The Momentum of News

Ying Wang, Bohui Zhang, and Xiaoneng Zhu*

This Draft: October 2018

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*Ying Wang is from School of Finance, Central University of Finance and Economics, 39 South College Road, Beijing, China, 100081; Bohui Zhang is from Shenzhen Finance Institute and School of Management and Economics, The Chinese University of Hong Kong, Shenzhen (CUHK-Shenzhen), 2001 Longxiang Road, Longgang District, Shenzhen China, 518172 ; and Xiaoneng Zhu is from School of Finance, Shanghai University of Finance and Economics, and Shanghai Institute of Finance and Economics, Guoding Road 777, Shanghai, China, 200433. Authors' contact information: Wang: wang0371@e.ntu.edu.sg, (86) 10 62288607; Zhang: bohuizhang@cuhk.edu.cn, (86)755 23518868; Xiaoneng Zhu: xiaonengz@gmail.com, (86) 21 65908162. We are grateful for the valuable comments from Sohnke Bartram, Stephen Brown, Jie Cao, Chen Chen, Zhi Da, Li Ge, Philip Gharghori, Liyan Han, Shiyang Huang, Thanh Huynh, Andrew Karolyi, Sophia Zhengzi Li, Xindan Li, Bo Liu, Paul Tetlock, Neng Wang, Hongjun Yan, Liyan Yang, Yu Yuan, Xin Zhang, and the conference and seminar participants at the 2018 China International Conference in Finance in Tianjin, the 2017 American Finance Association Annual Meetings in Chicago, the 2016 Conference on Corporate Finance and Capital Markets in Shanghai, the 2016 Chinese Finance Annual Meeting in Dalian, CUHK-Shenzhen, Deakin University, Fudan University, Monash University, Shangdong University, Southern University of Science and Technology, University of International Business and Economics, and Zhejiang University. We also thank the program committee of the 2016 Chinese Finance Annual Meeting for awarding us the Best Paper Award. Ying Wang acknowledges the financial support from the Natural Science Foundation of China (Grant No. 71702113). Xiaoneng Zhu acknowledges the financial support from the Natural Science Foundation of China (Grant No. 71473281), the Program for Innovative Research Team of Shanghai University of Finance and Economics and Shanghai Institute of Finance and Economics.

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Abstract

Relying on a comprehensive data set of news releases, we construct monthly firm-level news sentiment scores during the 2000–2016 period and document a news momentum phenomenon of stocks with more positive news in the past generating more positive news in the future. We propose three hypotheses to explain this phenomenon and find that news momentum is driven by the persistence of firms' fundamentals rather than stale news or firms' strategic disclosure. A trading strategy that combines a long position in a good news quintile portfolio with a short position in a bad news portfolio generates a 7.45% risk-adjusted return annually. This return anomaly appears on both news and non-news days. Overall, these findings suggest that the cross-sectional prediction of news 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 the potential explanations for cross-sectional predictability, mispricing is identified as a key factor (e.g., Mclean and Pontiff, 2016; Engelberg, McLean, and Pontiff, 2018). 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 a given, the property of news is left unexplored. Given that 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 data set collected by RavenPack, we construct a sample of real-time news releases for stocks listed on the New York Stock Exchange (NYSE), American Stock Exchange (Amex), and National Association of Securities Dealers Automated Quotations (Nasdaq) over the 17-year period between 2000 and 2016. 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 a monthly frequency. We aggregate news articles for each firm over a month and then calculate the monthly news sentiment scores by averaging the news sentiment scores over a month.

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

To understand the nature of news momentum, we propose three hypotheses to explain the phenomenon. First, news momentum is driven by stale information. In a competitive information market, news is a nonrival good with a high discovery cost and a low replication cost (e.g., Veldkamp, 2006). The high cost of information production makes the dissemination of old news by information intermediaries relatively price efficient. Therefore, stale news is likely to be disseminated repeatedly in the form of repetitions, reprints, and recombinations. The release of stale information becomes meaningful when investors cannot appropriately distinguish between new and old information due to limited attention or other reasons (e.g., Tetlock, 2011; Gilbert, Kogan, Lochstoer, and Ozyildirim, 2012; Fedyk and Hodson, 2017). We call this view *the stale information hypothesis*.

The second hypothesis relates news momentum to a firm's disclosure strategies. When insiders' disclosure preferences are not aligned with those of outside investors, various incentives can motivate managers to strategically disclose or withhold firm-specific information (e.g., Kothari, Shu, and Wysocki, 2009; Ahern and Sosyura, 2014; Edmans, Goncalves-Pinto, Groen-Xu, and Wang, 2018). For example, firms may release more positive news stories during merger negotiations (Ahern and Sosyura, 2014) or in equity vesting months (Edmans et al., 2018). These properties of news dissemination associated with firms' disclosure strategies may induce news momentum, meaning that 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 strategic disclosure hypothesis*.

The third possibility is that news momentum could be induced by the dynamics of firms' fundamentals. It has been well documented that earnings are persistent and predictable (e.g., Ball and Brown, 1968; Beaver, Clarke and Wright, 1979; Fama and French, 2000, 2006; Markov and Tamayo, 2006; Li, 2010; Novy-Marx, 2015). If news articles fairly reflect firms' fundamentals (e.g., Tetlock, Saar-Tsechansky, and Macskassy, 2008), the persistent earnings stream is likely to generate a persistent stream of sequential news releases. More specifically, positive (negative) news is more likely to follow positive (negative) news in the future because news reports should also disseminate fundamental information. We call this view *the fundamental persistence hypothesis*.

To test *the stale information hypothesis*, we check whether the news pattern also appears across different news categories, based on the rationale that stale news articles typically concentrate on the same news category. We document an interesting pattern of cross-category news momentum. For example, in terms of revenue-related news, news sentiment for other news categories (analyst ratings, credit ratings, and earnings) in the current period predicts news sentiment for revenue-related news in the future, and vice versa. This finding is inconsistent with the stale information hypothesis.

We further investigate *the strategic disclosure hypothesis* based on the idea that a firm's information environment determines its disclosure strategies and thus should affect the presence of new momentum. We use firm size, analyst coverage, and institutional holdings as proxies for information environments. We find no systematic difference in news momentum between stocks with small firm size, low analyst coverage, and fewer institutional holdings and those with large firm size, high analyst coverage, and more institutional holdings. This observation is inconsistent with the strategic disclosure hypothesis.

We then move on to test whether news momentum is driven by firms' fundamentals. In support of *the fundamental persistence hypothesis*, we find that firms with high current news sentiment scores have higher profitability or earnings surprises in the future. When we further decompose news into hard news (news that is more relevant to firms' fundamentals) and soft news (news that is less relevant to firms' fundamentals), we show that the fundamental prediction is driven mainly by hard news. In sum, we find supporting evidence for *the fundamental persistence hypothesis*.

Whereas RavenPack news sentiment scores have been widely used in the finance and accounting literature, how these scores are constructed is not publicly available for business reasons. To transparently check the robustness of the news momentum pattern, we collect a large sample of news articles from the LexisNexis database and construct a simple news sentiment score in the spirit of Tetlock, Saar-Tsechansky, and Macskassy (2008) and Loughran and McDonald (2011). We calculate the average fraction of positive minus negative words over the total number of words for every news article as the news sentiment variable. Our empirical analysis shows that news momentum is still highly significant in this alternative news sentiment specification.

To link news momentum with asset prices, we proceed to explore the asset pricing implication of news momentum. If investors are aware of news momentum and news is therefore correctly incorporated into stock prices, then stocks in the highest news score portfolio should have future returns similar to those of stocks in the lowest news score portfolio. Interestingly, we find significant news-driven return predictability: the strategy that buys the good news portfolio and sells the bad news portfolio generates a return of 7.45% per year. This news-driven return predictability is significant only in short horizons and for stocks with poor information environments, such as those with small firm size, low analyst coverage, and fewer institutional holdings. This finding is consistent with the mispricing view of return predictability.

In the context of mispricing, two forms of underreaction may account for the observed return predictability. The first form of mispricing is that market participants do not realize the presence of news continuation and underestimate the persistence of news (fundamentals). The other form is that investors underreact to current news and induce return continuation, such as the post earnings announcement drift anomaly. To test these two types of investor underreaction, we decompose future returns into returns on news days and non-news days. We show that news-driven return predictability is caused by investors' underreaction to both news momentum and news itself.

Finally, we conduct additional tests and show that the return predictability of news is more pronounced for hard news than for soft news and is robust to various specifications, such as the Fama and MacBeth (1973) approach, daily or weekly data, the inclusion of neutral news articles, negative or positive news sorting, and decile portfolios.

Our paper contributes to two strands of the literature. First, it is related to the literature on the capital market impact of business media. The media disseminates or rebroadcasts a large amount of financial news or signals regarding 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 informational role of the media through various channels, such as drawing attention (Fang and Peress, 2009; Da, Engelberg, and Gao, 2011), resolving information asymmetry (e.g., Tetlock, 2010), delivering fundamental information (e.g., Tetlock, Saar-Tsechansky, and Macskassy, 2008), or inflating market sentiment (e.g., Tetlock, 2007). Our study documents a cross-sectional pattern of news and indicates an asset pricing implication of the news pattern.

Second, our paper contributes to the literature on the predictability of stock returns based on news stories. Hillert, Jacobs, and Muller (2014) show that firms covered by the media exhibit stronger return momentum, indicating that news dissemination exacerbates investor biases.

Using a comprehensive sample of intraday firm-specific news data, Jiang, Li, and Wang (2018) 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 finding is consistent with imperfect investor reactions to news and limits to arbitrage. More broadly, using a sample of 97 stock return anomalies documented in published studies, Engelberg, McLean, and Pontiff (2018) show that anomaly returns are seven times higher on earnings announcement days and two times higher on corporate news days. We offer a new insight that investors not only misprice news but also misprice the cross-sectional pattern of news.

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

2. Data, variable construction, and descriptive statistics

2.1. Data and sample

Our data come from a variety of sources. First, we obtain stock returns and market capitalization data from CRSP and firms' fundamentals from Compustat. After merging the CRSP and Compustat data, our initial sample covers all common stocks listed on the NYSE, Amex, and Nasdaq. We further require stocks to have a price greater than one dollar and nonmissing information on market capitalization and the book-to-market ratio.

Then, we obtain news data from RavenPack News Analytics and include only firms with at least one news story covered by RavenPack, which is a leading global news database used by practitioners in quantitative and algorithmic trading and by scholars in accounting and finance research (e.g., Kolasinski, Reed, and Ringgenberg, 2013; Schroff, Verdi, and Yu, 2014; Dai, Parwada, and Zhang, 2015; Dang, Moshirian, and Zhang, 2015; Jiang, Li, and Wang, 2018). RavenPack collects and analyzes real-time, firm-level business news from leading news providers (e.g., *Dow Jones Newswire*, *The Wall Street Journal*, and *Barron's*) and other major publishers and web aggregators, including industry and business publications, regional and local newspapers, government and regulatory updates, and trustworthy financial websites.

Our final sample consists of 530,283 firm-month observations (2,600 firms on average) spanning January 2000 to December 2016. The sample period is determined by the availability of RavenPack. In a series of additional analyses, we also use a battery of firm characteristics, including analyst coverage, institutional ownership, return on assets (ROA), earnings surprises, idiosyncratic volatility, market beta, past stock returns, and illiquidity (Amihud, 2002). These firm characteristics either serve as proxies for firms' information environments or predict future stock returns. Appendix A lists the data sources and definitions of these characteristic variables.

2.2. News sentiment

Our analysis is based on the enormous volume of news flows: 6,766,424 news articles in total, which is equivalent to approximately 33,168 news articles per month, or 13 news articles per firm per month. To measure the informational content of a news article, RavenPack implements two steps. First, it classifies news articles into news event categories according to the RavenPack taxonomy, and both the topic and a firm's role in the news article are tagged and categorized. For example, a news article with the headline "IBM Completes Acquisition of Telelogic AB" is categorized into the "acquisition" event and tagged as "acquisition-acquirer" for IBM and "acquisition-acquiree" for Telelogic AB. Similarly, a news article titled "Xerox Sues Google over Search-Query Patents" is categorized into the "patent-infringement" event. Xerox receives the tag "patent-infringement-plaintiff", while Google obtains the tag "patent-infringement-defendant". All the news articles in our study can be grouped into 32 news categories, which are listed in Appendix B. Among all the news stories, the top five news categories are "earnings" (18.99%), "insider-trading" (13.87%), "technical-analysis" (9.40%), "products-services" (7.68%), and "revenues" (5.48%).

Second, RavenPack constructs the news sentiment score for each news article based on professional algorithms, which were developed and evaluated by effectively combining traditional language analyses, financial expert consensuses, and market response methodologies.[1] Specifically, the news sentiment score indicates whether 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

[1] For example, RavenPack algorithms can analyze the actual figures, estimates, ratings, revisions, magnitudes, and recommendations disclosed in news articles. The algorithms can also compare actual with estimated figures for earnings, revenues or dividends and produce the news sentiment score based on these comparisons. In addition, these algorithms can calculate percentage differences between financial figures and analyze the stock and credit ratings disclosed by analysts. They algorithms can also process information such as the Richter scale in the case of an earthquake or the number of casualties in a suicide bombing event. The use of emotionally charged language by authors is also incorporated into these algorithms when shaping the strength component of the news sentiment score.

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 story. A score of 50 represents neutral sentiment. To facilitate our empirical analysis, we subtract 50 from the news sentiment score and scale it by 50. The adjusted sentiment score falls within an interval between minus one and one.

The news sentiment score is economically intuitive. For example, a firm has a news sentiment score of -0.2 for a news article about its analyst downgrade from "Buy" to "Neutral". In terms of the relative magnitude, the firm may obtain a more negative news sentiment score, such as -0.4, if the analyst downgrade is from "Strong Buy" to "Strong Sell". For complicated news stories, including financial variables and economic indicators, the news sentiment score can intellectually measure the percentage change between the announced actual figures and the market consensus (or any other benchmarks). For example, a firm beating earnings by 70% may enjoy a news sentiment score of 0.6, while the firm exceeding a benchmark by 1% may have a news sentiment score of 0.1.

To exclude as much repeated news as possible, we use the event novelty score (ENS) provided by RavenPack and retain only news articles with the highest event novelty score (100). As such, the cross-sectional pattern of news is less likely to be driven by the repetitive dissemination of the same or similar news articles.

Our main analysis is conducted at the monthly frequency. To obtain monthly observations, we calculate the average news sentiment scores for each firm over the month and use this variable as the key news sentiment measure (*News*). The value of *News* is zero if there is no news for a firm in a particular month.

To differentiate news articles with respect to their relevance to firms' fundamentals, we split news articles into two groups: hard news and soft news. The hard news group consists of four news categories: "revenues", "earnings", "analyst ratings", and "credit ratings". All other news categories are included in the soft news group. Appendix B shows the details of the two news groups. In our sample of news articles, 29.8% are defined as hard news, and the remaining 70.2% are defined as soft news. Following the same definition of *News*, we calculate the sentiment of hard news (*HardNews*) and the sentiment of soft news (*SoftNews*) for each firm and month.

2.3. Summary statistics

Table 1 reports the descriptive statistics of the main variables used in our empirical analysis. In our sample, we exclude firms with news scores of zero each month.[2] We find that on average, firms in our sample have positive news ($News_t$=0.079). Another notable observation that emerges from the table is the symmetric distribution of our news sentiment variable. For example, the mean of $News_t$ is very close to the median of $News_t$. Moreover, the sentiment of hard news seems to be more volatile than that of soft news. For example, the means of $HardNews_t$ and $SoftNews_t$ are 0.108 and 0.075, respectively, but the standard deviations of $HardNews_t$ and $SoftNews_t$ are 0.258 and 0.145, respectively.

In addition to these news variables, the table also shows reasonable summary statistics for other variables: next month returns (R_{t+1}), logarithm of market capitalization ($Size_t$), analyst coverage ($Analyst_t$), institutional ownership ($InstOwn_t$), book-to-market ratio (B/M_t), market beta ($Beta_t$), idiosyncratic volatility ($IdioVol_t$), 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 ($Return_{t-12,\, t-7}$), Amihud's (2002) illiquidity ($Illiquidity_t$), earnings surprise (SUE_t), and ROA (ROA_t).

[Insert Table 1 Here]

Table 2 provides an overview of the extent of news coverage for six periods (2000-2002, 2003-2005, 2006-2008, 2009-2011, 2012-2014, and 2015-2016) across size portfolios. Firms are sorted into size quintiles by their market capitalizations (*Size*). Panel A reports the total number of news articles covering a specific firm in a month. It is evident from the panel that large firms have a larger number of news articles. For example, in the 2015-2016 period, firms in the large *Size* quintile have approximately 40 news articles in a month, while firms in the small *Size* quintile have only approximately nine news articles per month. This fact not only is consistent with the media literature that indicates that large firms attract higher media coverage but is also aligned with the intuition that large firms typically generate more news events.

We also find that the number of news articles increases substantially over the past 17 years across all size portfolios. For example, the average number of news articles covering firms in the

[2] About 27.4% of total firm-month observations have news scores of zero, indicating that those firms have either neutral news or no news in the month. However, our main results always hold even, including those scores of zero observations in the analysis, as our robustness tests show (see Internet Appendix Table IA1 and Table IA5),

large *Size* quintile increases from nine in the 2000-2002 period to 40 in the 2015-2016 period. This time-series pattern could be explained by either the increasing intensity of media coverage or the growing amount of firm activities.

Panels B and C present the number of positive and negative news articles, respectively. We consistently find more positive news reports than negative news reports in each portfolio. Regarding news patterns, we find cross-sectional and time-series patterns for both positive and negative news articles similar to those in Panel A.

[Insert Table 2 Here]

2.4. Simple quantitative measure of sentiment

While RavenPack news sentiment scores have been widely used in accounting and finance research, the algorithm used to calculate sentiment scores is not publicly available for business reasons. This issue raises a concern about whether RavenPack news sentiment scores are a "black box" because researchers have no way to verify the correctness of the news patterns. Therefore, a more transparent and simple news sentiment measure would provide additional insights into news patterns and facilitate replication. The quantitative measure of language is particularly challenging and still controversial. This alternative measure of news sentiment can serve as a robustness check. Toward this end, relying on 635,343 new articles, we follow Tetlock, Saar-Tsechansky, and Macskassy (2008) and Loughran and McDonald (2011) and use the simple quantitative method to construct alternative news sentiment scores.

Our news sample consists of 500 common stocks included in the S&P Composite 1500 index.[3] We collect new articles on these companies from LexisNexis.[4] To be consistent with RavenPack coverage and the literature based on RavenPack data, we collect news articles from the maximum set of news sources, including national and local newspapers, web-based publications, newswires and press releases, newsletters, and industry trade press. To restrict ourselves to articles that truly address a specific company, we use the "relevance score" measure of LexisNexis. In our empirical tests, we report results based on a relevance score of 90%, but we stress that our results are robust to a reasonable relevance score (i.e., 80% or 70%).

[3] We select the first 500 stocks according to the alphabetical order of their ticker numbers.
[4] To gather all company-related articles, we rely on an algorithm that automatically searches the LexisNexis database using company names as keywords in the company search function.

In total, we extract 635,343 news articles, which cover 500 companies from January 2000 to December 2016, in our sample. This number corresponds to 82,477 firm-month observations. Among firms that are covered by the media in a given month, the mean number of articles is approximately 71, but the median is only 22, and the 25th percentile is 11.

To identify positive and negative words in news articles, we use domain knowledge from positive and negative word categories in Loughran and McDonald's (2011) sentiment word lists. Compared with the Harvard-IV-4 psychosocial dictionary, Loughran and McDonald (2011) show that their list better reflects the tone of financial texts. We then use a professional textual analysis algorithm to count total words, positive words, and negative words in each news article. In our baseline tests, we construct the alternative news sentiment measure *PNNews* by calculating the average fraction of positive minus negative words over the total number of words for every news article released in month t for a particular firm. In the online appendix, we construct a similar news score *NNews* by counting negative words only for every news article released in month t for a specific firm.

3. The cross-section of news

3.1. Baseline results

This section investigates the cross-sectional pattern of news. Following the standard method in the asset pricing literature, we construct monthly news portfolios according to firms' news sentiment scores. Specifically, at the end of month t, we sort all stocks into five portfolios based on their news sentiment scores in month t ($News_t$). We then compute equally weighted average news scores for the current month t and future months from t+1 to t+24 across all firms in each portfolio. The quintile of stocks releasing the most negative information (below the 20th percentile) in month t is called the bad *News* portfolio, and the quintile of stocks releasing the most positive information (above the 80th percentile) in month t is called the good *News* portfolio.

Table 3 presents the cross-section of news. The bad *News* portfolio has a sentiment score of -0.128 at the formation period, while the good *News* portfolio has a corresponding sentiment score of 0.285. The 2nd to 4th quintiles of stocks have news sentiment scores of 0.008, 0.080, and 0.152, respectively. To facilitate the comparison between the bad *News* portfolio and the good *News* portfolio, we construct a hedging portfolio by selling stocks in the bad *News* portfolio and buying stocks in the good *News* portfolio. By construction, the "good minus bad" (GMB) *News* portfolio has a positive sentiment score of 0.413, which is statistically significant at the 1% level.

[Insert Table 3 Here]

How does the sentiment of the GMB portfolio fluctuate? If we hold the GMB *News* portfolio for a number of months, from *t*+1 to *t*+24 following the formation month, the GMB *News* portfolio exhibits a pattern of news sentiment continuation in the subsequent periods. We first examine the GMB portfolio sentiment at time *t*+1. The GMB *News* portfolio has an average positive sentiment score of 0.037, with a heteroscedasticity and autocorrelation consistent *t*-value of 28.5. The magnitude of news sentiment has an economical significance that is equivalent to 24.5% of the standard deviation of *News*. Given that this pattern coincides with the tendency of an object in motion to stay in motion – momentum – we label the cross-sectional pattern of news sentiment *the momentum of news* or *news momentum*.

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 of 0.043 with a *t*-statistic of 49.4, suggesting that news sentiment stays in motion. Furthermore, we observe a monotonic relationship between current and future news sentiment scores. When we examine the holding period from *t*+7 to *t*+12 and from *t*+13 to *t*+24, it is evident that the GMB *News* portfolio has a persistent significant positive sentiment score.[5] Taken together, these findings suggest the presence of news momentum, which implies that firms with more current positive (negative) news are likely to release more positive (negative) news in the future.[6]

Despite the strong evidence shown in Table 3, a concern arises as to whether our finding of news momentum is caused by the measurement of news sentiment scores.[7] Because RavenPack's algorithms for calculating the news sentiment score could be viewed as a "black box", any measurement issues can result in the stickiness of news sentiment. To address this concern, we

[5] At longer horizons, news momentum still continues for some periods and finally becomes insignificant.

[6] We examine the robustness of the momentum of news using different specifications in the Internet Appendix Table IA1. These robustness checks include analyses based on daily and weekly data, including neutral news stories, forming decile portfolios or positive-negative sentiment portfolios, using extreme-news-day returns, and using aggregate news sentiment scores.

[7] The RavenPack data set has two advantages that may account for why our main results rely on this data set. First, it allows us to test the stale news hypothesis, as it divides news into various categories. Second, it removes the news volume of repetitions, reprints, and recombinations as much as possible.

use an alternative news sentiment measure and examine whether news momentum still emerges. The alternative news sentiment measure, *PNNews*, is constructed by calculating the fraction of positive and negative words in a news article. Because *PNNews* is simple and replicable, the analysis based on this news sentiment measure ensures a plausible comparison with the media literature.

[Insert Table 4 Here]

Table 4 reports the news momentum results based on the alternative news sentiment measure *PNNews*. Using the same portfolio construction procedure as in Table 3, the table reveals a significant news momentum pattern: firms in the good *PNNews* portfolio release relatively good news in the future, while firms in the bad *PNNews* portfolio disseminate relatively bad news in the periods after portfolio formation. This news momentum phenomenon remains statistically significant over the two-year period.

In sum, the news momentum phenomenon emerges regardless of whether RavenPack sentiment scores or the positive and negative word count measure are used to gauge news sentiment, suggesting the robustness of news momentum.

3.2. Hypothesis development

This section develops three hypotheses regarding the economic mechanisms of news momentum formation. The first conjecture is that news momentum is explained by stale information. In a competitive information market, news is a nonrival good with a high discovery cost and a low replication cost (e.g., Veldkamp, 2006). The high cost of information production makes the dissemination of old news by information intermediaries relatively price efficient. As such, stale news is likely to be disseminated repeatedly. The release of stale information is particularly meaningful when investors cannot appropriately distinguish between new and old information (Tetlock, 2011; Gilbert et al., 2012; Fedyk and Hodson, 2017). For example, Fedyk and Hodson (2017) explain that the recombination of old information from multiple sources is difficult to identify as stale. These repeated news releases finally induce new momentum.

Although we exclude repeated news stories from the construction of our news sample using the ENS, it is still plausible that the media reports the same news events by rearticulating the tone and content of news articles.[8] For example, Gurun and Butler (2012) find that local media reports news about local companies using fewer negative words than the same reporting by nonlocal media. Their evidence suggests that different media reports the same news stories in a textually different way. When news stories are essentially reprinted in a quite dissimilar form, stale information will drive news momentum. Considering the above discussion, we develop our first hypothesis, *the stale information hypothesis*, as follows:[9]

H1: *Stale information drives news momentum.*

Our second conjecture is that news momentum is driven by firms' strategic disclosure behavior. When insiders' disclosure preferences are not aligned with those of outside investors, various incentives can motivate managers to strategically disclose or withhold firm-specific information (Healy and Palepu, 2001; Verrecchia, 2001). For example, in fear of litigation, managers are willing to quickly reveal bad news (e.g., Skinner, 1994; Baginski, Hassell, and Kimbrough, 2002). Moreover, to reduce the exercise price of their employee options, managers may accelerate the dissemination of bad news and withhold good news (e.g., Yermack, 1997; Aboody and Kasznik, 2000).

In contrast to these incentives to disclose bad news early, firms also prefer to withhold bad news and advance good news under certain circumstances. For example, firms may release more positive news stories during merger negotiations (Ahern and Sosyura, 2014) or in equity vesting months (Edmans et al., 2018). Generally, managers choose to withhold bad news because they may suffer a reduction in compensation and face higher career concerns when bad news is released to the public (e.g., Nagar, Nanda, and Wysocki, 2003; Graham, Harvey, and Rajgopal, 2005; Kothari, Shu, and Wysocki, 2009). When this motivation becomes strong, firms may even hire investor relations firms to spin their news by creating more positive media coverage (Bushee and Miller, 2007; Solomon, 2012).

[8] Repeated news stories are typically identified based on similarities between the two texts. For example, a simple [0, 1] measure (i.e., Tetlock, 2011) is the number of unique words present in the intersection of the two texts divided by the number of unique words present in the union of the two texts.
[9] *The stale information hypothesis* has important implications for asset pricing. Due to various reasons, such as limited attention (e.g., Da, Engelberg, and Gao, 2011) or limited access to all news sources, some readers of a news story may not realize that other sources have already reported similar stories. These readers may trade on the previously released information, leading to return momentum. For example, Tetlock (2011) suggests that market participants cannot appropriately distinguish between new and old information so that stale information can predict stock returns and trading volumes.

Taken together, the pattern of news releases tends to be influenced by firms' disclosure strategies. Among these disclosure possibilities, managers who disclosed bad (good) news in the past may release more bad (good) news in the future. This situation forms our *strategic disclosure hypothesis* for the understanding of news momentum:

H2: *Firms' strategic disclosure behavior induces news momentum.*

Our third conjecture of what induces news momentum is related to firms' fundamentals. It has been well documented that earnings are persistent and hence predictable (e.g., Ball and Brown, 1968; Beaver, Clarke and Wright, 1979; Fama and French, 2000, 2006; Markov and Tamayo, 2006; Li, 2010; Novy-Marx, 2015). In particular, Hou, van Dijk, and Zhang (2011) construct cross-sectional earnings models by regressing firms' future earnings on their current earnings, total assets, dividends, and accruals. They show that these models are able to explain a large fraction of the variation in expected profitability across firms. The average regression R^2s are 82% for earnings regressions of the first three years ahead, and the average coefficients of current earnings in regressions are equal to 0.80, which is consistent with earnings persistence.

If firm-specific news stories fairly reflect firms' fundamentals (e.g., Tetlock, Saar-Tsechansky, and Macskassy, 2008), the persistent earnings stream is likely to generate a positive correlation between the sentiment of sequential news releases. That is, current positive news is more likely to be followed by positive news in the future. Therefore, we propose *the fundamental persistence hypothesis* to explain the news momentum phenomenon:

H3: *Firms with more current positive news fundamentally perform well, and they will have more positive news about their superior fundamentals in the future; the persistence in firms' fundamentals induces news momentum.*

Even though the economic mechanisms of the three hypotheses underlying news momentum are substantially different, we emphasize that the three hypotheses are not mutually exclusive. For instance, it is likely that firms with persistent outstanding fundamentals attract media attention and have stale news rebroadcast in the future.

3.3. Hypothesis tests

3.3.1. News momentum and stale news

This section tests whether news momentum is driven by stale information. Stale information appears in financial markets when the same information is reported multiple times through repetitions, reprints, and recombinations of news (Fedyk and Hodson, 2017). To identify stale information, we assume that the key focus of stale news articles should be on the same theme. For example, different media may repeatedly report the information regarding a negative earnings surprise of a company in different manners, but it is less likely that these media will change the focus of their coverage from earnings to credit ratings; thus, these stale news articles should be classified into the same "Earnings Category".

Following the same logic, if the news momentum effect is driven mainly by stale news, we are unlikely to observe systematic news pattern across different news categories. For example, firms with more current positive (negative) "analyst ratings" related news release more positive (negative) "revenue" news in the future. To test our conjecture, we divide our news articles into four categories: "revenues", "earnings", "analyst ratings", and "credit ratings". We then examine whether current news sentiment in a particular news category can predict future news sentiment in another news category.

[Insert Table 5 Here]

Table 5 reports the news momentum effects across different news categories. At the end of month *t*, we sort all stocks with nonzero news scores into five portfolios within revenues, analyst ratings, credit ratings, and earnings news categories based on their news sentiment scores in each category. As in Table 3, stocks in the bad *News* portfolio have the lowest news sentiment scores, while stocks in the good *News* portfolio have the highest news sentiment scores. The GMB *News* portfolio is the hedge portfolio that takes a long position in the good *News* portfolio and a short position in the bad *News* portfolio in each news category. We then compute equally weighted average news scores for revenue-related news across stocks over the different time periods after the portfolio formation month.

It is evident from Table 5 that in addition to revenue-related news, current news sentiment from other news categories (analyst ratings, credit ratings, and earnings) predicts future news sentiment for revenue-related news. This news continuation pattern is also called *cross-category news momentum*. Table IA2 in the Internet Appendix further shows that our conclusion still holds when we examine news momentum related to analyst ratings (credit ratings or earnings). Overall, the news momentum analysis across news categories suggests that news momentum is less likely to be explained by stale information.

In addition to the above tests across news categories, the presence of news momentum at a monthly frequency also mitigates the plausible explanation of stale information. While news stories tend to be reprinted or recombined in the short term, such as a day or a week, it is less likely that news articles will be systematically released again a month later. The existence of news momentum at the monthly frequency seems to indicate that news momentum is not driven by stale information.

3.3.2. News momentum and strategic disclosure

To examine the strategic disclosure hypothesis, we follow the literature (e.g., Zhang, 2006) and adopt several firm-level characteristics as proxies for firms' information environments. These characteristics include firm size, analyst coverage, and institutional holdings. Firms with large market capitalization, high analyst coverage, and more institutional holdings tend to have more transparent information environments. If news momentum is driven by strategic disclosure, we would expect the news momentum phenomenon to be less significant for stocks with good information environments. The rationale is that insiders can hardly withhold or quickly disclose private information if the firms' information environment is generally good. Examining the magnitude of news momentum across groups sorted by firm size, analyst coverage, and institutional holdings provides insights into the strategic disclosure story of news momentum.

Table 6 presents the news momentum results using the independent double-sorting approach. Specifically, at the end of month *t*, we sort all stocks into five portfolios based on their news sentiment scores. We further independently sort all stocks into three portfolios (below the 30^{th} percentile and above the 70^{th} percentile) based on their previous year-end market capitalization (*Size*), analyst coverage (*Analyst*), or institutional holdings (*InstOwn*).

Panel A reports the results for independent double sorting according to firm size and news sentiment scores. It is evident that news momentum is consistently present in both the large *Size* tercile and the small *Size* tercile, confirming the robustness of news momentum. More importantly, if we examine the news sentiment difference between the GMB *News* portfolio of small firms and the GMB *News* portfolio of large firms, we find no consistent difference in the news momentum pattern. For example, at the one-month horizon, large firms show slightly stronger news momentum. For the holding period from t+2 to t+12, however, small firms exhibit news momentum similar to that of large firms. When the holding period is longer than a year, large firms again show slightly stronger news momentum. These results do not support the second hypothesis that firms' strategic disclosure causes news momentum.

[Insert Table 6 Here]

Panels B and C report the double-sorting results for news momentum based on analyst coverage and institutional ownership. We again find either stronger news momentum for firms with more analyst coverage (higher institutional holdings) or nonsignificant difference in news momentum across stock portfolios with different levels of analyst coverage (institutional ownership). Intuitively, stocks with more analyst coverage or institutional holdings are more closely monitored by professional market participants. As such, firms with more analyst coverage or institutional holdings have a more transparent information environment. If news momentum is due to strategic disclosure, firms with more analyst coverage or higher institutional holdings should exhibit weaker news momentum. Our evidence is thus in opposition to the strategic disclosure hypothesis.

In sum, our double-sorting analysis leads to two conclusions: first, news momentum is a relatively robust phenomenon that is not attenuated by firm characteristics such as firm size, analyst coverage, or institutional holdings; second, news momentum is unlikely to be driven by firms' strategic disclosure behavior.

3.3.3. News momentum and firms' fundamentals

If news momentum is driven by firms' fundamentals, we would expect current news reports to predict firms' *future* fundamentals. To test *the fundamental persistence hypothesis*, we formally examine whether the news sentiment of the GMB portfolio contains information about firms' future fundamentals. Specifically, we use the return-on-assets ratio (*ROA*) and earnings surprise (*SUE*) as proxies for firms' fundamentals. In the spirit of Tetlock, Saar-Tsechansky, and

Macskassy (2008), we compute each firm's SUE as

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

where E_t denotes announced earnings, and μ_t and σ_t denote the mean and standard deviation of forecast earnings.

[Insert Table 7 Here]

For the sake of data availability, we conduct our empirical tests on the relation between news sentiment and future *ROA* based on quarterly data. An interesting pattern that emerges from Table 7 is that current news stories indeed predict firms' future profitability. That is, firms with bad news stories have lower future *ROA*, while firms with good news releases generate more future profits. Combined, we find that the GMB *News* portfolio implies a positive one-quarter-ahead *ROA* of 1.89 with a *t*-value of 7.28. The magnitude also has an economic significance that is equivalent to 29.2% of the standard deviation of *ROA*. The results are robust to the prediction of future *ROA*s at longer time horizons, implying the persistence of the predictive power of the GMB portfolio sentiment.

Panel B summarizes the results of the relationship between current news sentiment scores and future *SUE*. Consistent with the evidence of *ROA*, firms in the good (bad) *News* portfolio experience a higher (lower) future *SUE* at various forecasting horizons. The differences in future *SUEs* between the good and bad *News* portfolios are all statistically significant at the 1% level. These results indicate that the GMB *News* portfolio persistently predicts the difference in firms' fundamentals, thus providing supporting evidence for *the fundamental persistence hypothesis*.[10]

To further establish the fundamental explanation of news momentum, we divide news articles into two categories: hard news and soft news. Given that hard news by definition is relevant to firms' fundamentals, we expect it to have a stronger effect in predicting firms' future fundamentals than soft news. To test this conjecture, we use hard and soft news sentiment to form GMB *News* portfolios and compute the future *ROA* and *SUE* of GMB *News* portfolios. Table IA3 in the Internet Appendix presents the empirical results. To summarize the results, we find that only hard news can significantly and positively forecast firms' future fundamentals.

[10] We also examine the fundamental prediction of news using the Fama-Macbeth (1973) approach by controlling for current *ROA* or *SUE* in the Internet Appendix Table IA4.

This finding is consistent with *the fundamental persistence hypothesis*.

4. News momentum and return predictability

4.1. Baseline results

How news is incorporated into the stock price is central to the efficiency of the stock market. Given the cross-sectional pattern of news documented in Section 3, we investigate whether investors are aware of news momentum. Specifically, we examine whether news sentiment scores predict cross-sectional future stock returns. If news is correctly incorporated into stock prices, then stocks in the highest news score portfolio should have future returns similar to those of stocks in the lowest news score portfolio, and vice versa.

To test the pricing implications of news and its pattern, we form a news trading strategy by buying stocks with high news sentiment scores and selling stocks with low news sentiment scores. Equivalent to the sorting strategy discussed in Section 3.1, 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. Finally, we calculate equally weighted average future returns for this GMB *News* portfolio. It is noteworthy that our news trading strategy is completely different from the traditional momentum strategy (Jegadeesh and Titman, 1993): while our news strategy sorts stocks based on news sentiment scores, the traditional strategy sorts stocks based on past return performance.[11]

Table 8 reports the one-month-ahead portfolio returns obtained from the news trading strategy. The first column indicates that there is significant news-driven return momentum: the strategy that buys the good *News* portfolio and sells the bad *News* portfolio generates a return of 0.621% per month (t-statistic=4.15), which is equivalent to a return of 7.45% per year. Over all the five portfolios, the momentum profits rise monotonically.

[Insert Table 8 Here]

A major concern is whether the positive return of the news trading strategy is obtained from its exposures to risk factors. To alleviate this concern, we use the CAPM model, the Fama-

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

French (1992) three-factor model, the Fama-French-Cahart (Fama and French, 1993; Carhart, 1997) four-factor model, and the Fama-French (2015) five-factor model to control for the risk exposures of GMB *News* portfolio profits. Specifically, we regress the excess returns of GMB *News* portfolios against the respective factors and calculate the regression intercepts that 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 that this negative sentiment score leads to a negative return within one month after risk adjustment. In contrast, the raw return without adjusting for risk exposures is positive. More importantly, after risk adjustment, we find that the news trading strategy even generates higher future stock returns. For example, the Fama-French three-factor model adjusted monthly return is 0.736, which is significant at the 1% level. After the adjustment of the Fama-French five factors, the alpha of the GMB *News* portfolio is 0.716, which is higher than the unadjusted raw return.

Overall, these findings suggest that stocks in the highest news score portfolio have higher future returns than stocks in the lowest news score portfolio, and the return profit of the news trading strategy cannot be explained by its exposure to popularly used risk factors.[12]

Thus far, we show the presence of return momentum induced by news based on RavenPack data. As an alternative approach to that used in Section 3.1, we use positive and negative word classifications to measure news sentiment. This simple quantitative method is largely effective, as reflected by significant correlations with other financial variables (e.g., Tetlock, Saar-Tsechansky, and Macskassy, 2008). Thus, we also examine whether news induces return prediction based on the simple news sentiment measure. This investigation serves as a robustness check.

[Insert Table 9 Here]

Table 9 reports return predictability induced by news using the simple quantitative method. Specifically, we sort all stocks into five portfolios according to $PNNews_t$. Stocks in the bad *PNNews* portfolio have the lowest news sentiment scores, while stocks in the good *PNNews*

[12] We examine the robustness of the return predictability of news using different specifications in the Internet Appendix Table IA5. These robustness checks include the analysis based on daily and weekly data, including neutral news stories, forming decile portfolios or positive-negative sentiment portfolios, using extreme-news-day returns, and using aggregate news sentiment scores.

portfolio have the highest news sentiment scores. The GMB portfolio is the hedge portfolio that takes a long position in the good *PNNews* portfolio and a short position in the bad *PNNews* portfolio. We then compute equally weighted average returns in the next month (or week or day).

It is evident from Table 9 that *PNNews* predicts stock returns at the weekly or daily frequency, and return predictability is still significant after the adjustment of the Fama-French five-factor model at the monthly frequency. As we will discuss in Section 4.2, the evidence of daily or weekly return predictability is consistent with the mispricing interpretation of return momentum induced by news.

4.2. Mispricing or risk

There are two explanations for the cross-sectional return predictability: mispricing and risk. The mispricing explanation is that investors are not aware of news momentum and underreact to news. In this case, news momentum would induce price continuation in the short run, but price continuation would not last for a long period, largely because underreaction shocks are stationary and cannot last forever (e.g., Delong, Shleifer, Summers, and Waldmann, 1990). Moreover, the return predictability implied by news momentum should be stronger in firms with opaque information environments, where market participants are more likely to make a false inference.

In contrast, the rational asset pricing theory posits that stock return predictability can result from exposure to time-varying aggregate risk, and to the extent that news sentiment is consistently linked to this time-varying aggregate risk premium, news sentiment will likely remain successful in return forecasts. If return momentum is caused by risk, we should observe that return momentum caused by news sentiment lasts for a long period and does not disappear quickly. In addition, return predictability induced by news momentum should not be affected by firms' information environments.

To shed light on the mispricing and risk-based explanations, we conduct two tests. First, we investigate the profitability of the news trading strategy for longer holding periods. Specifically, we compute the equally weighted Fama-French five-factor alphas for each portfolio and the GMB *News* portfolio with a holding period from t+2 to t+6, from t+7 to t+12, and from t+13 to t+24. The results are presented in Table 10.

[Insert Table 10 Here]

The strategy that buys the good *News* portfolio and sells the bad *News* portfolio generates a return of 0.275% per month with a *t*-statistic of 4.20 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 profits of this trading strategy are 0.032 and 0.022% per month, respectively, which are economically and statistically nonsignificant. These results suggest that the return predictability of news (momentum) is less likely to be explained by risk.

Second, we examine whether the trading profit of the news trading strategy varies according to firms' information environments. We use firm size, analyst coverage, and institutional holdings as proxies for firms' information environments. At the end of each month t, we independently sort all stocks into five portfolios based on news sentiment scores and into three portfolios based on these firm characteristics. We then calculate the equally weighted future stock returns for these portfolios.

Panel A of Table 11 reports the results for independent double sorting according to firm size and news sentiment scores. The return predictability implied by news is pronounced in the small *Size* tercile but not in the large *Size* tercile. The raw return of the GMB *News* portfolio is 1.08% per month. After the adjustment for risk exposures to the Fama-French five factors, the next period return is 1.18% per month (*t*-statistic=6.34). These results are consistent with the mispricing view of return predictability. Because small firms attract less attention and have fewer news releases, information is likely to be more asymmetric and to be diffused more slowly for these stocks. Therefore, we would expect to observe stronger trading profits for small firms. We find similar results for stocks with low analyst coverage in Panel B and stocks with less institutional ownership in Panel C.

[Insert Table 11 Here]

In sum, these results suggest that the future return of the GMB *News* portfolio is pronounced only at short time horizons and in firms with opaque information environments, thus providing supportive evidence for the mispricing view of return predictability.

4.3. Understanding mispricing channels

Up to this point, our analysis indicates that news-driven momentum is attributable to mispricing, more specifically, underreaction. In the context of mispricing, two forms of underreaction can account for observed return predictability. The first form of mispricing is that market participants do not realize the presence of news continuation and underestimate the persistence of news (fundamentals). The other form is that investors underreact to current news and induce return continuation, as in the post earnings announcement drift anomaly.[13] The two forms of mispricing represent the two different economic channels through which news releases affect stock returns. While the *second* channel has been well documented in the literature, the *first* channel has never been examined.

This section attempts to enrich our insights into the two economic channels. To accomplish this objective, we decompose future returns into returns on news days and on non-news days. If news-driven return predictability is completely caused by the underestimation of news momentum, we should observe positive abnormal returns on news days but not on non-news days. The intuition is that investors will realize underestimation only on subsequent news days. However, if news-driven return predictability is induced by underreaction to news at time t, we should observe positive abnormal returns only on non-news days because subsequent stock prices will adjust to correctly reflect the news sentiment at time t before the next news releases.

Empirically, we decompose the return in a month next to the formation of the GMB portfolio into news-day returns and non-news-day returns. If news is reported on day t, then day t-1, t, and t+1 are treated as news days. Days without news are defined as non-news days. News-day returns (non-news-day returns) are the accumulative daily returns for all news days (non-news days) for a particular stock in a month. Table 12 presents the one-month-ahead portfolio returns of taking the news trading strategy on news and non-news days. Panel A indicates that there is significant news-driven return momentum on news days: the strategy that buys the high-news-sentiment portfolio and sells the low-news-sentiment portfolio delivers a return of 0.293% per month with a t-value of 3.96 after the adjustment of the Fama-French five factors. These results are consistent with the *first* channel, investors' underestimation of news momentum.

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[13] On the theoretical side, the conservatism-bias model of Barberis, Shleifer, and Vishny (1998) and the heterogeneity model of Hong and Stein (1999) can account for the underreaction behavior of investors.

[Insert Table 12 Here]

Panel B reports the returns of the GMB trading strategy on non-news days. Similarly, we find evidence of return continuation. Indeed, the news trading strategy generates a return of 0.416% on non-news days after the adjustment of the Fama-French five factors. These results provide supporting evidence for the second economic channel, investors' underreaction to news sentiment at time *t*, which is associated with firms' fundamentals.

Overall, news-driven return predictability is jointly caused by the two economic channels. On the one hand, market participants do not realize the existence of news momentum and thus underreact to the persistence of news. On the other hand, investors underreact to news itself.

4.4. Additional results

Hard vs soft news: in light of the evidence regarding the information content of the hard and soft news categories, we analyze how soft and hard news reports generate return predictability. Specifically, we explore whether the effect of news sentiment on stock returns concentrates among specific news categories. Toward this end, we regroup 36 news categories originally divided by RavenPack into the hard news category and the soft news category.

Table IA6 in the Internet Appendix confirms that the news-driven momentum is significant mainly for hard news. Using the Fama-French five-factor model to adjust returns, the alpha (the excess return) is 0.862% per month or 10.3% per annum. Turning to the soft news category, we find that the alpha is 0.278% per month. The alpha difference between the hard news GMB portfolio and the soft news GMB portfolio is 0.584% per month with a t-value of 2.42.

Fama and MacBeth (1973) approach: to ensure the robustness of our findings presented in the portfolio approach, we also use the multivariate Fama and MacBeth (1973) regressions to check whether news sentiment predicts future stock returns. Specifically, we perform the following regressions:

$$R_{t+1} = a + b_1 News_t + \sum_{i=1}^{k} b_i Z_{i,t} \quad + \varepsilon_{t+1}, \qquad (2)$$

where R_{t+1} is the stock return in month *t*, $News_t$ is news sentiment at time *t*, and $Z_{i,t}$ includes the control variables observed at time *t*. We use five measures of stock returns as the dependent variable: the raw return, the CAMP-adjusted return, the Fama-French 3-factor model adjusted return, the Fama-French-Carhart 4-factor model adjusted return, and the Fama-French 5-factor model adjusted return. The control variables include the 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*).

Table IA7 in the Internet Appendix presents the multivariate Fama and MacBeth regression results. We confirm that news sentiment predicts stock returns. The regressions consistently generate a positive slope coefficient (b_1), which is significant at the conventional level. These results are consistent with those from the portfolio analysis. To illustrate the magnitude of news impact, column M1 indicates a slope coefficient of 0.469 with a *t*-statistic of 1.98. This finding implies that one unit increase in news sentiment predicts a rise of approximately 5.6% per annum in future returns. We also find that the coefficient of news sentiment is roughly stable across the five regressions. In sum, the Fama-Macbeth regressions provide further supporting evidence of the effect of news sentiment on stock returns.

5. Conclusions

The cross-sectional pattern of news is underinvestigated. 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 current sentiment scores have lower sentiment scores in the future. New momentum is persistent and lasts up to more than two years. We explore what drives news momentum and provide three hypotheses. The first hypothesis views news momentum as caused by stale information. The second hypothesis attributes news momentum to firms' strategic disclosure behavior. The third hypothesis argues that the persistence of firms' fundamentals drives news momentum. A set of empirical tests provides supporting evidence of the fundamental-driven news momentum.

We then investigate the asset pricing implications of news momentum. The empirical analysis shows that news releases induce significant return momentum. Two alternative explanations for news-driven return momentum are a risk-based story and a mispricing interpretation. We design a set of tests and conduct the empirical exercise to show that mispricing or underreaction is the main driving force of news-based return predictability. To enhance our understanding of underreaction, we distinguish underreaction to current news releases from underreaction to news momentum. The empirical analysis shows that both channels play a role in understanding mispricing that induces return predictability.

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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
PNNews	$PNNews_t$	Average fraction of positive minus negatives words over total words for every news article for a particular firm over a month (week/day) t.	LexisNexis
Next month returns	R_{t+1}	Stock returns 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.	Compustat, 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	Earnings	18.99%
	Revenues	5.48%
	Analyst ratings	4.16%
	Credit ratings	1.15%
	Subtotal	**29.77%**
Soft news	Insider trading	13.87%
	Technical analysis	9.40%
	Products services	7.68%
	Order imbalances	5.42%
	Investor relations	5.33%
	Labor issues	5.32%
	Stock prices	5.07%
	Acquisitions mergers	3.61%
	Equity actions	3.39%
	Marketing	3.22%
	Dividends	2.50%
	Partnerships	1.40%
	Assets	1.32%
	Legal	0.97%
	Credit	0.73%
	Price targets	0.57%
	Regulatory	0.24%
	Corporate responsibility	0.05%
	Bankruptcy	0.04%
	Indexes	0.03%
	Exploration	0.02%
	Industrial accidents	0.02%
	Security	0.01%
	Crime	0.01%
	War conflict	0.01%
	Government	0.00%
	Transportation	0.00%
	Civil unrest	0.00%
	Balance of payments	0.00%
	Taxes	0.00%
	Public opinion	0.00%
	Pollution	0.00%
	Subtotal	**70.23%**

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 (R_{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 ($Return_{t-12,\ t-7}$), Amihud's (2002) illiquidity (*Illiquidity*), earnings surprise (SUE_t) and ROA (ROA_t). 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 December 2016 and observations with zero news scores are not included.

Variable	NObs	Mean	STD	5%	25%	Median	75%	95%
$News_t$	530,283	0.079	0.151	-0.163	-0.011	0.080	0.173	0.319
$HardNews_t$	326,197	0.108	0.258	-0.322	-0.063	0.117	0.284	0.525
$SoftNews_t$	453,374	0.075	0.145	-0.151	-0.015	0.069	0.166	0.309
R_{t+1}	530,283	0.980	13.578	-18.198	-5.745	0.424	6.752	21.552
$LogSize_t$	530,283	6.443	1.938	3.343	5.093	6.393	7.695	9.793
$Analyst_t$	530,283	7.034	6.977	0.000	1.645	4.941	10.382	21.463
$InstOwn_t$	530,283	0.543	0.272	0.063	0.331	0.589	0.760	0.915
B/M_t	530,283	0.687	0.577	0.113	0.310	0.548	0.880	1.733
$Beta_t$	471,859	1.176	0.795	0.183	0.617	1.027	1.577	2.691
$IdioVol_t$	530,223	0.028	0.017	0.011	0.017	0.024	0.035	0.057
$Return_{t-3,\ t-2}$	528,952	2.847	20.818	-24.453	-7.752	1.231	10.818	34.352
$Return_{t-6,\ t-4}$	526,257	4.061	26.153	-29.114	-9.340	1.669	13.693	43.397
$Return_{t-12,\ t-7}$	515,917	8.749	41.020	-37.817	-11.992	3.558	21.332	69.814
$Illiquidity_t$	530,218	0.038	0.297	0.000	0.000	0.000	0.002	0.118
SUE_t	375,544	0.881	7.362	-4.203	-0.497	0.752	2.379	7.013
ROA_t	502,932	-0.172	6.486	-9.176	-0.219	0.664	1.916	4.642

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 six time periods including 2000-2002, 2003-2005, 2006-2008, 2009-2011, 2012-2014 and 2015-2016. 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 December 2016.

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

Portfolios	2000-2002	2003-2005	2006-2008	2009-2011	2012-2014	2015-2016
Small *Size*	2.28	3.95	5.31	5.92	7.34	8.73
2	2.84	5.10	6.63	7.82	11.71	13.21
3	3.36	6.13	8.12	9.94	15.62	17.56
4	4.05	7.35	10.19	12.80	19.97	22.31
Large *Size*	8.71	14.26	20.98	25.88	35.52	40.12

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

Portfolios	2000-2002	2003-2005	2006-2008	2009-2011	2012-2014	2015-2016
Small *Size*	1.07	1.69	2.36	2.35	3.04	3.56
2	1.30	2.02	2.73	2.95	4.68	5.33
3	1.53	2.28	3.22	3.68	6.03	7.03
4	1.91	2.89	4.20	5.04	8.07	9.31
Large *Size*	4.64	6.62	10.04	12.85	17.22	19.36

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

Portfolios	2000-2002	2003-2005	2006-2008	2009-2011	2012-2014	2015-2016
Small *Size*	0.57	0.86	1.04	1.10	1.52	1.92
2	0.65	1.19	1.44	1.68	3.06	3.61
3	0.76	1.59	1.94	2.41	4.63	5.29
4	0.96	1.89	2.51	3.26	6.23	7.08
Large *Size*	2.18	3.19	5.28	6.88	11.09	13.06

Table 3: Momentum of News

This table presents the momentum effects of news. At the end of month t, we sort all stocks with non-zero news scores into five portfolios based on their news scores ($News_t$). Stocks in the Bad *News* portfolio have the lowest news scores while stocks in the Good *News* portfolio have the highest news scores. "Good-Bad" is the hedge portfolio that takes a long position in the Good *News* portfolio and a short position in the Bad *News* portfolio. We then compute the equally weighted average news scores of each portfolio over different time periods after the portfolio formation. $News_t$ shows the average news score of each portfolio in month t; $News_{t+1}$ shows the average news score of each portfolio in month t+1; $News_{t+2,\, t+6}$ shows the average news score over five months from t+2 to t+6; $News_{t+7,\, t+12}$ shows the average news score over six months from t+7 to t+12; and $News_{t+13,\, t+24}$ shows the average news scores over 12 months from t+13 to t+24. The sample period is from January 2000 to December 2016. 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*	-0.128	0.040	0.038	0.042	0.046
2	0.008	0.054	0.052	0.052	0.052
3	0.080	0.062	0.063	0.061	0.058
4	0.152	0.070	0.072	0.067	0.063
Good *News*	0.285	0.077	0.081	0.073	0.067
Good-Bad	**0.413***** **(26.10)**	**0.037***** **(28.46)**	**0.043***** **(49.36)**	**0.031***** **(37.97)**	**0.021***** **(28.45)**

Table 4: Momentum of News – The Simple Quantitative Measure

This table presents the momentum effects of news using the simple quantitative measure. At the end of month t, we construct an alternative news sentiment score $PNNews_t$ by calculating the average fraction of positive minus negative words over total words for every news article released in month t for a particular firm. Then we sort all stocks with non-zero news scores into five portfolios based on their $PNNews_t$. Stocks in the Bad *PNNews* portfolio have the lowest news score while stocks in the Good *PNNews* portfolio have the highest news scores. "Good-Bad" is the hedge portfolio that takes a long position in the Good *PNNews* portfolio and a short position in the Bad *PNNews* portfolio. We then compute the equally weighted average news score of each portfolio over different time periods after the portfolio formation. $PNNews_t$ shows the average news scores of each portfolio in month t; $PNNews_{t+1}$ shows the average news score of each portfolio in month t+1; $PNNews_{t+2,\, t+6}$ shows the average news score over five months from t+2 to t+6; $PNNews_{t+7,\, t+12}$ shows the average news score over six months from t+7 to t+12; and $PNNews_{t+13,\, t+24}$ shows the average news score over 12 months from t+13 to t+24. The sample period is from January 2000 to December 2016. Newey-West adjusted t-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Portfolios	$PNNews_t$	$PNNews_{t+1}$	$PNNews_{t+2,\, t+6}$	$PNNews_{t+7,\, t+12}$	$PNNews_{t+13,\, t+24}$
Bad *PNNews*	-2.867	-0.926	-0.858	-0.813	-0.759
2	-1.386	-0.712	-0.692	-0.669	-0.667
3	-0.831	-0.560	-0.567	-0.578	-0.586
4	-0.332	-0.431	-0.466	-0.481	-0.505
Good *PNNews*	0.638	-0.280	-0.308	-0.327	-0.356
Good-Bad	**3.505*****	**0.646*****	**0.550*****	**0.486*****	**0.403*****
	(33.97)	**(24.25)**	**(24.62)**	**(22.26)**	**(19.98)**

Table 5: Stale News

This table presents the momentum effects of news across different news categories. At the end of month *t*, we sort all stocks with non-zero news scores into five portfolios within "Revenues", "Analyst ratings", "Credit ratings," and "Earnings" news categories, based on their respective category news scores. Stocks in the Bad *News* portfolio have the lowest category news scores and stocks in the Good *News* portfolio have the highest category news scores. "Good-Bad" is the hedge portfolio that takes a long position in the Good *News* portfolio and a short position in the Bad *News* portfolio in each news category. We then compute the equally weighted average news scores of each portfolio for revenues-related news over different time periods after the portfolio formation. $News_t$ shows the average news score of each portfolio in month *t*; $News_{t+1}$ shows the average news score of each portfolio in month *t*+1; $News_{t+2,\, t+6}$ shows the average news score over five months from *t*+2 to *t*+6; $News_{t+7,\, t+12}$ shows the average news score over six months from *t*+7 to *t*+12; and $News_{t+13,\, t+24}$ shows the average news score over 12 months from *t*+13 to *t*+24. The sample period is from January 2000 to December 2016. Newey-West adjusted *t*-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

News Categories	Portfolios	Revenues				
		$News_t$	$News_{t+1}$	$News_{t+2,\, t+6}$	$News_{t+7,\, t+12}$	$News_{t+13,\, t+24}$
Revenues	Bad *News*	-0.234	-0.001	-0.003	0.014	0.024
		(-26.8)	(-0.87)	(-1.39)	(5.29)	(8.51)
	Good *News*	0.464	0.037	0.072	0.051	0.04
		(33.91)	(17.52)	(14.72)	(13.49)	(11.45)
	Good-Bad	**0.698*****	**0.039*****	**0.075*****	**0.037*****	**0.016*****
		(48.59)	**(19.84)**	**(15.73)**	**(14.6)**	**(8.77)**
Analyst ratings	Bad *News*	0.024	0.021	0.023	0.024	0.027
		(5.59)	(6.29)	(6.97)	(7.29)	(7.88)
	Good *News*	0.041	0.039	0.039	0.035	0.032
		(6.82)	(6.81)	(9.01)	(7.66)	(7.49)
	Good-Bad	**0.017*****	**0.018*****	**0.016*****	**0.011*****	**0.004****
		(4.75)	**(3.94)**	**(8.43)**	**(4.70)**	**(2.56)**
Credit ratings	Bad *News*	0.009	0.012	0.016	0.019	0.023
		(2.79)	(5.02)	(5.95)	(6.09)	(6.92)
	Good *News*	0.040	0.035	0.035	0.035	0.032
		(11.05)	(10.73)	(11.50)	(11.56)	(10.44)
	Good-Bad	**0.031*****	**0.023*****	**0.019*****	**0.016*****	**0.010*****
		(8.62)	**(7.21)**	**(8.90)**	**(8.50)**	**(6.69)**
Earnings	Bad *News*	0.006	0.007	0.014	0.018	0.021
		(1.41)	(7.69)	(6.68)	(7.74)	(8.39)
	Good *News*	0.094	0.019	0.036	0.030	0.027
		(10.14)	(14.66)	(10.66)	(9.74)	(9.21)
	Good-Bad	**0.089*****	**0.012*****	**0.022*****	**0.012*****	**0.006*****
		(12.17)	**(10.96)**	**(11.65)**	**(9.38)**	**(7.30)**

Table 6: Strategic disclosure

This table presents the momentum effects of news by different information environments using the independent double sorting approach. At the end of month t, we sort all stocks with non-zero news scores into five portfolios based on their news scores ($News_t$). Stocks in the Bad *News* portfolio have the lowest news scores and stocks in the Good *News* portfolio have the highest news scores. 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. We then compute the equally weighted average news score of the "Good-Bad" (GMB) portfolios for Small/Large *Size* subsamples, Low/High *Analyst* subsamples, Low/High *InstOwn* subsamples, as well as the GMB news scores for "Small-Large" *Size*, "Low-High" *Analyst* and "Low-High" *InstOwn* hedge portfolios over different time periods after the portfolio formation. $News_t$ shows the average GMB news score of each portfolio in month t; $News_{t+1}$ shows the average GMB news score of each portfolio in month t+1; $News_{t+2,\ t+6}$ shows the average GMB news score over five months from t+2 to t+6; $News_{t+7,\ t+12}$ shows the average GMB news score over six months from t+7 to t+12; and $News_{t+13,\ t+24}$ shows the average GMB news score over 12 months from t+13 to t+24. The sample period is from January 2000 to December 2016. 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	GMB Portfolio News Scores				
	$News_t$	$News_{t+1}$	$News_{t+2,\ t+6}$	$News_{t+7,\ t+12}$	$News_{t+13,\ t+24}$
Small *Size*	0.442***	0.034***	0.045***	0.030***	0.020***
	(27.66)	(26.53)	(42.05)	(33.04)	(24.81)
Large *Size*	0.374***	0.043***	0.043***	0.032***	0.023***
	(23.79)	(26.55)	(36.74)	(25.43)	(20.67)
Small-Large	**0.068*****	**-0.008*****	**0.002**	**-0.002**	**-0.003*****
	(22.91)	**(-5.00)**	**(1.24)**	**(-1.21)**	**(-2.70)**

Panel B: Momentum of News across Analyst Coverage Subsamples

Portfolios	GMB Portfolio News Scores				
	$News_t$	$News_{t+1}$	$News_{t+2,\ t+6}$	$News_{t+7,\ t+12}$	$News_{t+13,\ t+24}$
Low *Analyst*	0.440***	0.035***	0.045***	0.030***	0.019***
	(27.19)	(23.05)	(46.12)	(30.94)	(23.00)
High *Analyst*	0.377***	0.044***	0.045***	0.034***	0.023***
	(24.20)	(25.16)	(34.84)	(26.06)	(17.36)
Low-High	**0.064*****	**-0.009*****	**0.000**	**-0.004*****	**-0.004*****
	(21.87)	**(-5.03)**	**(-0.35)**	**(-3.18)**	**(-3.08)**

Panel C: Momentum of News across Institutional Holdings Subsamples

Portfolios	GMB Portfolio News Scores				
	$News_t$	$News_{t+1}$	$News_{t+2,\ t+6}$	$News_{t+7,\ t+12}$	$News_{t+13,\ t+24}$
Low *InstOwn*	0.440***	0.034***	0.045***	0.030***	0.020***
	(27.62)	(19.35)	(49.40)	(31.77)	(23.82)
High *InstOwn*	0.389***	0.041***	0.042***	0.032***	0.022***
	(24.89)	(30.01)	(32.78)	(33.85)	(25.31)
Low-High	**0.050*****	**-0.008*****	**0.003****	**-0.002**	**-0.003****
	(18.01)	**(-3.66)**	**(2.44)**	**(-1.37)**	**(-2.43)**

Table 7: 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 with non-zero news scores into five portfolios based on their news scores ($News_t$). Stocks in the Bad *News* portfolio have the lowest news scores and stocks in the Good *News* portfolio have the highest news scores. "Good-Bad" is the hedge portfolio that takes a long position in the Good *News* portfolio and a short position in the Bad *News* 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 average ROA (SUE) of each portfolio in quarter *t*+1; ROA_{t+2} (SUE_{t+2}) shows the average ROA (SUE) in quarter *t*+2; $ROA_{t+3,t+4}$ ($SUE_{t+3,t+4}$) shows the average ROA (SUE) over two quarters from *t*+3 to *t*+4; and $ROA_{t+5,t+8}$ ($SUE_{t+5,t+8}$) shows the average ROA (SUE) over four 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* SUE for portfolios formed based on news ($News_t$). The sample period is from January 2000 to December 2016. 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*	-1.839	-1.763	-1.778	-1.750	-1.548
2	-0.601	-0.575	-0.621	-0.613	-0.498
3	0.006	-0.069	-0.081	-0.125	-0.130
4	0.286	0.197	0.085	0.054	0.033
Good *News*	0.202	0.130	0.039	-0.015	-0.086
Good-Bad	**2.041*****	**1.893*****	**1.816*****	**1.736*****	**1.463*****
	(7.32)	**(7.28)**	**(7.43)**	**(6.99)**	**(6.84)**

Panel B: Future SUE

Portfolios	SUE_t	SUE_{t+1}	SUE_{t+2}	$SUE_{t+3,\ t+4}$	$SUE_{t+5,\ t+8}$
Bad *News*	-0.974	0.072	0.230	0.345	0.671
2	0.380	0.683	0.691	0.770	0.834
3	1.148	0.969	1.034	1.000	0.984
4	1.508	1.050	0.936	0.932	1.014
Good *News*	1.853	1.176	0.962	1.014	0.913
Good-Bad	**2.828*****	**1.103*****	**0.732*****	**0.669*****	**0.242*****
	(13.99)	**(7.86)**	**(8.48)**	**(6.19)**	**(3.99)**

Table 8: 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 with non-zero news scores into five portfolios based on news scores ($News_t$). Stocks in the Bad *News* portfolio have the lowest news scores and stocks in the Good *News* portfolio have the highest news scores. "Good-Bad" is the hedge portfolio that takes a long position in the Good *News* portfolio and a short position in the Bad *News* portfolio. We then compute the equally weighted one-month-ahead average return (R_{t+1}), CAPM alpha ($R_{CAPM,\ t+1}$), Fama and French three factor alpha ($R_{FF3,\ t+1}$), four factor alpha ($R_{FF4,\ t+1}$), and five factor alpha ($R_{FF5,\ t+1}$) for each portfolio. The sample period is from January 2000 to December 2016. Newey-West adjusted *t*-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Portfolios	R_{t+1}	$R_{CAPM,\ t+1}$	$R_{FF3,\ t+1}$	$R_{FF4,\ t+1}$	$R_{FF5,\ t+1}$
Bad *News*	0.661	0.007	-0.227	-0.130	-0.193
2	0.902	0.277	0.034	0.105	0.003
3	0.934	0.343	0.122	0.168	0.096
4	1.113	0.522	0.301	0.332	0.294
Good *News*	1.282	0.712	0.509	0.549	0.523
Good-Bad	**0.621*****	**0.705*****	**0.736*****	**0.679*****	**0.716*****
	(4.15)	**(5.14)**	**(5.26)**	**(5.29)**	**(4.95)**

Table 9: Return Predictability of News – The Simple Quantitative Measure

This table presents the return predictability of news using the simple quantitative measure. At the end of month (or week, or day) t, we construct a news score $PNNews_t$ by calculating the average fraction of positive minus negative words over total words for every news article released in month (or week, or day) t for a particular firm. Then we sort all stocks with non-zero news scores into five portfolios based on their $PNNews_t$. Stocks in the Bad *PNNews* portfolio have the lowest news scores while stocks in the Good *PNNews* portfolio have the highest news scores. "Good-Bad" is the hedge portfolio that takes a long position in the Good *PNNews* portfolio and a short position in the Bad *PNNews* portfolio. We then compute the equally weighted next month (or week, or day) average return (R_{t+1}), CAPM alpha ($R_{CAPM,\, t+1}$), Fama and French three factor alpha ($R_{FF3,\, t+1}$), four factor alpha ($R_{FF4,\, t+1}$), and five factor alpha ($R_{FF5,\, t+1}$) for each portfolio. Panels A, B, and C report the monthly, weekly, and daily return predictability of news, respectively. The sample period is from January 2000 to December 2016. Newey-West adjusted t-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Panel A: Monthly Frequency Portfolios

Portfolios	R_{t+1}	$R_{CAPM,\, t+1}$	$R_{FF3,\, t+1}$	$R_{FF4,\, t+1}$	$R_{FF5,\, t+1}$
Bad *PNNews*	0.867	0.265	-0.007	0.079	-0.124
2	1.061	0.470	0.230	0.274	0.192
3	0.908	0.317	0.080	0.122	0.027
4	1.011	0.420	0.211	0.241	0.164
Good *PNNews*	0.973	0.369	0.230	0.278	0.192
Good-Bad	**0.106**	**0.103**	**0.237**	**0.199**	**0.316***
	(0.65)	**(0.57)**	**(1.48)**	**(1.27)**	**(1.83)**

Panel B: Weekly Frequency Portfolios

Portfolios	R_{t+1}	$R_{CAPM,\, t+1}$	$R_{FF3,\, t+1}$	$R_{FF4,\, t+1}$	$R_{FF5,\, t+1}$
Bad *PNNews*	0.173	0.031	-0.033	-0.009	-0.044
2	0.267	0.122	0.076	0.092	0.087
3	0.251	0.112	0.071	0.087	0.070
4	0.327	0.184	0.144	0.153	0.141
Good *PNNews*	0.272	0.131	0.100	0.120	0.117
Good-Bad	**0.099***	**0.099***	**0.132****	**0.128****	**0.161*****
	(1.76)	**(1.72)**	**(2.48)**	**(2.40)**	**(3.00)**

Panel C: Daily Frequency Portfolios

Portfolios	R_{t+1}	$R_{CAPM,\, t+1}$	$R_{FF3,\, t+1}$	$R_{FF4,\, t+1}$	$R_{FF5,\, t+1}$
Bad *PNNews*	0.005	-0.026	-0.037	-0.033	-0.033
2	0.088	0.057	0.049	0.051	0.054
3	0.063	0.033	0.025	0.028	0.027
4	0.106	0.075	0.068	0.072	0.072
Good *PNNews*	0.088	0.057	0.051	0.053	0.053
Good-Bad	**0.083*****	**0.083*****	**0.088*****	**0.086*****	**0.087*****
	(3.83)	**(3.98)**	**(4.26)**	**(4.16)**	**(4.19)**

Table 10: 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 with non-zero news scores into five portfolios based on their news scores ($News_t$). Stocks in the Bad *News* portfolio have the lowest news scores and stocks in the Good *News* portfolio have the highest news scores. "Good-Bad" is the hedge portfolio that takes a long position in the Good *News* portfolio and a short position in the 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. $R_{FF5,\, t+1}$ shows the average FF alpha in month *t*+1; $R_{FF5,\, t+2,\, t+6}$ shows the average FF alpha over five months from *t*+2 to *t*+6; $R_{FF5,\, t+7,\, t+12}$ shows the average FF alpha over six months from *t*+7 to *t*+12; and $R_{FF5,\, t+13,\, t+24}$ shows the average FF alpha over 12 months from *t*+13 to *t*+24. The sample period is from January 2000 to December 2016. Newey-West adjusted *t*-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Portfolios	$R_{FF5,\, t+1}$	$R_{FF5,\, t+2,\, t+6}$	$R_{FF5,\, t+7,\, t+12}$	$R_{FF5,\, t+13,\, t+24}$
Bad *News*	-0.193	0.134	0.297	0.294
2	0.003	0.127	0.216	0.187
3	0.096	0.109	0.216	0.166
4	0.294	0.210	0.248	0.190
Good *News*	0.523	0.409	0.329	0.316
Good-Bad	**0.716***** **(4.95)**	**0.275***** **(4.20)**	**0.032** **(0.62)**	**0.022** **(0.69)**

Table 11: Return Predictability of News in 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 with non-zero news scores 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 the Bad *News* portfolio have the lowest news scores and stocks in the Good *News* portfolio have the highest news scores. "Good-Bad" (GMB) is the hedge portfolio that takes a long position in the Good *News* portfolio and a short position in the Bad *News* portfolio. We then compute the equally weighted average returns of the GMB portfolios for Small/Large *Size* subsamples, Low/High *Analyst* subsamples, Low/High *InstOwn* subsamples, as well as the GMB returns for "Small-Large" *Size*, "Low-High" *Analyst* and "Low-High" *InstOwn* hedge portfolios over different time periods after the portfolio formation. Return measures include the equally weighted one-month-ahead average return (R_{t+1}), CAPM alpha ($R_{CAPM,\ t+1}$), Fama and French three factor alpha ($R_{FF3,\ t+1}$), four factor alpha ($R_{FF4,\ t+1}$), and five factor alpha ($R_{FF5,\ t+1}$) for each portfolio. The sample period is from January 2000 to December 2016. 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	GMB Portfolio Returns				
	R_{t+1}	$R_{CAPM,\ t+1}$	$R_{FF3,\ t+1}$	$R_{FF4,\ t+1}$	$R_{FF5,\ t+1}$
Small *Size*	1.079***	1.168***	1.191***	1.135***	1.180***
	(5.64)	(6.61)	(6.60)	(6.59)	(6.34)
Large *Size*	0.071	0.131	0.213	0.137	0.229
	(0.43)	(0.80)	(1.30)	(0.94)	(1.35)
Small-Large	**1.008*****	**1.036*****	**0.979*****	**0.998*****	**0.951*****
	(4.53)	**(5.08)**	**(4.75)**	**(4.84)**	**(4.50)**

Panel B: Return predictability of News for Analyst Coverage Subsamples

Portfolios	GMB Portfolio Returns				
	R_{t+1}	$R_{CAPM,\ t+1}$	$R_{FF3,\ t+1}$	$R_{FF4,\ t+1}$	$R_{FF5,\ t+1}$
Low *Analyst*	1.083***	1.163***	1.195***	1.168***	1.185***
	(6.11)	(7.52)	(7.61)	(7.51)	(7.33)
High *Analyst*	0.003	0.077	0.123	0.034	0.106
	(0.02)	(0.43)	(0.67)	(0.21)	(0.56)
Low-High	**1.079*****	**1.086*****	**1.071*****	**1.134*****	**1.079*****
	(4.86)	**(5.12)**	**(4.96)**	**(5.46)**	**(4.86)**

Panel C: Return predictability of News for Institutional Holdings Subsamples

Portfolios	GMB Portfolio Returns				
	R_{t+1}	$R_{CAPM,\ t+1}$	$R_{FF3,\ t+1}$	$R_{FF4,\ t+1}$	$R_{FF5,\ t+1}$
Low *InstOwn*	1.109***	1.201***	1.184***	1.129***	1.094***
	(5.72)	(6.64)	(6.48)	(6.44)	(5.87)
High *InstOwn*	-0.032	0.009	0.101	0.020	0.148
	(-0.20)	(0.05)	(0.62)	(0.14)	(0.88)
Low-High	**1.141*****	**1.192*****	**1.084*****	**1.110*****	**0.946*****
	(4.97)	**(5.67)**	**(5.34)**	**(5.48)**	**(4.59)**

Table 12: News-day Returns and Non-news-day Returns

This table presents the return predictability of news by separating the next month returns into news-day returns and non-news-day return. If news is reported in day *n*, then day *n*-1, *n*, and day *n*+1 are treated as news days. Days without news are defined as non-news days. News-day returns (Non-news-day returns) are the accumulative daily returns for all news days (non-news days) for a particular stock in a month. At the end of month *t*, we sort all stocks with non-zero news scores into five portfolios based on their news scores ($News_t$). Stocks in the Bad *News* portfolio have the lowest news scores and stocks in the Good *News* portfolio have the highest news scores. "Good-Bad" is the hedge portfolio that takes a long position in the Good *News* portfolio and a short position in the Bad *News* portfolio. We then compute the equally weighted one-month-ahead average return (R_{t+1}), CAPM alpha ($R_{CAPM,\, t+1}$), Fama and French three factor alpha ($R_{FF3,\, t+1}$), four factor alpha ($R_{FF4,\, t+1}$), and five factor alpha ($R_{FF5,\, t+1}$) for each portfolio. Panel A reports the news-day returns and Panel B reports the non-news day returns. The sample period is from January 2000 to December 2016. Newey-West adjusted *t*-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Panel A: News-day Returns

Portfolios	R_{t+1}	$R_{CAPM,\, t+1}$	$R_{FF3,\, t+1}$	$R_{FF4,\, t+1}$	$R_{FF5,\, t+1}$
Bad *News*	0.710	0.355	0.193	0.224	0.150
2	0.749	0.359	0.196	0.229	0.128
3	0.730	0.356	0.213	0.232	0.151
4	0.834	0.476	0.349	0.361	0.303
Good *News*	0.879	0.574	0.469	0.477	0.443
Good-Bad	**0.169****	**0.219*****	**0.275*****	**0.252*****	**0.293*****
	(2.10)	**(3.00)**	**(3.86)**	**(3.72)**	**(3.96)**

Panel B: Non-news-day Returns

Portfolios	R_{t+1}	$R_{CAPM,\, t+1}$	$R_{FF3,\, t+1}$	$R_{FF4,\, t+1}$	$R_{FF5,\, t+1}$
Bad *News*	-0.005	-0.438	-0.497	-0.431	-0.424
2	0.183	-0.187	-0.258	-0.219	-0.224
3	0.254	-0.096	-0.164	-0.136	-0.132
4	0.311	-0.055	-0.136	-0.117	-0.099
Good *News*	0.441	0.044	-0.045	-0.012	-0.008
Good-Bad	**0.446*****	**0.482*****	**0.452*****	**0.419*****	**0.416*****
	(3.82)	**(4.48)**	**(4.14)**	**(4.00)**	**(3.72)**

Table IA1: Momentum of News—Robustness Tests

The table examines the robustness of momentum effects of news by using different specifications. "Aggregate News" means that each month all stocks are grouped into five portfolios based on their aggregate news scores (*News*$_t$), which is the sum of ESS score of all news for a particular firm over a month *t*. "Extreme-News-day Returns" means that all stocks are grouped into five portfolios based on their average extreme-news-day returns over a month t. Each month, we sort all firms' non-zero daily news scores into five groups and the days with the scores ranked either in the top or in the bottom quintiles are defined as the extreme news day. Extreme-news-day return is the average 3-day returns (-1, 1) around extreme news day for a particular firm. "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 zero news scores (neutral news or no 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 six specifications, stocks in the lowest group are defined as Bad *News* portfolio and stocks in highest group are defined as Good *News* portfolio. For the specification "Negative vs. Positive", stocks in the Bad *News* portfolio have the negative news scores and stocks in the Good *News* portfolio have the positive news scores. "Good-Bad" (GMB) is the hedge portfolio that takes a long position in the Good *News* portfolio and a short position in the Bad *News* portfolio. We then compute the equally weighted average news score of the GMB portfolio over different time periods after the portfolio formation. *News*$_{t+1}$ shows the average news score in month (or week, or day) *t*+1; *News*$_{t+2,\, t+6}$ shows the average news score over five months from *t*+2 to *t*+6 (or four days from *t*+2 to *t*+5, or three weeks from *t*+2 to *t*+4); *News*$_{t+7,\, t+12}$ shows the average news score over six months from *t*+7 to *t*+12 (or five days from *t*+6 to *t*+10, or eight weeks from *t*+5 to *t*+12); and *News*$_{t+13,\, t+24}$ shows the average news score 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.

	GMB Portfolio News Scores				
Specifications	*News*$_t$	*News*$_{t+1}$	*News*$_{t+2,\, t+6}$	*News*$_{t+7,\, t+12}$	*News*$_{t+13,\, t+24}$
Aggregate News	4.365***	1.195***	1.277***	1.139***	1.027***
	(21.20)	(16.51)	(20.61)	(19.64)	(21.02)
Extreme-News-Day Returns	15.850***	0.150***	0.048**	0.028*	-0.008
	(18.78)	(3.30)	(2.46)	(1.75)	(-0.68)
Daily	0.567***	0.019***	0.017***	0.012***	0.010***
	(215.05)	(40.85)	(52.43)	(47.97)	(51.08)
Weekly	0.549***	0.044***	0.027***	0.020***	0.019***
	(81.50)	(36.19)	(37.75)	(41.11)	(41.21)
Neutral News Included	0.361***	0.034***	0.040***	0.029***	0.020***
	(28.97)	(27.34)	(44.57)	(40.31)	(31.46)
Negative vs. Positive	0.247***	0.025***	0.028***	0.020***	0.014***
	(23.07)	(33.74)	(32.10)	(35.79)	(32.25)
Decile Portfolios	0.536***	0.044***	0.049***	0.035***	0.022***
	(26.43)	(29.13)	(47.48)	(36.97)	(25.45)

Table IA2: Stale News

This table presents the momentum effects of news across different news categories. At the end of month *t*, we sort all stocks with non-zero news scores into five portfolios within "Revenues", "Analyst ratings", "Credit ratings" and "Earnings" news categories, based on their respective category news scores. Stocks in the Bad *News* portfolio have the lowest category news scores and stocks in the Good *News* portfolio have the highest category news scores. "Good-Bad" is the hedge portfolio that takes a long position in the Good *News* portfolio and a short position in the Bad *News* portfolio in each news category. We then compute the equally weighted average news scores of each portfolio over different time periods after the portfolio formation for analyst rating-related news, credit rating-related news and earnings-related news respectively. The results are displayed in Panels A, B, and C, respectively. The sample period is from January 2000 to December 2016. Newey-West adjusted *t*-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

News Categories	Portfolios	**Panel A: Analyst ratings**				
		$News_t$	$News_{t+1}$	$News_{t+2,\ t+6}$	$News_{t+7,\ t+12}$	$News_{t+13,\ t+24}$
Revenues	Bad *News*	0.018	0.031	0.034	0.036	0.037
		(4.81)	(9.71)	(11.84)	(12.48)	(15.54)
	Good *News*	0.062	0.054	0.051	0.046	0.042
		(15.43)	(13.37)	(16.87)	(16.48)	(17.35)
	Good-Bad	**0.044*****	**0.023*****	**0.017*****	**0.010*****	**0.005*****
		(14.26)	**(10.97)**	**(10.59)**	**(5.83)**	**(3.63)**
Analyst ratings	Bad *News*	-0.397	0.027	0.041	0.046	0.045
		(-46.16)	(7.12)	(12.68)	(13.32)	(15.26)
	Good *News*	0.559	0.053	0.062	0.059	0.053
		(1083.64)	(5.30)	(10.60)	(11.33)	(12.57)
	Good-Bad	**0.957*****	**0.026****	**0.022*****	**0.013*****	**0.008****
		(109.30)	**(2.54)**	**(4.15)**	**(3.48)**	**(2.59)**
Credit ratings	Bad *News*	0.015	0.030	0.034	0.037	0.038
		(3.07)	(7.79)	(10.27)	(11.93)	(14.33)
	Good *News*	0.071	0.064	0.062	0.058	0.052
		(14.89)	(12.81)	(17.66)	(18.13)	(17.62)
	Good-Bad	**0.056*****	**0.034*****	**0.029*****	**0.021*****	**0.014*****
		(11.81)	**(6.71)**	**(12.36)**	**(8.19)**	**(6.38)**
Earnings	Bad *News*	0.015	0.028	0.029	0.030	0.029
		(5.99)	(9.96)	(11.54)	(12.73)	(17.66)
	Good *News*	0.052	0.040	0.039	0.038	0.035
		(14.74)	(13.70)	(17.68)	(17.39)	(18.27)
	Good-Bad	**0.037*****	**0.013*****	**0.011*****	**0.008*****	**0.006*****
		(13.51)	**(6.95)**	**(8.31)**	**(7.25)**	**(6.33)**

Table IA2: Stale News (Continued)

News Categories	Portfolios	Panel B: Credit ratings				
		News$_t$	*News*$_{t+1}$	*News*$_{t+2,\ t+6}$	*News*$_{t+7,\ t+12}$	*News*$_{t+13,\ t+24}$
Revenues	Bad *News*	-0.009	-0.007	-0.006	-0.006	-0.004
		(-7.83)	(-5.96)	(-6.31)	(-6.06)	(-5.07)
	Good *News*	0.002	0.001	0.002	0.001	0.001
		(2.24)	(1.13)	(3.49)	(1.93)	(0.93)
	Good-Bad	**0.011*****	**0.008*****	**0.008*****	**0.007*****	**0.005*****
		(11.54)	**(6.76)**	**(10.38)**	**(9.57)**	**(8.70)**
Analyst ratings	Bad *News*	-0.009	-0.008	-0.005	-0.005	-0.002
		(-6.26)	(-5.91)	(-4.77)	(-4.32)	(-1.68)
	Good *News*	0.004	-0.002	0.001	0.004	0.002
		(1.06)	(-0.63)	(0.58)	(2.16)	(1.80)
	Good-Bad	**0.013*****	**0.007****	**0.007*****	**0.009*****	**0.003*****
		(3.75)	**(2.29)**	**(3.02)**	**(4.71)**	**(3.68)**
Credit ratings	Bad *News*	-0.426	-0.052	-0.042	-0.031	-0.017
		(-68.5)	(-14.38)	(-16.27)	(-12.76)	(-8.32)
	Good *News*	0.382	0.029	0.022	0.024	0.016
		(71.44)	(11.47)	(12.77)	(13.15)	(8.71)
	Good-Bad	**0.807*****	**0.082*****	**0.064*****	**0.055*****	**0.033*****
		(107.01)	**(19.71)**	**(24.43)**	**(27.04)**	**(19.86)**
Earnings	Bad *News*	-0.010	-0.008	-0.006	-0.005	-0.003
		(-9.48)	(-8.77)	(-8.66)	(-8.05)	(-5.52)
	Good *News*	0.002	0.003	0.002	0.002	0.001
		(4.26)	(4.83)	(5.48)	(3.22)	(1.78)
	Good-Bad	**0.013*****	**0.010*****	**0.009*****	**0.007*****	**0.004*****
		(11.67)	**(11.15)**	**(12.72)**	**(12.43)**	**(9.79)**

Table IA2: Stale News (Continued)

News Categories	Portfolios	Panel C: Earnings				
		$News_t$	$News_{t+1}$	$News_{t+2,\ t+6}$	$News_{t+7,\ t+12}$	$News_{t+13,\ t+24}$
Revenues	Bad *News*	-0.016	0.001	0.010	0.020	0.026
		(-2.46)	(0.52)	(4.21)	(8.59)	(11.26)
	Good *News*	0.130	0.030	0.049	0.040	0.033
		(24.94)	(13.32)	(25.58)	(20.34)	(19.80)
	Good-Bad	**0.146*****	**0.029*****	**0.039*****	**0.020*****	**0.007*****
		(16.84)	**(14.49)**	**(21.18)**	**(14.92)**	**(5.70)**
Analyst ratings	Bad *News*	0.025	0.023	0.025	0.026	0.033
		(6.95)	(7.76)	(9.88)	(8.85)	(13.86)
	Good *News*	0.052	0.038	0.039	0.037	0.034
		(11.93)	(15.97)	(16.96)	(13.00)	(13.16)
	Good-Bad	**0.028*****	**0.016*****	**0.015*****	**0.011*****	**0.001**
		(7.15)	**(6.66)**	**(7.80)**	**(5.27)**	**(0.56)**
Credit ratings	Bad *News*	-0.007	0.000	0.006	0.018	0.027
		(-1.63)	(0.05)	(2.48)	(7.26)	(13.52)
	Good *News*	0.063	0.055	0.056	0.050	0.044
		(20.43)	(14.96)	(22.20)	(20.65)	(15.01)
	Good-Bad	**0.070*****	**0.055*****	**0.050*****	**0.033*****	**0.017*****
		(16.11)	**(14.56)**	**(25.41)**	**(17.27)**	**(7.12)**
Earnings	Bad *News*	-0.288	-0.005	-0.005	0.011	0.019
		(-30.31)	(-3.33)	(-2.85)	(5.96)	(12.54)
	Good *News*	0.419	0.028	0.071	0.052	0.042
		(43.86)	(16.43)	(36.81)	(22.25)	(20.02)
	Good-Bad	**0.706*****	**0.033*****	**0.076*****	**0.040*****	**0.023*****
		(41.90)	**(16.03)**	**(50.80)**	**(20.95)**	**(14.59)**

Table IA3: Hard News vs. Soft News and Firm Fundamentals

This table compares the firm fundamental difference between hard news and soft news. At the end of quarter *t*, we sort all stocks with non-zero news scores into five portfolios based on their hard news scores (Hard *News*) and soft news scores (Soft *News*), respectively. Stocks in the Bad *News* portfolio have the lowest news scores and stocks in the Good *News* portfolio have the highest news scores. "Good-Bad" (GMB) is the hedge portfolio that takes a long position in the Good *News* portfolio and a short position in the Bad *News* portfolio. We then compute the equally weighted ROA and earnings surprise of the GMB portfolios for the Hard *News* portfolio, the Soft *News* portfolio as well as the "Hard-Soft" hedge portfolio. Panel A (Panel B) reports the future ROA (earnings surprise) for hard and soft news. ROA_t (SUE_t) shows the average ROA (SUE) of each portfolio in quarter *t*; ROA_{t+1} (SUE_{t+1}) shows the average ROA (SUE) of each portfolio in quarter *t*+1; ROA_{t+2} (SUE_{t+2}) shows the average ROA (SUE)) in quarter *t*+2; $ROA_{t+3,\ t+4}$ ($SUE_{t+3,\ t+4}$) shows the average ROA (SUE) over two quarters from *t*+3 to *t*+4; and $ROA_{t+5,\ t+8}$ ($SUE_{t+5,\ t+8}$) shows the average ROA (SUE) over four quarters from *t*+5 to *t*+8. The sample period is from January 2000 to December 2016. Newey-West adjusted *t*-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Panel A: Future ROA for Hard and Soft news

	GMB Portfolio ROA				
News Categories	ROA_t	ROA_{t+1}	ROA_{t+2}	$ROA_{t+3,\ t+4}$	$ROA_{t+5,\ t+8}$
Hard *News*	4.271***	4.003***	3.901***	3.715***	3.269***
	(23.05)	(19.37)	(21.28)	(20.05)	(20.74)
Soft *News*	-1.361***	-1.494***	-1.537***	-1.465***	-1.412***
	(-9.28)	(-14.08)	(-13.94)	(-11.76)	(-11.80)
Hard-Soft	**5.632*****	**5.496*****	**5.438*****	**5.180*****	**4.681*****
	(38.79)	**(31.38)**	**(39.18)**	**(33.68)**	**(30.14)**

Panel B: Future SUE for Hard and Soft news

	GMB Portfolio SUE				
News Categories	SUE_t	SUE_{t+1}	SUE_{t+2}	$SUE_{t+3,\ t+4}$	$SUE_{t+5,\ t+8}$
Hard *News*	4.201***	1.595***	1.261***	0.970***	0.499***
	(14.51)	(8.3)	(10.83)	(6.78)	(6.05)
Soft *News*	-0.195*	0.000	-0.150	-0.041	-0.104
	(-1.76)	(0.00)	(-0.97)	(-0.60)	(-1.57)
Hard-Soft	**4.396*****	**1.595*****	**1.410*****	**1.011*****	**0.603*****
	(12.72)	**(6.67)**	**(6.27)**	**(5.40)**	**(4.94)**

Table IA4: News and Firm Fundamentals—Regression Approach

This table examines the relation between the news ($News_t$) and firm fundamentals (ROA, SUE) using pool regressions. The dependent variables are future ROAs in Panel A and future SUEs in Panel B respectively. ROA_{t+1} (SUE_{t+1}) represents a firm's ROA (SUE) in quarter t+1; ROA_{t+2} (SUE_{t+2}) represents a firm's ROA (SUE) in quarter t+2; $ROA_{t+3,t+4}$ ($SUE_{t+3,t+4}$) shows the average ROA (SUE) over two quarters from t+3 to t+4; and $ROA_{t+5,t+8}$ ($SUE_{t+5,t+8}$) shows the average ROA (SUE) over four quarters from t+5 to t+8. $Total\ Assets_t$ is the total assets at the end of previous year. B/M_t is the book-to-market ratio defined as the ratio of book value of equity to market value of equity in the previous year. $Asset\ Growth_t$ is the growth rate in total assets. $Leverage_t$ is the ratio of total long-term debt over total assets. The regressions also include the year-quarter fixed effect and industry fixed effect. The table also reports the number of observations (*NObs*), number of firms (*Firms*), and adjusted R square ($Adj\text{-}R^2$). The sample period is from January 2000 to December 2016. Standard errors are clustered by firms. The t-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Panel A: Future ROA

	ROA_{t+1}	ROA_{t+2}	$ROA_{t+3,\,t+4}$	$ROA_{t+5,\,t+8}$
Variables	M1	M2	M3	M4
$News_t$	**2.084*****	**2.108*****	**1.821*****	**1.325*****
	(13.27)	**(11.70)**	**(9.15)**	**(6.59)**
ROA_t	0.547***	0.509***	0.505***	0.442***
	(31.43)	(18.27)	(18.85)	(18.26)
$Total\ Assets_t$	0.405**	0.498**	0.530**	0.569**
	(2.39)	(2.40)	(2.31)	(2.09)
B/M_t	-0.246***	-0.227***	-0.164***	-0.079*
	(-8.98)	(-6.73)	(-4.46)	(-1.94)
$Asset\ Growth_t$	-0.002**	-0.003**	-0.005***	-0.004***
	(-2.29)	(-2.02)	(-3.70)	(-4.78)
$Leverage_t$	0.523***	0.678***	0.936***	1.190***
	(4.96)	(5.30)	(6.64)	(6.85)
Year-Quarter fixed effect	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
NObs	207,771	202,931	193,254	174,114
Firms	6,952	6,874	6,520	5,877
Adj-R^2	35.40%	29.90%	33.70%	31.90%

Table IA4: News and Firm Fundamentals (Continued)

Panel B: Future SUE				
	SUE_{t+1}	SUE_{t+2}	$SUE_{t+3,\ t+4}$	$SUE_{t+5,\ t+8}$
Variables	M1	M2	M3	M4
$News_t$	**3.415********	**2.274********	**1.758********	**0.715********
	(11.95)	**(7.14)**	**(6.23)**	**(2.55)**
SUE_t	0.079***	0.073***	0.048***	0.053**
	(5.16)	(4.58)	(5.58)	(2.48)
$Total\ Assets_t$	1.067***	1.181***	1.201***	1.260***
	(4.32)	(4.30)	(3.85)	(3.22)
B/M_t	-0.570***	-0.547***	-0.362***	-0.213**
	(-5.58)	(-5.04)	(-3.92)	(-2.20)
$Asset\ Growth_t$	0.001***	0.001*	-0.000	-0.008
	(2.92)	(1.93)	(-0.27)	(-1.51)
$Leverage_t$	-0.076	-0.217	-0.113	-0.119
	(-0.45)	(-1.03)	(-0.63)	(-0.68)
Year-Quarter fixed effect	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
NObs	128,840	124,556	112,015	92,035
Firms	5,332	5,236	4,761	3,875
Adj-R^2	2.00%	1.80%	2.60%	4.20%

Table IA5: Return Predictability of News—Robustness Tests

The table examines the robustness of return predictability of news by using different specifications. "Aggregate News" means that all stocks are grouped into five portfolios based on their aggregate news scores at the end of month *t*, which is the sum of ESS score of all news for a particular firm over a month *t*. "Extreme-News-day Returns" means that all stocks are grouped into five portfolios based on their average extreme-news-day returns over a month *t*. Each month, we sort all firms' non-zero daily news scores into five groups and the days with the scores ranked either in the top or in the bottom quintiles are defined as the extreme news day. Extreme-news-day return is the average 3-day returns (-1, 1) around extreme news day for a particular firm. "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 zero news scores (neutral news or no 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 six specifications, stocks in the lowest group are defined as Bad *News* portfolio and stocks in highest group are defined as Good *News* portfolio. For the specification "Negative vs. Positive", stocks in the Bad *News* portfolio have the negative news scores and stocks in the Good *News* portfolio have the positive news scores. "Good-Bad"(GMB) is the hedge portfolio that takes a long position in the Good *News* portfolio and a short position in the Bad *News* portfolio. We then compute the equally weighted next month (or week, or day) average return (R_{t+1}), CAPM alpha ($R_{CAPM,\ t+1}$), Fama and French three factor alpha ($R_{FF3,\ t+1}$), four factor alpha ($R_{FF4,\ t+1}$) and five factor alpha ($R_{FF5,\ t+1}$) for each GMB portfolio. The sample period is from January 2000 to December 2016. Newey-West adjusted *t*-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

	GMB Portfolio Returns				
Specifications	R_{t+1}	$R_{CAPM,\ t+1}$	$R_{FF3,\ t+1}$	$R_{FF4,\ t+1}$	$R_{FF5,\ t+1}$
Aggregate News	0.380**	0.450***	0.561***	0.488***	0.546***
	(2.43)	(2.73)	(3.58)	(3.49)	(3.35)
Extreme-News-Day Returns	0.480***	0.567***	0.532***	0.516***	0.536***
	(2.94)	(3.34)	(3.09)	(3.00)	(3.08)
Daily	0.497***	0.499***	0.499***	0.498***	0.495***
	(31.89)	(38.01)	(37.97)	(37.93)	(37.65)
Weekly	0.277***	0.284***	0.294***	0.281***	0.284***
	(7.53)	(8.82)	(9.18)	(9.06)	(8.81)
Neutral News Included	0.529***	0.607***	0.640***	0.588***	0.626***
	(4.10)	(4.83)	(5.00)	(4.99)	(4.73)
Negative vs. Positive	0.341***	0.404***	0.429***	0.387***	0.403***
	(3.15)	(3.85)	(4.07)	(3.99)	(3.72)
Decile Portfolios	0.771***	0.865***	0.872***	0.788***	0.863***
	(3.91)	(4.74)	(4.68)	(4.71)	(4.52)

Table IA6: Return Predictability of Hard News vs. Soft News

This table compares the difference of return predictability between hard news and soft news. At the end of month (or quarter) *t*, we sort all stocks with non-zero news scores into five portfolios based on their hard news scores (Hard *News*) and soft news scores (Soft *News*), respectively. Stocks in the Bad *News* portfolio have the lowest news scores and stocks in the Good *News* portfolio have the highest news scores. "Good-Bad" (GMB) is the hedge portfolio that takes a long position in the Good *News* portfolio and a short position in the Bad *News* portfolio. We then compute the equally weighted average returns of the GMB portfolios for the Hard *News* portfolio, the Soft *News* portfolio as well as the "Hard-Soft" hedge portfolio. Return measures include equally weighted one-month-ahead average return (R_{t+1}), CAPM alpha ($R_{CAPM, t+1}$), Fama and French three factor alpha ($R_{FF3, t+1}$), four factor alpha ($R_{FF4, t+1}$) and five factor alpha ($R_{FF5, t+1}$) for each portfolio. The sample period is from January 2000 to December 2016. Newey-West adjusted *t*-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

News Categories	GMB Portfolio Returns				
	R_{t+1}	$R_{CAPM, t+1}$	$R_{FF3, t+1}$	$R_{FF4, t+1}$	$R_{FF5, t+1}$
Hard *News*	0.642***	0.753***	0.848***	0.707***	0.862***
	(2.65)	(3.51)	(3.92)	(4.27)	(3.84)
Soft *News*	0.142	0.158	0.212**	0.217**	0.278***
	(1.33)	(1.41)	(2.05)	(2.08)	(2.64)
Hard-Soft	**0.500***	**0.595****	**0.636*****	**0.490*****	**0.584****
	(1.82)	**(2.54)**	**(2.71)**	**(2.64)**	**(2.42)**

Table IA7: 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 (R_{t+1}), CAPM alphas in M2 ($R_{CAPM,\ t+1}$), Fama and French three factor alphas in M3 ($R_{FF3,\ t+1}$), four factor alphas in M4 ($R_{FF4,\ t+1}$) and five factors alphas in M5 ($R_{FF5,\ t+1}$). The control variables include ROA (ROA_t), earnings surprise (SUE_t), 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*), number of firms (*Firms*), and adjusted R square ($Adj\text{-}R^2$). The sample period is from January 2000 to December 2016. Newey-West adjusted *t*-statistics are reported in the parentheses and ***, **, * denote 1%, 5%, and 10% significant levels, respectively.

	R_{t+1}	$R_{CAPM,\ t+1}$	$R_{FF3,\ t+1}$	$R_{FF4,\ t+1}$	$R_{FF5,\ t+1}$
Variables	M1	M2	M3	M4	M5
$News_t$	**0.469****	**0.418***	**0.510****	**0.541****	**0.496****
	(1.98)	**(1.82)**	**(2.34)**	**(2.51)**	**(2.20)**
ROA_t	0.053***	0.053***	0.054***	0.054***	0.044***
	(3.85)	(3.88)	(4.18)	(4.24)	(3.74)
SUE_t	-0.002	-0.003	-0.003	-0.003	-0.001
	(-0.36)	(-0.52)	(-0.54)	(-0.63)	(-0.17)
$Return_{t-3,\ t-2}$	-0.001	-0.001	-0.000	0.000	-0.001
	(-0.31)	(-0.13)	(-0.08)	(0.01)	(-0.28)
$Return_{t-6,\ t-4}$	-0.003	-0.003	-0.003	-0.003	-0.005
	(-0.76)	(-0.82)	(-0.81)	(-0.91)	(-1.35)
$Return_{t-12,\ t-7}$	-0.002	-0.002	-0.002	-0.001	-0.002
	(-0.95)	(-0.92)	(-0.84)	(-0.67)	(-0.74)
$LogSize_t$	-0.149***	-0.136***	-0.072**	-0.067**	-0.055**
	(-3.31)	(-2.99)	(-2.45)	(-2.28)	(-1.97)
B/M_t	0.143	0.212	0.086	0.092	0.003
	(0.91)	(1.33)	(0.77)	(0.84)	(0.03)
$Beta_t$	-0.063	-0.332**	-0.264**	-0.196	-0.229*
	(-0.37)	(-2.33)	(-2.00)	(-1.60)	(-1.67)
$IdioVol_t$	-12.751	-12.548	-9.378	-9.862	-1.221
	(-1.33)	(-1.54)	(-1.27)	(-1.41)	(-0.17)
$Illiquidity_t$	-3.330	-2.970	0.085	1.480	-0.207
	(-0.47)	(-0.44)	(0.01)	(0.24)	(-0.03)
Intercept	2.056***	1.805***	0.986**	0.943**	0.629*
	(4.16)	(3.52)	(2.55)	(2.57)	(1.75)
NObs	320,467	320,467	320,467	320,467	320,467
Firms	4,622	4,622	4,622	4,622	4,622
Adj-R^2	8.30%	6.20%	4.40%	4.00%	4.30%