News vs. Sentiment: Predicting Stock Returns from News Stories

Steven L. Heston and Nitish Ranjan Sinha

Steven L. Heston is professor of finance at the Robert H. Smith School of Business, University of Maryland, College Park. Nitish Ranjan Sinha is senior economist at the Board of Governors of the Federal Reserve System, Washington, DC.

The authors used a dataset of more than 900,000 news stories to test whether news can predict stock returns. They measured sentiment with a proprietary Thomson Reuters neural network and found that daily news predicts stock returns for only one to two days, confirming previous research. Weekly news, however, predicts stock returns for one quarter. Positive news stories increase stock returns quickly, but negative stories receive a long-delayed reaction. Much of the delayed response to news occurs around the subsequent earnings announcement.

Machine learning and textual information processing have become a growing part of financial practice. Duhigg (2006) and Ro (2012) wrote about general artificial intelligence for stock picking, and Lo (1994) reviewed neural networks. Specific applications include bankruptcy prediction (Atiya 2001), corporate distress diagnosis (Altman, Marco, and Varetto 1994), and consumer credit risk (Khandani, Kim, and Lo 2010). Although industry has led the applications (e.g., Hillert, Jacobs, and Müller 2014; Hagenau, Hauser, Liebmann, and Neumann 2013), academic empirical research is increasingly confirming the value of textual analysis. Tetlock's pioneering studies (Tetlock, Saar-Tsechansky, and Macskassy 2008; Tetlock 2007) demonstrated that news stories contain information relevant to predicting both earnings and stock returns. Subsequent studies have applied similar techniques with a variety of news sources. Researchers have generally found that textual information can briefly predict returns at the aggregate market level (Tetlock 2007; Dougal, Engelberg, García, and Parsons 2012; García 2013; Dzielinski and Hasseltoft 2013) as well as at the individual stock level (Boudoukh, Feldman, Kogan, and Richardson 2013; Chen, De, Hu, and Hwang 2014). However, most research has been limited to a comparatively narrow event window within two days after the news release, although Sinha (2016) showed that news stories can predict stock returns for up to 13 weeks.

Empirical studies have found different types of predictability in applications at the aggregate market level and the individual stock level. Early work by Tetlock (2007) showed that short-term return predictability is quickly reversed at the market level. Loughran and McDonald (2011) found a greater response for individual stocks within a multi-day event window. Jegadeesh and Wu (2013) found limited predictability at the individual stock level, and García (2013) also found predictability at the

Disclosure: The authors report no conflicts of interest.

CE Credits: 1

The authors thank Tim Loughran, CFA, Paul Tetlock, seminar participants at the University of Maryland (finance brown bag), Acadian Asset Management, and the Office of Financial Research. The analysis and conclusions set forth are those of the authors and do not indicate concurrence by other members of the research staff or the Board of Governors of the Federal Reserve System.

market level, predominantly during recessions. These differences might reflect different predictability in aggregate market returns versus individual stocks, or they might stem from different sources of text and different methodologies. The duration and reversal of return predictability are important because they affect the economic interpretation of news in terms of permanent news impact or transient sentiment. As Tetlock (2007, p. 1143) summarized, "The sentiment theory predicts short-horizon returns will be reversed in the long run, whereas the information theory predicts they will persist indefinitely."

In our study, we explored the temporal pattern of predictability in individual stock returns using a sophisticated neural network.[1] We applied these techniques to a large common set of Reuters news releases. We found that the neural network appears to extract permanent information that is not fully incorporated into current stock prices. The duration of return predictability depends critically on the portfolio formation procedure. Research by Tetlock et al. (2008), Loughran and McDonald (2011), and Lerman and Livnat (2010) has established a short-term response of stock prices to news. We also found that stocks with positive (negative) news on one day have predictably high (low) returns for the subsequent one to two days. But in addition, we found that aggregating news over one week produces a dramatic increase in predictability of returns. A decile spread of stocks based on news over the past week earns average excess returns exceeding 2% over the subsequent 13 weeks.

In our study, we controlled for neutral news stories to distinguish a publication effect from an informative news effect. We confirmed the finding of Fang and Peress (2009) that companies without news have different returns from companies with news. By controlling for neutral news, we found that news tone has an independent effect on future stock returns. Positive news predicts positive returns for only about one week, but negative news predicts negative returns for up to a quarter. Reaction to negative news over longer horizons suggests that short-sale constraints might slow the incorporation of information extracted by our textual processing techniques. Finally, much of the predictable effect occurs around subsequent earnings announcements.

Textual Processing

The primary purpose of our study was to forecast individual stock returns using textual analysis of news stories based on a neural network. Internet news sources and social media provide a growing universe of textual information, including internet searches (Da, Engelberg, and Gao 2015), Facebook networks (Simon and Heimer 2015), and Twitter broadcasts (Bollen, Mao, and Zeng 2011). Analysis of these sources typically requires complex analytic tools, which potentially provide the power to predict returns but also make the analysis inherently opaque.[2] Therefore, we performed diagnostics to find patterns that suggest economic reasons for predictability. A distinguishing feature of our analysis is a broad dataset of news items. For example, Tetlock (2007) analyzed the *Wall Street Journal*'s "Abreast of the Market" column, and Tetlock et al. (2008) extended the analysis to company-specific stories in the *Wall Street Journal* and the Dow Jones News Service. Loughran and McDonald (2011) used a more specialized list of financial words to analyze companies' 10-K reports. Our analysis addresses the question of whether the improvement in results from specialized processing persists when a broad dataset is used or whether it requires suitably specialized textual input.

Another motivation for using a large, broad dataset is to increase the power to distinguish different types of return predictability. Temporary market sentiment or news-induced trading liquidity should be quickly reversed. Boudoukh et al. (2013) predicted that markets will overreact to simple news and underreact to complex news. In particular, complex new information should have a permanent impact on stock prices. Larger datasets and more powerful textual analysis methods have the potential to detect these distinct patterns of predictability. For example, we found that weekly news predicts returns much longer than daily news.

Our dataset includes a measure of the "tone" or sentiment of each news story.[3] The story-specific sentiment measure allows us to distinguish the effect of news publication from the effect of favorable or unfavorable news. The publication of news may draw attention to a stock, inducing both rational and irrational trading. This trading may affect the liquidity of the stock and, consequently, change the expected return. We show that stocks with news have different expected returns from stocks without news. Controlling for this publication effect shows that both positive and negative news are incorporated into stock prices at different speeds.

Our empirical analysis uses 900,754 articles tagged with company identifiers from the Thomson Reuters news system over the calendar years 2003–2010.

Thomson Reuters provides a dataset of news sentiment called Thomson Reuters NewsScope Data (sentiment data). The dataset is broader and larger than many of the datasets previously studied.[4] The dataset identifies the time of the news story (with millisecond resolution), the company mentioned in the story, the headline of the news story, the story identification number, the relevance of the news article to the company, the staleness of a news item, and measures from a neural-network-based sentiment engine. Thomson Reuters also provides a dataset called the Thomson Reuters News Archive (text data), which contains the time of the news story, the story identification number, the headline of the news story, and the full text of the news item. We matched the sentiment data with the text data using the time stamp and story identification number for all the items in the sentiment data and obtained a dataset that contains the text as well as the respective probabilities for the article being positive, negative, or neutral. We excluded news items linked to more than one article in the sample to ensure that this information did not appear in the sample before. We also excluded news about companies that could not be matched to any ticker symbol in the CRSP dataset and articles about companies with relevance scores below 35%.[5]

These stories are tagged by Thomson Reuters with several topic codes. Appendix A provides a list of all the topic codes, along with brief descriptions and the proportion of news articles being tagged with a particular topic code. The three most commonly used topic codes are "STX," "RES," and "MRG." The topic code STX indicates additions and deletions from stock indexes, new listings, delistings, and suspensions; it has been assigned to 13% of the news articles in our sample. The topic code RES indicates all corporate financial results, tabular and textual reports, dividends, and annual and quarterly reports; it has been assigned to 14% of the news articles in our sample. The topic code MRG indicates mergers and acquisitions; it has been assigned to 18% of the news articles. Most of the remaining topic codes indicate economic news.

The Thomson Reuters sentiment engine has three sequential steps: (1) preprocessing, (2) lexical and sentiment pattern identification, and (3) sentiment classification. The first two stages of the sentiment engine identify parts of speech and morphologically stem the words by matching each word to its root word. For example, "gone," "went," and "goes" are all identified as "go." The sentiment engine performs shallow parsing whereby it identifies the subject of the sentence and then identifies words as adjectives, adverbs, intensifiers, nouns, and verbs. The shallow parsing helps the classifier assign relevance of the article across multiple subjects. This lexical identification is important for sentiment processing because certain phrases and parts of speech tend to convey tone. The lexical identification also recognizes negation, intensification, and verb resolution.

The computations from the first two steps feed into the input layer of the final sentiment classification at five nodes: nouns, verbs, adjectives, adverbs, and intensifiers. The neural network then computes an intermediate "hidden" layer, which connects to the final output classification layer. The weights of connections within the neural network are chosen to optimize the accuracy of prediction compared with the human classification of articles. If satisfactory accuracy is not achieved, the connections between the layers are modified through backpropagation to improve accuracy. To prevent overfitting, the network measures the accuracy by cross-validation against a holdout sample of articles.

The classifier was trained using a random sample of 3,000 triple-annotated news articles spanning the 14 months from December 2004 to January 2006. Analysts of blogs and other outlets of public opinion annotated the news articles. The annotation order was randomized so that manual annotators would not have been able to anticipate stock returns from reading the news articles. Given that the training sample was less than 1% of our data, the effect of data snooping is minuscule.[6] The system had about 75% accuracy against the average assessment of human analysts. The engine is described in greater detail in Sinha (2016) and Infonic (2008). **Table 1** presents summary statistics for our text data. The neural network predicts an average 29.9% chance that an article is positive and a 27.5% chance that an article is negative.

Table 1. Characteristics of News Sentiment Variables

Sentiment Variable	Mean	Standard Deviation
Thomson Reuters net sentiment	2.4%	39.0%
Thomson Reuters negative sentiment	27.5	24.6
Thomson Reuters positive sentiment	29.9	21.7

Note: This table shows the average net company sentiment (positive minus negative), positive sentiment, and negative sentiment for 900,754 articles using the Thomson Reuters sentiment engine.

Table 2 shows summary statistics for companies sorted by size. Companies in the largest decile had frequent stories—22.42 stories per week, which exceeds 3 stories per day—but the small companies were comparatively neglected in news coverage. Companies in the smallest two deciles averaged less than one article per week, and more than 90% of companies in the smallest three deciles received no news in a given week. The greater news coverage of large companies ensured that small companies did not dominate our news-based return strategies, alleviating concerns that profits were associated with exposure to illiquidity. Over the 10-year sample period, small companies underperformed large companies; the smallest decile lost 0.14% per week, whereas the largest decile gained 0.06% per week. The last column reveals a critical feature relevant to our study of textual analysis. Companies that received news coverage in a given week had average returns that differed from those of typical companies of their size in the subsequent week. Because these "no news" returns occurred in the ensuing weeks, they were not subject to survivorship bias or a short-term informational effect, as in "the dog that didn't bark." The most dramatic difference occurred in the smallest decile, where the average small company lost 0.14% in a given week but small companies with news averaged 2.00% in the week following the news. Given that small companies are often illiquid and costly to trade, the return differential between small companies with and without news may not represent a profit opportunity. But it documents that companies with news are distinctly different from companies without news. When measuring the effect of news sentiment, it is important to control for the existence of news.

Predicting Returns

Our simplest test of news sentiment used portfolios based on net sentiment, positive minus negative. In contrast to previous studies that used SEC filings or periodic newspaper columns, our dataset has almost 1 million news stories, sometimes with multiple stories about a particular company. Therefore, we measured the sentiment for a given company as the average positive-minus-negative sentiment on all stories about that company in a formation period. **Table 3** presents excess returns on quintile spreads—that is, the difference between returns on the highest- and lowest-sentiment portfolios. The quintiles were formed daily on Day 0, and returns were reported daily. We used quintiles instead of deciles or even more granular portfolios because many stocks do not have news

Table 2. Weekly Summary Statistics by Market Capitalization

Decile	Log Market Cap	News Stories per Week	Proportion of Companies without News	Return	Return with News	Return without News	Difference	*t*-Statistic
1 (smallest)	9.42	0.16	0.95	−0.14%	2.00%	−0.24%	2.24%	3.47
2	10.56	0.59	0.94	−0.12	1.51	−0.23	1.75	3.59
3	11.22	1.33	0.92	−0.14	−0.02	−0.15	0.12	0.4
4	11.8	2.49	0.89	−0.06	−0.04	−0.06	0.01	0.04
5	12.35	4.01	0.87	−0.05	−0.28	−0.01	−0.26	−0.86
6	12.88	5.81	0.85	−0.01	−0.26	0.03	−0.29	−0.99
7	13.43	7.63	0.82	0.04	−0.07	0.06	−0.13	−0.48
8	14.04	10.19	0.76	0.05	0.08	0.04	0.04	0.15
9	14.83	13.3	0.66	0.09	0.12	0.07	0.05	0.25
10 (largest)	16.48	22.42	0.34	0.06	0.07	0.04	0.04	0.18

Notes: This table presents weekly statistics for decile portfolios grouped on market capitalization over calendar years 2003–2010 (417 weeks). We divided the companies into deciles based on the market capitalization at the beginning of the month. For each week, we noted the number of news articles with relevance of at least 0.35, the proportion of companies without news, the average return, the average returns for companies with news and for companies without news, the difference in returns for companies with and without news, and the *t*-statistic for the difference in returns.

Table 3. Long–Short Excess Return Based on News Sentiment on Day 0

	Thomson Reuters Quintiles	
Day after News	Mean	*t*-Statistic
–9	0.09%	6.0
–8	0.07	4.5
–7	0.09	5.9
–6	0.10	6.3
–5	0.12	7.4
–4	0.08	4.7
–3	0.12	6.9
–2	0.18	10.8
–1	0.50	22.4
0	1.99	63.9
1	0.17	9.8
2	0.04	2.5
3	0.02	1.2
4	0.04	2.5
5	0.03	1.6
6	0.06	0.4
7	0.02	1.1
8	0.01	0.9
9	–0.02	–1.2
10	–0.00	0.0

Notes: We sorted all stocks on a given day on the basis of the news sentiment from a lagged day and took a long position in the highest quintile (positive-news stocks) and a short position in the lowest quintile (negative-news stocks). This table shows the average daily returns and *t*-statistics on a long–short portfolio based on sentiment scores from the Thomson Reuters sentiment engine.

results on any given day. Note that we can interpret these excess returns as differences between returns in excess of a benchmark market portfolio, consistent with the methodology of Brown and Warner (1985). In particular, these excess returns remove components attributable to the risk-free rate or market return.

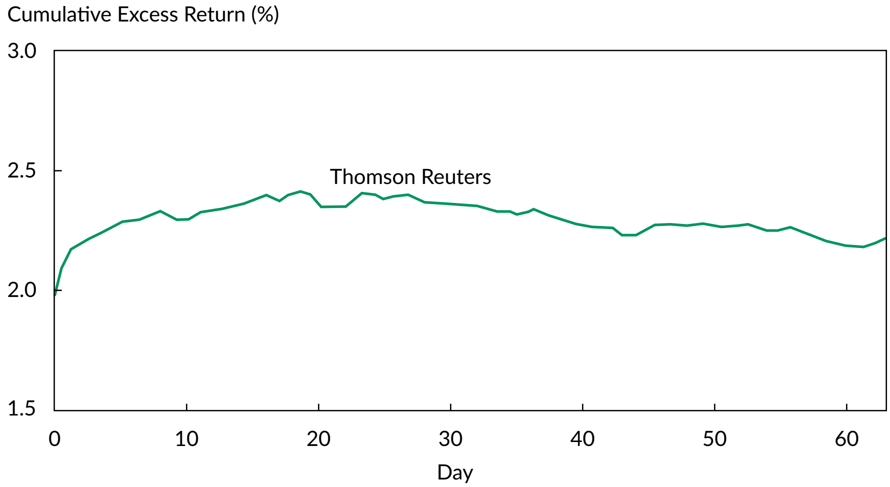
The contemporaneous returns on the Day 0 news release show an economically and statistically significant announcement day return of 1.99%, which is quite large for a single-day return; it shows the impact of news on stock prices. Note that average excess returns on the quintile spreads are invariably positive in the 10 days preceding the publication of news, with most of the *t*-statistics exceeding 2. This result is expected, because news stories may lag events that affect stock prices. It suggests that stock returns predict news, rather than the converse.

The more interesting result is the postpublication returns. The neural network produced returns of 0.17% on Day 1 and 0.04% on Day 2, both significant at the 95% level. It appears that this method of textual processing predicts stock returns that are not immediately reversed. In particular, these returns do not appear to be an artifact of bid–ask bounce or temporary liquidity imbalances.

Figure 1 contrasts these methods by showing cumulative daily excess returns for one quarter, or 63 business days, after the news date. The subsequent performance is rather flat, suggesting that information is quickly absorbed into prices.

These daily results are consistent with previous findings based on daily data. Tetlock et al. (2008), Loughran and McDonald (2011), and Lerman and Livnat (2010) all found predictability over event windows of one to four days, with varying degrees of reversal. This previous research used periodic news columns and SEC filings. Those datasets typically have only one news item per company. In contrast, our dataset often has multiple news stories about companies spread over several adjacent days. Given the frequency of stories in our dataset, daily aggregation might not be the best choice. Sinha (2016) showed that news from this dataset can predict stock returns. Sinha also showed that this predictability is not limited to small stocks, low-analyst-coverage stocks, low-institutional-ownership stocks, or loser stocks. Sinha's news portfolio did not suffer from short-term reversals, which suggests that the predictability stems from the permanent, albeit delayed, incorporation of news, as opposed to a transient effect caused by overreaction or temporary liquidity effects. We wanted to measure the predictability of returns at different horizons and perform diagnostics to explore the resulting patterns. Panel A of **Table 4** shows that the daily predictability changes dramatically when decile portfolios are formed on the basis of weekly news.[7] The announcement week decile spread produced an excess return of 3.75%. This number must be interpreted with caution because the news stories may be published subsequent to a day on which news actually caused high returns. But the subsequent weekly returns are truly out of sample. The neural network predicts subsequent returns for 13 weeks after the news story

Figure 1. Cumulative Excess Returns on Daily News and Post-News Quintile Spreads



release. Most of them are statistically significant at the 95% level, including a 0.21% return in Week 13.

Figure 2 graphs the cumulative returns from the weekly news strategy. In contrast to the daily results (shown in Figure 1), it shows a persistent upward trend of profitability.

Positive news is often anticipated by high stock returns or associated with good earnings releases. Therefore, Figure 2 compares the average news sentiment strategy from Table 4 with two decile spread strategies based on historical stock momentum and earnings surprise. Momentum is measured as the 26-week historical stock return through Week 0. Earnings surprise is measured by the three-day return around the most recent quarterly Compustat earnings release field "rdq." To ensure that the results are truly out of sample, the graph starts at the end of Week 1 instead of Week 0.[8] All three strategies produce average decile spreads of about 2%–3% by the end of Week 13. It is likely that positive news stories are positively related to recent stock momentum and earnings. Panel A of **Table 5** confirms this, showing that all three strategies are positively correlated. The highest correlation of 80% is between the news strategy and the momentum strategy, which raises the concern that the positive returns of the news strategy might be solely a consequence of momentum. Panel B of Table 5 addresses this concern by regressing the news (excess) returns on the momentum and earnings surprise (excess) returns. The positive intercepts from univariate and bivariate linear regressions of the news strategy on the other two strategies show that the news effect remains positive and statistically significant at the 99% level even when controlling for momentum and earnings surprise effects. Recall that Table 4 reports the excess return of the news strategy as 2.15% over 13 weeks, or 0.165% per week. Because all the estimated intercepts in Panel B exceed 0.09% per week, we conclude that most of the news effect is not spanned by momentum or earnings surprise. In this case, investors who are already using these other strategies will still improve their alphas by using news.

It is conceivable that the large post-news returns are compensation for exposure to company risk or characteristics. Two likely candidates are size and momentum. As Table 2 shows, size is clearly negatively related to the volume of news stories. To the extent that size represents exposure to risk or proxies for some other anomalous return factors, it is useful to control for it. Momentum is an even more related factor because we have already shown that good news tends to be preceded by positive returns. Hence, the returns owing to news might be a byproduct of the Jegadeesh and Titman (1993) momentum factor. Therefore, Table 4 presents two additional columns that control for size and momentum, respectively. For each week, we assigned companies to deciles based on their size or momentum. Then, instead of using company returns, we used returns in excess of their size or momentum categories. The results show that size and momentum do not subsume the return predictability of news.

These results still leave open the question of why weekly news formation predicts returns for 13 weeks but daily formation predicts returns for only two days. There are two explanations for the striking improvement in predictability when using weekly returns.

Table 4. Weekly Returns from Long–Short Portfolio Based on News in Week 0

Week after News	Return	*t*-Statistic	Momentum-Adjusted Return	*t*-Statistic	Size-Adjusted Return	*t*-Statistic
A. Long–short excess returns from weekly portfolio for all stocks with news						
0	3.75%	37.0	3.61%	41.9	3.62%	36.8
1	0.32	3.9	0.31	2.5	0.36	2.5
2	0.20	2.6	0.12	1.0	0.20	1.4
3	0.26	3.6	0.22	1.7	0.25	1.8
4	0.10	1.4	0.01	0.1	0.02	0.1
5	0.19	2.6	0.13	1.0	0.21	1.5
6	0.14	1.9	0.22	1.8	0.25	1.9
7	0.11	1.5	0.00	0.0	0.02	0.2
8	0.08	1.2	0.14	1.1	0.19	1.4
9	0.12	1.6	0.23	1.8	0.24	1.8
10	0.21	2.8	0.23	1.6	0.22	1.5
11	0.20	2.9	0.29	2.3	0.36	2.6
12	0.01	0.2	0.05	0.4	0.06	0.5
13	0.21	2.6	0.27	2.1	0.27	2.0
Weeks 1–13	2.15	8.2	2.22	4.8	2.65	5.3
Weeks 2–13	1.83	7.4	1.91	4.3	2.29	4.8

B. Excess weekly returns from long–short portfolio by days of news in week

	One Article	*t*-Statistic	Multiple Articles	*t*-Statistic
0	3.37%	41.08	4.22%	24.46
1	0.19	3.13	0.48	3.94
2	0.11	1.98	0.21	1.79
3	0.15	2.92	0.21	1.86
4	0.08	1.29	−0.04	−0.36
5	0.09	1.67	0.20	1.85
6	0.09	1.56	0.10	1.00
7	0.12	2.09	0.01	0.14
8	0.06	1.13	0.13	1.24
9	0.08	1.33	0.21	1.88
10	0.11	2.05	0.13	1.17
11	0.11	2.06	0.06	0.64
12	−0.05	−0.99	0.07	0.69
13	0.10	1.69	0.25	2.32
Weeks 1–13	1.24	5.68	2.02	4.80
Weeks 2–13	1.05	5.44	1.54	4.24

Notes: We sorted all stocks in a week on the basis of the news sentiment from Week 0 and took a long position in the highest decile (positive-news stocks) and a short position in the lowest decile (negative-news stocks). Panel A shows the average weekly returns on a long–short portfolio using sentiment scores from the Thomson Reuters sentiment engine, as well as returns adjusted for 26-week momentum and the logarithm of market capitalization. To control for momentum, we assigned stocks to 10 momentum deciles on the basis of returns over the past 26 weeks and calculated the benchmark return for each momentum decile. For each stock, we then calculated the excess return over its benchmark. Long–short returns in excess of the benchmark return are reported. We similarly adjusted for size. The last two rows show the sum of returns for the news long–short strategy for Weeks 1–13 and Weeks 2–13, respectively. In Panel B, the "One Article" column shows the average excess returns from a long–short portfolio of stocks that had only one news article in Week 0. The "Multiple Articles" column shows the excess returns from a long–short portfolio of stocks with more than one news article in Week 0. The last two rows show the sum of returns for the news long–short strategy over Weeks 1–13 and Weeks 2–13, respectively.

Figure 2. Cumulative Excess Returns on Weekly News Sentiment, 26-Week Momentum, and Earnings Surprise Decile Spreads

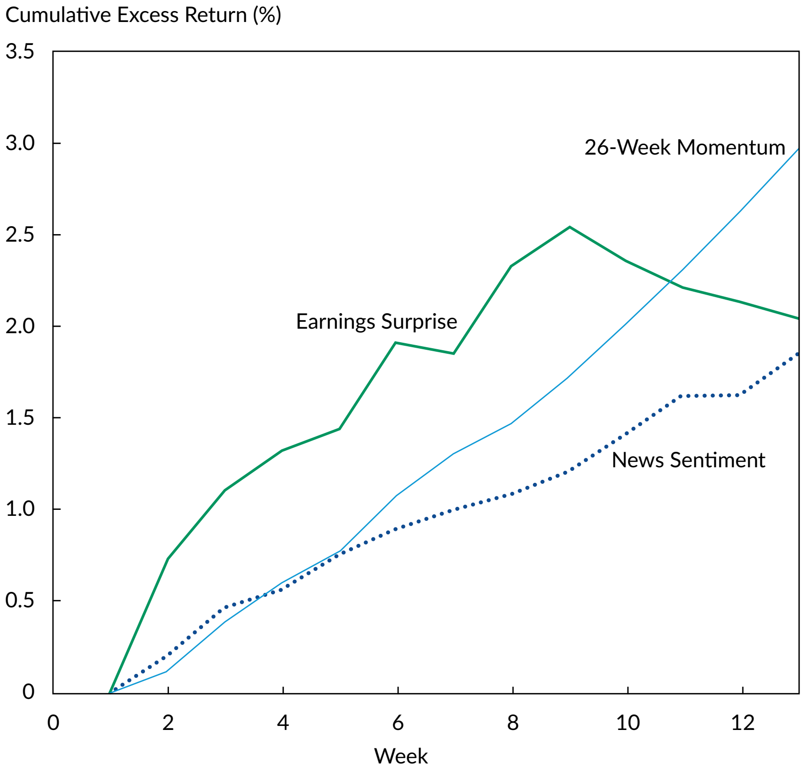


Table 5. Comparisons between News, Momentum, and Earnings Surprise Strategies

Strategy	News	Momentum	Earnings Surprise
A. Correlations			
News	1		
Momentum	.80	1	
Earnings surprise	.20	.16	1
B. Regressions of news strategies on momentum and earnings surprise strategies			
Intercept	.148%	.092%	.096%
	(.047%)	(.029%)	(.029%)
Momentum	.229		.226
	(.0084)		(.0085)
Earnings surprise		.88	.031
		(.022)	(.013)

Notes: Panel A shows the correlations between weekly excess returns on three strategies. The news strategy uses an average of decile spreads formed on the basis of Thomson Reuters sentiment over each of the past 13 weeks. The momentum strategy is a decile spread of stocks sorted by their historical return over the past 26 weeks. The earnings surprise strategy is a decile spread of stocks based on the three-day return around the most recent earnings announcement. Panel B shows the ordinary least-squares intercepts and slopes from regressing the weekly excess returns of the news strategy on the excess returns of the momentum and earnings surprise strategies. Standard errors are in parentheses.

One explanation is that some companies have multiple news stories over different days within a week, and the predictability stems from the information confirmation of these clustered news stories. Of the companies with news in a given week, only 35% have more than one news story and only 9% have more than two. These companies with multiple news stories tend to be larger than companies with less news coverage. This explanation suggests that this minority of companies drives the profitability of weekly strategies.

A second, more prosaic explanation is that the distribution of daily news is quite variable over time. **Figure 3** illustrates the higher volatility for daily news sentiment by graphing the 20th and 80th percentiles of Thomson Reuters news sentiment based on daily and weekly news. It clearly shows that the thresholds for daily quintile sentiment are quite volatile.[9] Some days simply have little news or little news with strong sentiment, whereas others have an abundance of news with strong positive or negative sentiment. At a few points, the daily 20th and 80th percentile lines almost touch each other. The small difference between the 20th and 80th percentiles on such days means that companies with stories in the highest quintile of sentiment on one day would be in the lowest quintile on an adjacent day. Clearly, daily news sentiment is a noisy way of classifying companies on the basis of sentiment. The weekly cutoffs still show some variation but are much more stable over time.

Panel B of Table 4 reports the weekly decile returns for subsamples of companies that have one news story and multiple news stories in Week 0. Both subsamples are profitable in 12 of the 13 post-news weeks. The decile spread of companies with multiple news stories is positive at the 95% level of significance in Week 11, whereas the decile spread of companies with a single weekly news story is significantly positive at the 95% level in Week 13. **Figure 4** graphs the cumulative returns to these strategies over 13 weeks. It shows that the decile strategy based on companies with multiple weekly news items is more profitable over the quarter, but both subsamples generate a strong, profitable trend. These positive decile spreads based on weekly news are quite different from the flat daily results in Figure 1.

News, Sentiment, and Earnings

The previous results show a delayed reaction to weekly news about companies. Specifically, companies with good news over a one-week period subsequently outperform companies with bad news over a one-week period. Portfolios formed on this basis earn excess returns for up to 13 weeks.

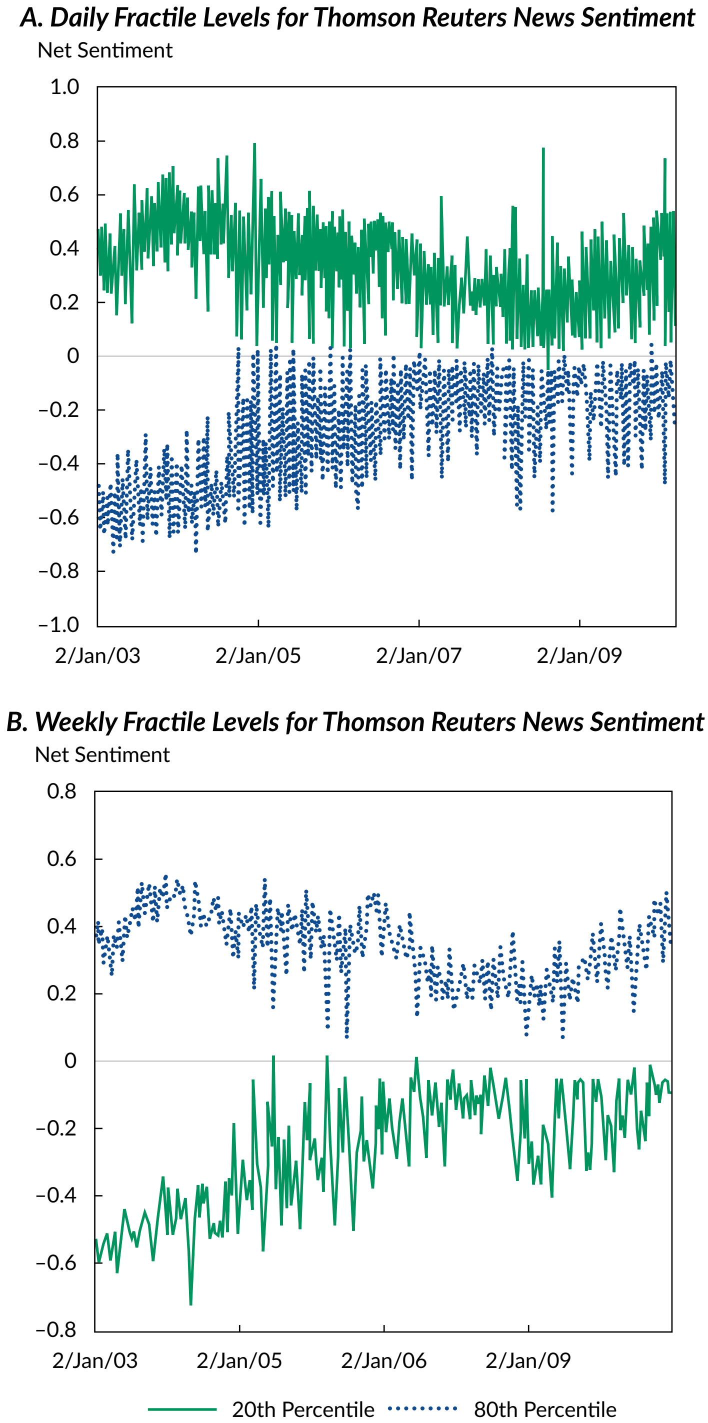
However, this exercise does not completely disentangle the "news effect" from the "sentiment effect." It is conceivable that the mere publication of news about a company affects its returns, regardless of the content or sentiment of the news. For example, a news article with little new information might nevertheless make its information common knowledge. Such a news story could resolve information asymmetry and thereby change the liquidity of a market. Like "the dog that didn't bark," the mere fact that articles were published or not published about a company contains information.

Another limitation of the decile spread results is that they do not reveal whether the predictability stems from positive or negative news. For example, Tetlock (2011) and Loughran and McDonald (2011) found that the preponderance of return response stems from negative news. In addition, to gauge the distinct effects of positive and negative news, it is necessary to isolate the "news effect." In order to compare the potentially dissimilar effects of positive and negative news, we need to compare the effects with an appropriate return benchmark. The summary statistics in Table 2 show that companies without news underperformed companies with news over our sample period. Inclusion of those companies using a portfolio methodology would bias the relative comparison of companies with different types of news. Specifically, companies with news would appear to outperform companies without news, regardless of the sentiment of the news, which would exaggerate the impact of positive news while reducing the apparent effect of negative news. In order to distinguish a publication effect from the quality of the information and to separately evaluate the effect of positive and negative news, we must use a multivariate technique. This technique must separately measure the news effect, the effect of positive sentiment in news, and the effect of negative sentiment in news.

We used the cross-sectional regression technique of Fama and MacBeth (1973). For a given lag k ranging from 0 to 13, we regressed stock returns on sentiment score:

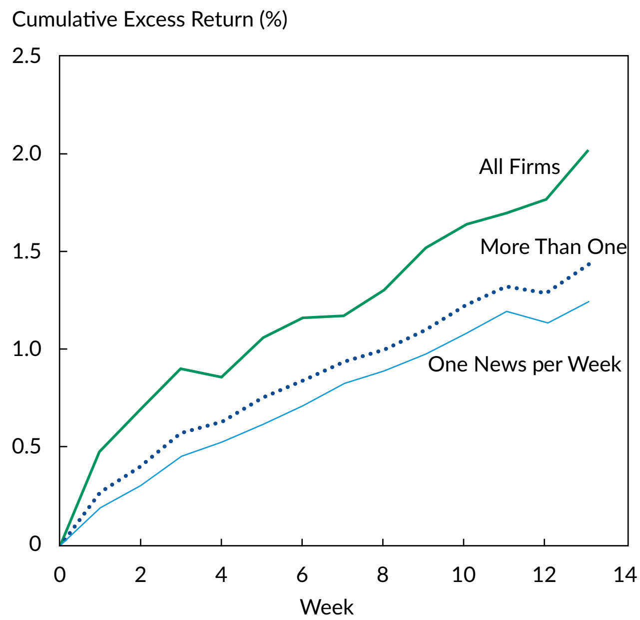
$$\begin{aligned} r_{i,t} &= \alpha_{k,t} + \gamma_{k,t}\text{If\_news}_{i,t-k} + \beta_{k,t}\text{Positive}_{i,t-k} \\ &\quad + \delta_{k,t}\text{Negative}_{i,t-k} + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

Figure 3. Daily and Weekly Fractile Levels for Thomson Reuters News Sentiment



where $r_{i,t}$ is the return on stock *i* in week *t*; If_news$_{i,t-k}$ is a dummy variable for companies with news over the given lag *k*; and Positive$_{i,t-k}$, Neutral$_{i,t-k}$, and Negative$_{i,t-k}$ represent the evaluation of sentiment in news articles published in the lagged week. Following Fama (1976), we can interpret $\alpha_{k,t}$ as the return on an equally weighted portfolio of companies with no news at lag *k*. The term $\gamma_{k,t}$ represents the return premium for firms that have neutral published news over firms with no news. If "no news is good news," then neutral news will be bad news and $\gamma_{k,t}$ will tend to be negative. However, the summary statistics show that

Figure 4. Cumulative Weekly Post-News Long–Short Quintile Spreads



firms without news tend to underperform. Therefore, we expect the effect of neutral news and the corresponding $\gamma_{k,t}$ to be positive. The $\beta_{k,t}$'s and $\delta_{k,t}$'s represent excess returns on costless, well-diversified portfolios that have 100% net loadings on positive or negative sentiment variables at a given lag.

Table 6 presents the average results of the regression coefficient time series, along with time-series *t*-statistics using the Thomson Reuters sentiment engine. The "no news" intercept is negative at all lags, ranging from –1 bp per week to –6 bps per week. Although these average returns are not statistically significantly different from zero, the consistently negative intercept shows that companies without news performed poorly over the sample period.

The premium for neutral news is $\gamma_{k,t}$. It represents the weekly return premium of companies with 100% neutral news over companies with no news. The average point estimates are positive at all nonzero lags, which shows that neutral news has a positive effect. The positive coefficient for neutral news contradicts Campbell and Hentschel (1992) and the well-known adage that "no news is good news."

If neutral news is good, then we should expect positive news to be even better. The positive sentiment columns in Table 6 confirm this intuition. The average contemporaneous (Lag 0) effect ($\beta_{0,t}$) is positive and highly statistically significant for all measures of sentiment. If news travels slowly, then good news should also have a positive lagged effect. However, this does not appear to be the case. The estimates for positive news in Table 6 are marginally significant at the 95% level at the first weekly lag but are not statistically significantly positive at further lags. The subsequent point estimates are near zero and have different signs at higher lags. It appears that the market quickly incorporates positive information into returns.

Negative news also has a strong immediate effect on returns. In addition, Table 6 shows a strong lagged effect. The influence of Thomson Reuters sentiment is negative at all 13 lags, and the individual weeks are statistically significant at the 95% level at Lags 1–6 and Lag 10. The pattern echoes the finding that "bad news travels slowly" (Hong, Lim, and Stein 2000). The findings are not consistent with Pound and Zeckhauser (1990), who found that rumors are already incorporated into prices.

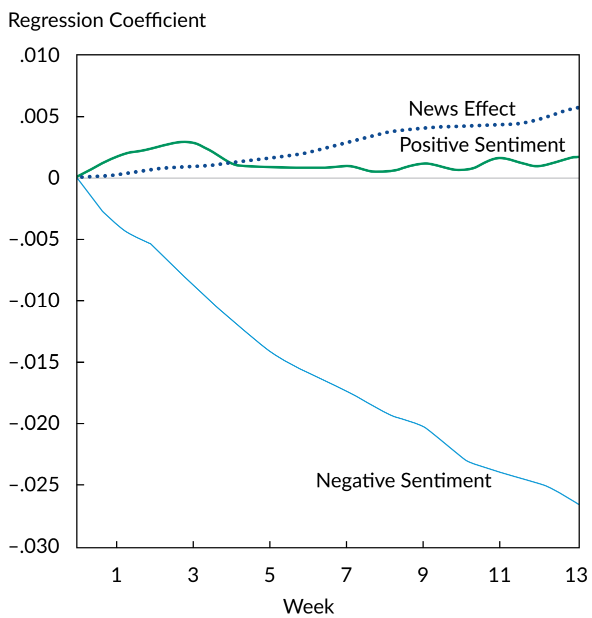
Figure 5 graphs cumulative coefficients from Table 6 for horizons ranging from 1 week to 13 weeks. The figure illustrates the pattern of news impact over different time periods. It shows that the effect of neutral news, although small, accumulates positively for a full quarter. The incremental effect of positive sentiment is positive for only two or three weeks and then flattens out to negligible levels. In contrast, the impact of negative sentiment continues to be strong for the full 13-week period. Overall, neutral news, positive news, and negative news have

Table 6. Cross-Sectional Regressions of Weekly Returns Based on Thomson Reuters Sentiment in Week 0: Average Cross-Sectional Regression Coefficient on Thomson Reuters Sentiment Variables

Week after News	$\mathcal{D}$	*t*-Statistic	News Effect	*t*-Statistic	Positive Sentiment	*t*-Statistic	Negative Sentiment	*t*-Statistic
0	−0.0005	−0.3	−0.0003	−0.4	0.0304	27.6	−0.0329	−23.5
1	−0.0005	−0.3	0.0008	1.4	0.0017	2.0	−0.0037	−3.7
2	−0.0006	−0.4	0.0008	1.5	0.0008	0.9	−0.0018	−1.9
3	−0.0006	−0.4	0.0012	2.2	0.0004	0.5	−0.0032	−3.5
4	−0.0005	−0.3	0.0019	3.4	−0.0016	−1.9	−0.0027	−2.7
5	−0.0004	−0.3	0.0012	2.2	−0.0003	−0.4	−0.0026	−2.9
6	−0.0003	−0.2	0.0009	1.5	−0.0002	−0.2	−0.0018	−1.9
7	−0.0003	−0.2	0.0010	1.8	0.0002	0.2	−0.0015	−1.6
8	−0.0003	−0.2	0.0012	2.1	−0.0005	−0.7	−0.0018	−1.9
9	−0.0002	−0.2	0.0004	0.7	0.0007	0.9	−0.0011	−1.1
10	−0.0001	0.0	0.0011	2.0	−0.0005	−0.7	−0.0026	−2.8
11	−0.0004	−0.3	0.0003	0.6	0.0009	1.2	−0.0011	−1.3
12	−0.0004	−0.3	0.0013	2.4	−0.0005	−0.7	−0.0009	−1.0
13	−0.0002	−0.2	0.0004	0.8	0.0008	1.0	−0.0017	−1.8
Total					0.0321		−0.0593	

Note: We report the time-series average of $\gamma_{k,t}$ in the "News Effect" column and the time-series averages of $\beta_{k,t}$ and $\delta_{k,t}$ in the "Positive Sentiment" and "Negative Sentiment" columns.

Figure 5. Cumulative Weekly Average Cross-Sectional Regression Coefficients



Note: This figure plots the cumulative coefficients from Table 6 for horizons ranging from 1 week to 13 weeks.

different patterns of predicting stock returns over time. These findings demonstrate the importance of careful measurement of news sentiment and the distinct patterns of return predictability for positive, negative, and neutral sentiment. The cross-sectional regression reinforces the portfolio results, which also show that a neural network predicts stock returns. The persistent predictive ability of negative Thomson Reuters sentiment is interesting in this regard. The findings are consistent with short-sale constraints that prevent a small informed minority from fully affecting stock prices.

In the previous section, we showed that abnormal returns persist when controlling for size and momentum. These variables are strongly correlated with the quantity and quality of news. Another relevant variable is earnings. In particular, Foster, Olsen, and Shevlin (1984) showed the existence of post-earnings-announcement drift—that is, abnormally high returns in response to unexpectedly high earnings. The table of topic codes in the appendix shows that the second most common topic tag in the database is corporate financial results (RES), and the fourth most common topic is forecasts of financial results (RESF). Even if news is not specifically about earnings, we can expect it to be correlated with earnings. If earnings reports are a vehicle for quantifying and disseminating this news, then we might expect the good news to affect prices around the release of earnings reports, rather than before or after.

Table 7 addresses this issue by examining post-news returns relative to earnings announcements. For the week subsequent to a news story, we divided companies into three categories on the basis of whether they (1) have not yet announced earnings since the news ("Pre-Earnings"), (2) announced earnings in that week ("Earnings"), or (3) have already announced earnings between the news release and the current week ("Post-Earnings"). Then, we formed decile spreads based on news sentiment within these

Table 7. Long–Short Excess Returns before, during, and after Earnings Announcement Weeks

	Pre-Earnings		Earnings		Post-Earnings	
Week after News	Average	*t*-Statistic	Average	*t*-Statistic	Average	*t*-Statistic
0	3.40%	31.34	5.90%	13.39		
1	0.32	1.88	0.81	1.71		
2	0.09	0.42	0.80	1.27	0.04%	0.08
3	0.30	1.32	1.44	2.91	0.37	1.05
4	0.10	0.35	−0.13	−0.21	−0.31	−1.19
5	0.31	1.01	0.57	0.81	−0.08	−0.39
6	0.07	0.20	1.16	1.82	0.23	1.12
7	−0.89	−2.21	−0.20	−0.37	0.04	0.21
8	−0.23	−0.51	0.09	0.17	0.13	0.79
9	0.24	0.44	0.66	0.93	0.15	0.90
10	−0.19	−0.27	0.10	0.18	0.23	1.27
11	−0.95	−1.17	0.93	1.75	0.27	1.77
12	0.00	0.00	−1.52	−2.91	0.42	2.67
13	1.09	0.81	0.85	1.73	0.36	2.26
Weeks 1–13	0.25	0.11	5.57	2.66	1.83	2.14
Weeks 2–13	−0.07	−0.03	4.76	2.33	1.83	2.14

Notes: We sorted all stocks in a given week on the basis of the news sentiment from a lagged week and took a long position in the highest decile (positive-news stocks) and a short position in the lowest decile (negative-news stocks). The "Pre-Earnings" column shows the average weekly returns on the long–short portfolio using sentiment scores before the latest earnings release. The "Earnings" column shows the long–short returns from a weekly long–short strategy during the earnings release week. The "Post-Earnings" column shows the returns after the latest earnings news. The last two rows show the total returns over Weeks 1–13 and Weeks 2–13, respectively.

three categories, as in Table 4. The "Pre-Earnings" column of Table 7 shows that news sentiment does not predict statistically significant returns prior to companies' next earnings announcement. The cumulative abnormal return over 13 weeks is only 0.25%, and over Weeks 2–13, it is (insignificantly) negative. To the extent that the Thomson Reuters sentiment measures information, it appears that this information is not incorporated into stock prices prior to the next earnings release. But the "Earnings" column of Table 7 shows that quintile spread returns are mostly positive in earnings announcement weeks. Because of the smaller sample, the individual weeks are usually not statistically significant, but the cumulative excess return over 13 weeks is a healthy 5.57%, with a *t*-statistic of 2.7. This result reinforces the results of Bernard and Thomas (1990), who found a delayed reaction to past earnings around subsequent announcements. The "Post-Earnings" quintile spreads are smaller but still positive through Week 13, at 1.83%, with a *t*-statistic of 2.1. This finding is consistent with the post-announcement earnings surprise anomaly of Foster et al. (1984). Table 7 suggests that earnings announcements act as a channel of price discovery for information that was not immediately incorporated into stock prices when published. Hendershott, Livdan, and Schürhoff (2015) showed that institutional trading anticipates news announcements. Whether institutions exploit news around the earnings announcements as well is an open question.

Conclusion

In this study, we investigated the usefulness of textual processing for predicting stock returns. We specifically used a neural network applied to a broad dataset of news stories. The duration of stock return predictability depends on the temporal aggregation of news. Predictability lasts only a few days when news is measured over a day. But when news is aggregated over a week, the predictability lasts for up to a quarter. The longer-lasting predictability establishes that the effect of news on prices is not merely the result of transient sentiment or liquidity. Instead, the deep textual analysis of the neural network appears to detect news that is persistently underincorporated into current stock prices.

In our study, we distinguished the effect of news from the positive or negative sentiment of that news. We also found a news publication effect, where firms with neutral news outperform firms without any news. Controlling for this publication effect, we showed that positive news affects stock prices within one week. However, negative news predicts low stock returns for up to one quarter, which is consistent with short-sale constraints that delay the incorporation of bad news. We found that most of the delayed reaction to news occurs around subsequent earnings announcements. This finding is consistent with earnings releases and earnings-related trading acting as a channel to incorporate information into stock prices.

Future research can further explore patterns of predictability. For example, Chan (2003) found price reversals associated with returns that were unaccompanied by news, and Tetlock (2011) found overreaction to stale news. Boudoukh et al. (2013) found differential responses of returns to different types of news, including a greater response to relevant news. Other commercial products, such as Ravenpack, also analyze text. Comparison of return patterns across different types of news may enhance our understanding of how markets process information.

Appendix A. Topic Codes

Table A1 lists all the topic codes, provides brief descriptions of each, and shows the proportion of news articles tagged with a particular topic code. Note that many news items have more than one tag.

Table A1. List of Topic Codes

Topic Code	Brief Description	Percentage of News
MRG	Mergers and acquisitions (including changes of ownership)	17.7%
RES	Corporate results	14.0
STX	Stock markets	13.4
RESF	Corporate results forecasts	9.2
NEWS	Major breaking news	8.2
DBT	Debt markets	6.3
RCH	Broker research and recommendations	4.9
HOT	Hot stocks	4.9
CORA	Corporate analysis	4.4
INV	Investing	3.0
REGS	Regulatory issues	2.7
PRO	Biographies, personalities, people	2.1
MNGISS	Management issues/policy	1.6
AAA	Ratings	1.5
DIV	Dividends	1.4
PRESS	Press digests	1.4
IPO	Initial public offerings	1.0
WIN	Reuters exclusive news	0.7
ECI	Economic indicators	0.5
EXCA	Exchange activities	0.5
BKRT	Bankruptcies	0.3
RSUM	Reuters summits	0.2
FED	Federal Reserve Board	0.2
CFIN	Corporate finance	0.0
ERR	Error	0.0
FES	Editorial special analysis and future stories	0.0
INSI	Technical analysis	0.0
TRN	Translated news	0.0
CONV	Convertible bonds	0.0
CDM	Credit market news	0.0
NEWR	Original corporate news releases	0.0
DDEAL	Directors’ dealings	0.0
DIARY	Diaries	0.0
KEY	Key personnel moves at corporations or banks	0.0
TOP	Top news	0.0

Editor's Note

Submitted 10 November 2015

Accepted 28 December 2016 by Stephen J. Brown

Notes

1. Antweiler and Frank (2004) used a naive Bayes classifier to classify text. Das and Chen (2007) examined the effect of message board posts on stock prices using a voting scheme across multiple classifiers.

2. Butler (2013) criticized this lack of transparency and the associated interpretation problems when assessing the ability of Google searches to forecast influenza outbreaks.

3. In contrast, Akbas, Boehmer, Erturk, and Sorescu (2013) used the observed stock return to classify the tone of an article. The Ravenpack database used by von Beschwitz, Keim, and Massa (2013) also uses sentiment analytics.

4. The Thomson Reuters sentiment dataset has also been used by Riordan, Storkenmaier, Wagener, and Zhang (2013), Leinweber and Sisk (2011), Uhl, Pedersen, and Malitius (2015), and Healy and Lo (2011), among others.

5. Boudoukh et al. (2013) showed that relevant news affects stock returns more than irrelevant news does.

6. Informal inspection of the results indicates no significant difference in predictability in the post-training period.

7. We found similar results with biweekly and monthly aggregation.

8. Our three-day measure of earnings surprise in Week 0 occasionally bleeds into Week 1. In addition, the 26-week momentum return through Week 0 might be subject to bid–ask bounce or other microstructure frictions in Week 1.

9. One can also see that the news thresholds shrank after the Thomson Reuters database was expanded in 2005.

References

Akbas, F., E. Boehmer, B. Erturk, and S.M. Sorescu. 2013. "Short Interest, Returns, and Fundamentals." Working paper (August).

Altman, E.I., G. Marco, and F. Varetto. 1994. "Corporate Distress Diagnosis: Comparisons Using Linear Discriminant Analysis and Neural Networks (the Italian Experience)." *Journal of Banking & Finance*, vol. 18, no. 3 (May): 505–529.

Antweiler, W., and M.Z. Frank. 2004. "Is All That Talk Just Noise? The Information Content of Internet Stock Message Boards." *Journal of Finance*, vol. 59, no. 3 (June): 1259–1294.

Atiya, A.F. 2001. "Bankruptcy Prediction for Credit Risk Using Neural Networks: A Survey and New Results." *IEEE Transactions on Neural Networks*, vol. 12, no. 4 (July): 929–935.

Bernard, V.L., and J.K. Thomas. 1990. "Evidence That Stock Prices Do Not Fully Reflect the Implications of Current Earnings for Future Earnings." *Journal of Accounting and Economics*, vol. 13, no. 4 (December): 305–340.

Bollen, J., H. Mao, and X. Zeng. 2011. "Twitter Mood Predicts the Stock Market." *Journal of Computational Science*, vol. 2, no. 1 (March): 1–8.

Boudoukh, J., R. Feldman, S. Kogan, and M. Richardson. 2013. "Which News Moves Stock Prices? A Textual Analysis." NBER Working Paper 18725 (January).

Brown, S.J., and J.B. Warner. 1985. "Using Daily Stock Returns: The Case of Event Studies." *Journal of Financial Economics*, vol. 14, no. 1 (March): 3–31.

Butler, D. 2013. "When Google Got Flu Wrong." *Nature*, vol. 494, no. 7436 (14 February): 155–156.

Campbell, J.Y., and L. Hentschel. 1992. "No News Is Good News: An Asymmetric Model of Changing Volatility in Stock Returns." *Journal of Financial Economics*, vol. 31, no. 3 (June): 281–318.

Chan, W.S. 2003. "Stock Price Reaction to News and No-News: Drift and Reversal after Headlines." *Journal of Financial Economics*, vol. 70, no. 2 (November): 223–260.

Chen, H., P. De, J. Hu, and B.-H. Hwang. 2014. "Wisdom of Crowds: The Value of Stock Opinions Transmitted through Social Media." *Review of Financial Studies*, vol. 27, no. 5 (May): 1367–1403.

Da, Z., J. Engelberg, and P. Gao. 2015. "The Sum of All FEARS: Investor Sentiment and Asset Prices." *Review of Financial Studies*, vol. 28, no. 1 (January): 1–32.

Das, S.R., and M.Y. Chen. 2007. "Yahoo! for Amazon: Sentiment Extraction from Small Talk on the Web." *Management Science*, vol. 53, no. 9 (September): 1375–1388.

Dougal, C., J. Engelberg, D. García, and C.A. Parsons. 2012. "Journalists and the Stock Market." *Review of Financial Studies*, vol. 25, no. 3 (March): 639–679.

Duhigg, C. 2006. "A Smarter Computer to Pick Stocks." *New York Times* (24 November): www.nytimes.com/2006/11/24/business/24trading.html.

Dzielinski, M., and H. Hasseltoft. 2013. "Aggregate News Tone, Stock Returns, and Volatility." Working paper (June).

Fama, E.F. 1976. *Foundations of Finance: Portfolio Decisions and Securities Prices*. New York: Basic Books.

Fama, E.F., and J.D. MacBeth. 1973. "Risk, Return, and Equilibrium: Empirical Tests." *Journal of Political Economy*, vol. 81, no. 3 (May–June): 607–636.

Fang, L.H., and J. Peress. 2009. "Media Coverage and the Cross-Section of Stock Returns." *Journal of Finance*, vol. 64, no. 5 (October): 2023–2052.

Foster, G., C. Olsen, and T. Shevlin. 1984. "Earnings Releases, Anomalies, and the Behavior of Security Returns." *Accounting Review*, vol. 59, no. 4 (October): 574–603.

García, D. 2013. "Sentiment during Recessions." *Journal of Finance*, vol. 68, no. 3 (June): 1267–1300.

Hagenau, M., M. Hauser, M. Liebmann, and D. Neumann. 2013. "Reading All the News at the Same Time: Predicting Mid-Term Stock Price Developments Based on News Momentum." In *Proceedings of the Forty-Sixth Annual Hawaii International Conference on System Sciences*. Edited by Ralph H. Sprague, Jr. Los Alamitos, CA: Institute of Electrical and Electronics Engineers.

Healy, A., and A.W. Lo. 2011. "Managing Real-Time Risks and Returns: The Thomson Reuters NewsScope Event Indices." In *The Handbook of News Analytics in Finance*. Edited by G. Mitra and L. Mitra. Chichester, UK: John Wiley & Sons.

Hendershott, T., D. Livdan, and N. Schürhoff. 2015. "Are Institutions Informed about News?" *Journal of Financial Economics*, vol. 117, no. 2 (August): 249–287.

Hillert, A., H. Jacobs, and S. Müller. 2014. "Media Makes Momentum." *Review of Financial Studies*, vol. 27, no. 12 (December): 3467–3501.

Hong, H., T. Lim, and J. Stein. 2000. "Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies." *Journal of Finance*, vol. 55, no. 1 (February): 265–295.

Infonic. 2008. "Reuters NewsScope Sentiment Engine." White paper, Infonic Sentiment Technologies.

Jegadeesh, N., and S. Titman. 1993. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *Journal of Finance*, vol. 48, no. 1 (March): 65–91.

Jegadeesh, N., and D. Wu. 2013. "Word Power: A New Approach for Content Analysis." *Journal of Financial Economics*, vol. 110, no. 3 (December): 712–729.

Khandani, A.E., A.J. Kim, and A.W. Lo. 2010. "Consumer Credit-Risk Models via Machine-Learning Algorithms." *Journal of Banking & Finance*, vol. 34, no. 11 (November): 2767–2787.

Leinweber, D., and J. Sisk. 2011. "Event-Driven Trading and the 'New News.'" *Journal of Portfolio Management*, vol. 38, no. 1 (Fall): 110–124.

Lerman, A., and J. Livnat. 2010. "The New Form 8-K Disclosures." *Review of Accounting Studies*, vol. 15, no. 4 (December): 752–778.

Lo, A.W. 1994. "Neural Networks and Other Nonparametric Techniques in Economics and Finance." In *Blending Quantitative and Traditional Equity Analysis*. Edited by H.R. Fogler. Charlottesville, VA: Association for Investment Management and Research.

Loughran, T., and B. McDonald. 2011. "When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks." *Journal of Finance*, vol. 66, no. 1 (February): 35–65.

Pound, J., and R. Zeckhauser. 1990. "Clearly Heard on the Street: The Effect of Takeover Rumors on Stock Prices." *Journal of Business*, vol. 63, no. 3 (July): 291–308.

Riordan, R., A. Storkenmaier, M. Wagener, and S.S. Zhang. 2013. "Public Information Arrival: Price Discovery and Liquidity in Electronic Limit Order Markets." *Journal of Banking & Finance*, vol. 37, no. 4 (April): 1148–1159.

Ro, S. 2012. "Art Cashin: We May Have Just Witnessed the Presence of Artificial Intelligence in the Stock Market." *Business Insider* (1 March): www.businessinsider.com/art-cashin-artificial-intelligence-stock-market-2012-3.

Simon, D., and R. Heimer. 2015. "Facebook Finance: How Social Interaction Propagates Active Investing." Federal Reserve Bank of Cleveland Working Paper 15-22 (October).

Sinha, N.R. 2016. "Underreaction to News in the US Stock Market." *Quarterly Journal of Finance*, vol. 6, no. 2 (June).

Tetlock, P.C. 2007. "Giving Content to Investor Sentiment: The Role of Media in the Stock Market." *Journal of Finance*, vol. 62, no. 3 (June): 1139–1168.

———. 2011. "All the News That's Fit to Reprint: Do Investors React to Stale Information?" *Review of Financial Studies*, vol. 24, no. 5 (May): 1481–1512.

Tetlock, P.C., M. Saar-Tsechansky, and S. Macskassy. 2008. "More than Words: Quantifying Language to Measure Firms' Fundamentals." *Journal of Finance*, vol. 63, no. 3 (June): 1437–1467.

Uhl, M.W., M. Pedersen, and O. Malitius. 2015. "What's in the News? Using News Sentiment Momentum for Tactical Asset Allocation." *Journal of Portfolio Management*, vol. 41, no. 2 (Winter): 100–112.

von Beschwitz, B., D.B. Keim, and M. Massa. 2013. "Media-Driven High Frequency Trading: Evidence from News Analytics." Working paper (October).