. Overall, these findings suggest a cross-sectional prediction of news, which is not fully incorporated into the stock price by investors.

Keywords: News; Momentum; Fundamentals; Information Environments; Future Returns
JEL Code: G02; G10; G14

1. Introduction

Over the past four decades, hundreds of anomalies have been uncovered in the cross-section of stock returns. Among potential explanations for cross-sectional predictability, mispricing is identified as the key one (e.g., Mclean and Pontiff, 2016; Engelberg, McLean, and Pontiff, 2016). In particular, behavioral theories attribute mispricing to investors' inability to price news correctly (e.g., Daniel, Hirshleifer, and Subrahmanyam, 1998; Barberis, Shleifer, and Vishny, 1998; Hong and Stein, 1999). Because these theories typically take news as given, the property of news is left unexplored. Given price movement is a function of news, the predictability of news is essential to the understanding of return anomalies. In this paper we fill this void by examining the cross-sectional predictability of news.

Using a comprehensive news dataset collected by RavenPack, we construct a sample of real-time news releases for stocks listed on the NYSE, Amex, and Nasdaq over the 15-year period between 2000 and 2014. We focus on news articles commonly used by institutional and sophisticated individual investors. Specifically, RavenPack quantifies the positive (or negative) information (i.e., news-sentiment score) in each news article based on professional algorithms. For example, a news article on a corruption scandal involving a firm's executives is associated with a low news-sentiment score, and a news article regarding the successful development of a firm's new product is associated with a high news-sentiment score. Our main analysis is conducted at the monthly frequency. We aggregate the news sentiment scores for each firm for each day, and then calculate monthly news sentiment scores by averaging daily scores over a month.

We perform the following analyses. First, we examine whether there is a cross-sectional pattern of news. Specifically, we construct monthly news portfolios by sorting stocks into five quintile portfolios based on their current news scores. We then compute the equally-weighted average news scores of each portfolio. We find that stocks in the highest news score portfolio outperform stocks in the lowest news score portfolio in future, which is called *the news momentum phenomenon*. This phenomenon is robust to various specifications such as the daily or weekly frequency, the inclusion of neutral news articles, negative or positive news sorting, and decile portfolios.

Second, we propose two hypotheses to explain the news momentum phenomenon. One view is that news momentum is driven by firms' information environments. For instance, *pro forma* earnings disclosure (e.g., Hirshleifer and Teoh, 2003) may generate some specific pattern of news flow. By distinguishing bad news from good news, Kothari, Shu, and Wysocki (2009) report that managers tend to delay disclosure of bad news and immediately reveal good news to investors. In firms with poor information environments, companies with more positive information continue to disseminate more positive news, and companies with less positive information continue to disclose less positive news. We call this view *the information environment hypothesis*.

One the other hand, news momentum could be caused by the pattern of firms' fundamentals. It has been well documented (e.g., Ball and Brown, 1968; Beaver, Clarke and Wright, 1979; Graham, Harvey, and Rajgopal, 2005; Markov and Tamayo, 2006; Li, 2010) that earnings are predictable and persistent. If news articles fairly reflect firms' fundamentals, the persistent earning stream is likely to generate a persistent stream in sequential news releases. More specifically, positive (negative) news is more likely to be followed by positive (negative) news. We call this view *the fundamental hypothesis*.

To test the two hypotheses, we start by checking whether news momentum concentrates among stocks with poor information environments proxed by small firm size, low analyst coverage, and less institutional holdings. Inconsistent with *the information environment hypothesis*, we find no systematic difference in news momentum between stocks with small firm size, low analyst coverage, and less institutional holdings and stocks with large firm size, high analyst coverage, and more institutional holdings. We move forward by testing whether news momentum is driven by firms' fundamentals. In supportive of *the fundamental hypothesis*, we find that firms with current good news scores have higher profitability in future.

Finally, we investigate whether investors are aware of news momentum. If news momentum is correctly incorporated into the stock price, stocks in the highest news score portfolio should have similar future returns as stocks in the lowest news score portfolio. Interestingly, we find significant news-driven price momentum: the strategy that buy the good news portfolio and sell bad news portfolio generates 8.352 percent per year. News-driven price momentum is mainly significant in stocks with poor information environments such as stocks with small firm size, low analyst coverage, and less institutional holdings. This is consistent with the view that investors' underreact to news and news momentum. The return predication of news is robust to various specifications such as the daily or weekly frequency, the inclusion of neutral news articles, negative or positive news sorting, and decile portfolios.

The remainder of the paper proceeds as follows. We explain the sample construction for the news variable and describe sample characteristics in Section 2. In Section 3, we examine news momentum and test two hypotheses on news momentum. In Section 4, we study the return prediction of news momentum. Finally, we provide concluding remarks in Section 5.

2. Data and Variable Construction

Our data come from a variety of sources. The stock returns and the market capitalization data are from the CRSP stock combined File, which includes the firms listed on the New York Stock Exchange (NYSE), National Association of Securities Dealers Automated Quotations (NASDAQ), and American Stock Exchange (AMEX). Our analysis includes the firms that at least have one news story covered by RavenPack, but excludes other firms. In our analysis, we control for a battery of firm-specific characteristics that are likely to be correlated with firm-specific information production or stock returns. These control variables include analyst coverage, institutional ownership, the return of asset, earnings surprises, idiosyncratic volatility, illiquidity (Amihud, 2002). Appendix A lists data sources for these control variables. The sample period is from January 2000 to October 2014. It is determined by the availability of news data.

Our primary data are news variables. The data for news variables are obtained from RavenPack News Analytics, a leading global news database used in quantitative and algorithmic trading, which has recently been used in finance research (e.g., Kelley and Tetlock 2013; Kolasinski, Reed, and Ringgenberg, 2013; Schroff, Verdi, and Yu, 2014; Dai, Parwada, and Zhang, 2015, Dang, Moshrian, and Zhang, 2015; Jiang, Li, and Wang, 2015). RavenPack collects and analyzes real-time, firm-level business news from leading news providers, including Dow Jones Newswire, the Wall Street Journal (all editions), Barron's, other major publishers and Web aggregators, including industry and business publications, regional and local newspapers, government and regulatory updates, and trustworthy financial websites. Ravenpack dividends news into 32 categories. To capture news stories that are more likely to be related to firms' fundamentals, we form two groups. The hard news group consists of the revenue category, the earnings category, the analyst-ratings category, and the credit-ratings category, all other news categories are included in the soft news group. Appendix B lists 32 categories and the two groups. Among all news stories, 30.4% is related to hard information. The other 69.6% portion is linked to soft information.

The most fascinating thing is that RavenPack not only provide firm-specific news stories, but also provide value-relevant information in each news article based on professional algorithms, which were developed and evaluated by effectively combing traditional language analysis, financial expert consensus, and market response methodologies. Specifically, the news sentiment score indicates whether or not, and to what extent a news story may have a positive, neutral, or negative effect on stock prices. This score is assigned to all relevant firms listed in the news report. The sentiment score ranges from 0 to 100, with a value below (above) 50 indicating the negative (positive) sentiment of a given news. A score of 50 represents a neutral sentiment. To facilitate our empirical analysis, we minus 50 from the news sentiment scores and scale it by 100.

We want to emphasize that our sample excludes repeated news by setting the "event novelty score" (ENS) provided by RavenPack to be 100, which captures only the fresh news about a company. As such, our news momentum is unlikely to be induced by reproduction or re-dissemination of the same or similar articles. The original news data include daily observations. Our main analysis is based on monthly data. To obtain monthly observations, we aggregate the news sentiment scores for each firm for event days during the month.

[Insert Table 1 Here]

Table 1 reports the descriptive statistics of the main variables used in our empirical analysis. Our sample includes 473,941 news articles. The average sentiment of these news articles is 0.083. A striking thing that emerges from the table is the asymmetric distribution of the sentiment scores of news events. It seems that news stories are more likely to provide positive content. Another striking thing that comes from the table is that many firms show up as having zero analyst coverage. Indeed, all firms below 10 percentile have zero analyst coverage. The two striking features suggest that RavenPack has a wider coverage.

[Insert Table 2 Here]

Table 2 provides an overview of the extent of news coverage for five periods (2000-2002, 2003-2005, 2006-2008, 2009-2011, and 2012-2014) as well as for different size groups. A key fact that emerges from Table 2 is what is the trend of news coverage. It is evident from the table that large firms have higher news coverage. This fact is consistent with the literature on analyst coverage and media coverage, which suggests that large firms have higher coverage. We also find that the number of news articles is an increasing function of time for all size groups and for both positive and negative news articles. This is not surprising given the progress of information technology and is consistent with the literature documenting that media coverage and analyst coverage is getting higher over time.

3. The cross-section of News

3.1 The Cross-section of News?

This section studies the production of firm-specific information flows by examining patterns of information disclosures. Following the standard in the return momentum literature, we construct monthly news momentum portfolios according to news sentiment index. Specifically, at the end of month t, we sort all stocks into five portfolios based on their news scores ($News_t$). We then compute the equally-weighted average news scores of each portfolio. The quantile of stocks releasing the most negative information (below the 20th percentile) is the bad news portfolio. Table 1 shows that the bad news portfolio has a sentiment score of -0.134 at the formation period. Stocks releasing the most positive news (above the 80th percentile) form the good news portfolio, which has a sentiment score of 0.296. Other quantiles of stocks have respectively a news sentiment score of 0.009, 0.083, 0.159. We construct a hedging portfolio by selling the bad news portfolio and buying the good news portfolio. The "good minus bad" (GMB) portfolio has a sentiment score of 0.431, which is statistically significant at the 1% level.

[Insert Table 3 Here]

Momentum is the tendency of an object in motion to stay in motion. Hypothesis 1 thus implies that the GMB portfolio should exhibit a pattern of sentiment continuation in the subsequent periods. Table 1 presents the empirical results. We construct the GMB portfolio at the formation period and hold this portfolio for a number of months (1, 6, 12, 24) following the formation month. Our results indicate that the top quartile outperforms the bottom at month t+1. It is evident that all quantile portfolios show a monotonically increasing sentiment score. The GMB portfolio has an average sentiment score of 0.037, with a heteroscedasticity and autocorrelation consistent t-value of 25.7. Taken together, these results is an indication of news momentum. At the same time, we note that the GMB portfolio sentiment has a substantial drop from 0.431 to 0.037. This is consistent with the view that firms manage information disclosure to smooth its information flow. For example, Chuprinin (2011) demonstrate that firms use reserves of positive private information as insurance against unanticipated negative events. Kothari, Shu, and Wysocki (2009) suggest that firms delay the release of bad news up to a certain threshold in an attempt to wait for good news to accommodate negative news.

Turning to the holding period from t+2 to t+6, which removes the impact of news sentiment at period t+1, we find that the GMB portfolio still exhibits a positive sentiment score with a Newey-West adjusted t-statistic of 49.8, suggesting that news sentiment stays in motion. Furthermore, all quantile portfolios also show a monotonic relation in terms of sentiment score. We further check the holding period from t+7 to t+12 and from t+13 to t+24. It is evident that the GMB portfolio has a significant positive sentiment score during these period.[1] Thus, positive news releases is positively correlated with future news disseminations. For these holding periods, again, we find a monotonic relation in term of sentiment among all quantile portfolios, though news sentiment of these portfolios become more converged. Overall, our empirical findings suggest the presence of news momentum.

3.2 Hypothesis Development

[1] At longer horizons, news momentum still continues and finally becomes insignificant.

The media disseminates or rebroadcasts a large amount of financial news or signals regarding to firms' earnings, management, and investment decisions, among others. These pieces of information affect investors' expectations about stock returns and may improve market efficiency. Indeed, a flood of research highlights the information dissemination effect of media coverage through various channels such as drawing attention (Fang and Peress, 2009; Da, Engelberg, and Gao, 2011), resolving information asymmetry (Tetlock, 2010), delivering fundamental information (e.g., Tetlock, Saar-Tsechansky, and Macskassy, 2008), or inflating market sentiment (e.g., Tetlock, 2007).

Because the flow of information plays a critical role in financial markets, a few recent studies examine the production of financial news. On the theoretical side, Gentzkow and Shapiro (2010) show that media coverage is the product of profit maximization by media. Veldkamp (2006) develops a model for understanding information production in competitive news markets. Hirshleifer and Teoh (2003) show that alternative means of presenting information have different effects on market prices. Furthermore, Chuprinin (2011) uses a simple model to study patterns of firm-level information disclosures. Overall, these studies suggest that news flow is not random and is likely to have some specific patterns. Ahern and Sosyura (2015), Engelberg and Parsons (2011) and Gentzkow ans Shapiro (2004, 2006) confirm the non-randomness of news flows.

Non-random news flow can be driven by the promotion of financial news stories. In this regard, Bushee and Miller (2007) and Solomon (2012) demonstrates that investor relations firms spin their clients' news, generating more media coverage of positive press releases than negative press releases. Similarly, Reuter and Zitzewitz (2006) and Gurun and Butler (2012) find that when local media report more news about local companies, they use fewer negative words compared to the same media reporting about nonlocal companies. They also document that a potential explanation for this positive slant is the firms' local media advertising. In particular, firms have incentive to promote news stories during major events. For example, bidder firms (Ahern and Sosyura, 2014) in stock mergers promote substantially more news stories after the start of merger negotiations, but before the public announcement.

Non-random news flow can also be driven by firms' selective information disclosure choices. For instance, *pro forma* earnings disclosure (e.g., Hirshleifer and Teoh, 2003) may generate some specific pattern of news flow. By distinguishing bad news from good news, Kothari, Shu, and Wysocki (2009) report that managers tend to delay disclosure of bad news and immediately reveal good news to investors. Consistent with this finding, Frankel, McNichols, and Wilson (1995) and Lang and Lundholm (2000) find firms tend to promote positive news stories prior to raising capital. While firms have incentives to withhold bad news and disseminate good news, there are also incentives to spin bad news stories. Yermack (1997) and Aboody and Kasznik (2000), for instance, find that managers accelerate the dissemination of bad news and/or withhold good news to lower the exercise price of their employee options. While this stream of literature emphasizes selective information dissemination, another strand of literature (see, for example, Burns and Kedia, 2006) report the behavior of misreporting, which may generate non-random new patterns.

Another possible force that drives non-random news patterns is company's fundamentals. It has been well documented (e.g., Ball and Brown, 1968; Beaver, Clarke and Wright, 1979; Graham, Harvey, and Rajgopal, 2005; Markov and Tamayo, 2006; Li, 2010) that earnings are predictable and persistent. It is also well documented that the properties of earnings time series is related to firm-specific characteristics, including firm size, return volatility, the book-to-market ratio, competition, and product types. If firm-specific news stories fairly reflect company's fundamentals, the persistent earning stream is likely to generate a positive correlation between sequential news releases. More specifically, positive news is more likely to be followed by positive news.

These aforementioned studies seem to suggest that news is perhaps persistent. Combined with two pervasive anomalies in the financial markets: the earnings momentum and the stock return momentum,[2] we propose news momentum as our major hypothesis:

H1. News releases exhibit momentum: Companies with more positive information continue to disseminate more positive news, and companies with less positive information continue to disclose less positive news.

If there is news momentum, it is important to investigate economic mechanisms underlying news momentum. One possibility is that the difference in firms' selective information disclosure leads to news momentum. One more possibility is that news momentum fairly reflects persistent differential improvements in firms' fundamentals. In this paper, we focus on the fundamental explanation. Our second hypothesis is:

[2] The seminal work of Jegadeesh and Titman (1993) documents price momentum. Similar effects are found in other equity markets (Rouwenhorst, 1998), in other asset classes (Asness, Moskowitz, and Pedersen, 2013), in country stock indices (Asness, Liew, and Stevens, 1997), and in industry portfolios (Moskowitz and Grinblatt, 1999). Daniel and Moskowitz (2013) and Barroso and Santa-Clara (2015) document momentum crashes. Earnings momentum is also a pervasive anomaly (e.g., Ball and Brown, 1968). Chordia and Shivakumar (2006) find price momentum is captured by the systematic component of earnings momentum.

H2. News momentum is induced by persistent difference in firm's fundamentals: Firms with more positive news have better fundamentals, and firms with less positive news have worse fundamentals.

Why we focus on the possibility related to firms' fundamental? It is because this hypothesis produces coherent rejectable predictions. We have two methods to test this hypothesis. The first method is to check whether news momentum can predict future earnings surprises or ROA. The second method is to check stock return patterns. The first possibility and the second possibility have different implications for the behavior of stock returns. However, since there are more possibilities, we want to emphasize that the rejection of H2 does not necessarily mean the acceptance of the first possibility. In the same spirit, non-rejection of H2 does not necessarily imply the rejection of the first possibility since the first and second channels are not mutually exclusive. The truth may be the possibility that news momentum is jointly driven by selective information releases and firms' fundamentals.

News Momentum and Information Environments

Firm characteristics might affect the way in which news stories are disseminated. In this section, we investigate the cross-sectional determinants of new momentum. Our attempt is to provide insights on the nature of news momentum. Specifically, we investigate whether news momentum concentrates among stocks with certain characteristics. The specific characteristics we consider include firm size, analyst coverage, and institutional holdings.

Large firms tend to have better information disclosures due to various reasons such as high litigation risk (Jiang, Li, and Wang, 2015). If news momentum is driven by selective information disclosure, this implies that large firms should have less significant news momentum. On the other hand, large firms are more likely to hire IR firms and generate information distortion. Simliarly, large firms can put more funds on advertising, which is likely to distort media coverage (e.g., Gurun and Butler, 2012). If so, new momentum is expected to be more significant for large firms. If news momentum is related to firms' fundamental, firm size seems no explicit implication for news momentum.

[Insert Table 4 Here]

We perform independent double sorting to investigate how firm size affects new momentum. At the end of month t, we sort all stocks into five portfolios (equal quantiles) based on their news scores. We further independently sort all stocks into three portfolios (below the 30th percentile and above the 70th percentile) based on their previous year-end market capitalization (Size). Table 3 summarizes the sorting results. Panel A reports the results for independent double sorting according to firm size and news sentiment scores. It is evident that news momentum consistently presents in both large firms and small firms, confirming the robustness of news momentum. If we look at the news sentiment difference between the GMB portfolio of small firms and the GMB portfolio of large firms, we find there is no consistent patterns. At the one-month horizon, large firms seem to show stronger news momentum. For the holding period from t+2 to t+6, however, small firms exhibit stronger momentum, which is marginal significant. When the holding period is longer than half year, the stronger/weaker new momentum becomes insignificant.

The second characteristic for double sorting is financial coverage. Financial coverage has long taken as an important of firms' information environment. Analyst coverage is a proxy for the level of interim information for a firm. Firms with more analyst coverage are likely to be more closely monitored by professional market participants. As such, firms with more analyst coverage have a more transparent information environment. If new momentum is due to information environment, firms with more analyst coverage should exhibit weaker news momentum. Alternatively, fundamental-driven new momentum has no explicit implications for the strength of new momentum since how information environment is related to firms' fundamentals is not straightforward.

We perform independent double sorting to explore the effect of analyst coverage on news momentum. First, we sort all stocks into five portfolios (equal quantiles) based on their news scores. We further independently sort all stocks into three portfolios (below the 30th percentile and above the 70th percentile) based on their previous year-end analyst coverage. Panel B of Table 3 presents the double sorting results for new momentum. The results indicate that news momentum is robust across analyst coverage portfolios. We further compare the GMB portfolio for stocks with more or less analyst coverage. The results demonstrate that there is some weak pattern across stocks different levels of analyst coverage. For those significant news momentum, we find that firms with high analyst coverage display stronger news momentum. Note that at time t, firms with high analyst coverage has a lower new sentiment score, but these firms have a higher sentiment score in the following holding periods. This pattern is against the hypothesis that news momentum is driven by information environments. This may provide the supporting evidence for the fundamental-driven new momentum (hypothesis 2).

We turn to discuss the choice of institutional holdings. As institutional holdings increases, institutions are more likely to monitor management, including gathering firm-specific information and influencing management to protect investors' property rights (e.g., Chen, Harford, and Li, 2007). Hence, stocks with more institutional holdings is related to a less opaque information environment. The implication of institutional holdings is ceteris paribus weaker news momentum for stocks with more institutional holdings, if new momentum is driven by information environments. In contrast, fundamental-driven new momentum implies that stocks with more institutional holdings will exhibit a stronger news momentum, because institutional investors are professional investors and are more likely to pick up those stocks with better future performance.

We perform independent double sorting to explore the effect of institutional holdings on news momentum. The double sorting procedure is similar to the double sorts for firm size and analyst coverage. Panel C of Table 4 presents the empirical result for the double sorting based on news sentiment scores and institutional holdings. It is evident that new momentum is very robust across stock portfolios with different levels of institutional holdings. For the hold period from t+2 to t+6, the news momentum difference in the DMB portfolios across stocks with different levels of institutional holdings is insignificant. For all other holding periods under investigation, we find that stocks with more institutional holdings exhibit stronger news momentum, which are statistically significant. These findings are against the hypothesis that news momentum is driven by information environment, but perhaps support the hypothesis that news momentum is driven by firms' fundamentals.

To summarize, our double sorting analysis leads to two conclusions: (1) news momentum is a relatively robust phenomenon, which is not attenuated by firm characteristics such as firm size, analyst coverage, or institutional holdings; (2) news momentum is more likely to be driven by firms' fundamentals, but less likely to be driven by information environments.

3.3 News Momentum and Firm Fundamentals

If news momentum is driven by firms' fundamentals, we would expect that current news sentiment predict future firms' fundamentals.[3] Otherwise, it is more likely that news momentum is driven by information environments or other reasons. We new formally examine whether the GMB strategy contains information about future firms' fundamentals. Our tests in this section focus on whether the GMB strategy can predict earnings and return of asset (ROA), two proxies for cash flows and profitability. Specifically, our earnings measure is the equal-weighted firms' standardized unexpected earnings (SUE). In the spirit of Bernard and Thomas (1989) and Tetlock, Saar-Tsechansky, and Macskassy (2008), we compute each firm's SUE as

$$SUE_t = \frac{UE_t - \mu_t}{\sigma_t}, \qquad (1)$$

Where UE_t is unexpected earnings, and μ_t and σ_t are the trend and volatility of unexpected earnings.

[Insert Table 5 Here]

We begin our discussion of the relationship between news momentum and firms' fundamentals in Panel A of Table 5, which presents the empirical results for predicting the next

[3] However, even if the GMB strategy predicts future fundamentals, it cannot exclude the possibility that news momentum is partially driven by information environments.

period *SUE*. An interesting pattern is that bad news stories predict lower profitability of firms. This is consistent with our conjecture. Another important pattern is that good news releases generally forecast rising profitability, though there is a reversion at longer horizons. Combined together, we find that the GMB strategy is positively related to relative profitability of firms included in the good and bad news portfolios. To provide further insights on the relationship between ROA and news releases, Panel B of Table 5

We now turn to discuss the relationship between news momentum and standardized unexpected earnings. Panel C suggests that sentiment of the good news portfolios predict higher future SUE than does sentiment of bad news portfolios for various forecasting periods. The difference is all statistically significant at the 1% level. It is consist with the prediction that the GMB strategy should persistently predict a difference in firm's fundamentals.

3.4 Robustness Checks

In this section, we perform a variety of modifications to our primary sorting. These modified sorts serves as robustness tests. Our first test is to check news patterns using daily data. Note that monthly news sentiment scores are the aggregation of daily news sentiment scores. Some information may lost during this aggregation process. In this sense, daily data can better capture the nature of news stories. In this spirit, we use daily observations to sort stocks based on their sentiment scores. We now discuss the variation on the baseline analysis of Table 6. The sorting based on daily observations suggest that the GMB portfolio exhibits strong news momentum. Compared with the results presented in Table 3, we find that the daily news momentum is statistically more significant. The t-statistics for various holding periods are respectively 209, 38, 48, 42, and 45. This robustness check thus confirms the presence of news momentum.

[Insert Table 6 Here]

In the same spirit, we also use daily data to investigate the robustness of news momentum. As can be seen in Table 6, weekly news releases display statistically very significant news momentum, suggesting the robustness of news momentum. Our third robustness check is to include neutral news releases in monthly observations. Previously, we exclude these news stories because their sentiment scores are zero. Table 4 reports the sorting results based on monthly data with the neutral news stories included. It is evident that these neutral news releases do not attenuate the significance of news momentum.

Our fourth robustness check is to form two portfolios instead of five portfolios. There is a natural threshold for news stories: negative news sentiment scores imply media pessimism, and positive news sentiment scores mean media optimism. This nature of news stories encourage us to sort monthly observations into three groups: the positive sentiment portfolio, the negative sentiment portfolio, and the neutral sentiment portfolio. The GMB hedging strategy is to buy the positive sentiment portfolio and sell the negative sentiment portfolio. In Table 6, we find that this type of sorting still suggest the presence of news momentum. Our last robustness check is to form decile portfolios instead of five portfolios and see how news momentum varies. It is evident from Table 4 that the variation in sorting method does not attenuate the magnitude of news momentum. All robustness test results taken together, it is safe to argue that news momentum is a significant pattern of new stories releases.

4. News Momentum and the Cross-section of Stock Returns

4.1 News Momentum and Return Preditability

The media are recognized as a key player in modern financial markets. It contributes to the efficiency of the stock market by improving information efficiency, that is, make new information more efficiently incorporated into stock prices. In this spirit, a flood of research demonstrates strong correlations between news stories disseminated by the media and stock market reactions. This is not surprising since qualitative information from news reports may contains important information about firms' future cash flows (see, for example, Tetlock, Tsechansky, and Macskassy (2011), while the stock price is equal to the expected discounted value of firms' future cash flows conditions investors' information set.

In light of the effect of the media in stock prices, what are the asset pricing implications of news momentum? The answer for this question depends on the driving force of news momentum. If news momentum is driven by opaque information environment and/or media bias, news momentum would induce return momentum in the short run, but stock prices will finally reverse to fundamentals, largely due to the reason that these media shocks are stationary and cannot last forever (e.g., Delong, Bradford, Shleifer, Summers, and Waldmann, 1990). This point is consistent with a large amount of empirical evidence. For example, Tetlock (2007) indicates that high media pessimism predicts falling downward pressure on market prices followed by a reversion to fundamentals. In another influential study, Solomon (2012) finds that firms that spin news by creating more positive media coverage experience subsequent lower stock returns, though the positive media coverage drives up firms' stock prices around new announcements. He attributes this reversal to investor disappointment due to the effects of firms' past spin.

If news momentum is driven by firms' fundamentals, we should observe return momentum induced by news momentum and no subsequent reversal. Toward this end, Tetlock, Tsechansky, and Macskassy (2008) find that qualitative firm-specific news stories contain value-relevant information about fundaments. This type of information is quickly incorporate into prices and leads to immediate stock market reactions. When qualitative news stories are more appropriately processed, Loughran and Mcdonald (2014) demonstrates that these news reports contains more information about fundamentals than we think, further confirming the value of qualitative news stories. The slow diffusion of information perhaps strengthens return momentum induced by news momentum. Using newspaper strikes data in several countries, Peress (2014) find that information diffuses gradually across investor population. This is consistent with the evidence from Sinha (2011) and Tetlock (2011), who argue that the market is slow in incorporating the qualitative content of the news into prices.

However, the presence of reversal is not necessarily against fundamental-driven momentum. Even if qualitative information is related to firms' fundamentals, investors may underreact or overreact to these qualitative fundamental news. The positive-feedback-trader model of Delong, Bradford, Shleifer, Summers, and Waldmann (1990) and the overconfidence model of Daniel, Hirshleifer, and Subrahmanyam (1998) are examples of overreaction. More recently, Alti and Tetlock (2014) show that information processing biases due to overreaction and overextrapolation of price trends distort investors' expectations and lead to return predictability and On the other hand, the conservatism-bias model of Barberis, Shleifer, and Vishny (1998) and the heterogeneity model of Hong and Stein (1999) account for the underreaction behavior of investors.

In the content of news stories, Hillert, Jacobs, and Muller (2014) firms covered by the media exhibit ceteris paribus stronger return momentum, indicating that news dissemination exacerbate investor biases. Using a comprehensive sample of intraday firm-specific news data, Jiang, Li, and Wang (2015) decompose stock returns to news-driven and non-news-driven components. They find that the news-driven return is particularly pronounced for firms with less analyst coverage, higher volatility, and lower liquidity. This is consistent with imperfect investor reaction to news and limits to arbitrage. Even professional investors are subject to reaction bias. Fang, Peress, and Zheng (2014) explore the relation between mutual fund trades and mass media coverage of stocks. They uncover a negative relation between fund managers' propensity to buy stocks covered by the media and subsequent fund performance. These findings is read as the evidence in support of limited attention of fund managers.

It is impossible to discuss all possible channels through which some force drives news momentum. If we focus on the possibilities of the fundamental-driven and information-environment-driven news momentum, then return momentum not followed by subsequent reversal is in support of the fundamental-driven news momentum. Alternatively, return momentum followed by reversal may support both the fundamental-driven news momentum and the information-environment-driven news momentum

4.2 Baseline Results

We begin our analysis by examining the profitability of return momentum induced by news momentum. Our news momentum strategy is to buy stocks with high news sentiment scores and sell stocks with low news sentiment scores. Equivalent to the sorting strategy discussed in section 3.2, at the end of month t, we sort our sample stocks into five portfolios based on news sentiment scores. We then hold the "good news" portfolio and sell the "bad news" portfolio. We then examine the profitability of this GMB portfolio by computing the equally weighted future average returns. It is noteworthy that our news momentum trading strategy is totally different from the traditional momentum strategy (Jegadeesh and Titman, 1993): while our news momentum strategy sorts stocks based on news sentiment scores, the traditional strategy sorts stocks based on past performance.[4]

[Insert Table 7 Here]

Table 7 reports the one-month-ahead portfolio returns of taking the news momentum trading strategy. The first column indicates that there is significant news-driven return momentum: the strategy that buy the good news portfolio and sell bad news portfolio generates 0.696 percent per month (t-statistic=4.31). Look at all five portfolios, momentum profits rise monotonically to the point 1.337. The monotonic effect of the portfolio returns can be easily understood: since these portfolios have monotonic sentiment scores, in the short run, both the fundamental-driven and information-environment-driven news momentums suggest that the portfolio with a higher sentiment score should deliver a higher return.

A major concern is whether the return of the news momentum trading strategy is from their exposures to other return factors. To provide insights on this concern, we respectively use the CAPM model, the Fama-French (1992) three factor model, the Fama-French-Cahart (Fama and French, 1993; Carhart, 1997) four factor model, and the Fama-French (2012) five factor model to

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[4] Daniel and Moskowitz (2013) and Barroso and Santa-Clara (2015) find that the traditional momentum strategy crashes during our sample period. Our news momentum strategy is return cannot be explained by the traditional momentum.

control for the risk exposures of new momentum profits. Specifically, we regress excess returns of news momentum portfolios against the respective factors and calculate the regression intercepts which represent risk-adjusted returns, namely, alpha.

We know from Table 3 that the bad news portfolio has a negative news sentiment score at the end of month t. Interestingly, we find this negative sentiment score leads to a negative return in one month after risk adjustment. In contrast, the raw return without adjusting for risk exposures is positive. More importantly, after risk adjustment, we find the news momentum strategy generates higher returns. The Fama-French three-factor model adjusted monthly return is 0.800, which is significant at the 1% level. These findings suggest that the market factor, the size factor, the value factor, the momentum factor, the profitability factor, and the investment factor cannot account for the return of our news momentum strategy. In addition, these findings provide the strong support for news momentum.

Low news sentiment result in downward pressure on prices. If news sentiment reflects firms' fundamentals, one would expect that low sentiment predicts low returns in the future and no reversion in the long run. Alternatively, if news sentiment reflects firms' information environments, one would expect high news sentiment forecasts high returns at short horizons and a reversion to fundamentals at longer horizons. To shed light on the hypotheses of fundamental-driven news momentum and information environment driven momentum, we investigate the profitability of the news momentum strategy for longer holding periods. To accomplish this, we compute the equal-weighted returns for each portfolios and the GMB portfolio with a holding period from t+2 and t+6, from t+7 to t+12, and from t+13 to t+24. To eliminate the effect of other pervasive factors in the financial markets, we use the popular Fama-French five factor model to control for the risk exposures of news momentum returns.

[Insert Table 8 Here]

How long does the news-driven return momentum persist? Table 8 reports the excess returns after the adjustment of the Fama-French five factors. It indicates that there is a news-driven return momentum. The GMB strategy that buys the good news portfolio and sell the bad news portfolios generates 0.243 percent per month with a t-statistic of 3.32 for the half year holding period. At longer horizons, news momentum profits disappear quickly. For the holding periods from t+7 to t+12 and from t+13 to t+24, the profit is respectively -0.011 and -0.048 percent per month, which are economically and statistically insignificant. Though at longer horizons, profits are negative, due to its insignificance, it is safe to say there is no reversion in stock returns.

4.3 Information Environments and News Attributes

Our first set of checks investigates whether the performance of the news momentum strategy concentrates amongst stocks with certain characteristics. Given the endogeneity of news stories, it is important to control for additional factors that might be correlated with the effect of information dissemination and exert an influence on news momentum returns. By doing so, it may provide insights on the nature of the news-driven return momentum. In this regard, the traditional momentum is a paradigm. A number of studies (e.g, Lesmond, Schill, and Zhou, 2004; Sagi ans Seasholes, 2007) show that firm characteristics affect the profitability of momentum trading strategy. It is generally documented that small stocks, illiquid stocks, and low analyst coverage stocks are more profitable.

The firm-specific characteristics include firm size, analyst coverage, and institutional holdings. These characteristics are related to firms' information environments. The methodology is independent double sorting. At the end of each month t, we independently sort all stocks into five portfolios along one dimension based on news sentiment scores and three portfolios along another dimension based on firm characteristics. We then calculate the equal-weighted returns for these portfolios.

[Insert Table 9 Here]

In Panel A of Table 9, we disaggregate the analysis of Table 8 by size. There are two motivations for doing this disaggregation. First, it is reasonable to conjecture that small firms attract less attention and analyst coverage, so information is likely to be more asymmetric for these stocks. Second, firm-specific information might diffuse more slowly for these stocks. As such, we would expect to observe stronger news-driven return momentum for small firms. The results presented in Panel A confirm this view. As can be seen from the table, small firms exhibit a significant news-driven return momentum. The raw return is After the adjustment for the risk exposures to the Fama-French five factors, the next period return is 1.653 percent per month (t-statistic = 6.44). This return momentum persists up to 2 years. In contrast, the large size class does not exhibit the news-driven return momentum. This is consistent with the view that large firms obtain more attention and the pattern of news momentum is recognized by investors.

Next we turn to the cuts based on analyst coverage. More analyst coverage implies that these firms are more monitored by professional investors. Thus, more analyst coverage may attract more investor attention and could potentially speed up information diffusion. Analyst coverage has also been argued to reduce information asymmetry. Given these insights, we would expect stocks with more analyst coverage exhibit weaker news-driven return momentum. Indeed, analyst coverage is related to firm size. It is found that the vast majority of small stocks (see, for example, Hong, Lim, and Stein, 2000) never has any financial coverage.

Panel B of Table 9 reports the returns numbers. An interesting pattern emerges in the table is the news-driven return momentum is only significant for stocks with little analyst coverage. The excess return after the Fama-French five factor model adjustment is 1.244 percent per month with a t-value of 7.37 for low coverage stocks. On the contrary, the news momentum strategy for high coverage stocks are economically and statistically insignificant. These findings are consistent with the argument that analyst coverage is especially important in propagating news. These attention and information diffusion effects make investors recognize news momentum for stocks with high coverage and induce the disappearing of return momentum.

To assess how the impact of news momentum on return reversal varies with institutional holdings, Panel C of Table 9 report the results for the independent double sorting based on news sentiment scores and institutional holdings. Professional investors can better collect firm-specific information and process information.[5] So, we could expect that stocks with high institutional ownership show weaker news-driven return momentum. Broadly speaking, the results are consistent with this wisdom. We find that stocks with low institution ownership exhibit significant news-driven momentum. By contrast, stock with high institution ownership display

[5] Indeed, institutional holdings are positively correlated with media coverage (e.g., Tetlock, 2010).

insignificant return momentum. Another key finding is that the return difference between the GMB portfolio of high ownership stocks and the GMB portfolio of low ownership stocks is significant.

Taken together, these patterns suggest that the news momentum is more likely to be recognized when firms' information environment is more transparent. The intuition behind the argument is such an environment makes financial markets more information efficient. In these markets, information is more symmetric, and stock prices incorporate news more efficiently.

Our second set of checks explore whether the effect of news sentiment on stock returns concentrates amongst some specific news categories. Toward this end, we regroup the news categories. RavenPack divides news stories into 36 categories (see Appendix A). We select revenues, earnings, analyst-rating, and credit-rating to form a "hard news" category, which may capture firms' fundamentals. Other 32 news categories form a "soft news" categories, which is less value-relevant, very volatile, or of extremely low-frequency releases. In summary, the hard news group has a release frequency of 30.3%, and the soft news category has a release frequency of 69.7%.

[Insert Table 10 Here]

While our grouping is somewhat random, we justify our grouping by using news sentiment scores to predict firms' fundamentals. Specifically, we perform the following time-series regressions:

$$SUE_{t+i,t+j} = a + bNews_t + u_{t+i}, \qquad (2)$$

Where $SUE_{t+i,t+j}$ is the firms' standardized unexpected earnings for the period from t+i to t+j, $News_t$ is news sentiment scores, and u_t is the innovation term.

Panel C in Table 10 presents the results of two regressions respectively using the sentiment scores of the hard and soft news categories. Two patterns come out of our analysis. First, the hard news sentiment can predict future analyst forecast errors (SUE), suggesting that hard news stories contain additional information for firms' fundamentals, beyond and above that contained in analysts' information sets. Second, soft news releases cannot predict analyst forecast errors, as the regression coefficient, b, is generally insignificant for different holding periods. More surprisingly, the regression coefficient is consistently negative. As a result, high sentiment heralds deterioration of firms' fundamentals, but low sentiment hints the improvement of firms' fundamentals. Taken together, these patterns suggest that the hard news group is more value relevant.

In light of the evidence regarding the information content of the hard and soft news categories, we analyze how soft and hard news releases affect return predictability. Panel A of Table 10 confirms that hard news releases induce significant return momentum. Using the Fama-French five factor model to adjust returns, the alpha (the excess return) is 0.948 percent per month or 11.4 percent per annum. Turing to the soft-news-driven return momentum, we find that the alpha is 0.363 percent per month. The alpha difference between the hard-news GMB portfolio and the soft-news GMB portfolio is 0.584 percent per month with a t-value of 2.26.

Do the magnitude of soft news momentum and hard news momentum account for the difference in excess returns? In Panel B, we report the news momentum results for hard news and soft news. An interesting pattern that emerges is that the soft-news momentum is of equivalent magnitude of or even slightly stronger than the hard-news momentum. Overall, the news momentum findings support both the fundamental-driven news momentum and the information environment driven momentum,[6] but the return momentum findings strongly support the view that only fundamental-driven news momentum leads to return momentum. This is consistently with the findings presented in Table 8.

4.4 Robustness Checks

This section performs a set of robustness tests to examine whether news momentum drives return momentum. The first several tests changes sorting methods, which are corresponding to the robustness tests of news momentum. The first test is to use daily news releases to investigate how news momentum driven stock returns. This is particularly important because a short time window provides us a better field for testing the effect of news momentum on stock returns. We sort stocks into five portfolios based on their daily news sentiment scores. As summarized in Table 11, we find that the GMB strategy generates 0.527% returns per day for the next period (after the adjustment for the risk exposures to the Fama-French five factors), which is much higher than stock returns predicted by monthly observations in terms of magnitude.

[Insert Table 11 Here]

A similarly motivated check is to sort stocks into five portfolios using weekly data. As indicated by Table 11, we find that the weekly GMB hedging strategy delivers 0.302% Fama-French 5-factor model adjusted return per week. Our daily and weekly data analysis thus

[6] As we emphasized in section 3.1, the fundamental-driven and information environment driven news momentums are not exclusive, they are possibly complementary.

provides strong supporting evidence on the news-driven momentum. Our third test is to include neutral news stories into our analysis. Using monthly data, we sort stocks into five portfolios by including neutral news stories. The GMB hedging strategy is to buy the good news portfolio and sell the bad news sentiment at the same time. The results in Table 11 indicates that the GMB strategy has a monthly return of 0.679% (after the adjustment for the risk exposures to the Fama-French five factors).

News stories can be naturally categorized into three groups: the positive sentiment portfolio, the negative sentiment portfolio. In this spirit, we use monthly data to sort stocks into three portfolios and check the profitability of news momentum. As can be seen in Table 11, we find that the GMB hedging strategy generate a risk-adjusted monthly return of 0.439%. In a similar spirit, we also sort stocks into to 10 portfolios using monthly observations. The results are presented in Table 11. After adjustment for risks, the GMB hedging strategy generates 0.947% return per month, which is statistically significant at the 1% level. In summary, these robustness checks suggest that news momentum drives returns momentum.

Given the endogeneity of news releases, our second method is to use the multivariate Fama and MacBeth (1973) regressions to check the effect of qualitative news on stock returns. Specifically, we run the following regressions:

$$R_{t+1} = a + b_1 News_t + \sum_{i=1}^{k} b_i Z_{i,t} \quad + \varepsilon_{t+1}, \qquad (3)$$

Where R_{t+1} is the stock return in month t, $News_t$ is news sentiment at time t, and $Z_{i,t}$ includes control variables observed at time t. We respectively use five stock returns as the dependent variable. They are respectively the raw return, the CAMP-adjusted return, the Fama-French 3-

factor model adjusted return, the Carhart 4-factor model adjusted return, the Fama-French 5-factor model adjusted return. The control variables include logarithm of market capitalization (*LogSize*), book-to-market ratio (B/M), market beta (*Beta*), idiosyncratic volatility (*IdioVol*), past two-month stock returns ($R_{t-3,t-2}$), past three-month stock returns($R_{t-6,t-4}$), past six-month stock returns ($R_{t-12,t-7}$), and Amihud's (2002) illiquidity measure (*Illiquidity*).

[Insert Table 12 Here]

Table 12 presents the multivariate Fama and MacBeth regression results. We confirm the influence of news sentiment on stock returns. The regressions consistently generate a positive slope coefficient (b_1), which are significant at the 1% level. These results are consistent with those from portfolio analysis. To illustrate the magnitude of news impact, column M1 indicate a slope coefficient of 1.374 with a t-statistic of 6.11. This implies that one unit increase in news sentiment predicts a rise of approximately 16.5% per annum in future returns. We also find that the coefficient of news sentiment is roughly stable across the five regression and its level of statistical significance increases. In summary, the Fama-Macbeth regressions provide further supporting evidence on the effect of news sentiment on stock returns.

5. Conclusions

While a number of studies have systematically explored the interaction between media coverage and stock market activity, the production and the pattern of news is far less investigated. However, the production of news articles is not random. Alternatively, it is the product of profit maximization by news database, newspapers, television, magazines, etc. Given the choice of news events, biased choice of words conveys a very different sentiment on what happened. This behavior of news dissemination would exert an important impact on stock prices.

Using a comprehensive sample of firm-level news articles, we investigate the patterns of news releases. We find a strong cross-sectional news momentum phenomenon: firms with relatively higher current news sentiment scores are likely to have higher sentiment scores in the future; firms with relatively lower sentiment scores have lower sentiment scores in the future. New momentum is persistent and lasts up to more than two years.

In light of news momentum, we explore what drives news momentum. We provide two hypotheses. The first hypothesis views news momentum as from opaque information environments. The second hypothesis argues that firms' fundamental drives news momentum. A set of empirical tests provides the supporting evidence on the fundamental-driven news momentum. We also investigate the asset pricing implication of new momentum. We find that news momentum drives return momentum. While we explore the pattern of information transmission, we do not explore the implications of the interactions between investor biases and news momentum. This constitutes an interesting future research agenda.

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Appendix A: Definitions of the Variables

Variable	Acronym	Definition	Source
News	$News_t$	Average ESS score of all news for a particular firm over a month (quarter/week/day) t.	RavenPack
Hard news	$HardNews_t$	Average ESS score of hard news for a particular firm over a month (quarter) t.	RavenPack
Soft news	$SoftNews_t$	Average ESS score of soft news for a particular firm over a month (quarter) t.	RavenPack
Next month returns	$Return_{t+1}$	Stock return in percentage in month t+1.	CRSP
Market capitalization	$Size_t$	Market capitalization at the end of previous year.	CRSP
Analyst coverage	$Analyst_t$	Number of analysts following in month t.	IBES
Institutional ownership	$InstOwn_t$	Number of shares held by institutional investors divided by total shares outstanding in the previous quarter.	Thomson Reuters
ROA	ROA_t	The ratio of net income in quarter t over total assets in quarter t-1, which is scaled by 100 in the analysis.	Compustat
Earnings surprise	SUE_t	Earning surprise (SUE score) in quarter t.	IBES
Book-to-market ratio	B/M_t	The ratio of book value of equity to market value of equity in the previous year, which is winsorized at 1% and 99% cutoffs.	CRSP
Market beta	$Beta_t$	Regression of $r_i=alpha+beta^*r_m+e$ from month t-59 to t.	CRSP
AHXZ's idiosyncratic volatility	$IdioVol_t$	Standard deviation of residuals from regression of $r_i=alpha+b_1^*(r_m-r_f)+b_2^*SMB+b_3^*HML+e$ over previous year by using daily returns.	CRSP, Fama & French
Past two-month stock returns	$\text{Return}_{t-3,t-2}$	Compounded return in percentage from month t-3 to t-2.	CRSP
Past three-month stock returns	$\text{Return}_{t-6,t-4}$	Compounded return in percentage from month t-6 to t-4.	CRSP
Past six-month stock returns	$\text{Return}_{t-12,t-7}$	Compounded return in percentage from month t-12 to t-7.	CRSP
Amihud's (2002) illiquidity	$Illiquidity_t$	Illiquidity is the daily ratio of absolute stock return to its dollar volume, averaged over previous year, which is scaled by 10,000 in the analysis.	CRSP

Appendix B: List of News by Categories

News Categories	News Groups	Frequency
Hard news	Revenues	5.96%
	Earnings	19.55%
	Analyst-ratings	3.57%
	Credit-ratings	1.26%
	Subtotal	**30.35%**
Soft news	Acquisitions-mergers	3.21%
	Assets	1.42%
	Balance-of-payments	0.00%
	Bankruptcy	0.04%
	Civil-unrest	0.00%
	Corporate-responsibility	0.04%
	Credit	0.82%
	Crime	0.00%
	Dividends	2.56%
	Equity-actions	2.88%
	Exploration	0.02%
	Government	0.01%
	Indexes	0.03%
	Industrial-accidents	0.01%
	Insider-trading	14.07%
	Investor-relations	5.29%
	Labor-issues	5.63%
	Legal	0.99%
	Marketing	3.44%
	Order-imbalances	6.99%
	Partnerships	1.41%
	Pollution	0.00%
	Price-targets	0.23%
	Products-services	8.47%
	Public-opinion	0.00%
	Regulatory	0.29%
	Security	0.01%
	Stock-prices	4.36%
	Taxes	0.00%
	Technical-analysis	7.42%
	Transportation	0.00%
	War-conflict	0.01%
	Subtotal	**69.65%**

Table 1: Summary Statistics

This table presents the summary statistics of main variables used in this study. The variables include news (*News*), hard news (*HardNews*), soft news (*SoftNews*), next month returns ($Return_{t+1}$), logarithm of market capitalization (*LogSize*), analyst coverage (*Analyst*), institutional ownership (*InstOwn*), book-to-market ratio (*B/M*), beta (*Beta*), idiosyncratic volatility (*IdioVol)*, past two-month stock returns ($Return_{t-3,\ t-2}$), past three-month stock returns ($Return_{t-6,\ t-4}$), past six-month stock returns ($Return_{t-12,\ t-7}$), and Amihud's (2002) illiquidity (*Illiquidity*). All the variables are defined in Appendix A. The table reports the number of observations (*NObs*), mean, median, standard deviation (*STD*), quartile (*75% and 25%*), and the bottom/top 5% (*5% and 95%*) distribution of the variables. The sample period is from January 2000 to October 2014.

Variables	NObs	Mean	STD	5%	25%	Median	75%	95%
$News_t$	473,941	0.083	0.157	-0.172	-0.012	0.083	0.181	0.332
$HardNews_t$	289,870	0.109	0.260	-0.323	-0.066	0.117	0.286	0.527
$SoftNews_t$	399,291	0.080	0.151	-0.157	-0.015	0.073	0.176	0.323
$Return_{t+1}$	473,941	1.004	13.750	-18.482	-5.908	0.397	6.897	22.044
$LogSize_t$	473,941	6.361	1.946	3.242	5.007	6.309	7.625	9.723
$Analyst_t$	473,941	6.932	6.916	0.000	1.517	4.865	10.287	21.191
$InstOwn_t$	473,941	0.568	0.289	0.061	0.339	0.615	0.800	0.965
B/M_t	473,941	0.696	0.585	0.116	0.316	0.555	0.888	1.756
$Beta_t$	423,821	1.178	0.823	0.175	0.596	1.013	1.587	2.765
$IdioVol_t$	473,881	0.029	0.017	0.012	0.018	0.025	0.036	0.059
$Return_{t-3,\ t-2}$	472,750	3.062	21.360	-24.667	-7.915	1.273	11.177	35.583
$Return_{t-6,\ t-4}$	470,391	4.480	27.048	-29.246	-9.475	1.793	14.272	45.338
$Return_{t-12,\ t-7}$	461,523	9.845	43.107	-37.813	-11.938	3.997	22.585	74.125
$Illiquidity_t$	473,876	0.040	0.303	0.000	0.000	0.000	0.002	0.131

Table 2: Number of News Articles per Month over Time

This table presents the number of news articles per month across different size groups over five time periods including 2000-2002, 2003-2005, 2006-2008, 2009-2011, and 2012-2014. Each month, firms are classified into 5 groups based on previous year end market capitalization (*Size*). Panel A reports the average number of all news articles per month. Panel B reports the average number of positive news articles per month. Panel C reports the average number of negative news articles per month. The sample period is from January 2000 to October 2014.

Panel A: The Number of All News Articles for Each Month

Portfolios	2000-2002	2003-2005	2006-2008	2009-2011	2012-2014
Small *Size*	2.28	3.95	5.31	5.92	7.33
2	2.84	5.10	6.63	7.82	11.74
3	3.36	6.13	8.12	9.94	15.69
4	4.05	7.35	10.19	12.80	20.05
Large *Size*	8.71	14.26	20.98	25.88	35.63

Panel B: The Number of Positive News Articles for Each Month

Portfolios	2000-2002	2003-2005	2006-2008	2009-2011	2012-2014
Small *Size*	1.07	1.69	2.36	2.35	3.03
2	1.30	2.02	2.73	2.95	4.67
3	1.53	2.28	3.22	3.68	6.05
4	1.91	2.89	4.20	5.04	8.10
Large *Size*	4.64	6.62	10.04	12.85	17.27

Panel C: The Number of Negative News Articles for Each Month

Portfolios	2000-2002	2003-2005	2006-2008	2009-2011	2012-2014
Small *Size*	0.57	0.86	1.04	1.10	1.51
2	0.65	1.19	1.44	1.68	3.06
3	0.76	1.59	1.94	2.41	4.63
4	0.96	1.89	2.51	3.26	6.22
Large *Size*	2.18	3.19	5.28	6.88	11.09

Table 3: Momentum of News

This table presents the momentum effects of news. At the end of month t, we sort all stocks into five portfolios based on their news scores (*News*$_t$). Stocks in *Bad News* portfolio have the lowest news scores while stocks in *Good News* portfolio have the highest news scores. "*Good-Bad*" is the hedge portfolio that is long in *Good News* portfolio and short in *Bad News* portfolio. We then compute the equally weighted average news scores of each portfolio over different time periods after the portfolio formation. *News*$_{t+1}$ shows the 1-month average news scores of each portfolio in month t+1; *News*$_{t+2,\ t+6}$ shows the average news scores over 5 months from t+2 to t+6; *News*$_{t+7,\ t+12}$ shows the average news scores over 6 months from t+7 to t+12; and *News*$_{t+13,\ t+24}$ shows average news scores over 12 months from t+13 to t+24. The sample period is from January 2000 to October 2014. Newey-West adjusted *t*-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Portfolios	*News*$_t$	*News*$_{t+1}$	*News*$_{t+2,\ t+6}$	*News*$_{t+7,\ t+12}$	*News*$_{t+13,\ t+24}$
Bad *News*	-0.134	0.042	0.038	0.044	0.049
2	0.009	0.056	0.054	0.054	0.055
3	0.083	0.064	0.065	0.063	0.062
4	0.159	0.072	0.075	0.069	0.066
Good *News*	0.296	0.078	0.083	0.074	0.069
Good-Bad	**0.431*****	**0.037*****	**0.044*****	**0.031*****	**0.020*****
	(26.41)	**(25.68)**	**(49.80)**	**(33.93)**	**(24.72)**

Table 4: Momentum of News by Different Information Environments

This table presents the momentum effects of news by different information environments. At the end of month t, we sort all stocks into five portfolios based on their news scores ($News_t$). We further independently sort all stocks into three portfolios based on their previous year end market capitalization (*Size*), analyst coverage (*Analyst*), and institutional ownership (*InstOwn*), respectively. Stocks in *Bad News* portfolio have the lowest news scores and stocks in *Good News* portfolio have the highest news scores. "*Good-Bad*" is the hedge portfolio that is long in *Good News* portfolio and short in *Bad News* portfolio. We then compute the equally weighted average news scores of the "*Good-Bad*" portfolios for *Small/Large Size* subsamples, *Low/High Analyst* subsamples, *Low/High InstOwn* subsamples, as well as *"Small-Large" Size*, *"Low-High" Analyst* and *"Low-High" InstOwn* hedge portfolios over different time periods after the portfolio formation. $News_{t+1}$ shows the 1-month average news scores of each portfolio in month t+1; $News_{t+2, t+6}$ shows the average news scores over 5 months from t+2 to t+6; $News_{t+7, t+12}$ shows the average news scores over 6 months from t+7 to t+12; and $News_{t+13, t+24}$ shows average news scores over 12 months from t+13 to t+24. The sample period is from January 2000 to October 2014. Newey-West adjusted *t*-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Panel A: Momentum of News across Size Subsamples

Portfolios	$News_t$	$News_{t+1}$	$News_{t+2, t+6}$	$News_{t+7, t+12}$	$News_{t+13, t+24}$
Small *Size*	0.460***	0.034***	0.046***	0.031***	0.020***
	(27.70)	(24.25)	(42.35)	(29.84)	(22.58)
Large *Size*	0.393***	0.042***	0.043***	0.031***	0.022***
	(24.41)	(24.07)	(33.74)	(23.30)	(18.12)
Small-Large	0.068***	-0.008***	0.003*	0.000	-0.002
	(20.06)	(-4.32)	(1.79)	(-0.33)	(-1.60)

Panel B: Momentum of News across Analyst Coverage Subsamples

Portfolios	$News_t$	$News_{t+1}$	$News_{t+2, t+6}$	$News_{t+7, t+12}$	$News_{t+13, t+24}$
Low *Analyst*	0.459***	0.034***	0.046***	0.030***	0.019***
	(27.41)	(20.55)	(46.93)	(27.24)	(20.42)
High *Analyst*	0.394***	0.042***	0.045***	0.033***	0.023***
	(24.58)	(22.83)	(31.54)	(23.38)	(14.96)
Low-High	0.064***	-0.008***	0.000	-0.004**	-0.003**
	(19.54)	(-4.04)	(0.25)	(-2.40)	(-2.26)

Panel C: Momentum of News across Institutional Holdings Subsamples

Portfolios	$News_t$	$News_{t+1}$	$News_{t+2, t+6}$	$News_{t+7, t+12}$	$News_{t+13, t+24}$
Low *InstOwn*	0.458***	0.033***	0.046***	0.030***	0.020***
	(27.88)	(17.46)	(47.63)	(28.39)	(21.01)
High *InstOwn*	0.407***	0.042***	0.044***	0.033***	0.022***
	(25.22)	(27.22)	(35.14)	(32.46)	(22.43)
Low-High	0.051***	-0.009***	0.002	-0.003**	-0.003**
	(16.17)	(-4.04)	(1.39)	(-1.98)	(-2.13)

Table 5: News and Firm Fundamentals

This table examines the relation between the news and firm fundamentals. At the end of quarter t, we sort all stocks into five portfolios based on their news scores ($News_t$), ROA (ROA_t) and earnings surprise (SUE_t) respectively. Stocks in *Bad News* portfolio have the lowest news scores and stocks in *Good News* portfolio have the highest news scores. Stocks in *Low ROA (SUE)* portfolio have the lowest ROA (SUE) and stocks in *High ROA (SUE)* portfolio have the highest ROA (SUE). "*Good-Bad*" is the hedge portfolio that is long in *Good News* portfolio and short in *Bad News* portfolio. "*High-Low*" is the hedge portfolio that is long in *High ROA (SUE)* and short in *Low ROA (SUE)* portfolio. We then compute the equally weighted average ROA (SUE) of each portfolio over different time periods after the portfolio formation. ROA_{t+1} (SUE_{t+1}) shows the 1-quarter average ROA (SUE) of each portfolio in quarter t+1; ROA_{t+2} (SUE_{t+2}) shows the 1-quarter average ROA (SUE) in quarter t+2; $ROA_{t+3,t+4}$ ($SUE_{t+3,t+4}$) shows the average ROA (SUE) over 2 quarters from t+3 to t+4; and $ROA_{t+5,t+8}$ ($SUE_{t+5,t+8}$) shows the average ROA (SUE) over 4 quarters from t+5 to t+8. Panel A reports the average *future ROA* for portfolios formed based on news ($News_t$). Panel B reports the average *future ROA* for portfolios formed based on ROA (ROA_t). Panel C reports the average *future SUE* for portfolios formed based on news ($News_t$). Panel D reports the average *future SUE* for portfolios formed based on earnings surprise (SUE_t). The sample period is from January 2000 to October 2014. Newey-West adjusted *t*-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Panel A: Future ROA

Portfolios	ROA_t	ROA_{t+1}	ROA_{t+2}	$ROA_{t+3,\,t+4}$	$ROA_{t+5,\,t+8}$
Bad *News*	-1.825	-1.756	-1.775	-1.749	-1.522
2	-0.591	-0.596	-0.630	-0.639	-0.475
3	0.035	-0.068	-0.084	-0.127	-0.097
4	0.318	0.211	0.077	0.035	0.055
Good *News*	0.252	0.166	0.069	0.011	-0.030
Good-Bad	**2.077***** **(6.61)**	**1.922***** **(6.56)**	**1.844***** **(6.79)**	**1.759***** **(6.54)**	**1.492***** **(6.57)**

Panel B: Future ROA

Portfolios	ROA_t	ROA_{t+1}	ROA_{t+2}	$ROA_{t+3,\,t+4}$	$ROA_{t+5,\,t+8}$
Low *ROA*	-8.071	-6.382	-6.314	-6.336	-5.742
2	-0.101	-0.259	-0.231	-0.270	-0.136
3	0.589	0.443	0.429	0.355	0.327
4	1.537	1.306	1.212	1.139	1.010
High *ROA*	4.234	2.793	2.466	2.430	2.021
High-Low	**12.305***** **(38.68)**	**9.174***** **(29.59)**	**8.781***** **(26.83)**	**8.766***** **(28.26)**	**7.763***** **(26.28)**

Table 5-Continued

Panel C: Future SUE					
Portfolios	SUE_t	SUE_{t+1}	SUE_{t+2}	$SUE_{t+3,\,t+4}$	$SUE_{t+5,\,t+8}$
Bad *News*	-1.014	0.035	0.202	0.336	0.650
2	0.373	0.658	0.657	0.763	0.839
3	1.110	0.932	1.023	0.989	0.985
4	1.446	1.034	0.902	0.920	1.021
Good *News*	1.828	1.157	0.967	1.014	0.916
Good-Bad	**2.841*****	**1.122*****	**0.765*****	**0.678*****	**0.266*****
	(12.53)	**(7.26)**	**(8.54)**	**(5.91)**	**(4.33)**

Panel D: Future SUE					
Portfolios	SUE_t	SUE_{t+1}	SUE_{t+2}	$SUE_{t+3,\,t+4}$	$SUE_{t+5,\,t+8}$
Low *SUE*	-5.237	-0.766	-0.339	-0.140	0.182
2	-0.313	0.151	0.319	0.492	0.586
3	0.693	0.737	0.727	0.744	0.879
4	1.917	1.382	1.188	1.162	1.136
High *SUE*	6.681	2.262	1.801	1.703	1.551
High-Low	**11.918*****	**3.028*****	**2.140*****	**1.843*****	**1.369*****
	(22.23)	**(16.30)**	**(14.15)**	**(13.10)**	**(13.14)**

Table 6: Momentum of News—Robustness Tests

The table examines the robustness of momentum effects of news by using different specifications. *"Daily"* and *"Weekly"* means that all stocks are grouped into five portfolios based on their news scores ($News_t$) at the end of day t and week t, respectively. "*Neutral News Included*" means that all stocks including those with neutral news are grouped into five portfolios based on their news scores ($News_t$) at the end of month t. *"Decile Portfolios"* means that all stocks are grouped into ten portfolios based on news scores ($News_t$) at the end of month t. For these four specifications, stocks in *Bad News* portfolio have the lowest news scores and stocks in *Good News* portfolio have the highest news scores. For the specification *"Negative vs. Positive"*, stocks in *Bad News* portfolio have the negative news scores and stocks in *Good News* portfolio have the positive news scores. "*Good-Bad*" is the hedge portfolio that is long in *Good News* portfolio and short in *Bad News* portfolio. We then compute the equally weighted average news scores of *"Good-Bad"* hedge portfolio over different time periods after the portfolio formation. $News_{t+1}$ shows the average news scores in month (or week, or day) t+1; $News_{t+2,\,t+6}$ shows the average news scores over 5 months from t+2 to t+6 (or 4 days from t+2 to t+5, or 3 weeks from t+2 to t+4); $News_{t+7,\,t+12}$ shows the average news scores over 6 months from t+7 to t+12 (or 5 days from t+6 to t+10, or 8 weeks from t+5 to t+12); and $News_{t+13,\,t+24}$ shows average news scores over 12 months from t+13 to t+24 (or 10 days from t+11 to t+20, or 12 weeks from t+13 to t+24). The sample period is from January 2000 to October 2014. Newey-West adjusted *t*-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Specifications	$News_t$	$News_{t+1}$	$News_{t+2,\,t+6}$	$News_{t+7,\,t+12}$	$News_{t+13,\,t+24}$
Daily	0.576***	0.018***	0.016***	0.011***	0.010***
	(208.71)	(37.61)	(47.52)	(41.73)	(44.81)
Weekly	0.566***	0.042***	0.027***	0.020***	0.019***
	(82.17)	(32.43)	(33.76)	(37.64)	(39.47)
Neutral News Included	0.380***	0.034***	0.042***	0.029***	0.020***
	(30.91)	(23.93)	(46.75)	(36.06)	(27.50)
Negative vs. Positive	0.258***	0.025***	0.029***	0.021***	0.014***
	(23.00)	(30.28)	(33.12)	(34.19)	(29.92)
Decile Portfolios	0.558***	0.043***	0.050***	0.034***	0.022***
	(26.69)	(26.29)	(47.77)	(33.02)	(22.19)

Table 7: Return Predictability of News

This table presents the return predictability of news by examining the average next month returns of portfolios constructed based on monthly news scores. At the end of month t, we sort all stocks into five portfolios based on news scores ($News_t$). Stocks in *Bad News* portfolio have the lowest news scores and stocks in *Good News* portfolio have the highest news scores. "*Good-Bad*" is the hedge portfolio that is long in *Good News* portfolio and short in *Bad News* portfolio. We then compute the equally weighted one-month-ahead average return ($Return_{t+1}$), CAPM alpha ($Return_{CAPM, t+1}$), Fama and French three factor alpha ($Return_{FF3, t+1}$), four factor alpha ($Return_{FF4, t+1}$) and five factor alpha ($Return_{FF5, t+1}$) for each portfolio. The sample period is from January 2000 to October 2014. Newey-West adjusted *t*-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Portfolios	$Return_{t+1}$	$Return_{CAPM, t+1}$	$Return_{FF3, t+1}$	$Return_{FF4, t+1}$	$Return_{FF5, t+1}$
Bad *News*	0.642	-0.001	-0.233	-0.153	-0.189
2	0.909	0.294	0.045	0.103	-0.001
3	0.981	0.399	0.176	0.215	0.143
4	1.142	0.561	0.329	0.355	0.319
Good *News*	1.337	0.776	0.568	0.602	0.581
Good-Bad	**0.696*****	**0.777*****	**0.800*****	**0.755*****	**0.770*****
	(4.31)	**(5.22)**	**(5.26)**	**(5.40)**	**(4.88)**

Table 8: Return Predictability of News for Different Time Horizon

This table presents the return predictability of news for different time horizon by examining the average monthly Fama-French five factor alphas of portfolios constructed based on monthly news scores for different holdings periods. At the end of month t, we sort all stocks into five portfolios based on their news scores ($News_t$). Stocks in *Bad News* portfolio have the lowest news scores and stocks in *Good News* portfolio have the highest news scores. "*Good-Bad*" is the hedge portfolio that is long in *Good News* portfolio and short in *Bad News* portfolio. We then compute the equally weighted average monthly Fama and French five factor alpha for different holdings periods after the portfolio formation. $Return_{FF5,\ t+1}$ shows the 1-month average FF alpha in month t+1; $Return_{FF5,\ t+2,\ t+6}$ shows the average FF alpha over 5 months from t+2 to t+6; $Return_{FF5,\ t+7,\ t+12}$ shows the average FF alpha over 6 months from t+7 to t+12; and $Return_{FF5,\ t+13,\ t+24}$) shows the average FF alpha over 12 months from t+13 to t+24. The sample period is from January 2000 to October 2014. Newey-West adjusted *t*-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Portfolios	$Return_{FF5,\ t+1}$	$Return_{FF5,\ t+2,\ t+6}$	$Return_{FF5,\ t+7,\ t+12}$	$Return_{FF5,\ t+13,\ t+24}$
Bad *News*	-0.189	0.219	0.406	0.424
2	-0.001	0.176	0.289	0.270
3	0.143	0.142	0.270	0.233
4	0.319	0.270	0.298	0.241
Good *News*	0.581	0.462	0.394	0.375
Good-Bad	**0.770*****	**0.243*****	**-0.011**	**-0.048**
	(4.88)	**(3.32)**	**(-0.20)**	**(-1.37)**

Table 9: Return Predictability of News by Different Information Environments

This table presents the return predictability of news in different information environments. At the end of month t, we sort all stocks into five portfolios based on their news scores (*News$_t$*). We further independently sort all stocks into three portfolios based on their previous year end market capitalization (*Size*), analyst coverage (*Analyst*), and institutional ownership (*InstOwn*), respectively. Stocks in *Bad News* portfolio have the lowest news scores and stocks in *Good News* portfolio have the highest news scores. "*Good-Bad*" is the hedge portfolio that is long in *Good News* portfolio and short in *Bad News* portfolio. We then compute the equally weighted average returns of the "*Good-Bad*" portfolios for *Small/Large Size* subsamples, *Low/High Analyst* subsamples, *Low/High InstOwn* subsamples, as well as *"Small-Large" Size*, *"Low-High" Analyst* and *"Low-High" InstOwn* hedge portfolios over different time periods after the portfolio formation. Return measures include equally weighted one-month-ahead average return ($Return_{t+1}$), CAPM alpha ($Return_{CAPM, t+1}$), Fama and French three factor alpha ($Return_{FF3, t+1}$), four factor alpha ($Return_{FF4, t+1}$) and five factor alpha ($Return_{FF5, t+1}$) for each portfolio. The sample period is from January 2000 to October 2014. Newey-West adjusted *t*-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Panel A: Return Predictability of News for Size Subsamples

Portfolios	$Return_{t+1}$	$Return_{CAPM, t+1}$	$Return_{FF3, t+1}$	$Return_{FF4, t+1}$	$Return_{FF5, t+1}$
Small *Size*	1.168***	1.261***	1.274***	1.232***	1.253***
	(5.74)	(6.87)	(6.78)	(6.85)	(6.44)
Large *Size*	0.065	0.120	0.190	0.129	0.228
	(0.36)	(0.65)	(1.04)	(0.79)	(1.21)
Small-Large	1.103***	1.142***	1.084***	1.103***	1.025***
	(4.64)	(5.26)	(4.94)	(5.04)	(4.55)

Panel B: Return Predictability of News for Analyst Coverage Subsamples

Portfolios	$Return_{t+1}$	$Return_{CAPM, t+1}$	$Return_{FF3, t+1}$	$Return_{FF4, t+1}$	$Return_{FF5, t+1}$
Low *Analyst*	1.172***	1.253***	1.272***	1.254***	1.244***
	(6.18)	(7.83)	(7.81)	(7.75)	(7.37)
High *Analyst*	-0.007	0.058	0.087	0.015	0.066
	(-0.03)	(0.29)	(0.43)	(0.08)	(0.32)
Low-High	1.178***	1.194***	1.185***	1.239***	1.177***
	(4.80)	(5.09)	(4.95)	(5.42)	(4.77)

Panel C: Return Predictability of News for Institutional Holdings Subsamples

Portfolios	$Return_{t+1}$	$Return_{CAPM, t+1}$	$Return_{FF3, t+1}$	$Return_{FF4, t+1}$	$Return_{FF5, t+1}$
Low *InstOwn*	1.199***	1.293***	1.271***	1.229***	1.147***
	(5.68)	(6.64)	(6.46)	(6.50)	(5.71)
High *InstOwn*	0.065	0.100	0.175	0.110	0.253
	(0.38)	(0.56)	(1.00)	(0.72)	(1.40)
Low-High	1.135***	1.194***	1.096***	1.119***	0.894***
	(4.42)	(5.18)	(4.92)	(5.06)	(4.01)

Table 10: Hard News vs. Soft News

This table compares the difference between hard news and soft news. At the end of month (or quarter) t, we sort all stocks into five portfolios based on hard news (*Hard News*) and soft news (*Soft News*), respectively. Stocks in *Bad News* portfolio have the lowest news scores and stocks in *Good News* portfolio have the highest news scores. "*Good-Bad*" is the hedge portfolio that is long in *Good News* portfolio and short in *Bad News* portfolio. We then compute the equally weighted average returns, news scores and earnings surprise of the "*Good-Bad*" portfolios for *Hard News* portfolio, *Soft News* portfolio as well as "*Hard-Soft*" hedge portfolio which is long in Hard News and short in Soft News. Panel A reports the return predictability of hard and soft news. Return measures include equally weighted one-month-ahead average return ($Return_{t+1}$), CAPM alpha ($Return_{CAPM, t+1}$), Fama and French three factor alpha ($Return_{FF3, t+1}$), four factor alpha ($Return_{FF4, t+1}$) and five factor alpha ($Return_{FF5, t+1}$) for each portfolio. Panel B reports the momentum of hard and soft news. $News_{t+1}$ shows the 1-month average news scores of each portfolio in month t+1; $News_{t+2, t+6}$ shows the average news scores over 5 months from t+2 to t+6; $News_{t+7, t+12}$ shows the average news scores over 6 months from t+7 to t+12; and $News_{t+13, t+24}$ shows average news scores over 12 months from t+13 to t+24. Panel C reports the future earnings surprise for hard and soft news. SUE_{t+1} shows the 1-quarter average SUE of each portfolio in quarter t+1; SUE_{t+2} shows the 1-quarter average SUE in quarter t+2; $SUE_{t+3,t+4}$ shows the average SUE over 2 quarters from t+3 to t+4; and $SUE_{t+5,t+8}$ shows the average SUE over 4 quarters from t+5 to t+8. The sample period is from January 2000 to October 2014. Newey-West adjusted *t*-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Panel A: Return Predictability of Hard and Soft News

News Categories	$Return_{t+1}$	$Return_{CAPM, t+1}$	$Return_{FF3, t+1}$	$Return_{FF4, t+1}$	$Return_{FF5, t+1}$
Hard News	0.750***	0.861***	0.950***	0.836***	0.948***
	(2.89)	(3.78)	(4.12)	(4.86)	(3.96)
Soft News	0.205*	0.219*	0.273**	0.277**	0.364***
	(1.77)	(1.78)	(2.42)	(2.45)	(3.19)
Hard-Soft	0.544*	0.642**	0.677***	0.559***	0.584**
	(1.80)	(2.55)	(2.70)	(2.88)	(2.26)

Panel B: Momentum of Hard and Soft News

News Categories	$News_{t}$	$News_{t+1}$	$News_{t+2, t+6}$	$News_{t+7, t+12}$	$News_{t+13, t+24}$
Hard News	0.731***	0.049***	0.065***	0.038***	0.021***
	(64.52)	(24.27)	(27.30)	(26.61)	(17.92)
Soft News	0.413***	0.057***	0.044***	0.037***	0.029***
	(32.32)	(18.93)	(18.37)	(18.86)	(20.21)
Hard-Soft	0.318***	-0.009**	0.021***	0.001	-0.007***
	(28.57)	(-2.18)	(5.62)	(0.38)	(-3.89)

Table 10-Continued

Panel C: Future SUE for Hard and Soft News					
News Categories	SUE_t	SUE_{t+1}	SUE_{t+2}	$SUE_{t+3,\, t+4}$	$SUE_{t+5,\, t+8}$
Hard News	4.166***	1.626***	1.279***	0.988***	0.501***
	(12.74)	(7.62)	(10.09)	(6.36)	(5.61)
Soft News	-0.229*	-0.012	-0.143	-0.057	-0.104
	(-1.93)	(-0.12)	(-0.84)	(-0.76)	(-1.44)
Hard-Soft	4.395***	1.638***	1.422***	1.044***	0.605***
	(11.34)	(6.16)	(5.78)	(5.14)	(4.53)

Table 11: Return Predictability of News—Robustness Tests

The table examines the robustness of return predictability of news by using different specifications. *"Daily"* and *"Weekly"* means that all stocks are grouped into five portfolios based on their news scores ($News_t$) at the end of day t and week t, respectively. *"Neutral News Included"* means that all stocks including those with neutral news are grouped into five portfolios based on their news scores ($News_t$) at the end of month t. *"Decile Portfolios"* means that all stocks are grouped into ten portfolios based on news scores ($News_t$) at the end of month t. For these four specifications, stocks in *Bad News* portfolio have the lowest news scores and stocks in *Good News* portfolio have the highest news scores. For the specification *"Negative vs. Positive"*, stocks in *Bad News* portfolio have the negative news scores and stocks in *Good News* portfolio have the positive news scores. "*Good-Bad*" is the hedge portfolio that is long in *Good News* portfolio and short in *Bad News* portfolio. We then compute the equally weighted next month (or week, or day) average return ($Return_{t+1}$), CAPM alpha ($Return_{CAPM,\ t+1}$), Fama and French three factor alpha ($Return_{FF3,\ t+1}$), four factor alpha ($Return_{FF4,\ t+1}$) and five factor alpha ($Return_{FF5,\ t+1}$) for "Good-Bad" hedge portfolios. The sample period is from January 2000 to October 2014. Newey-West adjusted *t*-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Specifications	$Return_{t+1}$	$Return_{CAPM,\ t+1}$	$Return_{FF3,\ t+1}$	$Return_{FF4,\ t+1}$	$Return_{FF5,\ t+1}$
Daily	0.531***	0.533***	0.532***	0.531***	0.527***
	(30.57)	(36.12)	(36.04)	(36.01)	(35.69)
Weekly	0.302***	0.313***	0.324***	0.305***	0.302***
	(7.44)	(8.71)	(9.02)	(8.81)	(8.44)
Neutral News Included	0.599***	0.674***	0.699***	0.657***	0.679***
	(4.32)	(4.91)	(4.99)	(5.10)	(4.68)
Negative vs. Positive	0.394***	0.456***	0.475***	0.441***	0.439***
	(3.34)	(3.98)	(4.11)	(4.14)	(3.69)
Decile Portfolios	0.877***	0.968***	0.965***	0.901***	0.947***
	(4.22)	(4.98)	(4.85)	(5.03)	(4.66)

Table 12: Return Predictability of News—Fama-MacBeth Regressions

This table presents Fama-MacBeth Regressions of next month returns or alphas on news scores (*News*$_t$) and control variables. The dependent variables are stock returns in M1 ($Return_{t+1}$), CAPM alphas in M2 ($Return_{CAPM,\ t+1}$), Fama and French three factor alphas in M3 ($Return_{FF3,\ t+1}$), four factor alphas in M4 ($Return_{FF4,\ t+1}$) and five factors alphas in M5 ($Return_{FF5,\ t+1}$). The control variables include logarithm of market capitalization (*LogSize*), book-to-market ratio (*B/M*), beta (*Beta*), idiosyncratic volatility (*IdioVol)*, past two-month stock returns ($Return_{t-3,\ t-2}$), past three-month stock returns($Return_{t-6,\ t-4}$), past six-month stock returns ($Return_{t-12,\ t-7}$), and Amihud's (2002) illiquidity (*Illiquidity*). All the variables are defined in Appendix A. The table also reports the number of observations (*NObs*), average number of firms per month (*Firms*), and adjusted R square ($Adj\text{-}R^2$). The sample period is from January 2000 to October 2014. Newey-West adjusted *t*-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

	$Return_{t+1}$	$Return_{CAPM,\ t+1}$	$Return_{FF3,\ t+1}$	$Return_{FF4,\ t+1}$	$Return_{FF5,\ t+1}$
Variables	M1	M2	M3	M4	M5
News$_t$	**1.374*****	**1.321*****	**1.330*****	**1.362*****	**1.386*****
	(6.11)	**(6.29)**	**(7.30)**	**(7.49)**	**(7.09)**
LogSize$_t$	-0.077**	-0.060	-0.046*	-0.047*	-0.053*
	(-2.01)	(-1.58)	(-1.68)	(-1.68)	(-1.95)
B/M$_t$	0.129	0.208	0.109	0.114	0.006
	(0.97)	(1.53)	(1.06)	(1.17)	(0.06)
Beta$_t$	0.066	-0.212	-0.119	-0.071	-0.083
	(0.34)	(-1.35)	(-0.87)	(-0.59)	(-0.58)
IdioVol$_t$	-14.740*	-13.165*	-12.398*	-13.202*	-2.438
	(-1.66)	(-1.80)	(-1.77)	(-1.91)	(-0.40)
$Return_{t-3,\ t-2}$	0.001	0.002	0.001	0.001	0.001
	(0.31)	(0.54)	(0.32)	(0.37)	(0.22)
$Return_{t-6,\ t-4}$	0.002	0.002	0.002	0.002	0.000
	(0.69)	(0.73)	(0.74)	(0.91)	(0.11)
$Return_{t-12,\ t-7}$	0.000	0.000	0.000	0.001	0.000
	(0.16)	(0.22)	(0.26)	(0.62)	(0.14)
Illiquidity$_t$	0.617	0.435	0.690*	0.691*	0.482
	(1.26)	(0.96)	(1.81)	(1.79)	(1.34)
Intercept	1.372***	1.111***	0.696**	0.715**	0.504*
	(3.74)	(2.99)	(2.34)	(2.49)	(1.79)
NObs	423,504	423,504	423,504	423,504	423,504
Firms	2,379	2,379	2,379	2,379	2,379
Adj-R^2	6.1%	4.3%	3.2%	3.0%	3.2%