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Underreaction to News in the US Stock Market

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Using a score that quantifies the tone of news articles, I construct a weekly measure of qualitative information that predicts returns over the next 13 weeks. A portfolio long stocks with past positive tone and short stocks with past negative tone has an average return of 16.54 basis points per week (8.60% per year). The findings suggest the market underreacts to the content of news articles. The underreaction is not constrained to small stocks, low analyst-coverage stocks, low institutional ownership, or loser stocks. The findings also suggest the tone of news articles is different from sentiment which is assumed to have no permanent impact on stock prices.

Keywords: Information; news; momentum; sentiment; text analysis.

JEL Classification: G12, G14.

1. Introduction

News events appear to affect stock prices quickly, suggesting the market incorporates information quickly but few studies document the reaction of news articles on stock prices in a systematic manner. Only recently has quantifying the content of a large set of news articles become practical, allowing for the measurement of the reaction to positive and negative news over a long time period.[1] The speed of information absorption is an important

[1] Berry and Howe (1994), Mitchell and Mulherin (1994), and, more recently, Tetlock *et al.* (2008) are important papers that have undertaken comprehensive studies of how news is incorporated in stock prices. Whereas Berry and Howe (1994), and Mitchell and Mulherin (1994) study the arrival of news and its impact on volume, Tetlock *et al.* (2008) focus on how the textual information is incorporated into prices.

concern, because it is fundamentally related to market efficiency. I find the market takes 13 weeks (almost a quarter) to incorporate information from a news article after the story first appears. Past news predicts returns regardless of firm-size, book-to-market ratio, analyst coverage, and institutional ownership, and all weekly returns history except the loser stocks. From 2003 to 2010, a portfolio of large stocks exploiting the trading strategy generates an alpha of 24.81 basis points per week (12.9% per year) after controlling for the Fama–French three-factors and the momentum factor. The findings are consistent with the assertions of Grossman and Stiglitz (1980) and more recently Stein (2009) that the mere presence of a large number of institutional traders or information intermediaries does not make the market efficient. The findings also shed light on the nature of information in news articles. The tone of news articles could simply reflect sentiment about the stock which is considred non-informative or contain information. Tetlock (2007) points out that "The sentiment theory predicts short-horizon returns will be reversed in the long run, whereas the information theory predicts they will persist indefinitely." I observe that effect of news articles persist for 13 weeks, suggesting the tone of news articles contains information, not "sentiment".

I exploit a Thomson Reuters' firm-level measure of the tone of news articles, or "sentiment score."[2] The score is derived from the words and phrases the article uses to describe the firm, that is, the qualitative information. The score varies from 1 to −1, 1 being an article with an extremely positive tone. If the article mentions multiple firms, the score is specific to each firm based on the sentences that are specific to the firm. Any given week may have many news items for a firm. I obtain weekly average scores for each firm and call this score the weekly qualitative information (WQI) for a firm. If the US stock market incorporates this information quickly, these scores, which are based on the week's news, should not have any predictive ability. I examine a trading strategy based on WQI by taking a long position in stocks with past positive scores and a short position in stocks with past negative scores. The portfolio, which I label the "underreaction portfolio," is held for 13 weeks.

The underreaction portfolio return is highly correlated (over 70%) with a momentum portfolio return (the up-minus-down, UMD, factor), though the underreaction portfolio is profitable during the sample period and the

[2] The word "sentiment score" is similar to the usage in the computational linguistics literature where it refers to the emotive state of the author of an article. This use is different from the word "sentiment" in finance, where "sentiment" means the irrational reaction of investors, which over time dissipates.

momentum portfolio is not. The high correlation between these two portfolios suggests the slow absorption of news tone might explain some portion of momentum.[3] Jegadeesh and Titman (1993) suggest momentum could be a result of underreaction to information. Although other examples of slow incorporation of information by the financial markets exist, for example, post-earnings-announcement-drift (Ball and Brown, 1968), the accrual anomaly (Sloan, 1996), and the related industry information (Cohen and Frazzini, 2008) this study is one of the first to show the relationship between slow incorporation of tangible information and the momentum phenomenon.[4]

One of the puzzles in the momentum literature is that of short-term reversal.[5] A portfolio that takes a long position among the winners and a short position among the losers (the momentum portfolio) tends to have immediate negative returns. If momentum were driven by underreaction to information, the short-term reversal would suggest initial overreaction. The magnitude of short-term reversal is smaller than the momentum returns that ensue, however. Consequently, justifying the initial reversal as overreaction is hard. I find that no short-term reversal occurs in the news-based underreaction portfolio. Furthermore, I find that when the news affirms the direction of returns, continuation exists. Whenever the market reacts positively to a negative tone in news articles and negatively to a positive tone, short-term reversal tends to occur, although it is smaller in magnitude and statistically insignificant. In an average week, almost 90% of stocks in the winner–loser portfolio do not have any news; these stocks have the most pronounced reversal.

Figure 1 shows the cumulative return over 13 weeks for the weekly momentum portfolio as in Gutierrez and Kelley (2008) and the underreaction portfolio. In Week 0, the formation week, I partition stocks into deciles on the basis of WQI score, with the 10th decile containing stocks with the most positive tone. I construct the underreaction portfolio by taking an equally-weighted long position in stocks in the highest WQI decile and a short

[3] Jegadeesh and Titman (1993) document momentum, the profitable trading strategy of selling stocks with poor return in the past 3–12 months, and buying stocks with good return during the same time period.

[4] Jackson and Johnson (2006) connect momentum with underreaction to information by showing that excluding reaction to corporate events, the momentum effect almost disappears. Unlike Jackson and Johnson, I attempt to include information in all news articles rather than specific corporate events.

[5] Jegadeesh (1990) documents short-term reversal among US stocks. Gutierrez and Kelley (2008) show the reversal is present among weekly returns as well, though the magnitude is small relative to the 52-week continuation that follows the initial reversal.

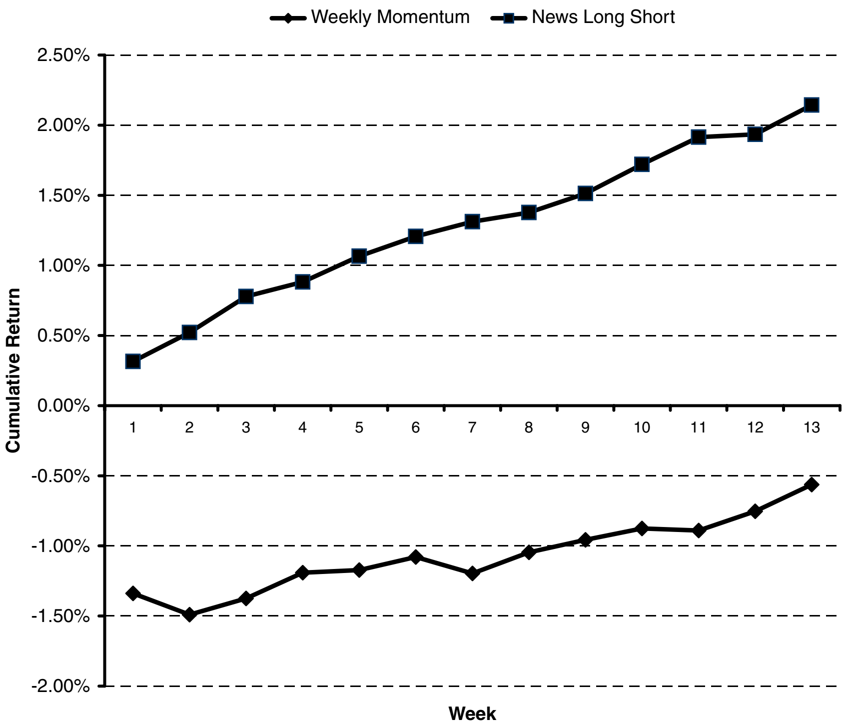

Fig. 1. Cumulative weekly return for underreaction and momentum portfolio following formation.

Note: This figure shows the cumulative weekly return for the 13 weeks following formation. The two lines indicate the news-based "underreaction portfolio" and the weekly momentum portfolio.

position in stocks with the lowest WQI decile. I construct the weekly momentum portfolio as in Gutierrez and Kelley (2008) by taking a long position among stocks with extremely positive returns in Week 0 and a short position among stocks with extremely negative returns in Week 0. The figure presents two important features of the underreaction to news. First, the underreaction portfolio has no return reversal, that is, negative returns in Weeks 1, 2, and 3. Second, the underreaction portfolio has positive returns over 13 weeks, whereas the weekly momentum portfolio has negative returns in the same time frame.[6]

To better understand the source of the predictive ability of the WQI, I examine two-way portfolio sorts. The two-way sorts create long-short portfolios by first sorting all stocks with news into quintiles on the basis of control

[6] The negative return for the momentum portfolio is consistent with Heston and Sadka (2008) and Novy-Marx (2012), who show momentum profits do not accumulate until six months after the formation.

characteristics such as size, analyst coverage, institutional holding, and various controls for momentum, and then by sorting within each quintile on the basis of WQI. These long-short portfolios have statistically and economically significant positive returns and alpha controlling for the Fama–French three-factors and the Carhart UMD factor.[7] The predictive ability of WQI suggests the US stock market underreacts to firm-specific news.

My findings on the impact of qualitative information on financial markets differ from prior research. I observe that the effect of the tone of news articles lasts 13 weeks, longer than the three days reported by Tetlock *et al.* (2008).[8] I also find the underreaction portfolio correlates with the UMD factor, unlike Tetlock *et al.* (2008), who report the returns from news-based trading are not strongly related to any of the Fama–French factors or the UMD factor. Therefore, I conclude the stock market is somewhat inefficient with respect to qualitative information. In particular, usual indicators of market efficiency, such as firm size, analyst coverage, and institutional holdings, do not seem to drive market efficiency with respect to qualitative information. This finding is in contrast to Tetlock *et al.* (2008), who note "the stock market is relatively efficient with respect to firms' hard-to-quantify fundamentals."

The observed underreaction is consistent with a model formalized by Kyle (1985), in which information is correctly processed by a strategic trader who understands her advantage and trades slowly over time. Unlike other examples of underreaction to information, the underreaction to news is even *more* pronounced among larger stocks. The prevalence of underreaction to news among large stocks seems consistent with models of a strategic investor because such models do not distinguish between large and small stocks. The evidence suggests behavioral biases that might lead to underreaction to information could be prevalent among large stocks and stocks with high institutional holdings as well.

Because interpreting results from higher-dimension portfolio sorts is difficult, I conduct a firm-specific regression in which I regress firm-specific returns on WQI while controlling for market, book-to-market ratio, size, previous-week returns, previous six-month returns and previous six month to 12 month returns. The WQI predicts future returns as proposed by Grossman and Stiglitz (1980).

[7] UMD is the return of a portfolio of stocks with high-past-twelve month returns, minus return on a portfolio of stocks with low past-twelve-month returns.

[8] Tetlock *et al.* (2008) also report the news coverage predicts earnings next quarter.

Extant literature shows two aspects of news are informative at the firm level: The amount of news and the tone of news.[9] Chan (2003), Fang and Peress (2009), and Akbas *et al.* (2008) have studied the effect of the amount of news on stock returns. However, they create long-short portfolios of stocks with news and no news at monthly intervals. Conditioning on news versus no news is unlikely to capture the information content of news, instead it focuses on absence of news or the presence of news. As I report here, firms with news are larger firms with an average market capitalization of almost $2 billion, whereas firms without news have an average market capitalization of $233 million. This paper focuses on the tone of news and continues the line of research pursued by Tetlock (2007), Tetlock *et al.* (2008), Engelberg (2009) and Demers and Vega (2008), all of which analyze the tone of news articles or press releases. However, some key differences exist between this paper and its precursors.

Prior research relied on dictionaries of positive and negative words to infer the tone of news articles.[10] For the first time, this intuitive dictionary-based approach allowed finance researchers to quantify the information embedded in text. The dictionary-based approach cannot, however, determine whether those positive words or negative words are referring specifically to the firm in question; this problem is particularly troublesome when an article mentions more than one firm. In this paper, the unit of textual analysis is a sentence rather than a word. The text-analysis engine used in this paper assigns each sentence to a specific firm. Using the sentence as a unit of analysis for the identification of firm-specific tone for multiple firms mentioned in the news story is important because over 30% of the news stories in my dataset mention more than one firm.

Previous research analyzed the content of firm press releases or articles from newspapers such as *The Wall Street Journal*. Firm press releases are written by the management of the firm, who may have a vested interest in controlling the message. Graham *et al.* (2005) surveyed more than 400 finance executives and find that almost one-third of respondents package bad news with other news. Such concerted effort by firms is likely to have an effect on the content of press releases. In these cases, the market reaction is a function of how well the firm crafts its press release rather than the information disclosed in the press release.

[9] At the aggregate level, Dzielinski and Hasseltoft (2013) show that if the monthly news tone from one firm to another is very different, there is greater trading volume, negative stock returns and increased realized volatility.

[10] Except Dzielinski and Hasseltoft (2013) who use the same dataset as this paper.

Newspapers have short-term pressures to cater to the whims of their potential customers as in Mullainathan and Shleifer (2005), a possible concern when using newspapers as a source of textual information. Information that newspaper editors deem marketable might not fully overlap with economically meaningful information. Newspapers also have space constraints; a story appears in the newspaper only if no other story out-competes it for scarce column inches. Therefore, all economically relevant information might not be included in the pages of the newspaper. Furthermore, Solomon (2012) shows firms can influence coverage of their events in newspapers through investor-relations professionals. Word choices in newspaper articles may reflect not just information about the firms operations, but also the skill of public relations staff in packaging the information. All these forces could make investors skeptical to the information content of news articles. This in turn could cause underreaction to news. Indeed the finding that underreaction to news is pronounced among larger stocks would also be consistent with the skepticism of investors, who simply dimiss the first few news articles as firm-motivated "spin."

In contrast to previous research, I use news articles from a wire service, which I believe has distinct advantages over newspaper articles or press releases. The content of newspaper articles are determined both by the importance of the news and the space available, whereas wire services have no space constraint. Also, wire services do not have the pressure to publish sensational headlines but rather must meet their customers' need for economically-relevant information.

The remainder of the paper is organized as follows. Section 2 describes the data used in the study. Section 3 provides the portfolio-based evidence for underreaction to WQI. Section 4 provides cross-sectional regression-based evidence regarding underreaction to qualitative information. Section 5 sums up the implications of the findings for various models of underreaction and concludes.

2. Data

I obtain the news data from the Thomson Reuters NewsScope dataset. Between 2003 and 2010, it consists of 9.4 million firm-specific news items (for over 15,000 firms globally) transmitted to institutional investors over Thomson Reuters' electronic terminals. The news items consist of "alerts," "articles," and "overwrites." "Alerts" are time-sensitive one line messages, whereas "articles" are more substantive commentary on the firm. "Overwrites" are messages that identify errors in the original message. "Overwrites" are relatively rare; 36,781 out of 9.4 million news items are "overwrites." "Alerts" constitute almost 30% of the dataset; 2.84 million news items are "alerts" and the rest are "articles."

Thomson Reuters NewsScope dataset provides firm-level tone information for all the firms mentioned in a news item. The tone-score is expressed through three probabilities, *Sent_Pos* (the probability of the article being positive), *Sent_Neg* (the probability of the article being negative), and *Sent_Neut* (the probability of the article being neutral). These three probabilities sum to 1. When a news item mentions more than one firm, Thomson Reuters provides relevance score for each firm named in the news. The relevance score ranges from 0 to 1, where the relevance value of 1 indicates the news item is highly relevant to the firm. Some news items repeat information from a previous article. The Thomson Reuters database contains "Lcnt" (link count), which conveys how many similar stories about the firm have appeared in the past 12 h, by comparing the text of all stories about the firm. If the "Lcnt" is a high number that indicates the story has been repeated often (due to new information or additions) in the past 12 h, similarly low "Lcnt" indicates a novel story.

The key difference between the text-processing engine and the popular dictionary-based method for analyzing text is that the text-processing engine analyzes an article at the sentence level rather than the word level.[11] Analyzing a document at the sentence level rather than the word level has at least three benefits. First, the sentence level analysis ensures the word is analyzed in its context. In the English language, a modifier (a negative, an adjective, or an adverb) alters the meaning of the word. Second, firms choose positive names, for example, "Best", a positive word in the Harvard IV dictionary. Every time the author uses the name of the firm "Best Buy", the word-based approach will count the name of the firm as a positive word. Finally, the Reuters sentence-based sentiment engine keeps track of the "subject" of the sentence. If the same story mentions multiple firms, each sentence is correctly attributed to the corresponding firm. Heston and Sinha (2013) compare the predictive ability of different techniques for text processing and find that the sentence-based tone measure has small positive correlation with financial dictionary based measure as well as non-financial Harvard IV dictionary measure. The two dictionary methods have negative correlation with each

[11] Loughran and McDonald (2011) provide a dictionary especially designed for text analysis of financial documents. They also analyze a document word by word.

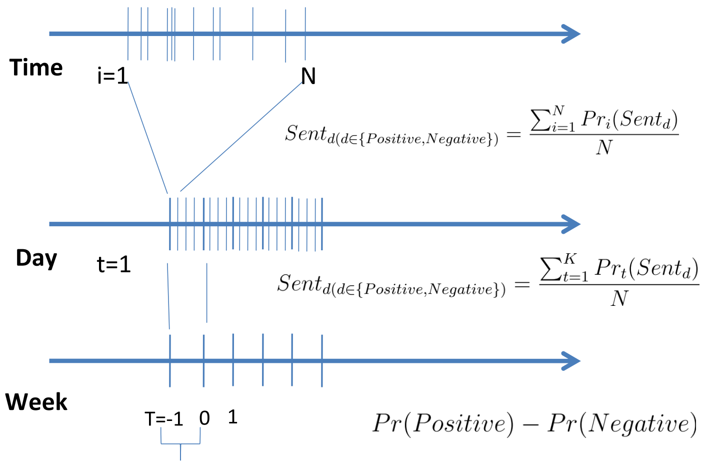

Fig. 2. Aggregation of news to obtain WQI.

Note: Each week, a WQI score is obtained by first averaging the document-specific tone scores (Sent_Pos and Sent_Neg) over each trading date to obtain a daily tone score (Sent_Pos and Sent_Neg). From the daily tone scores, a measure of WQI is obtained by taking the average of the difference of daily positive (Sent_Pos) and negative (Sent_Neg) tone scores.

other. They also show sentiment extracted from these different text-analysis methods seem to affect stock prices differently. Arguably the information content of these three tone methods are different from each other. I provide an example of text processing in Appendix A and more details of the text-processing engine in Appendix B. More details are also available in Infonic (2008).

I use the following fields for the construction of the sample: Reuters' instrument code (ticker and exchange); the probability of the article being positive, and the probability of the article being negative; the relevance of the article for the firm; "Item type," which indicates whether the item was an "article" or an "alert;" and "Lcnt," which indicates the novelty of the item. I retain news items that have relevance of at least 0.35 and link count less than 2.[12] Because "Alerts" contain only the headline, I drop them from my sample.

In Fig. 2, I show the averaging methodology to obtain the WQI score from individual stories about a firm. I map each news item to a trading day by assigning the news to the nearest trading day. If the news arrives after the markets are closed, I assign the news to the closest open date after the news

[12]For all the stories about the constituents in the S&P 500, I obtained the 50 min realized volatility and volume subsequent to the story being published and compared them to pre-event volatility and volume, respectively. I find that for stories below a relevance score of 0.30, volatility and volume change little, indicating that perhaps the market considered the stories to be non-events. I choose a conservative cutoff of 0.35 in admitting stories to my sample.

arrival. I obtain the daily firm-specific scores by averaging the tone scores (Sent_Pos and Sent_Neg) over all the news for a firm on a trading day. I construct the WQI score by taking the average of firm-specific daily scores over the previous week. At the weekly level as well as the daily level, the score Sent_Pos can be interpreted as the probability of the coverage being positive. Similarly, the score Sent_Neg can be interpreted as the probability of the coverage being negative. Because it is the difference between two probabilities, the WQI score is bounded between -1 and 1.

I choose weekly horizon for obtaining the qualitative information for two reasons. First, on any given day, most firms do not have any news. By aggregating over a longer time horizon, I ensure that more firms have a news item. Increasing the horizon over which the news is aggregated results in a trade-off. Whereas increasing the horizon increases the number of firms with some news items, I also lose the recency of the news articles. Second, I study the return at weekly intervals after news arrives. Gutierrez and Kelley (2008) note, "Using weekly returns to assess potential explanations of momentum affords researchers greater confidence in identifying the news that underlies the return," arguing in favor of studying stock returns at the weekly level. Indeed, because I use a weekly rather than monthly horizon for studying the return dynamics, I end up with 416 weeks of news data.

The sample of firms comprises of all US common stocks between 2003 and 2010. I obtain weekly returns using the daily Center for Research in Security Prices (CRSP) tapes provided through the Wharton Research Data Services (WRDS). I obtain weekly return as the cumulative sum of the daily log normal return from Wednesday close to Wednesday close. If the Wednesday was a trading holiday, I use the previous available day. WRDS also provided the Compustat accounting data, IBES analyst data, and SEC form 13F institutional-holding data. The book-to-market ratio is defined as book equity (BE) over market equity (ME).[13] I obtained the Fama–French three-factors as in Fama and French (1993) and the UMD factor from Ken French's website.[14]

My news sample consists of news on firms that are in the intersection of the WRDS-CRSP-Compustat database and Thomson Reuters news-sentiment database. I merge the two databases by the CUSIP of the firm at the year level. The merged sample has almost 1.79 million news articles over the entire sample

[13] BE is the book equity for all fiscal year-ends in the previous calendar year. BE is defined as Book equity = total assets − [total liabilities + preferred stock] + deferred taxes+ convertible debt ME is the market capitalization at the end of December of the previous year.

[14] I am grateful to Ken French for providing the Fama–French three-factors and the UMD factor on his website.

period. The number of stories increases over time and peaks in 2008. Appendix C provides the number of stories in each of the eight years of my sample. I record firms that do not have any news in the news sample as no-news firm.

Each week, by looking back at the previous 14 weeks in the IBES dataset, I obtain weekly analyst estimates, absolute dispersion in estimated earnings per share (EPS), and number of analysts covering the stock. If the same analyst issues two or more estimates within the previous 14 weeks, I retain the most recent estimate for the calculations. Analysts issue more updates around the time of the earnings report. Using a window of 14 weeks ensures any change in analyst opinion as a result of earnings announcement is incorporated in the weekly analyst estimate. I use the absolute dispersion in estimated EPS consistent with the evidence presented by Diether *et al.* (2002) and Payne and Thomas (2003). I obtain the institutional-holding data from the SEC form 13F filings. Each week, I record the institutional holding as holding reported on the closest reporting date prior to the week.

I consider a firm to be covered by Thomson Reuters NewsScope when I observe the first story above relevance of 0.35 regarding the firm in my dataset. Even when Thomson Reuters has a reporter covering the firm, I only consider a firm to be covered after I observe an article. Table 1 shows Thomson Reuters coverage aggregated at the end of each year of the sample. The largest size decile of the the sample covers over 90% of the firms of the Compustat-CRSP intersection during the sample period. For the smallest firms, the sample covers only 12% in the year 2003, though it covers 39% in 2004.[15] Thus, relative to the general population of US common stock, the news sample is biased toward larger firms.

Table 1 shows the distribution of Thomson Reuters coverage by the book-to-market (B/M) deciles and the past return deciles as well. For the largest B/M decile (value firms), only 34% of firms have any news in 2003, whereas in the smallest B/M decile (growth firms), 37% of the firms have some news. For the same period, fewer firms in the extreme past return deciles have coverage. In the year 2003, Deciles 1 and 10 have 35% and 44% of the firms with some news, respectively, whereas Decile 5 has 56% firms with some news.

Panel A of Table 2 shows average return, size (in million US dollars market capitalization as measured in the final week of the previous year), number of firms, institutional holding, number of days with news in a week, and the number of analysts covering the firm in the previous 14 weeks for firms with and

[15] As a robustness check, I dropped my entire sample for the year 2003. The results on underreaction are qualitatively similar.

Table 1. Percentage of firms with news coverage by Thomson Reuters by firm size, B/M ratio and past return.

Size Decile	2003(%)	2004(%)	2005(%)	2006(%)	2007(%)	2008(%)	2009(%)	2010(%)
1 (Small)	12	39	57	81	91	98	99	99
2	19	54	67	84	92	98	98	99
3	27	61	80	93	93	99	99	100
4	39	76	84	94	96	99	99	100
5	47	77	86	95	98	100	100	99
6	59	84	91	95	99	99	99	100
7	67	82	88	94	98	100	100	99
8	76	86	91	96	98	100	100	100
9	87	91	95	97	100	100	100	100
10 (large)	93	96	98	100	100	100	100	100
B/M decile								
1 (Growth)	34	53	60	72	75	86	81	57
2	68	73	83	92	93	98	98	96
3	64	79	87	93	97	98	100	98
4	61	80	85	93	97	97	99	97
5	55	80	88	96	98	99	100	98
6	54	80	86	94	96	97	100	99
7	49	78	84	94	95	99	100	99
8	46	72	83	93	97	99	99	98
9	43	67	81	90	97	98	99	99
10 (value)	37	63	73	89	94	98	98	98
Return decile								
1 (Loser)	35	55	72	82	90	96	95	90
2	55	69	79	89	92	97	97	92
3	54	72	81	91	96	98	97	94
4	60	72	84	90	95	98	98	96
5	56	76	79	91	97	99	99	95
6	53	80	87	94	95	98	98	95
7	51	79	83	94	93	99	98	95
8	55	76	84	92	89	98	99	96
9	49	73	84	94	98	92	98	96
10 (winner)	44	71	76	88	93	96	96	90
Total	4479	4273	4079	4043	3914	3822	3772	3594

Note: The table shows the percentage of CRSP-Compustat firms that are covered by Thomson Reuters NewsScope data. Each year the number of firms Thomson Reuters covers are expressed as a percentage of the total number of firms in each size decile. Decile 1 has the smallest firms, whereas Decile 10 has the largest firms. The middle panel shows coverage by book-to-market deciles, expressed as a percentage of the total number of firms in each book-to-market decile. Decile 1 has growth firms, whereas Decile 10 has value firms. The last panel shows coverage by past return decile, expressed as a percentage of the total number of firms in each past return decile. Decile 1 has firms with extremely negative returns in the previous 26 weeks, whereas Decile 10 has firms with extremely positive returns in the previous 26 weeks.

without news. Each week, firms that receive any news are classified as firms with news, whereas, firms that do not receive any news are classified as firms without news. I treat firms that are covered by Thomson Reuters, but did not receive any news, as no-news firms for the week. The first row contains the firm and investor characteristics for the firms with news, whereas the second row contains the firm and investor characteristics for firms without news. The table shows the firms with and without news do not have different returns from each other in the week of the news. Firms with news, however, are larger than firms without news. Firms with news have average market capitalization of almost \$2 billion, whereas, firms without news have market capitalization of \$864.4 million. Institutional investor holding is almost 54% for firms with news, but only 35% for firms without news. Firms with news received news on 1.6 days in a week. Firms with news have 14.3 analysts covering them in the previous 14 weeks, whereas only 4.8 analysts cover the firms without news. The average week has a 0.3 probability of the story being positive and a 0.27 probability of the story being negative. The difference between the two probabilities is small but statistically significant, indicating the average news coverage has a small but statistically significant tilt toward being positive.

Panel B of Table 2 shows that with an increasing WQI score, the contemporaneous return increases (from a -2.03% weekly return for Decile 1 to a 1.66% weekly return for Decile 10). WQI Decile 1 has a WQI of -0.67, whereas Decile 10 has a WQI of 0.70. The monotonic relationship between contemporaneous tone score and returns lends economic validity to the WQI score.[16] Average firm size is smaller at the extreme deciles of WQI. The market caps for WQI Deciles 1, 2, 9 and 10 are \$0.8 billion, \$1.7 billion, \$1.6 billion and \$1.2 billion, respectively, whereas caps for WQI Deciles 4, 5 and 6 are \$4.8 billion, \$3.4 billion and \$2.2 billion, respectively. Firms in the extreme WQI deciles have less analyst coverage compared to the firms in the middle WQI deciles. Similarly, institutional-holding for both Deciles 1, and 10 is 51%, whereas institutional holding for the WQI Decile 5 is 57%. Firms in the extreme WQI deciles get fewer days of news in a week than those in the middle.[17]

[16] The fact that the average probability of the article being positive (Sent_Pos) is increasing across groups and the average probability of the article being negative (Sent_Neg) is decreasing across deciles indicates that differencing the two probabilities does not lead to destruction of much information.

[17] Appendix D shows the average proportion of firms without any news in a week, days of news in a week for firms that get any news, the probability of the news being positive, and the probability of the news being negative across size, B/M ratio, and previous six-month return deciles.

Table 2. Summary statistics by news coverage across WQI.

News/No News	Return	Size	# Firms	Ins. Holding	News Days	# of Analysts	Sent_Pos	Sent_Neg
Panel A: Summary statistics across firms with and without news in a given week								
News	0.00%	2050	864.4	54%	1.6	14.3	0.30	0.27
	(0.167%)	(42.4)	(16.12)	(0.2%)	(0.01)	(0.10)	(0.002)	(0.003)
No news	−0.09%	233	3746.6	35%		4.8		
	(0.132%)	(4.1)	(24.45)	(0.1%)		(0.07)		
Panel B: Summary statistics across WQI decile								
1	−2.03%	801	86.0	51%	1.2	11.0	0.08	0.75
	(0.202%)	(27.6)	(1.61)	(0.4%)	(0.01)	(0.14)	(0.001)	(0.003)
2	−1.75%	1703	87.1	54%	1.7	14.6	0.16	0.54
	(0.203%)	(67.5)	(1.63)	(0.3%)	(0.02)	(0.19)	(0.002)	(0.007)
3	−0.97%	3510	87.2	58%	2.0	17.3	0.20	0.39
	(0.187%)	(117.6)	(1.63)	(0.2%)	(0.02)	(0.17)	(0.001)	(0.007)
4	−0.27%	4865	88.2	60%	2.0	17.9	0.20	0.27
	(0.175%)	(130.9)	(1.74)	(0.2%)	(0.02)	(0.16)	(0.002)	(0.006)
5	0.04%	3413	87.1	57%	1.8	16.2	0.19	0.18
	(0.168%)	(95.8)	(1.68)	(0.3%)	(0.02)	(0.17)	(0.003)	(0.005)
6	0.31%	2187	87.0	53%	1.7	14.4	0.23	0.16
	(0.168%)	(61.8)	(1.78)	(0.3%)	(0.02)	(0.16)	(0.004)	(0.003)
7	0.48%	1886	88.6	52%	1.7	13.9	0.30	0.15
	(0.167%)	(62.0)	(1.90)	(0.4%)	(0.01)	(0.15)	(0.004)	(0.003)
8	0.99%	1949	82.6	53%	1.6	14.0	0.40	0.13
	(0.165%)	(55.9)	(1.66)	(0.3%)	(0.01)	(0.14)	(0.005)	(0.002)
9	1.59%	1643	86.1	53%	1.5	12.7	0.53	0.10
	(0.163%)	(48.6)	(1.62)	(0.4%)	(0.01)	(0.12)	(0.004)	(0.001)
10	1.66%	1169	85.9	51%	1.2	10.9	0.75	0.05
	(0.159%)	(33.9)	(1.60)	(0.4%)	(0.00)	(0.11)	(0.003)	(0.000)

Note: This table shows the average return, market capitalization (in million USD), number of firms, institutional holding, number of trading days in a week with news stories, number of analysts who have expressed an opinion on the stock in the last 14 weeks, the probability of an average article being positive (Sent_Pos), and the probability of an average article being negative (Sent_Neg). It also shows standard errors for each of these variables. Panel A shows these statistics for firms with news (No News = 0) and firms without news in a given week (No News = 1). The panel shows these statistics for each WQI decile. The difference between the weekly Sent_Pos and Sent_Neg provides the WQI score.

3. Portfolio-Based Evidence

Table 3 shows the stock returns corresponding to news at a weekly interval. Each week, stocks with news are divided into 10 deciles based on the tone of the news in the week. Decile 1 contains stocks with extremely negative news in the initial week, whereas Decile 10 contains stocks with extremely positive news. I label the contemporaneous week as Week 0. Week 0 return is the contemporaneous return to the news. From weekly observations, I cannot ascertain whether the news is a reaction to the return of the stock or the stock is reacting to the news. Return contemporaneous to extremely positive news is positive, however. Similarly, return contemporaneous to extremely negative news is negative. The relationship between contemporaneous news and return is monotonic. Extremely positive news corresponds to a 1.68% weekly return, whereas extremely negative news corresponds to a −2.07% weekly return.[18]

Rows 3, 5, and 7 show the return for each one of the WQI categories for weeks 1, 2, and 3, respectively. Unlike the row 1, here I observe the stock return *after* the news and hence can infer stock return as reaction to the news. One week after the news, the stocks that received extremely positive news continue to have positive returns. Similarly, stocks that received extremely negative news continue to have negative returns. None of the returns are statistically different from zero. Returns for weeks 1, 2, and 3 for extremely negative news are negative, and they are consistently so for the next 52 weeks. Similarly, returns for weeks 1, 2 and 3 corresponding to extremely positive news are positive. As a result of this salience in returns following positive (negative) news, the long-short portfolio continues to have positive return over the next 52 weeks. The last row shows the average returns for the interval between weeks 1 and 52 for each of the WQI categories. By week 52, the extremely positive news portfolio's returns are not different from zero, whereas the extremely negative news portfolio's returns are significantly different from zero (and are negative). A long-short portfolio has significant positive returns but they are primarily driven by the extremely negative news portfolio. This observation provides support for the "bad news travels slowly" hypothesis proposed by Hong *et al.* (2000).

The second panel shows the return for each of the WQI deciles for 13-week intervals, starting from week 1. The first row shows the average weekly return

[18] Compared to the weekly returns, the returns corresponding to extreme news are less pronounced. If I sort stocks on the basis of weekly returns, rather than WQI, I find the extremely positive returns are almost 12%, whereas extremely negative returns are −12%.

Table 3. Weekly returns following observed news.

	1	2	3	4	5	6	7	8	9	10
Panel A: Reaction to news in weeks 0–52										
Week 0	−2.07%	−1.69%	−0.93%	−0.22%	0.06%	0.30%	0.54%	1.03%	1.62%	1.68%
	(0.20%)	(0.20%)	(0.19%)	(0.17%)	(0.17%)	(0.17%)	(0.16%)	(0.17%)	(0.16%)	(0.16%)
Week 1	−0.20%	−0.16%	−0.04%	−0.01%	0.00%	0.06%	0.02%	0.07%	0.06%	0.12%
	(0.19%)	(0.18%)	(0.17%)	(0.17%)	(0.16%)	(0.16%)	(0.15%)	(0.15%)	(0.15%)	(0.16%)
Week 2	−0.14%	−0.03%	0.03%	0.08%	0.03%	0.01%	−0.03%	0.07%	0.03%	0.06%
	(0.19%)	(0.18%)	(0.18%)	(0.17%)	(0.16%)	(0.16%)	(0.15%)	(0.15%)	(0.15%)	(0.15%)
Week 3	−0.20%	−0.06%	0.00%	0.01%	0.00%	0.07%	0.11%	0.17%	0.03%	0.05%
	(0.19%)	(0.18%)	(0.17%)	(0.17%)	(0.16%)	(0.16%)	(0.15%)	(0.15%)	(0.15%)	(0.15%)
Weeks 4–52	−0.12%	−0.08%	−0.03%	7.63E−05	−0.03%	−0.02%	−0.02%	−0.02%	−0.03%	−0.03%
	(0.03%)	(0.03%)	(0.02%)	(0.02%)	(0.02%)	(0.02%)	(0.02%)	(0.02%)	(0.02%)	(0.02%)
Weeks 1–52	−0.12%	−0.08%	−0.03%	0.01%	−0.03%	−0.02%	−0.02%	−0.02%	−0.03%	−0.02%
	(0.03%)	(0.03%)	(0.02%)	(0.02%)	(0.02%)	(0.02%)	(0.02%)	(0.02%)	(0.02%)	(0.02%)
Panel B: Reaction to news aggregated by 13 weeks										
Weeks 1–13	−0.11%	−0.02%	0.05%	0.07%	0.04%	0.03%	0.03%	0.08%	0.04%	0.06%
	(0.05%)	(0.05%)	(0.05%)	(0.05%)	(0.05%)	(0.04%)	(0.04%)	(0.04%)	(0.04%)	(0.04%)
Weeks 14–26	−0.08%	−0.06%	0.00%	0.03%	0.00%	0.00%	0.01%	0.01%	0.00%	0.01%
	(0.05%)	(0.05%)	(0.05%)	(0.05%)	(0.04%)	(0.04%)	(0.04%)	(0.04%)	(0.04%)	(0.04%)
Weeks 27–39	−0.11%	−0.11%	−0.07%	−0.01%	−0.05%	−0.03%	−0.04%	−0.05%	−0.05%	−0.07%
	(0.05%)	(0.05%)	(0.05%)	(0.04%)	(0.04%)	(0.04%)	(0.04%)	(0.04%)	(0.04%)	(0.04%)
Weeks 40–52	−0.17%	−0.13%	−0.10%	−0.05%	−0.08%	−0.09%	−0.07%	−0.10%	−0.09%	−0.09%
	(0.05%)	(0.05%)	(0.05%)	(0.05%)	(0.05%)	(0.05%)	(0.04%)	(0.05%)	(0.05%)	(0.05%)

Note: This table shows contemporaneous returns (week 0) as well as returns in the weeks following news. Each of the columns corresponds to observations in a particular news decile. Each week all the stocks with news are sorted on the basis of the WQI. Decile 1 corresponds to stocks with most negative WQI in week 0, whereas Decile 10 corresponds to stocks with the most positive WQI. Each row reports the average return from an equally weighted portfolio. Standard errors are reported in parentheses.

for holdings in each WQI decile for the first 13 weeks. Extremely positive news results in positive returns, whereas extremely negative news results in statistically significant negative returns. For the weeks beyond week 13, the positive WQI portfolio returns are not statistically different from zero, whereas the negative news portfolio continues to have negative returns for the entire 52-week time period. This panel is also consistent with the "bad news travels slowly" hypothesis.

The market reacts to positive news for almost 13 weeks (a quarter) and to negative news for almost 52 weeks (almost a year). In this paper, because I focus on the underreaction to news in general in the US stock market, rather than the differential reaction to positive and negative news, I construct portfolios with holding periods up to 13 weeks after the news arrival. I study the 13-week underreaction using a long-short portfolio that takes a long position in stocks that had positive news in the past 13 weeks, but takes a short position in stocks that had negative news in the past 13 weeks. I label this long-short portfolio the underreaction portfolio. This portfolio will have on average a positive return if the stock market incorporates tone information slowly into prices.

Table 4 shows the long-short portfolio has positive returns in each of the 13 weeks after formation. Weeks 1, 2, 3, 5, 10, 11, and 13 have statistically significant positive returns. Since they are spread out over the entire time period, I do not suspect that the WQI long-short portfolio returns are concentrated near the portfolio formation week, week 0. Figure 3 shows the performance of the underreaction portfolio over the sample period. Starting with \$0 in the first week of 2003, the underreaction portfolio ends up with almost 73 cents by the year end of 2010; by comparison, the market portfolio in excess of the risk-free rate ends up with 52 cents. Since my dataset period contains data from the financial crisis, as a robustness test, I drop all the samples from the financial crisis. The results, tabulated in Appendix F, are qualitatively similar.[19]

Figure 4 shows the performance of the underreaction portfolio on the same graph as that of the UMD portfolio. Visually, the two portfolios appear to be highly correlated over time; the performance, however, is different. The underreaction portfolio ends up with 73 cents by the end of 2010, whereas the UMD portfolio loses 29 cents.

[19] I define the financial crisis as the period between 15 September 2008 and 30 June 2009. 15 September 2008 corresponds to the failure of Lehman Brothers, whereas 30 June 2009 is the date when NBER considered US economy out of the recession induced by the financial crisis.

Table 4. Weekly returns following observed news weeks 1–13.

Week	Long Portfolio	Short Portfolio	Long–Short Portfolio	
0	1.68% (0.16%)	−2.07% (0.20%)	3.75% (0.10%)	37
1	0.12% (0.16%)	−0.20% (0.19%)	0.32% (0.08%)	3.9
2	0.06% (0.15%)	−0.14% (0.19%)	0.20% (0.08%)	2.6
3	0.05% (0.15%)	−0.20% (0.19%)	0.26% (0.07%)	3.6
4	−0.03% (0.15%)	−0.13% (0.19%)	0.10% (0.07%)	1.4
5	0.02% (0.16%)	−0.16% (0.19%)	0.19% (0.07%)	2.6
6	0.00% (0.15%)	−0.14% (0.18%)	0.14% (0.07%)	1.9
7	0.06% (0.15%)	−0.05% (0.18%)	0.11% (0.07%)	1.5
8	0.05% (0.16%)	−0.03% (0.18%)	0.08% (0.07%)	1.2
9	0.11% (0.16%)	−0.02% (0.19%)	0.12% (0.08%)	1.6
10	0.00% (0.15%)	−0.21% (0.19%)	0.21% (0.07%)	2.8
11	0.11% (0.16%)	−0.09% (0.18%)	0.20% (0.07%)	2.9
12	0.08% (0.15%)	0.06% (0.18%)	0.01% (0.07%)	0.2
13	0.09% (0.16%)	−0.12% (0.19%)	0.21% (0.08%)	2.6

Note: This table shows contemporaneous returns (week 0) as well as returns in the weeks following news. The second column corresponds to return to stocks with most positive WQI. The third column corresponds to return to stocks with most negative WQI. Fourth row presents the return to a long-short portfolio that takes a long position in WQI decile 10 and a short position in WQI decile 1. Each row reports the average return from an equally weighted portfolio. Standard errors are reported in parentheses. Final column presents the t-statistics for the long-short portfolio.

The underreaction portfolio has almost a 70% correlation with the Carhart UMD portfolio, the value-weighted portfolio of stocks that is long stocks with extremely positive returns and short stocks with extremely negative returns. Unlike the UMD portfolio, the underreaction portfolio has positive returns during the time period of the study. During the sample period, the long-short underreaction portfolio generated almost 16.5 basis points per week, whereas a value-weighed portfolio that is long stocks with extreme positive return and short stocks with extreme negative return (the UMD portfolio) generated an average return of −7 basis points.

Table 5 shows the average abnormal return over the 13 weeks following formation of the underreaction portfolio. I construct the underreaction portfolio by first sorting all stocks in a given week on the basis of the WQI. I take a long position in the stocks in Decile 10 (highest WQI decile) and a short position in the stocks in Decile 1 (lowest WQI decile). I hold the long-short position for the next 13 weeks. Thus, each week the portfolio has 13 cohorts, with each cohort corresponding to its week of formation. Each week, I drop one cohort (the one that has been in the portfolio for the past 13 weeks)

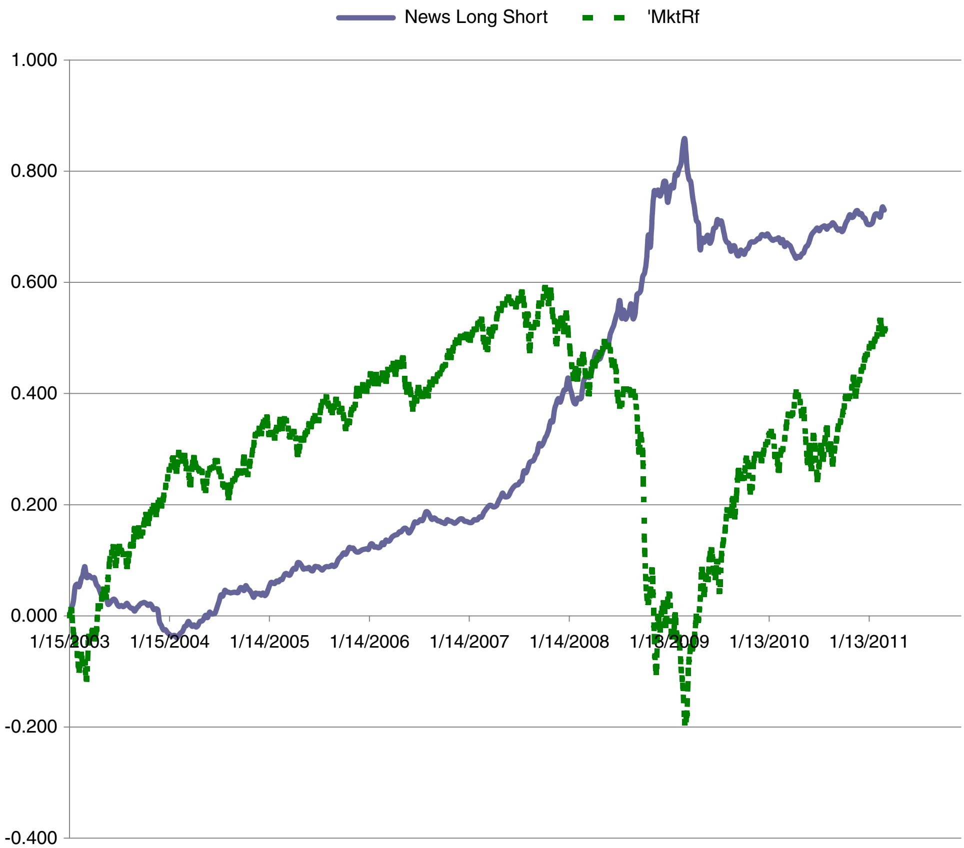

Fig. 3. Performance of long-short tone-based trading strategy over time.

Note: The blue solid line in the figure shows the performance of the long–short WQI portfolio during the sample period. The portfolio begins with zero dollars and ends with 73 cents. The green broken line shows market return in excess of the risk-free return portfolio, which ends with 52 cents.

and add a new cohort (the one corresponding to the most recent week). The return for the underreaction portfolio is the average return of these 13 cohorts.[20] The average return of the underreaction portfolio during my sample period is 16.49 basis points per week. I obtain the alphas in excess of various risk factors by regressing the underreaction portfolio return over the the Fama–French three-factors and the UMD portfolio. During the sample period, the alpha of the underreaction portfolio in excess of the market return is 19.05 basis points per week, 20.37 basis points in excess of the Fama–French three-factors, and 21.23 basis points in excess of the Fama–French

[20] The underreaction portfolio is a calendar-time portfolio, advocated by Fama (1998) and Mitchell and Stafford (2000).

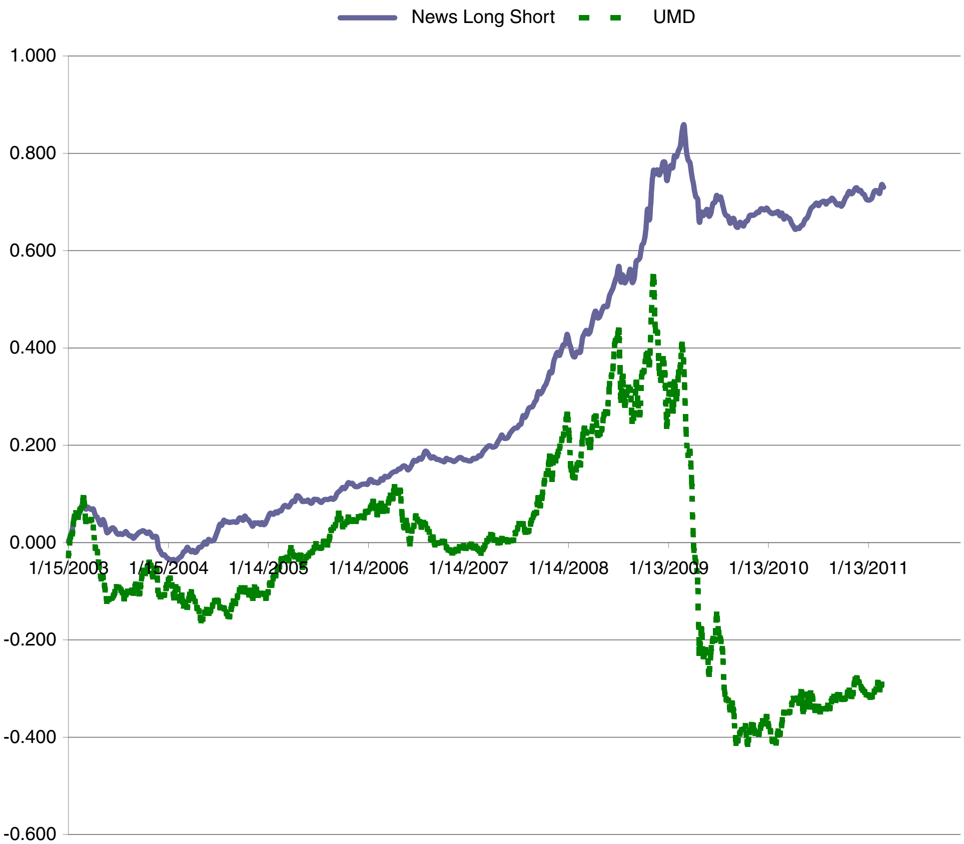

Fig. 4. Comparison of long–short tone-based trading strategy with the UMD factor over time.
Note: The blue solid line in the figure shows the performance of the long–short WQI portfolio during the sample period. The portfolio begins with zero dollars and ends with 73 cents. The green broken line shows the performance of the UMD portfolio, which ends with −29 cents.

three-factors and the Carhart UMD factor. Table 5 also shows the average return for a value-weighted underreaction portfolio. The value-weighted returns are statistically significant, albeit smaller than the equally-weighted returns. Excluding the data points from the financial crisis provides numerically higher return on the WQI portfolio, though the results are not materially different.

3.1. *Short-term reversal and news*

As Gutierrez and Kelley (2008) note, short-term reversal remains a puzzle in the momentum literature. Stocks with extremely positive weekly (or monthly) returns usually have statistically significant negative returns in the

Table 5. Alpha of underreaction portfolio.

	Period	Return	CAPM Adjusted	FF 3 Factors	Carhart 4 Factors
Decile 10-Decile 1 (EW)	2003–2010	16.49***	19.05***	20.37***	21.23***
		(2.05)	(1.95)	(1.90)	(1.75)
	Ex. Fin. Crisis	18.09***	19.75***	21.44***	18.72***
		(1.86)	(1.82)	(1.80)	(1.68)
Decile 10-Decile 1(VW)	2003–2010	8.58***	10.34***	11.11***	11.76***
		(2.49)	(2.45)	(2.44)	(2.36)
	Ex. Fin. Crisis	10.48***	11.35***	11.70***	9.48***
		(2.36)	(2.35)	(2.35)	(2.30)

Note: The table shows the weekly average excess return (in basis points) for the underreaction portfolio when adjusted for various controls. Each week, the underreaction portfolio takes a long position in stocks in Decile 10 (extremely positive WQI) and a short position in stocks in Decile 1 (extremely negative WQI). The long-short position is held for 13 weeks. Correspondingly, each week has 13 cohorts corresponding to a long–short position from each week of qualitative information. The return for the underreaction portfolio is the average return of these 13 cohorts. I have 418 weekly observations. Row 1 contains the alpha for the equally-weighted portfolio. Standard errors are in parentheses. Row 3 contains the alpha for a value-weighted portfolio where the weight is the market capitalization of the firm in June of the previous year. The alphas are calculated by regressing the weekly underreaction portfolio return on the weekly Fama–French three-factors and the UMD factor. Column 2 contains the alpha in excess of the market return (Mkt_Rf). Column 3 contains the alpha in excess of the Fama–French three-factors. Column 4 contains the alpha in excess of the Fama–French three-factors and the UMD factor.
***: 1%, **: 5%, *: 10%.

next few weeks (or months). Similarly, stocks with extreme negative returns usually have positive returns immediately thereafter. Explaining the momentum phenomenon as underreaction to information is difficult, because before the momentum strategy is profitable, stocks undergo reversal. I explain short-term reversal by examining information inferred from returns and news separately. In an efficient market, prices reflect all the available information. I argue that returns approximate information when the markets are efficient, but without market efficiency, returns are a poor proxy for information. In such an environment, observing information separate from returns is the key to understanding underreaction. I find that if concordant information exists, that is, when returns occur with information that matches return direction, no reversal occurs. In the short term, significant continuation occurs instead. Short-term reversal occurs when discordant information is present; returns are not accompanied by information that matches the return direction.

Table 6. Short-term reversal and news.

	Average Return	Market	FF 3	FF 3+ UMD
Weekly return momentum	−27.8	−26.0	−26.0	−25.8
	(4.34)	(4.14)	(4.14)	(4.10)
No-news	−36.1	−34.6	−34.7	−34.5
	(4.22)	(4.07)	(4.07)	(4.04)
Concordant	19.1	23.9	25.5	26.7
	(7.02)	(6.41)	(6.21)	(5.85)
Discordant	−5.3	−5.3	−4.7	−5.0
	(6.52)	(6.52)	(6.52)	(6.51)

Note: Each row of the table shows the weekly average excess return (in basis points) of different portfolios held for three weeks starting the week of formation. Standard errors are in parentheses. The three weeks after formation corresponds to the period during which the short-term reversal is pronounced for the weekly momentum effect. Column 1 provides the weekly average return over three weeks from the week of formation. Column 2 provides the alpha when controlled for market return (Mkt_Rf). Column 3 shows the alpha when controlled for the Fama–French three-factors. Column 4 presents the alpha in excess of the the Fama–French three-factors and the UMD factor. I construct the weekly momentum portfolio by sorting all the stocks on the basis of weekly return. I take a long position in the stocks of quintile 5 (extremely positive return) and a short position in the stocks of quintile 1 (extremely negative return). I hold the long-short portfolio for three weeks. I obtain the no-news portfolio by retaining the weekly momentum portfolio's position only among stocks without news in week 0. I create the concordant weekly momentum portfolio by only retaining a long position in the weekly momentum portfolio if the stock received positive news (denoted by WQI in quintiles 4 and 5) and retaining a short position if the stock received negative news (denoted by WQI in quintiles 1 and 2). The discordant weekly momentum portfolio retains a long position in the weekly momentum portfolio if the stock received negative news, and retains a short position if the stock received positive news.

The literature attempts to incorporate the distinction between information and return by recognizing implicit and explicit news (Chan, 2003). Extreme returns (positive or negative) in the absence of a news event is implicit news. A news event is explicit news. The accuracy of this categorization, implicit versus explicit news, depends on the completeness of the researcher's news dataset. News databases vary in their completeness in their coverage of firms as well as the type of events they cover. The difference in completeness of news databases means that although inference regarding explicit news is possible, one can only provide conjectures regarding implicit news.

Table 6 presents the short-term (three-week) average return for four different portfolios. First, I construct the weekly momentum portfolio by sorting all the stocks on the basis of weekly return. I take a long position in the stocks of quintile 5 (extremely positive return) and a short position in stocks of quintile 1 (extremely negative return). I hold the long-short portfolio for three weeks. Similar to extant empirical evidence, I observe negative average return as well as alpha over the three weeks following formation for the weekly momentum portfolio. The weekly momentum portfolio has an average return of −27.8 basis points per week and the Fama–French three-factor weekly alpha of −26 basis points (−13.52% annually). I then present the reversal in the no-news portfolio. I create this portfolio by first sorting the stocks on the basis of previous-week return. Within return-quintiles 1 and 5, I isolate the stocks that did not receive any news in the week of extreme return, and take a long position among stocks in quintile 5 and a short position among stocks in quintile 1. The no-news weekly momentum portfolio has an average weekly return of −36.1 basis points over the next three weeks. Though the average reversal in the simple weekly momentum strategy appears to be smaller than the reversal in the no-news weekly momentum strategy, the difference is not statistically different.

I create the concordant weekly momentum portfolio by retaining a long position in the weekly momentum portfolio only if the stock received positive news (denoted by WQI in quintiles 4 and 5) and retaining a short position only if the stock received negative news (denoted by WQI in quintiles 1 and 2). The average return of the concordant weekly momentum portfolio is 19.1 basis points (Fama–French three-factor alpha is 25.5 basis points per week). The difference between the average return of the concordant portfolio and the no-news portfolio is 55.2 basis points per week and is statistically significant. Finally, I present the average return over the next three weeks for a "discordant" weekly momentum portfolio. I create this portfolio by retaining a long position in the weekly momentum portfolio only if the stock received negative news and retaining a short position only if the stock received positive news. The discordant portfolio has an average weekly return of −5.3 basis points (statistically not different from 0). The difference between average return of the concordant and discordant weekly momentum portfolios is 24.4 basis points, which is both economically and statistically different from zero, though it is primarily driven by the concordant portfolio.

To summarize, the concordant portfolio shows continuation after formation, the discordant portfolio has zero return, and the no-news portfolio shows short-term reversal. The results presented in Table 6 are different from Table V of Gutierrez and Kelley (2008), where they note (emphasis mine), "Implicit-news stocks and explicit-news stocks display the *same* general behaviors, namely, short-run reversal and longer-run momentum." I find the market underreacts to explicit news as measured by the WQI. Although the difference between the concordant and the no-news portfolio supports the implicit versus explicit news hypothesis proposed by both Hong *et al.* (2000) and Daniel *et al.* (1998), the difference between the concordant and discordant portfolios suggests an alternate mechanism is at work.

3.2. *Underreaction to news and measures of investor attention*

Hong *et al.* (2000) suggests underreaction to news is more pronounced among small stocks, stocks with less analyst coverage, and perhaps stocks with lower institutional holdings. Lower underreaction among large stocks would be consistent with rational models of underreaction, such as Peng and Xiong (2006) and Nieuwerburgh and Veldkamp (2010), that model attention as a scarce resource. Investors must allocate their scarce attention among stocks in their portfolios and will allocate more attention to stocks that matter more to their portfolios, such as large stocks.[21] Lower underreaction among large stocks would also be consistent with behavioral models such as Hong and Stein (1999) and Daniel *et al.* (1998). Such models have behaviorally-impaired agents who in turn do not react to news rationally, leading to positive autocorrelation in returns following public news. Because the behaviorally impaired-agents are more likely to be marginal investors among small stocks, the resulting underreaction is higher among small stocks and stocks with lower analyst coverage. Given the emphasis on the size of the firm, analyst coverage, and perhaps institutional ownership in the models of underreaction, I examine the effect of firm size, analyst coverage, and institutional holdings on the underreaction to news.

To explore the effect of the measures of investor attention on the underreaction portfolio, I construct quintiles for all stocks by firm size, analyst coverage, and institutional holding. Within each control-variable quintile, I sort stocks according to the WQI score. I construct the underreaction portfolio by taking a long position in stocks in Decile 10 (highest WQI score) and a short position in stocks in Decile 1 (lowest WQI score). I end up with five long-short or underreaction portfolios. The first column of Table 7 presents the average return for the underreaction portfolios. The other columns present the alpha when controlled for market return in excess of the risk-free return, the Fama–French three-factors, and the Fama–French three-factors and the UMD factor.

[21] A related class of models, such as Barbosa (2011), suggest public information has private interpretation, and propose higher underreaction for information with more uncertainty. Barbosa (2011) also posits higher underreaction among stocks with lesser analyst coverage.

Table 7. Long-short qualitative information portfolio within size, analyst coverage, and institutional holding quintiles.

Control Quintile	Average Return	Market Adjusted	FF 3 Factor Adjusted	FF 3 Factor Plus UMD Adjusted
Panel A: Underreaction portfolio across size quintiles				
1 (Small)	5.8 (2.05)	9.5 (2.00)	7.3 (1.99)	8.2 (1.96)
2	13.9 (1.72)	14.3 (1.72)	12.2 (1.70)	12.9 (1.67)
3	16.4 (1.59)	18.1 (1.58)	18.7 (1.57)	19.5 (1.54)
4	16.5 (1.63)	20.0 (1.58)	23.1 (1.55)	24.0 (1.49)
5 (Large)	13.3 (1.72)	18.5 (1.61)	23.8 (1.52)	24.8 (1.46)
Panel B: Underreaction portfolio across analyst-coverage quintiles				
1 (Low coverage)	7.6 (1.89)	12.9 (1.79)	13.0 (1.78)	14.1 (1.73)
2	17.1 (1.68)	19.5 (1.66)	19.4 (1.65)	20.3 (1.60)
3	14.6 (1.59)	16.9 (1.57)	17.7 (1.56)	18.5 (1.53)
4	19.9 (1.62)	21.8 (1.61)	24.4 (1.58)	25.2 (1.54)
5 (High coverage)	15.5 (1.67)	16.6 (1.66)	20.3 (1.62)	21.2 (1.58)
Panel C: Underreaction portfolio across institutional-holding (IH) quintiles				
1 (Low IH)	4.9 (1.89)	8.7 (1.83)	9.0 (1.83)	10.1 (1.78)
2	16.5 (1.70)	19.1 (1.67)	20.3 (1.66)	21.1 (1.62)
3	19.5 (1.62)	22.4 (1.59)	24.0 (1.58)	24.9 (1.54)
4	22.7 (1.61)	25.0 (1.59)	27.1 (1.57)	27.9 (1.53)
5 (High IH)	12.9 (1.60)	14.5 (1.59)	16.3 (1.57)	16.9 (1.54)

Note: This table shows the alpha, and standard error from long-short equally weighted WQI portfolio returns with in size, analyst coverage and institutional-holding quintiles. For each one of the controls — size, analyst coverage and institutional holding — I first sort the stocks in five quintiles on the basis of the control variable. Within each control quintile, I sort all the stocks on the basis of the WQI and take a long position in stocks in decile 10 and a short position in stocks in decile 1. The portfolios are held for 13 weeks, with each week having 13 cohorts. The returns are calculated by averaging over these cohorts each week. Panel A shows the alphas in size quintile, quintile 1 has the smallest firms. Panel B shows the alphas in analyst coverage quintiles. Quintile 1 has firms with least analyst coverage. Panel C shows the alphas in institutional holding quintiles. Quintile 1 has stocks with least institutional holding. All returns are significant at 1% level.

The underreaction portfolio generates 5.8 basis points per week among the smallest stocks in the sample, whereas it yields 13.3 basis points per week among the largest stocks in the sample (Panel A). The returns are positive as I move down the size quintiles, as Quintiles 2, 3, and 4 generate 13.9, 16.4, and 16.5 basis points per week, respectively. Unlike the predictions of theoretical models of underreaction to information, the average return of the underreaction portfolio is higher among the largest firms than among the smallest firms. Returns for the five underreaction portfolios remain positive and the largest firms generate higher alpha than the smallest firms even after controlling for market (column 2), the Fama–French three-factors (column 3), and the Fama–French three-factors and the Carhart UMD (column 4). I do find, that the alpha among largest stock is somewhat smaller than among immediately smaller stocks.

The average return from the underreaction portfolio in the lowest analyst-coverage quintile is 7.6 basis points per week, compared to 15.5 basis points per week in the highest analyst-coverage quintile (Panel B). Controlling for the Fama–French three-factors and the Carhart UMD provides a qualitatively similar observation; the alpha of the underreaction portfolio is 14.1 basis points per week among the stocks with the least analyst coverage and 21.2 basis points per week among the stocks with the highest analyst coverage. Similar to the size quintiles, the alpha that the underreaction portfolio generates among firms with the most analyst coverage is larger than the alpha from the firms with the least analyst coverage.

Across institutional-holding quintiles, the lowest alpha from the news-based trading strategy is among the stocks with fewest institutional holding (Panel C). The underreaction portfolio generates alpha of 4.9 basis points per week among the stocks with fewest institutional holding, compared to 12.9 basis points among stocks with the most institutional holdings, a statistically significant difference. I do find that stocks with the highest institutional holding, have somewhat less underreaction than stocks with immediately lower institutional holding.

The underreaction is present in all firm size, analyst coverage, and institutional-holding quintiles. In all three panels, the average return as well as alphas (average return controlled for cross-sectional factors) of the underreaction portfolio are positive. The evidence across three different measures of investor attention, firm size, analyst coverage, and institutional holding shows the underreaction is not concentrated among neglected stocks. The evidence presented suggests the underreaction to news is pervasive, and an increase in institutional holdings in particular does not reduce the degree of underreaction consistent with Grossman and Stiglitz (1980) and Stein (2009). Zhang (2006) proposes that underreaction should be most pronounced when greater information uncertainty is present. Incorporating commonly-used proxies of information uncertainty, such as firm size and number of analysts covering the firm, yield no consistent pattern between information uncertainty and the underreaction portfolio (Table 7). I do find, although, among the largest quintile, underreaction is lower than the second largest quintile suggesting the markets are less inefficient for the largest stocks. The evidence suggests that while investor attention might attenuate some inefficiency, it does not completely deplete underreaction to news.

3.3. *Underreaction to news and momentum*

Table 7 demonstrates the prevalence of the underreaction to information in news articles across different measures of investor attention. Given that the underreaction portfolio is highly correlated with the UMD portfolio, the alpha of the underreaction portfolio may be driven by the alpha of the momentum strategy. To test whether the alpha of the underreaction portfolio is driven by the momentum effect in stock returns, I examine the alpha of the underreaction portfolio within each return quintile. If the underreaction portfolio has alpha independent of the return momentum, it should persist in each return quintile.

I first sort the stocks into previous-return quintiles, to form long-short portfolios within each quintile based on the WQI. Because the long-short portfolios comprise of stocks within the same previous-return quintile, they should have no exposure to the UMD factor. For example, one of these five long-short portfolios takes a long position among the winners and a short position among winners as well, the only difference between the long and the short side is the WQI. I measure previous return in three different ways. In Panel A, I use the weekly momentum as in Gutierrez and Kelley (2008). Stocks are first sorted by the weekly returns; then within each weekly return quintile, I sort stocks by the WQI. In Panel B, stocks are sorted by return in the past 26 weeks, omitting the week of formation. In Panel C, stocks are sorted by return in in the interval between 27 and 52 weeks before the formation. While controlling for momentum, controlling for return over the past 52 weeks is customary. I control for return between week -27 and week -52, following the findings of Heston and Sadka (2008) and Novy-Marx (2012), who show the momentum effect is primarily concentrated among the winners and the losers of six months ago.[22] In each of the panels, I present the average return for the underreaction portfolio, the market-adjusted alpha, the Fama–French three-factor alpha, and the Fama–French three-factor and the Carhart UMD alpha.[23]

[22] Qualitatively similar results are obtained when I use week $[-1, -52]$ return as a control for momentum.

[23] I do not report the correlation of the UMD factor with the underreaction portfolio. The correlation is positive for all 15 underreaction portfolios.

Table 8. Long-short tone score equally-weighted portfolio within return quintiles.

Control Quintile	Average Return	Market Adjusted	FF 3 Factor Adjusted	FF 3 Factor Plus UMD Adjusted
Panel A: Underreaction portfolio across weekly return quintiles				
1 (Loser)	0.8 (1.85)	−0.1 (1.84)	−0.4 (1.84)	−0.1 (1.83)
2	11.1 (1.63)	13.6 (1.61)	15.2 (1.60)	15.9 (1.57)
3	16.3 (1.63)	19.8 (1.58)	21.4 (1.57)	22.1 (1.54)
4	21.2 (1.62)	24.5 (1.58)	25.7 (1.57)	26.5 (1.54)
5 (Winner)	12.3 (1.78)	13.7 (1.77)	13.5 (1.76)	14.3 (1.72)
Panel B: Underreaction portfolio across 26-week return (week[−1,−26]) quintiles				
1 (Loser)	0.0 (2.00)	−1.9 (1.99)	−2.2 (1.98)	−3.2 (1.94)
2	16.9 (1.64)	18.8 (1.62)	20.5 (1.62)	20.4 (1.61)
3	18.7 (1.62)	22.0 (1.58)	23.6 (1.57)	24.0 (1.56)
4	15.4 (1.66)	18.5 (1.62)	19.9 (1.61)	20.7 (1.57)
5 (Winner)	13.3 (1.90)	13.8 (1.90)	13.8 (1.88)	15.5 (1.75)
Panel C: Underreaction portfolio across 26-week return (week[−27,−52]) quintiles				
1 (Loser)	5.4 (1.92)	4.6 (1.92)	3.8 (1.92)	3.6 (1.92)
2	18.5 (1.67)	20.8 (1.65)	21.7 (1.65)	21.9 (1.65)
3	18.6 (1.66)	22.0 (1.62)	23.5 (1.61)	24.2 (1.59)
4	18.7 (1.70)	22.7 (1.64)	24.7 (1.62)	25.7 (1.57)
5 (Winner)	9.6 (1.81)	10.5 (1.81)	11.1 (1.79)	12.4 (1.71)

Note: This table shows the alpha and standard error from long-short equally weighted WQI portfolio returns with in return quintiles. Three panels correspond to three different measures of past return. Panel A is first sorted by returns in week 0. Panel B is first sorted by 26-week return (week −26 to week −1). Panel C is first sorted by 26-week return (week −27 to week −52). Within each quintile, I sort all the stocks on the basis of the WQI and take a long position in stocks in Decile 10 and a short position in stocks in Decile 1. The portfolios are held for 13 weeks, with each week having 13 cohorts. The returns are calculated by averaging over these cohorts each week. All returns in quintiles 2–5 are significant at the 1% level.

I find alpha from underreaction portfolio is present in four out of five return quintiles. Among the loser stocks (based on return of the formation week), the underreaction portfolio has almost zero return (Panel A of Table 8). In the other four quintiles, 2, 3, 4, and 5, the average return over the next 13 weeks are 11.1, 16.3, 21.2 and 12.3 basis points per week, respectively. Controlling for the Fama–French three-factors and the Carhart UMD *increases* the alpha of the underreaction portfolio. Also, the underreaction portfolios have positive correlation with the UMD factor. Controlling for 26-week returns yields a qualitatively similar alpha, though the alpha of the underreaction portfolio is negative in the loser quintile. Panel C shows the performance of the underreaction portfolio in the week [−26, −52] return quintiles. Unlike Panels A and B, the underreaction portfolio is profitable in all momentum quintiles. The average return is lower in both the extreme winner and loser quintiles than the ones in the middle.

4. Firm-Level Regressions

I explore the effect of news on future stock return using cross-sectional regressions. For each week, I obtain the mean return for all the stocks in my sample over the next 13 weeks. Two news-related variables are present. The no-news dummy variable takes the value of 1 if no news article about a firm occurs in a particular week. The second news-related variable is WQI, which is the difference between the weekly positive and negative tone scores; I describe this variable in detail in Sec. 2. I assign the WQI of firms without news to 0. I regress the 13-week average-return on a no-news dummy, WQI, and several control variables. I provide the definitions for all the regression covariates in Appendix E. The model is formalized in Eq. (1):

$$r_{it} = \beta_{jt} \times X_{jit} + \beta_{\mathrm{WQI}_t} \times \mathrm{WQI}_{it} + \epsilon_{it}. \tag{1}$$

The average return over the next 13 weeks for firm i at week t is indicated by r_{it}. β_{jt} is the regression coefficient for the covariate X_{jit}. X_{jit} is the value of the characteristic j specific to firm i at week t. The coefficient for WQI, β_{WQI_t}, indicates the predictive ability of the WQI over the next 13 weeks. I obtain the Fama–Macbeth estimate β_j of the weekly cross-sectional coefficient β_{jt} and adjust for auto-correlation for up to three lags using the Newey–West procedure (Newey and West, 1987).

After controlling for size of the firm, B/M ratio, and negative book-to-market ratio, a no-news week for a firm results in an additional 7 basis points per week higher return for the next 13 weeks (model 1 of Table 9). A one-unit increase in the WQI corresponds to an additional 14 basis points per week over the next 13 weeks. This estimate is similar to the estimate obtained using the average return of the underreaction portfolio. The WQI changes by 1.37 units as I move from the WQI Decile 10 to the WQI Decile 1 (Panel B of Table 2), suggesting the "underreaction portfolio" should have an average return of 19.18 basis points per week, compared to 16.49 basis points per week return for the underreaction portfolio (Table 5).

Controlling for the firms return history (model 2) diminishes the WQI coefficient from 14 basis points per week to 8 basis points per week, a 43% reduction. Although the inclusion of the firm's return history diminishes the economic significance of the past news, it does not alter the statistical significance.

Table 9. A regression model for 13 week returns.

	Model 1	Model 2	Model 3
Intercept	−0.0109***	−0.0087***	−0.0061***
	(0.0022)	(0.0016)	(0.0022)
WQI	0.0014***	0.0008***	0.0006***
	(0.0003)	(0.0002)	(0.0002)
No-news	0.0007***	0.0006***	0.0005***
	(0.0002)	(0.0001)	(0.0001)
Controls			
Avg_est			−0.0204
			(0.0189)
Dispersion			−0.048
			(0.0414)
Pct_Inst			0.0009***
			(0.0004)
Log(beme)	0.0003**	0.0003*	0.0003*
	(0.0002)	(0.0002)	(0.0002)
Negative_BM	−0.0041***	−0.0036***	−0.0036***
	(0.0005)	(0.0004)	(0.0004)
Noanalyst			−0.0013
			(0.001)
Noinst			−0.0000***
			(−0.0000)***
Week[0]		−0.0004	−0.0008
		(0.0012)	(0.0012)
Week[−1,−26]		0.1314***	0.1284***
		(0.0159)	(0.0161)
Week[−27,52]		0.0695***	0.0701***
		(0.0133)	(0.0123)
Size	0.0008***	0.0006***	0.0004***
	(0.0001)	(0.0001)	(0.0001)

Note: This table shows the estimate of β_{WQI} from the specification. $r_{it} = \beta_{jt} \times X_{jit} + \epsilon_{it} r_{it}$ is the average weekly return over next 13 weeks for firm i at time t. The three models are different from one another with respect to the control variables. Model 1 controls for size, and book to market, model 2 controls for past returns in addition to controls in model 1, and model 3 controls for the proportion of shares of the firm held by institutional investors and analyst opinion in addition to the controls in model 2. The estimates show WQI predicts future return at the firm level over the next 13 weeks.
***: 1%, **: 5%, *: 10%.

In model 3, in addition to the controls in model 2, I control for institutional holdings as well as analyst research. "Avg_est" is the average of the analyst estimates in the IBES dataset for the firm's EPS over the past 14 weeks. "No-analyst" is a dummy variable with a value of 1 if no analyst update the firms estimate over the previous 14 weeks. "Dispersion" is the standard deviation of the analyst estimates of EPS over the previous 14 weeks. It indicates the level of agreement among analysts. "Pct_Inst" is the proportion of the firm's share held by the institutional investors. Among this new set of controls, only "Pct_Inst" is statistically significant.

After controlling for past returns, size, B/M ratio, and institutional investor holdings, an increase in one unit of WQI amounts to a 6 basis points higher return per week over the next 13 weeks (almost 57% decline).

The observed effect of WQI on returns might be driven by other factors such as past returns and institutional holdings. To isolate the effect of WQI from other salient factors, I construct an econometric model of WQI and extract the portion of WQI that is independent of size, B/M ratio, past returns, and institutional investor holdings. To find independent WQI, I subtract the portion of WQI that firm characteristics predict from the WQI. The econometric model in Eq. (2) obtains the expectation of WQI at time t given the firm characteristics at time t. I estimate the econometric model for WQI_{it} only for the firms that received news in a given week:

$$\begin{aligned} \mathrm{WQI}_{it} &= \theta_{jt} \times Z_{jit} + \delta_{it}, \\ \mathrm{WQI}^{\perp}_{it} &= \mathrm{WQI}_{it} - \widehat{\theta}_j \times Z_{jit}. \end{aligned} \tag{2}$$

I use the Fama–Macbeth Newey–West adjusted estimates $\widehat{\theta}_j$ to back out the unexpected WQI, $WQI^{\perp}_{it}$, for each firm at time t. Finally, I regress the firm-specific average return over the next 13 weeks on $\mathrm{WQI}^{\perp}_{it}$ and other control variables as in Eq. (3). Coefficient $\beta_{\mathrm{WQI}^{\perp}}$ is the effect of the WQI independent of firm-specific characteristics:

$$r_{it} = \beta_{\mathrm{WQI}^{\perp}} \times \mathrm{WQI}^{\perp}_{it} + \beta_{jt} \times X_{jit} + \eta_{it}. \tag{3}$$

$\mathrm{WQI}^{\perp}$ is calculated for all firms in the sample each week.[24]

In Table 10, I report the Fama–Macbeth Newey–West coefficients for three different models predicting WQI. Model 1 controls for firm size, B/M ratio, negative B/M dummy, average return over the past 26 weeks, and average return from week −52 to week −27. Model 2 adds a control for contemporaneous return. The average R-squared for model 2 (5.90%) is higher than model 1 (3.78%).

[24] As a robustness check, I also obtain the $\mathrm{WQI}^{\perp}$ only for the firms that have news in a given week. The point estimate for $\mathrm{WQI}^{\perp}$ from the alternate method for Eq. (3) is higher than those presented in the paper.

Table 10. Econometric models for WQI.

	Model 1	Model 2	Model 3
Intercept	0.0409*	0.038*	0.063***
	(0.0226)	(0.0226)	(0.0208)
Avg_est			0.025***
			(0.0033)
Dispersion			−0.090***
			(0.0077)
Pct_Inst			−0.017***
			(0.0051)
Log(beme)	−0.012***	−0.013***	−0.012***
	(0.0019)	(0.0019)	(0.0019)
Negative_BM	−0.0435***	−0.041***	−0.035***
	(0.0057)	(0.0056)	(0.0053)
Week[0]		0.695***	0.709***
		(0.0301)	(0.0306)
Week[−1,−26]	3.5934***	3.584***	3.565***
	(0.1488)	(0.1483)	(0.1479)
Week[−27,−52]	2.5717***	2.531***	2.506***
	(0.1408)	(0.1418)	(0.1351)
Size	−0.0008	−0.001	−0.002*
	(0.0013)	(0.0013)	(0.0012)
Average R^2	3.78%	5.90%	6.79%

Note: This table presents three different econometric models to describe the WQI scores at the firm level. Each week, I regress the firm-specific covariates in the model on the WQI for firms that receive any news in the week. I obtain the Fama–Macbeth Newey–West adjusted regression estimates from the model. $\mathrm{WQI}_{it} = \theta_j \times Z_{jit} + \delta_{it}$. The estimates show the WQI is influenced by firm size, book-to-market ratio, previous returns, institutional holdings and analyst opinion.
***: 1%, **: 5%, *: 10%.

Model 3 includes variables for institutional ownership and analyst estimates in addition to the controls in model 2. The R-squared of model 3 is 6.79%.[25] Because model 3 has the highest R-squared, I use the estimates presented in model 3 to obtain the expected WQI. I subtract the expected WQI from the actual WQI to obtain the $\mathrm{WQI}^{\perp}$, the "unexpected WQI."

I regress the unexpected WQI on the return of the firm over the next 13 weeks while controlling for other firm-specific characteristics. In Table 11, a one-unit increase in unexpected WQI corresponds to 6 basis points higher

[25] A model that includes the number of analysts covering the firm is similar to model 3 in terms of statistical fit, and is not reported.

Table 11. Firm-level regression to estimate the predictive ability of unexpected WQI.

	Model 1
Intercept	−0.0055**
	(0.0023)
$\text{WQI}^{\perp}$	0.0006***
	(0.0002)
No-news	0.0005***
	(0.0001)
Controls	
Avg_est	−0.0257
	(0.0226)
Dispersion	−0.0619
	(0.0504)
Pct_Inst	0.0009***
	(0.0004)
Log(beme)	0.0003*
	(0.0002)
Negative_BM	−0.0036***
	(0.0004)
Noanalyst	−0.0019
	(0.0012)
Noinst	−0.0000***
	(0.0000)
Week[0]	−0.0008
	(0.0012)
Week[−1,−26]	0.1307***
	(0.0163)
Week[−27,−52]	0.0717***
	(0.0125)
Size	0.0004***
	(0.0001)

Note: This table shows the effect of $\beta_{\text{WQI}^{\perp}}$ on future 13 weeks returns controlling for size, book-to-market ratio, previous returns over multiple horizons, institutional holdings, and analyst opinion. $\text{WQI}^{\perp} = \text{WQI}_{it} - \beta_j \times X_{jit}$
***: 1%, **: 5%, *: 10%.

return per week over the next 13 weeks. The estimate is the same as the estimate of WQI presented in models 2 and 3 of Table 9. The model suggests the effect of WQI on a firm's future returns is independent of the firm size, B/M ratio, previous returns, analyst opinion, and institutional holdings.

Table 12. Firm-level regression, clustered at date and firm level to estimate the predictive ability WQI.

	Model 1	Model 2	Model 3
Intercept	−0.0002**	−0.0005	−0.0002**
	(0.0001)	(0.0003)	(0.0001)
WQI	0.0011***		
	(0.0002)		
No-news	0.0006***	−0.0331***	0.0006***
	(0.0002)	(0.0031)	(0.0001)
$\text{WQI}^{\perp}$			0.0011***
			(0.0002)
Avg_est	0.0000	0.0001**	0.0000
	(0.0001)	(0.00004)	0.0005
Dispersion	−0.0000	0.0001	−0.0000
	(0.0000)	(0.0003)	(0.0000)
Pct_Inst	0.0012***	−0.0037***	0.0012***
	(0.0003)	(−0.0014)	(0.0003)
Log(beme)	0.0002	−0.0028***	0.0002
	(0.0001)	(0.0005)	(0.0001)
Negative_BM	−0.0040***	−0.0052***	−0.0040***
	(0.0006)	(0.0016)	(0.0006)
Noanalyst	−0.0002	0.0047***	−0.0001
	(0.0002)	(0.0010)	(0.0002)
Week[0]	−0.0016	0.1400***	−0.0014
	(0.0014)	(0.0055)	(0.0015)
Week[−1,−26]	0.112***	0.546***	0.113***
	(0.0168)	(0.0269)	(0.0169)
Week[−27,−52]	0.0294***	0.2690***	0.0297***
	(0.0094)	(0.0216)	(0.0094)
Size	0.0005***	0.0008**	0.0005***
	(0.0001)	(0.0004)	(0.0001)

Note: This table shows the effect of β_{WQI} and $\beta_{\text{WQI}^{\perp}}$ on future 13 weeks returns controlling for size, book-to-market ratio, previous returns over multiple horizons, institutional holdings, and analyst opinion. Model 1 shows the effect of WQI, in presence of various firm level controls on future return. Model 2 estimates a model of WQI. Model 3 shows the effect of unexpected WQI on future 13 weeks return. $\text{WQI}^{\perp} = \text{WQI}_{it} - \beta_j \times X_{jit}$
***: 1%, **: 5%, *: 10%.

In Table 12, I report the cross-sectional regression coefficient for WQI when controlled for date fixed effects along when clustered at date and firm level. Petersen (2009) show that Fama–Macbeth Newey–West coefficients may not properly control for the correlation structure of data. Model 1 controls for firm size, B/M ratio, negative B/M dummy, average return over the past 26 weeks, average return from week −52 to week −27, contemporaneous return, institutional ownership and analyst estimates. Model 1 is similar to model 3 in Table 10. A one-unit increase in WQI corresponds to 11 basis points higher return per week over the next 13 weeks, higher estimate than Table 10. Model 2 presents a model of WQI. Model 3 presents the effectof unexpected WQI, similar to Table 11. Unexpected WQI has economically similar effect as WQI.

5. Implications and Conclusion

5.1. *Implications*

The results suggest the US stock market underreacts to information contained in news articles. The underreaction is stronger among large stocks, stocks with high analyst coverage, and institutional ownership. This finding is puzzling, and inconsistent with efficient market reaction to the information in news articles.

Underreaction is stronger among large stocks and stocks with large analyst followings, the opposite of predictions of rational models of underreaction such as Peng and Xiong (2006) and Nieuwerburgh and Veldkamp (2010).[26] Profitability of the WQI-based trading strategy for large stocks, stocks with more analyst coverage, and stocks with higher institutional ownership rules out an explanation solely based on market frictions.

Contrary to the behavioral models' predictions (Daniel *et al.* (1998) and Hong and Stein (1999)), the WQI-based trading strategy is profitable among larger stocks and stocks with more analyst coverage. This finding suggests the behavioral forces that generate underreaction are not limited to small stocks, stocks with smaller analyst followings, and stocks with fewer institutional holdings. However, as suggested by Daniel *et al.* (1998), I find a positive correlation between the return immediately following the news event (as measured by WQI) and future returns.

The evidence is somewhat consistent with a model with private information as in Kyle (1985). The private information is not the news itself, but the tone of the news, which is hidden in plain sight. Although inferring the tone of one news article is a trivial exercise, processing 500 news articles a day is not. Investors who make the investment to decipher the tone of a large number of articles may glean private information. Because they understand their

[26] Peng and Xiong (2006) suggest underreaction emanates from the allocation of attention over different kinds of information. Nieuwerburgh and Veldkamp (2010) model an agent's attention allocation over various investment choices.

information is private, they trade patiently and prices are slow to reflect their information as in Foster and Viswanathan (1994).

6. Conclusion

This paper examines how stock react to news. I find that stocks underreact to news. Unlike, reaction to "sentiment" which by definition reverses over time, reaction to news is slow and seems to last 13 weeks, a longer horizon than found in most studies. The long lasting reaction to news suggests that the tone of news articles contain information, not sentiment. Furthermore, the underreaction is not limited to small stocks, stocks with few analysts, and stocks with few institutional holdings. A WQI-based strategy generates economically significant excess returns even for the largest quintile of stocks in the sample.

The portfolio resulting from the long-short WQI-based trading strategy is highly correlated with the UMD factor. Further examination shows the WQI-based trading strategy return cannot be explained by the momentum effect in stock returns. Also, the news provides a simple explanation for the short-term reversal of stock returns. Short-term reversal does not occur when returns are accompanied by information that matches the direction of returns.

The results on short-term reversal underscore the importance of seeking measures of information separate from past returns. I find the market responds differently to the information contained in news articles than to the information contained in past returns. During the sample period, although I observe underreaction to news, the return from a price-momentum strategy is negative. This finding raises an important question: Do investors respond differently to qualitative information, such as that contained in news articles, than to quantitative information, such as that contained in past returns?

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Appendix A. Text-Processing Example

Consider an example that describes the working of the text-processing engine. Because the unit of analysis is a sentence, the working of the sentiment engine is demonstrated with the sentence "BP gave analysts a negative surprise." Figure A.1 provides a schematic description of the same example.

The text-processing engine has three major sequential processes: (1) Pre-processing, (2) lexical and tonal pattern identifier and (3) tone classifier. In the pre-processing stage, the sentence is identified as being composed of a

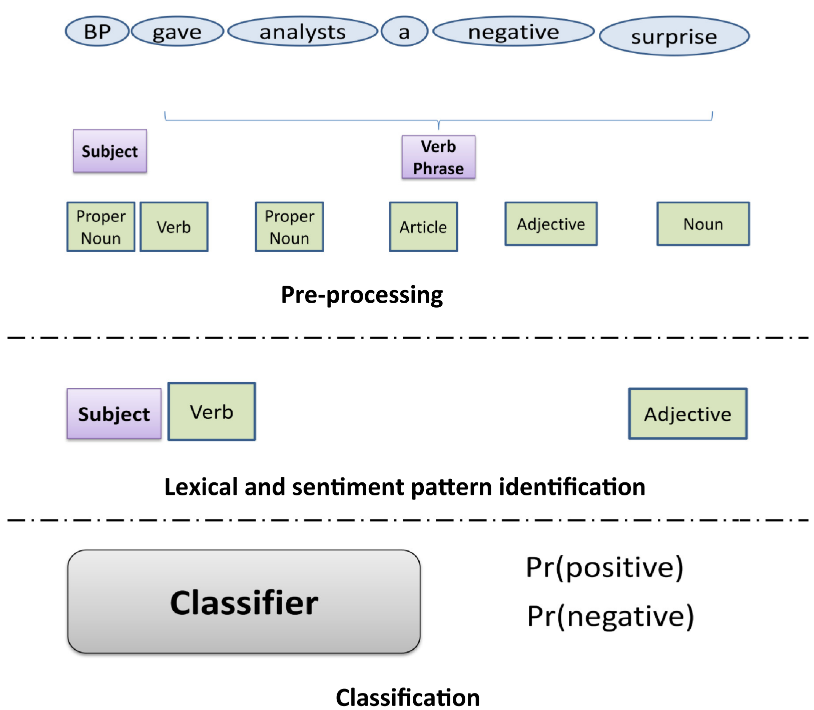

Fig. A.1. Schematic representation of the text-processing engine.

Note: This figure shows how an example sentence passes through the three different subprocesses of the Thomson Reuters text-processing engine.

subject and verb-phrase. In computational linguistics, the identification of the subject and the verb-phrase is known as shallow parsing. The parts of speech of each word in the sentence are identified. Output from this stage is fed into the lexical and tonal-pattern identifier. Some parts of speech are more important for the purposes of communicating the tone of the sentence. In this case, the verb ("gave") and adjective ("negative") are important. In this same stage, the verb "gave" is mapped to "give." Through these two processes, the subject is retained. The subject information is used for attributing the article's tone to the subject. The subject information is also used to assign relevance. Because the classifier keeps track of how many sentences are used for each firm, it identifies whether a particular article is about a firm or whether it mentions the firm in passing. The features from the lexical and tonal-pattern identifier are fed into a classifier.

Appendix B. Text-Processing Engine

The text processing engine has three major sequential steps: (1) Pre-processing, (2) lexical-and sentiment-pattern identifier and (3) sentiment classifier.

B.1. *Pre-processing*

The text-processing engine pre-processes the text before attempting to ascribe any sentiment. The pre-processing consists of (1) sentence splitting, (2) tokenization, (3) part-of-speech tagging, (4) morphological stemming, and (5) shallow parsing. The sentiment engine first splits the news item into individual sentences. It then further splits the sentences into individual words. Computational linguistics literature refers to this process as tokenization. Thereafter, the sentiment engine identifies the parts of speech of each word. The classifier also morphologically stems the words: for example, "gone," "went," and "goes" are all identified as "go." Morphological stemming identifies the root word for each word by matching each word to its root word. The sentiment engine does shallow parsing whereby it identifies the subject of the sentence and what is being said about the subject. For example, "BP disappoints analysts" is identified as a noun-phrase relationship with the "BP" as the noun. The shallow parsing or identification of entity (or subject) for each sentence is used for providing relevance scores. The classifier keeps track of the subject for each sentence. The ability to keep track of the entity in discussion allows the classifier to provide subject-specific sentiment. If a sentence has multiple subjects, the classifier assigns different words to different subjects. The classifier also provides a relevance score for each subject.

B.2. *Lexical- and sentiment-pattern identification*

Following pre-processing, the text-processing engine does a lexical analysis identifying words as adjectives, adverbs, intensifiers, nouns, and verbs. The lexical identification is important for sentiment processing because certain phrases and parts of speech tend to convey tone (or sentiment) information, whereas others just aid in making a coherent sentence. The lexical identification feeds into sentiment-pattern identification. Sentiment pattern consists of identification of negation, intensification, and verb resolution.

B.3. *Sentiment classifier*

The sentiment classification is done by a three-layer back-propagation neural network classifier with weight relaxation. Features extracted so far are used as input to the classifier. The classifier is trained using a random sample of triple-annotated news articles spanning 14 months from December 2004 to January 2006. Analysts who analyze blogs and other outlets of public opinion annotated the news articles. The annotation order was randomized; that is, the manual annotators got the articles in random order and would not have been able to form long-term opinions by reading the news articles. A linguist and a former trader supervised the whole process. The training articles are from the entire universe of Thomson Reuters coverage and include international stocks. The classifier produces three outputs between 0 and 1, which are probabilities of the article being positive, neutral, or negative. The system achieves 75% accuracy against the average assesment of human analysts.

Many of the aforementioned methods are fairly standard in computer science and are discussed at length in Manning and Schütze (1999). More details about the classifier are available in Infonic (2008).

Appendix C. Distribution of News Articles

See Table C.1.

Table C.1. Distribution of news articles by Year, Relevance and Lcnt.

Year	# of Articles	Filtered # of Articles
Panel A: Number of stories each year		
2003	196,756	68,468
2004	238,487	93,390
2005	285,085	127,049
2006	387,027	190,841

Table C.1. (*Continued*)

Year	# of Articles	Filtered # of Articles
2007	537,133	287,410
2008	794,368	442,902
2009	784,441	391,606
2010	529,782	186,897
Lcnt	**# of Articles**	**Filtered # of Articles**
Panel B: Distribution of Lcnt		
0	1,750,582	1,170,938
1	846,892	6,176,25
2	360,028	0
3	227,502	0
4	568,075	0
Relevance	**# of Articles**	**Filtered # of Articles**
Panel C: Distribution of Relevance		
1	1,362,936	962,323
$>= 0.90$–< 1.00	4,639	1,994
$>= 0.80$–< 0.90	19,700	9,665
$>= 0.70$–< 0.80	99,870	61,729
$>= 0.60$–< 0.70	27,228	13,621
$>= 0.50$–< 0.60	620,832	571,694
$>= 0.40$–< 0.50	101,718	63,312
$>= 0.30$–< 0.40	228,961	104,225
$>= 0.20$–< 0.30	345,474	0
$>= 0.10$–< 0.20	520,588	0
> 0–< 0.10	421,133	0

Note: Panel A shows the number of news articles each year between 2003 and 2010 as well the number of news articles that have "Lcnt" not more than 1 and "Relevance" of at least 0.35. Panel B shows the distribution of news articles by "Lcnt." Panel C shows the number of news articles by "Relevance."

Appendix D. Summary Statistics by Size, B/M Ratio, and Previous Return

See Table D.1.

Table D.1. Summary statistics by size, B/M ratio, and momentum.

	Prop_nonews	Daywnews	Sent_Pos	Sent_Neg
		Size decile		
1	0.96	1.11	0.29	0.27
2	0.94	1.08	0.29	0.27
3	0.93	1.10	0.30	0.28

Table D.1. (*Continued*)

	Prop_nonews	Daywnews	Sent_Pos	Sent_Neg
4	0.91	1.14	0.30	0.30
5	0.89	1.18	0.30	0.30
6	0.87	1.18	0.31	0.29
7	0.84	1.25	0.31	0.28
8	0.79	1.32	0.32	0.27
9	0.70	1.49	0.31	0.26
10	0.41	2.34	0.29	0.25
		B/M decile		
1	0.87	1.52	0.31	0.29
2	0.77	1.69	0.30	0.27
3	0.75	1.74	0.30	0.26
4	0.78	1.64	0.30	0.26
5	0.79	1.66	0.31	0.26
6	0.80	1.62	0.31	0.26
7	0.82	1.61	0.30	0.26
8	0.83	1.58	0.30	0.27
9	0.84	1.56	0.30	0.28
10	0.85	1.57	0.28	0.31
		Past return (week [−1,−26]) decile		
1	0.87	1.49	0.26	0.34
2	0.85	1.58	0.28	0.31
3	0.83	1.63	0.29	0.29
4	0.82	1.69	0.30	0.27
5	0.82	1.72	0.30	0.26
6	0.81	1.71	0.31	0.26
7	0.81	1.68	0.32	0.25
8	0.81	1.65	0.32	0.25
9	0.82	1.58	0.32	0.25
10	0.84	1.44	0.32	0.26

Note: The top panel shows the proportion of firms that do not receive any news in a given week (Prop_nonews), number of trading days in a week on which a firm that receives news receives it, the probability of the coverage being positive, and the probability of the coverage being negative by size deciles. Decile 1 has small firms. The middle panel shows the same variables by B/M ratio deciles. Decile 1 has growth firms, whereas Decile 10 has value firms. The bottom panel shows the same variables by previous return deciles. Decile 1 has firms with extremely negative returns in the previous 26 weeks, whereas Decile 10 has firms with extremely positive returns in the previous 26 weeks.

Appendix E. Definition of Variables

Avg_est: The average EPS estimate for the firm among all the analysts that have issued an opinion on the firm in past 14 weeks as noted by the IBES dataset. If an analyst updates her estimate over the previous 14 weeks, I retain the most recent estimate.

Dispersion: The standard deviation of earnings-per-share estimate issued by analyst covered by IBES over previous 14 weeks.

Pct_Inst: The percentage of shares held by institutional holders as reported by 13F filings.

Log(beme): Logarithm of the B/M ratio. The book value is obtained in the last week of June of the previous year. The market value is obtained as of the last Wednesday in December of the previous year.

Negative_BM: A dummy variable that is assigned to 1 if the firm has negative B/M value.

Noanalyst: The dummy variable corresponding to no analyst opinion being issued by the firm within the previous 14 weeks. Takes a value of 1 if there was no analyst opinion found in the previous 14 weeks.

Noinst: The dummy variable corresponding to no reported institutional holding in the 13f filings. Takes a value of 1 if no reported institutional holding is found.

No-news: If a firm does not receive news in a given week, this dummy variable is assigned 1, and otherwise 0.

Sent_Neg: The probability of an article being negative. This score is specific to the firm being mentioned.

Sent_Neut: The probability of an article being neutral.

Sent_Pos: The probability of an article being positive. The three probabilities sum up to 1.

Size: Logarithm of the market capitalization of the firm stated in million dollars. The market capitalization is obtained as of the last Wednesday in December of the previous year.

Week[0]: The weekly return corresponding to the week of formation. News variables are recorded concurrently with the return. The returns are measured from Wednesday close to Wednesday close as in Gutierrez and Kelley (2008).

Week[−1,−26]: The average weekly return over the previous 26 weeks, starting the week prior to 26 weeks prior.

Week[−27,−52]: The average weekly return starting the 27th week prior to 52nd weeks prior.

WQI: Each day, I take the average of Sent_Pos and Sent_Neg across all the news articles on the day. Furthermore, I take the average of these scores over all the trading days in the week. WQI is the difference between weekly Sent_Pos and Sent_Neg.

Appendix F. Financial Crisis and Profitibaility of News Tone Long-Short Portfolios

My sample includes financial crisis. Financial firms as well as others were affected by the crisis Campello *et al.* (2010). To ensure that the results on the profitability of the WQI strategy is not driven by negative media coverage during the crisis, I dropped the observations between 15 September 2008 and 30 June 2009. 15 September 2008 corresponds to the failure of Lehman Brothers. 30 June 2009 corresponds to the United States emerging out of the

Table F.1. Long-short tone score equally-weighted portfolio within return quintiles excluding the period between 15 September 2008 and 30 June 2009.

Control Quintile	Average Return	Market Adjusted	FF 3 Factor Adjusted	FF 3 Factor Plus UMD Adjusted
Panel A: Underreaction portfolio across weekly return quintiles				
1 (Loser)	−0.8 (1.76)	−1.07 (1.76)	−1.28 (1.76)	−2.80 (1.75)
2	13.89 (1.54)	15.73 (1.53)	17.52 (1.52)	15.57 (1.51)
3	20.03 (1.53)	22.85 (1.50)	24.87 (1.49)	22.75 (1.48)
4	22.97 (1.52)	25.39 (1.50)	26.90 (1.49)	24.46 (1.47)
5 (Winner)	13.41 (1.69)	13.88 (1.69)	14.18 (1.69)	11.30 (1.67)
Panel B: Underreaction portfolio across 26-week return (week[-1,-26]) quintiles				
1 (Loser)	−5.00 (1.83)	−5.87 (1.82)	−6.72 (1.83)	−3.78 (1.81)
2	16.07 (1.55)	18.44 (1.53)	20.18 (1.53)	20.48 (1.53)
3	19.54 (1.53)	22.45 (1.49)	24.44 (1.49)	22.91 (1.48)
4	19.17 (1.54)	21.36 (1.53)	22.98 (1.52)	20.10 (1.49)
5 (Winner)	16.53 (1.82)	15.46 (1.81)	15.99 (1.81)	10.12 (1.70)
Panel C: Underreaction portfolio across 26-week return (week[-27,-52]) quintiles				
1 (Loser)	4.83 (1.82)	4.19 (1.82)	3.65 (1.82)	4.55 (1.82)
2	20.81 (1.58)	23.09 (1.56)	24.23 (1.56)	23.41 (1.56)
3	20.99 (1.58)	23.68 (1.56)	25.52 (1.55)	23.66 (1.54)
4	21.25 (1.59)	23.87 (1.56)	26.28 (1.55)	23.28 (1.53)
5 (Winner)	12.97 (1.75)	12.34 (1.75)	13.39 (1.75)	8.60 (1.67)

Note: This table shows the alpha and standard error from long-short equally weighted WQI portfolio returns with in return quintiles. Three panels correspond to three different measures of past return. Panel A is first sorted by returns in Week 0. Panel B is first sorted by 26-week return (week −26 to week −1). Panel C is first sorted by 26-week return (week −27 to week −52). Within each quintile, I sort all the stocks on the basis of the WQI and take a long position in stocks in Decile 10 and a short position in stocks in Decile 1. The portfolios are held for 13 weeks, with each week having 13 cohorts. The returns are calculated by averaging over these cohorts each week. All returns in Quintiles 2 through 5 are significant at the 1% level.

Table F.2. Long-short qualitative information portfolio within size, analyst coverage, and institutional holding quintiles excluding the period between 15 September 2008 and 30 June 2009.

Control Quintile	Average Return	Market Adjusted	FF 3 Factor Adjusted	FF 3 Factor Plus UMD Adjusted
Panel A: Underreaction portfolio across size quintiles				
1 (small)	6.07 (1.96)	8.50 (1.95)	6.50 (1.94)	29.84 (1.91)
2	15.03 (1.65)	1.50 (1.65)	13.79 (1.63)	11.08 (1.61)
3	18.62 (1.53)	1.97 (1.53)	20.85 (1.52)	18.11 (1.50)
4	18.56 (1.54)	2.09 (1.53)	24.70 (1.50)	21.30 (1.45)
5 (large)	14.23 (1.63)	1.82 (1.56)	24.41 (1.48)	20.48 (1.42)
Panel B: Underreaction portfolio across analyst-coverage quintiles				
1 (low coverage)	10.81 (1.76)	14.48 (1.71)	15.03 (1.71)	11.41 (1.67)
2	20.01 (1.58)	21.37 (1.58)	21.66 (1.58)	18.51 (1.54)
3	17.60 (1.50)	19.08 (1.49)	20.64 (1.49)	17.95 (1.47)
4	20.35 (1.54)	21.36 (1.53)	24.88 (1.51)	22.10 (1.48)
5 (high coverage)	16.53 (1.60)	17.32 (1.60)	21.75 (1.56)	18.10 (1.51)
Panel C: Underreaction portfolio across institutional-holding (IH) quintiles				
1 (low IH)	8.39 (1.80)	10.64 (1.79)	11.38 (1.79)	7.96 (1.76)
2	18.00 (1.59)	19.65 (1.58)	21.51 (1.58)	18.63 (1.55)
3	20.63 (1.54)	22.67 (1.52)	24.86 (1.51)	21.87 (1.48)
4	23.89 (1.52)	25.53 (1.51)	27.73 (1.50)	24.77 (1.47)
5 (high IH)	15.66 (1.51)	16.76 (1.51)	18.86 (1.50)	16.31 (1.47)

Note: This table shows the alpha, and standard error from long-short equally weighted WQI portfolio returns with in size, analyst coverage and institutional-holding quintiles. For each one of the controls — size, analyst coverage and institutional holding — I first sort the stocks in five quintiles on the basis of the control variable. Within each control quintile, I sort all the stocks on the basis of the WQI and take a long position in stocks in decile 10 and a short position in stocks in decile 1. The portfolios are held for 13 weeks, with each week having 13 cohorts. The returns are calculated by averaging over these cohorts each week. Panel A shows the alphas in size quintile, quintile 1 has the smallest firms. Panel B shows the alphas in analyst coverage quintiles. Quintile 1 has firms with least analyst coverage. Panel C shows the alphas in institutional holding quintiles. Quintile 1 has stocks with least institutional holding. All returns are significant at 1% level.

recession induced by the financial crisis as classified by NBER (see Tables F.1 and F.2).

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