Chapter 20
Is No News Good News? The Streaming News Effect on Investor Behavior Surrounding Analyst Stock Revision Announcement

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> *Fundamentals might be good for the first third or first 50 or 60 percent of a move, but the last third of a great bull market is typically a blow-off, whereas the mania runs wild and prices go parabolic.*
>
> —Paul Tudor Jones

Abstract We investigate media influence on stock returns that are revised by sell-side analysts. Our main findings are twofold. First, post-announcement returns depend on whether the stock is covered by the media. Media-covered stocks demonstrate weaker post-announcement returns than their non-media-covered counterparts. Second, for media-covered event samples, we create a sentiment proxy using a unique news word count method and investigate whether pre-event sentiment affects post-event returns. Our results indicate that pre-event sentiment dictates short-run investor behavior and affects the post-announcement return in a significant manner.

Keywords News effect • Analysts' rate revision • Market sentiment

JEL Classification Codes G14

The original article first appeared in the International Review of Finance 14:29–51, 2014. A newly written addendum has been added to this book chapter

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S. Ikeda et al. (eds.), *Behavioral Interactions, Markets, and Economic Dynamics*,
DOI 10.1007/978-4-431-55501-8_20

1 Introduction

In an efficient market, stock prices at any given time thoroughly reflect all available information. A priori, there is good reason to believe that stock markets are efficient, because such markets are paradigmatic examples of competition. Yet, rather than adjusting immediately to news surprises, stock prices tend to drift over time in the same direction as the initial surprise. When sell-side analysts change the ratings of stocks, short-run drift occurs. Previous research suggests two explanations for the existence and persistence of drift. First, the persistence of this anomaly may be due to high transaction costs (limits of arbitrage). Thus, mispricing persists only if market frictions are severe enough to prevent arbitrageurs from exploiting it. Barber et al. (2001), for example, present evidence that supports this view. They find significant drift in analysts' post-recommendation stock price returns; however, they conclude that their anomaly-based trading strategies do not reliably beat a market index after accounting for transaction costs. Alternatively, the drift may be a function of whether investors pay attention to the stock or the type of information investors receive about the stock. The second explanation comprises a behavioral view that investors face a formidable search problem. Barber and Odean (2008) predict that individual investors actively buy stocks on high attention days. They argue that professional investors as a whole (inclusive of market-makers) will exhibit a lower tendency to buy, rather than sell, on high-attention days and a reverse tendency on low-attention days. This will create a short-term overreaction followed by subsequent reversal.

The goal of this research is to deepen our understanding of what type of information flows drive event-related anomalies. Interest in the relations between media and the market has been growing among both researchers and practitioners (e.g. Klibanoff et al. 1998; Tetlock 2007; Tetlock et al. 2008). In the hedge fund industry, a London-based family office launched a Twitter-based investment fund that claims to invest in the stock market at the appropriate time through measuring market psychology. The origin of this investment is an academic paper published by researchers in computer science, Bollen et al. (2011). We contribute to this strand of research by examining the relation between post-event abnormal stock returns and the media. Specifically, we look at news coverage of stocks that face analysts' rating revision (obvious good/bad fundamental information about the stock) and how attention-grabbing and non-attention-grabbing stocks respond to the fundamental information. Our approach is similar to that of Fang and Peress (2009), who examine the cross-sectional difference in monthly returns depending on the news coverage, but differs from them in three ways. First, we examine not only headlines, but also massive and comprehensive amounts of news disseminated by the major financial information vendor in Japan. These data are more appropriate for our study than newspaper articles because they affect market participants directly on a real-time basis. Second, we look into the contents of the news and the impact of mass media sentiment. Specifically, we are interested in the frequency of mass media coverage and its effect on stock prices following firm events. To examine how mass media mood affects subsequent stock market returns, we categorize market news based on the number of positive and negative words appearing in the news articles.[1] Third, we focus on event-related abnormal returns to investigate how investors react to the arrival of new fundamental information in conjunction with the prevailing market news.

Our prediction is that upon arrival of upgrading news, attention-grabbing stocks would go up less than their no-attention-grabbing (non-media-covered) counterparts. Presumably, there are two effects at play. First, Bayesian updating investors would be less surprised upon the arrival of news when they have been exposed to any news in the past. Second, as pointed out by Barber and Odean (2008), attention-grabbing stocks are likely to be bought by individual investors and sold by professional traders. Because professional traders sell to individual investors above the fair value, attention-grabbing stocks are overvalued at the time of analysts' announcement, thus limited response to good news. Our prediction is symmetrical in the case of downgrades. Bayesian updating investors would be less surprised when the firm is mentioned in the news. Non-media-covered stocks are expected to go down more than their media-covered counterparts due to the surprise effect of the event news. By the same token, frequency of news coverage is a proxy for attention intensity; therefore, we expect that the greater the news coverage, the lower the magnitude of stock price response upon arrival of new fundamental information.

First, as a preliminary examination, we calculate the post-announcement abnormal returns of stocks whose ratings are revised by sell-side analysts. Using a standard event study framework, we find a significant abnormal price reaction even after the first tradable price on the day following the announcement. We also find significant abnormal returns using industry, size and book-to-market control firms as a benchmark. Consistent with prior research (Stickel 1995; Womack 1996), stocks upgraded by analysts demonstrate limited or small-scale post-announcement drift, while stocks that are downgraded indicate a prolonged downward drift.

Next, we collected a large amount of news electronically disseminated from the QUICK database. Our news sample includes articles from QUICK news, NQN news and Nihon Keizai Shimbun news between January 2008 and December 2012. A total of 773,386 news articles were obtained, consisting of 10,068,140 sentences and 56,358,567 words. Based on these news articles, we classified our sample firms (12,148 firm events) into two groups: media-covered (6,353 firm events) and non-media-covered (5,795 firm events). If a news report covers a firm during the 10 business days prior to its event date, we categorize the firm as media-covered and non-media-covered otherwise.

Consistent with our prediction, we find that media coverage significantly mitigates the post-announcement abnormal returns. Our results in the short-term post-announcement return analysis show that stocks mentioned in the media demonstrate less post-announcement return difference than firms with no media mention.

[1]Negative and positive terms are called 'polarity' words. The polarity of each word appeared in the news texts is determined based on our own created sentiment dictionary.

Upgraded stocks demonstrate a positive post-announcement return, on average, but with stronger magnitude for firms without media attention. For downgraded events, a negative post-announcement return also appears stronger for stocks without media attention than for their media-covered counterparts.

Third, to investigate whether the level of attention affects post-announcement return, we divide the media-covered samples into three groups: highly covered, medium covered and marginally covered. The post-announcement return for three levels of coverage is consistent with our predication in upgraded samples; lower coverage is associated with stronger post-announcement drift. For the downgraded samples, the difference is unclear.

Finally, we further categorize the media-covered samples (6,353 firm events) into three groups: positive, neutral and negative. When a stock is quoted in an article that contains more negative words than positive, as defined by our dictionary,[2] the stock is categorized as having negative sentiment. If the number of positive words and negative words offset each other in the article, it is categorized as neutral. Likewise, if the article contains more positive words than negative, it is categorized as positive.

Negativity and positivity are defined as the simple addition of each type of word's appearance in the news for the stock. Using this unique sentiment scoring method, we create a sentiment proxy and observed the post-announcement performance of three classes (positive, neutral and negative) of stocks based on the sentiment.

We find that downgraded firms show little difference in returns regardless of their sentiment class. Upgraded stocks, however, show a difference: stocks with positive sentiment demonstrate almost zero post-announcement return while neutral and negative sentiment stocks marginally show abnormal returns. Our findings using our original sentiment proxy suggest that when the contents of the news have more positive expression than negative (defined as carrying positive sentiment), the subsequent rise following upgrades is limited. Sentiment effects on downgrades remain unclear.

Our empirical findings are consistent with the view that a market with many Bayesian updating investors would provide a window of opportunities for trading unnoticed stocks. They are also consistent with the view presented by Barber and Odean (2008) that individual investors are trading overpriced attention-grabbing stocks and professional traders are the sellers of such stocks. For profit-seeking investors, when stocks are upgraded, it is wise to purchase non-media-covered stocks or stocks that are media-covered but to a lessor extent. Ceteris paribus, it is wise to avoid stocks that are heavily covered by the media.

The remainder of this chapter is organized as follows. Section 1 reviews the literature. Section 2 describes our data. Section 3 explains our methodology. Section 4 presents and discusses the main empirical results. In Section 5, does the robustness check of our results. Section 6 concludes the chapter.

[2]We created a sentiment dictionary that identifies each word as positive/negative. The dictionary contains approximately 1,500 positive words and 1,500 negative words. We read each sentence in an article and count how many positive/negative words are used in each sentence.

2 Literature Review

Klibanoff et al. (1998) show that country-specific news reported on the front page of *The New York Times* affects the pricing of closed-end country funds. The authors find that during weeks of front-page news, price movements are more closely related to fundamentals. Therefore, they argue that news events lead some investors to react more quickly. More recently, Tetlock (2007) analyzed the linguistic content of the mass media and reports that media pessimism predicts downward pressure and a subsequent reversal. Tetlock et al. (2008) further document that the fraction of negative words used in news stories predicts earnings and stock returns. These findings suggest that qualitative information embedded in news stories contributes to the efficiency of stock prices.

Among papers that examine broadly-defined media exposure, ours is the first that documents post-event returns and their relation with media coverage. Several recent papers document a positive relation between media and liquidity but fail to find significant return differentials. For example, Antweiler and Frank (2004) find that stock messages predict market volatility but their effect on returns is small. Grullon et al. (2004) document that firms with larger advertising expenditures have more liquid stocks, and Frieder and Subrahmanyam (2005) report that individuals are more likely to hold stocks with strong brand recognition. Fang and Peress (2009) actually succeed in finding return differentials using media coverage. They examine cross-sectional return patterns and find that media-covered stocks have lower returns than non–media-covered stock. Chan (2003) examines momentum and reversal patterns following large price moves with and without accompanying news and supports the same findings.

This chapter is closely related to those of Fang and Peress (2009) and Chan (2003) but differs in one important aspect: These authors focus on news coverage and headline news, respectively, but do not distinguish between news positivity and negativity. Since assessment of true value is difficult and investors overreact to private information and underreact to public information (Daniel et al. 1998), how a news article is written is as important as the factual information it conveys. We obtained data mainly from the major financial information vendor QUICK. To measure news sentiment, we enumerate negative and positive words in the relevant news articles that are electronically disseminated through QUICK. Another distinction is that Fang and Peress (2009) examine cross-sectional differences in returns with and without news coverage and Chan (2003) looks at market reactions to news in time (and the differences therein between winners and losers), whereas we examine post-event differences in returns.

This chapter is also related to that of Barber and Odean (2008), who show that individual investors are the net buyers of attention-grabbing stocks, such as stocks in the news. These authors argue that individuals face difficulties choosing stocks to buy from a large pool of candidates; thus, attention-grabbing stocks such as those in the news are more likely to enter their choice set. Our evidence implies that investors trade among attention-grabbing stocks but the direction of their investment decisions is affected by news sentiment.

3 Data

Our sample consists of companies subject to analyst recommendation revisions. The recommendation revisions are identified using Bloomberg's database. We use Bloomberg only to identify analysts' rating revisions because QUICK does not offer such data. The sample firms are listed on the Tokyo Stock Exchange (TSE) and the Japan Securities Dealers Association Quotation System (JASDAQ). The recommendation revisions encompass the period from 1 January 2008 to 31 December 2012. The Bloomberg database includes, among other items, revision dates, new ratings, identifiers for the brokerage house issuing the recommendation, and the identity of the analyst writing the report (if known). Recommendations are expressed by a rating of between one and five. A rating of one reflects a strong buy recommendation, two a buy, three a hold, four a sell and five a strong sell. This five-point scale is commonly used by analysts. If an analyst uses a different scale, we convert the analyst's rating to the five-point scale.

Another characteristic of our data is that the data made available to us are incomplete. Certain brokerage houses have entered into agreements that preclude their recommendations from being distributed by Bloomberg to anyone other than their clients. Consequently, although the recommendations of the largest and the most well-known brokers are included by Bloomberg, they are not part of our dataset. Our event data originally contain 15,796 observations for the period between 1 January 2008 and 31 December 2012. These data include cases of double counting, such as follows. Suppose on day t, Toyota is upgraded by an analyst X. A different analyst, Y, downgrades Toyota on the following day, $t + 1$. In this case, the post-event performance of Toyota is affected by the adjacent rating revisions in time. Therefore, we exclude event samples whose rating revision occurs multiple times in our event window. The remaining total event sample subject to analysis is 12,148 observations.

We also use the number of electronic news articles about a stock to proxy for the stock's overall media sentiment. To collect this information, we systematically searched the QUICK database for articles in our sample referring to the company name. The QUICK database distributes news data from three sources: *Nihon Keizai Shimbun*, QUICK and NQN. The news is all from the Nikkei Group but each source has its own characteristics. For example, the *Nihon Keizai Shimbun* news is an electronic version of the newspaper, with articles by Nikkei Inc. writers, while the QUICK news is market-focused and articles are by writers from QUICK Inc., a subsidiary of Nikkei Inc. The NQN news is the real-time distributed market news with articles by both Nikkei and QUICK writers.

We obtain the company name for each article from the article itself. A writer entering a story into the news systems, will often manually write the company name and occasionally its four-digit TSE code. The manual input of the company name leads to variations, such as *NTT-Docomo* or *Docomo*. We then match these company names with our code dictionary. When the article provides the company code, we tag the article with that code. We exclude from our analysis news articles about an industry without specific mention of a company. To capture news about a given

Table 20.1 The number of rating revision events occurred during our sample period by year. Large firms tend to be revised more than once during the calendar year. Event total indicates the number of revision events during the calendar year including firms that are subject to revision for more than once

Year	Market	Number of listed firms	Number of covered firms	Coverage ratio (%)	Number of firms that are revised more than once	Up ward revision	Down ward revision	Total
2008	TSE	2,170	973	45	532	1,172	1,848	3,280
	JASDAQ	915	147	16	58	94	166	
2009	TSE	2,282	999	44	468	1,588	1,105	2,775
	JASDAQ	882	149	17	25	43	39	
2010	TSE	2,691	1,484	55	405	1,442	1,052	2,551
	JASDAQ	996	597	60	12	30	27	
2011	TSE	2,083	1,514	73	342	939	909	1,888
	JASDAQ	961	688	72	6	20	20	
2012	TSE	2,094	1,458	70	300	699	928	1,654
	JASDAQ	919	595	65	7	11	16	
Total					2,155	6,038	6,110	12,148

company, we retain articles with at least one mention of the company. If an article mentions more than one company name, the article is counted multiple times, once for each company mentioned.[3] Table 20.1 displays the descriptive statistics of our samples.

We quantify the news media sentiment, that is, its negativity and positivity, for the selected articles. Converting qualitative text into a machine-readable form requires several preliminary steps, but we skip the details in this chapter because they are in the realm of computer science. To distinguish whether a story's informational content is positive or negative, one needs to prepare standards against which to classify words and events. Because different groups of people are affected by events differently and have various interpretations of the same events, conflicts can arise. For example, the term *dividend cuts* can be classified as negative by a prevailing dictionary-based algorithm. In contrast, it can be interpreted as positive by market analysts, who believe such conduct indicates the company is saving money and, therefore, is better able to repay its debts. To avoid such problems, we produce a dictionary of 3,056, terms classified by experts. We give each firm in our sample a time-series sentiment number if there was any news in the 10 calendar days prior to the analysts' recommendation revision event. Sentiment numbers are calculated based on the simple addition and subtraction of the news content about a firm. For example, if negative words outnumber positive words by two, the sentiment number for the firm is −2.

Table 20.2 describes the summary statistics of our sample in relation to the news articles and the sentiment score of each sample. We divide our sample firms

[3]The percentage of multiple-used articles in our sample is a mere 1.6 %.

Table 20.2 Panel A indicates the total number of events and articles covered. Panel B shows the description of news articles associated with the recommendation revisions. Panel C describes the distribution of firms covered by the media with its sentiment

Panel A: News articles with a company name

	No. of stocks	No. of events	No. of articles	No. of sentences	No. of words
Small	2,596	281	14,736	166,961	934,723
Medium	1,419	1,654	61,959	633,521	3,382,126
Large	822	10,213	696,691	9,267,658	52,041,718
Total	4,837	12,148	773,386	10,068,140	56,358,567

Panel B: News articles associated with recommendation revisions

		No. of firms subject to revision	No. of events	No. of articles within 10 days prior to the events	No. of positive words prior to the events	No. of negative words prior to the events
Downgrades	Small	86	186	405	31	73
	Medium	296	912	1,585	478	498
	Large	513	5,012	68,571	49,408	55,445
	Sub-total	895	6,110	70,561	49,917	56,016
Upgrades	Small	51	95	139	22	27
	Medium	252	742	1,305	370	307
	Large	511	5,201	68,303	49,642	51,855
	Sub-total	814	6,038	69,747	50,034	52,189
Total		1,709	12,148	140,308	99,951	108,205

Panel C: Media coverage and sentiment						
		No. of media covered event*	No. of no-media covered event	No. of events with positive score	No. of events with neutral score	No. of events with negative score
Downgrades	Small	42	144	3	17	22
	Medium	354	558	85	188	101
	Large	4,076	936	993	1,593	1,490
	Sub-total	4,472	1,638	1,081	1,798	1,613
Upgrades	Small	20	75	4	10	6
	Medium	310	432	53	204	53
	Large	4,215	986	1,380	1,582	1,253
	Sub-total	4,545	1,493	1,437	1,796	1,312
Total		9,017	3,131	2,518	3,594	2,925

*No. of media covered event is based on all the news released, not limited to within 10 days prior to the events into three categories using market capitalization. Firms with market capitalization below 10 billion yen (US$111 million at the exchange rate of 90 yen per dollar) are categorized as small, those larger than 10 billion yen and less than 60 billion yen are categorized as medium, and those above 60 billion yen are categorized as large. Of 12,148 recommendation revisions, 10,213 are concentrated on large firms that represent merely one-sixth of all listed companies (of 4,873 listed firms, only 822 large companies are the subject of more than 80 % of news articles). As shown in Panel B of Table 20.2, out of 773,386 articles obtained from QUICK, 140,308 appeared during the 10 calendar days prior to the event. We calculate sentiment score based on news during that 10-day period. The score calculation is the simple addition of word polarity, with negative words scored as -1 and positive words as $+1$. A total of 99,951 positive words and 108,205 negative words appeared in the entire collection of news articles on our sample firms in the pre-announcement period. Panel C shows the composition of media-covered and non-media-covered sample firms. Out of 12,148 events, 3,131 were not media-covered in the whole pre-announcement period. The remaining 9,017 events had news coverage: 2,518 events have a positive score, 2,925 events have a negative score and 3,594 events have a neutral score.

4 Media Coverage and Stock Returns

This section focuses on the relation between media coverage and post-recommendation stock returns. We first examine the abnormal returns of recommendation revisions and then examine abnormal returns by subdividing the sample firms based on news sentiment.

4.1 Abnormal Returns of Stocks Revised by Sell-Side Analysts

Analysts deliberately plan most rating revisions and reiterations. These decisions are rarely made in haste. Although analysts act based on public information, the majority of the research suggests that market response to rating revisions is considerable. Stickel (1995) and Womack (1996) show that favorable (unfavorable) changes in individual analyst recommendations are accompanied by positive (negative) returns at their announcements. The authors document a post-recommendation stock price drift that lasts up to 1 month for upgrades and up to 6 months for downgrades. Although investors can exploit analyst information and generate abnormal profits, obtaining full information about analyst ratings ex ante is difficult. Generally, brokers only allow professional investors who have a trading account with them to fully access to their analysts' rating reports. In this sense, rating revision information is not completely in the public domain and individual investors are normally allowed to access partial or delayed information. An event study based only on news

Table 20.3 Average three-day cumulative abnormal return for firms that are upgraded and downgraded by analysts. Panel A describes results based on the benchmark return generated using the market model. Panel B shows the result based on the respective control firm. Control firm is chosen using industry, size and book-to-market criteria

	Total	Strong outperform	Outperform	Neutral	Underperform	Strong underperform
Panel A: Benchmark return based on market model						
Upgrade						
n	6,038	676	3,871	1,473	18	n/a
CAR	0.89 %	1.02 %	1.11 %	0.24 %	1.94 %	n/a
p-value	***0.000***	***0.000***	***0.000***	*0.102*	*0.305*	n/a
Downgrade						
n	6,110	n/a	576	4,001	1,205	328
CAR	−1.24 %	n/a	−0.79 %	−1.26 %	−1.54 %	−0.72 %
p-value	***0.000***	n/a	***0.000***	***0.000***	***0.000***	*0.059*
Panel B: Benchmark return based on industry, size and book-to-market adjusted control firm						
Upgrade						
n	6,038	676	3,871	1,473	18	n/a
CAR	0.81 %	1.23 %	1.00 %	0.12 %	2.20 %	n/a
p-value	***0.000***	***0.000***	***0.000***	*0.354*	***0.043***	n/a
Downgrade						
n	6,110	n/a	576	4,001	1,205	328
CAR	−1.09 %	n/a	−0.85 %	−1.09 %	−1.13 %	−1.32 %
p-value	***0.000***	n/a	***0.000***	***0.000***	***0.000***	***0.000***

available to the public would enable us to investigate whether the market discounts information in an efficient manner.

We define post-announcement drift as the return attainable by trading on the first tradable price after the rate revision announcement, which is the opening price of the first business day after the announcement. Table 20.3 indicates the average cumulative abnormal return (CAR) for a 3-day event window. The return is calculated from the opening price of the day following the announcement to the closing price of the third day. An abnormal return is defined as the sample return minus the benchmark return.

Panel A of Table 20.3 demonstrates the abnormal return based on the market model. We use the Tokyo Stock Exchange Tokyo Price Index (TOPIX) as a market portfolio proxy and the beta of each sample is estimated using 200 pre-event business days. In Table 20.3, the third column through seventh column indicate the destination of each upgrade and downgrade. For example, the 676 firms are upgraded from lower ratings to ‘strongly outperform’. These firms’ CAR is 1.02 % rejecting the null of a zero 3-day CAR. Note that rating revisions to ‘neutral,’ meaning the target stocks perform in line with the market index, significantly outperform or underperform depending on the path they follow. The stocks significantly outperform the market when they are announced to be upgraded to 'neutral' from 'underperform,' and underperform the market when they are announced to be downgraded to 'neutral' from 'outperform'. This is consistent with Francis and Soffer (1997), who argue that investors.

It is expected that small capitalization stocks are more prone to analysts' rating revisions than large capitalization firms. High book-to-market stocks tend to outperform the market when the value style is in sync with the market; therefore, size and value factors should be controlled. The industry can also be a determinant factor of returns, particularly when the market sector rotation is active. For example, a weak yen induces investors to invest in export-related industries. To control for these factors, we compare sample firm returns with the respective control firms based on industry, size and book-to-market ratio.

Panel B shows the abnormal returns using a control firm as a benchmark. The corresponding control firm is selected according to the following procedure. First, we select firms in the same industry as the sample, using the TSE's middle industry classification code. Among stocks in the same industry, we select firms whose market capitalization falls between 70 % and 130 % of the sample. Finally, we pick a single stock whose book-to-market ratio is the closest to the firm's. When there is no firm that satisfies these three selection criteria simultaneously, we drop the industry criterion and repeat the screening process. For 54 samples, we use only the size and book-to-market ratio criteria for selection.

The direction of the post-event period return in Table 20.3 is consistent with prior findings. Firms that are revised upward gain a positive abnormal return and those revised downward suffer from a negative abnormal return. A total of 6,038 stocks that are revised upward rise, on average, 0.89 % (0.81 % using control firms) more than expected. Symmetric results are found in downward revisions, with 6,110 firms losing −1.24 % (−1.09 % using control firms), on average, upon downgrade.

4.2 Media Coverage and Post-recommendation Returns

This subsection investigates whether the post-recommendation returns of firms that gain media attention are affected by the media coverage. In a long-run abnormal return analysis, Fang and Peress (2009) report that high-media-covered firms underperform their non-media-covered counterparts by 0.39 % per month (4.8 % per year). The authors also argue that non-covered stocks generate an alpha, while the high-covered stocks underperform the market index. They argue that the long-run performance difference caused by the media coverage is consistent with the hypothesis that investors demand a risk premium for stocks in oblivion. In contrast, according to Barber and Odean (2008), individuals face difficulties when choosing which stocks to buy from a large pool of candidates; thus, attention-grabbing stocks, such as those in the news, are more likely to enter their choice set. This buying pattern seems consistent with the media effect documented by Fang and Peress (2009) to the extent that individuals' buying pressure temporarily pushes up the prices of attention-grabbing (in-the-news) stocks, but such pressure subsequently reverses. To investigate the cause of the media effect on stocks, we divide our sample based on the news occurrence in the 10 business days prior to the announcement. We categorize stocks as media-covered if there is any single news item about the stock in the 10 business days, and non-media-covered otherwise.[4] Then, we look at how stock prices behave with new fundamental information flow, such as analyst recommendation revisions.

The results of our short-run analysis of stock prices are consistent with the Bayesian updating investor hypothesis and individual investors' trading behavior documented by Barber and Odean (2008). We find that non-media-covered stocks generate stronger abnormal post-recommendation drift in both directions. Figure 20.1 represents the abnormal return that investors would receive by trading at the opening price after the announcement. The benchmark return is the respective control firm's return. If the announcement is made before the market close, investors are able to trade before the close; however, estimating the intraday tradable price adds complexity, so we assume all announcement revisions are made after the market is closed. As shown in Fig. 20.1, the non-media-covered subset of firms demonstrate stronger positive drift toward the new level than their media-covered counterparts. Symmetrically, the non-media-covered downgraded subset demonstrates more severe negative drift in the post-announcement period. There are presumably two effects at play here. One is that the Bayesian updating investors would be more surprised with the new fundamental information when there is no information about the stock before the announcement. Therefore, investors would react more sensitively to the new information; thus, non-media-covered stocks have a more severe post-announcement reaction. The other effect at play in our upgrading sample is presumably the attention effect. Stock price behavior surrounding rating upgrades is consistent with Barber and Odean (2008). If individual investors are trading media-covered stocks at overvalued prices, the stock may not go up as much upon the arrival of good news because it is already in a state of overvaluation.[5]

4.3 Media Coverage Frequency and Post-recommendation Returns

We define media coverage as the proxy for the degree of attention by individual investors. Barber and Odean (2008) find that individual investors have a higher

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[4]We have experimented with different look back periods of −20 days, −15 days and −5 days. The number of sample stocks for covered and uncovered changes in each experiment but the implication of the result remains intact.

[5]Altıkılıç et al. (2013) argue that analysts' revisions are typically information-free and piggyback on news. Our evidence is consistent with their view. If some analysts are merely piggybacking their revisions on public information of news and events about the firm, revisions on media uncovered stocks are more likely to have information content and have stronger drift in returns.

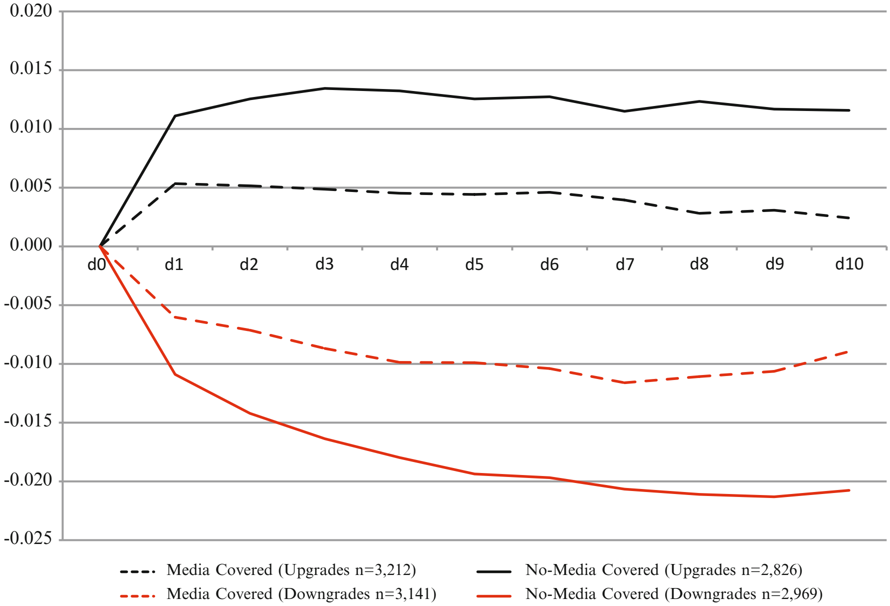

Fig. 20.1 Post-announcement performance by media coverage. Plot of cumulative abnormal return for the period of 10 business days after the announcement using the industry, size and book-to-market-based control firm. Cumulative return is calculated from the opening price of the following business day post-recommendation announcement (*dt*0). The *dotted line* indicates the cumulative abnormal return of stocks that are covered by the media, and the *solid line* stocks that are not media-covered. Among 6,038 upgraded stocks, 3,212 are media-covered and 2,826 not covered by the media. A total of 6,110 stocks are downgraded, with 2,969 media-covered and 3,141 not covered by the media

tendency to buy on high attention days. For every buyer there must be a seller. Professional investors as a whole exhibit a lower tendency to buy on high attention days. Therefore, stocks in high attention periods tend to be overvalued because professional investors would only agree to trade above the fair value. If this is the mechanism at play surrounding the revision, we should observe less post-announcement return in the stocks that are heavily covered by the media and more for those with lighter coverage.

To test this hypothesis, we have divided the media-covered samples into three subsets, heavily, medium and marginally covered, using the following criteria. The firms whose names are mentioned in more than 30 articles in the 10-day pre-event window are heavily covered; a mention in 10–30 articles is medium coverage; and those with fewer than 10 articles are marginally covered. If individual investors are buying on high attention days, it is likely that stocks heavily covered by the media are more overvalued than their marginally covered counterparts. We predict lower post-announcement drift for heavily covered firms.

Figure 20.2 represents the CAR that investors would receive when trading each subset of the sample firms at the opening price following the announcement.

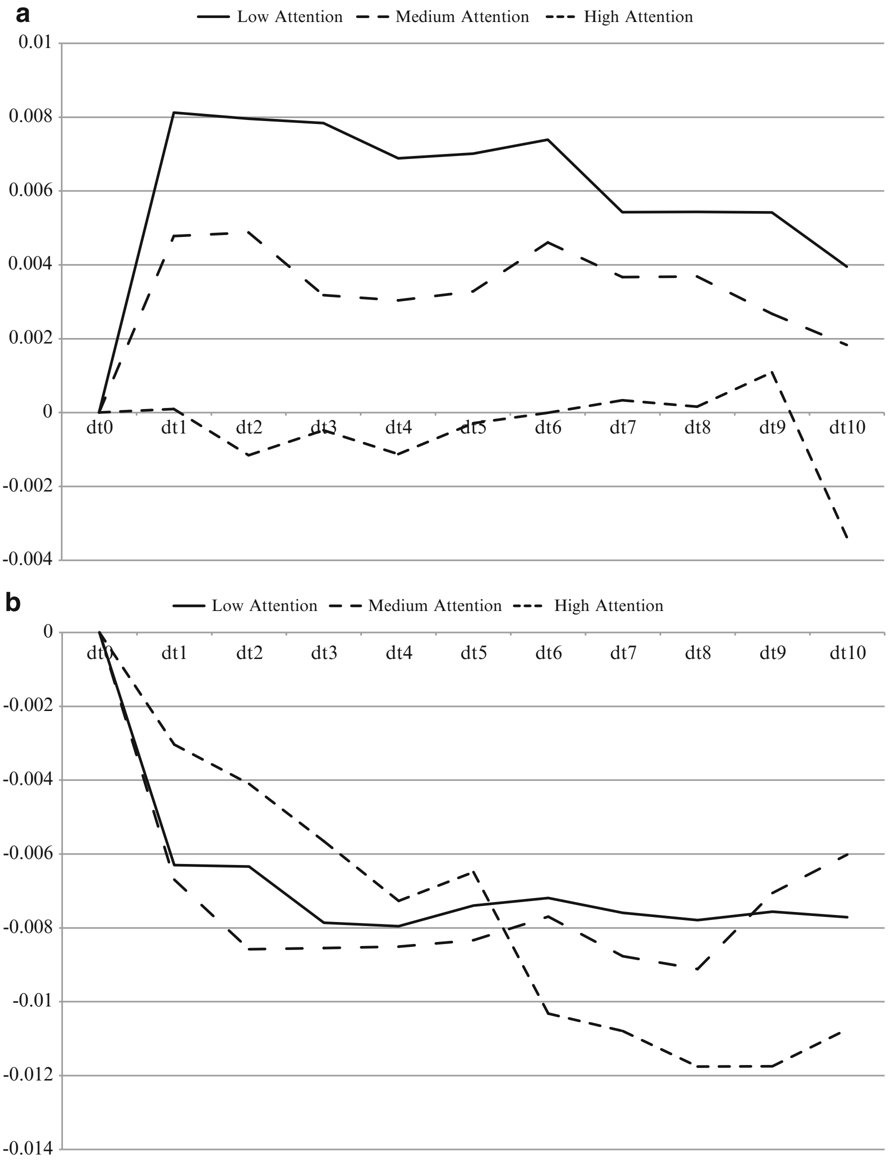

Fig. 20.2 Post-event cumulative abnormal return separately calculated for three subsets of samples. Low attention is defined as having less than 10 news articles disseminated during ten days prior to the event announcement date. Medium attention, 10–30 news articles; High attention more than 30 news articles

The results suggest that investors would be better off trading stocks that are less exposed to media. The greater the media coverage, the lower the post-announcement drift. Buying heavily media-covered stocks in accordance with the analysts' rating upgrades brings about zero abnormal return. Our evidence is consistent with the attention story for upgrading samples; however, downgrading samples generate an asymmetric result. There is no clear distinction among subsamples regardless of media coverage intensity. Conrad et al. (2006) argue that sell-side analysts are reluctant to downgrade in a timely manner. If this is the case, downgrading by analysts tends to occur when the outlook of the company becomes convincingly negative. This may be why downgraded samples drop in tandem regardless of the intensity of the media coverage.

4.4 Media Sentiment and Post-recommendation Returns

Measuring sentiment and its effect on stock market return has sparked the interest of many researchers in recent years. Our study is most closely related to Li (2006) and Davis et al. (2006), who analyze the tone of qualitative information using objective word counts from corporate annual reports and earnings press releases, respectively. Whereas Davis et al. (2006) examine the contemporaneous relationships between earnings, returns and qualitative information, Li (2006) focuses on the predictive ability of qualitative information, as do we. Li (2006) finds that the two words 'risk' and 'uncertain' in firms' annual reports predict low annual earnings and stock returns, which the author interprets as underreaction to 'risk sentiment.' Our study differs from Li (2006) in that we examine qualitative information in news stories at daily horizons rather than qualitative information in annual reports at annual horizons.

Some prior research analyzes qualitative information using more sophisticated subjective measures, rather than simple objective word counts. For example, Antweiler and Frank (2004) and Das and Chen (2006) design algorithms to reproduce humans' 'bullish,' 'neutral' or 'bearish' ratings of Internet chat room messages and news stories. Neither study finds any statistically significant return predictability in individual stocks. A study by Antweiler and Frank (2006), which uses an algorithm to identify news stories by their topic rather than their tone, does find some return predictability. For many of their topic classifications, Antweiler and Frank (2006) find significant return reversals in the 10-day period around the news, which they interpret as overreaction to news, regardless of the tone.

In this subsection, we concentrate our analysis on the fraction of words in *Nihon Keizai Shimbun*, *NQN* and *QUICK* stories about our sample firms and quantify the firm-specific sentiment based on the language used in the news. Merging the news stories and the financial information for a given firm requires matching firms' common names used in news stories. Although firms' common names usually resemble the firm names appearing in financial datasets, perfect matches are rare. To obtain the common names that we use as search strings for news stories, we begin with the company name variable in the Bloomberg data for all revised stocks during the relevant timeframe.

We obtain *Nihon Keizai Shimbun*, *NQN* and *QUICK* stories from QUICK terminal. For the period from January 2008 to December 2012 we collected 1,275,064 articles, or 68,740,386 words. We also include the date–time of submission (GMT + 0) and occasionally the contributor's name. Of 1,275,064 articles, 773,386 contain at least one company name. Because of the large number of firms and news stories, we implement an automated story retrieval system. For each target firm, the system constructs a query that specifies the sentiment of the stories to be retrieved. The system then submits the query and records the retrieved sentiment score. The sentiment score of the story is calculated as the number of positive words minus the negative words. To define the positivity and negativity of the text, we used a market expert, who constructed a dictionary of approximately 3,000 phrases. Each positive phrase is counted as +1 and negative as −1. The simple sum of these numbers per article defines the news sentiment score.

We illustrate the procedure for contents analysis for a sample firm, Mitsubishi Corporation (TSE code 8,058), a trading company whose market capitalization was US$36 billion in January of 2012. An analyst upgraded the firm on 18 January 2012. We look at news flow from 9 January 2012, which is 10 business days prior to the announcement. On 9 January, QUICK released a news story related to their airport management business. The story describes the government's new policy to sell the rights to manage domestic airports to the private sector. The sentiment score of this news is +6. When people read the news, it is generally agreed that the news is positive for the firm. On day $t-8$, there was no news. On day $t-7$, a story was issued about a copper mining company in Chile that sued the UK-based Anglo-American Co. Ltd. The sentiment score of the news is +1, but the contents are not necessarily positive. Our word count methodology has its own limitations in such a case because of its simplistic approach. However, in aggregate, it is unlikely to have many positive numbers if the firm's news story is bleak. The cumulative sentiment score over the 10-day period is +6 and Mitsubishi Corporation's subsequent 3-day CAR after the announcement is 5.03 %.

Table 20.4 reports typical examples of our sample stocks whose post-announcement returns are affected by sentiment in the 10 business days prior to the date.

Subsection 4.2 tests the hypothesis that investors trading behavior is influenced by whether investors are reminded of the stock through news. By comparing stocks covered by the media and stocks in oblivion, we find that the latter shows stronger post-announcement drift. When a stock is not mentioned by the media, the Bayesian updating investors do not have prior expectations of the stock; therefore, the arrival of new fundamental information moves the stock price by a larger margin. Our finding is also consistent with the view that individual investors are net buyers of attention-grabbing stocks at overvalued prices. Seasholes and Wu (2004) investigate the Shanghai Stock Exchange and find that individual investors are net buyers the day after a stock hits an upper price limit. Individual investors are attracted by the event of hitting a price limit (positive news) and individuals become the net buyers of stocks that catch their attention.

Table 20.4 Prior 10-day news appearance of four of our sample firms. The sentiment score of each day is the total number of positive word minus the negative word appearance of the day. We highlight some typical news for each stock of our choice

	CAR	Total	t-10	t-9	t-8	t-7	t-6	t-5	t-4	t-3	t-2	t-1
Mitsubishi Corporation upgraded on Jan 18, 2012	5.03 %		2012/1/8	1/9	1/10	1/11	1/12	1/13	1/14	1/15	1/16	1/17
Sentiment score		6	0	2	0	1	0	2	3	0	−2	0
Number of articles		15	0	1	0	4	3	1	1	1	4	0
Contents summary example	*Government announced domestic airport to be privatized. Mitsubisi Corp. has experience in it (t-9) *34bil dollar LNG project to start in Australia in 13th Jan. Mistubishi Corp has stake in it (t-5) *Mitsubishi Corp. and Hokuetsu Paper jointly open a state of the art plant to burn LNG (t-2)											
Mitsubishi Material Co. Ltd upgraded on May 29, 2009	7.99 %		2009/5/19	5/20	5/21	5/22	5/23	5/24	5/25	5/26	5/27	5/28
Sentiment score		4	0	0	−2	5	0	0	0	0	0	1
Number of articles		13	0	0	1	7	0	0	0	0	1	4
Contents summary example	*Mitsubishi Material to produce copper production with full capacity from August due to rising auto demand (t-7) *Lower coal price led five cement companies to have higher profit in the 2nd Q (t-2) *Non-ferrous metals industry is one of the best performers today (t-1)											
Sharp Corporation downgrade on Aug. 3, 2012	−2.32 %		2012/7/25	7/25	7/26	7/27	7/28	7/29	7/30	7/31	8/1	8/2
Sentiment score		−12	0	−8	0	−3	0	1	−2	1	−2	1
Number of articles		29	0	4	2	4	0	1	6	1	2	9
Contents summary example	*All electronic appliance companies are under pressure. Sharp made a new low (t-9) *Sharp developed smaller and lighter LCD panel for e-book. It is going to be in the market from Aug (t-5) *Sharp downward revised the earnings prospect. Also announced restructuring 5,000 workforce (t-1)											
Ricoh Co Ltd downgraded on April 27, 2012	−11.26 %		2012/4/17	4/18	4/19	4/20	4/21	4/22	4/23	4/24	4/25	4/26
Sentiment score		−11	0	0	0	−1	0	0	0	−3	−3	−4
Number of articles		−11	0	0	0	2	0	0	0	1	4	3
Contents summary example	*Nomura and its affiliated investor reduce their Ricoh's share holdings below 5 % (t-7) *Selling pressure mounts to the stocks that have high exposure to European economy including Ricoh (t-4) *Ricoh's earnings plunge to net loss, first time in its company history. 10,000 job cuts to follow (t-1)											

In this subsection, we test the hypothesis as follows. Among attention-grabbing (media-covered) stocks, the sentiment of the media determines the degree of overvaluation before the announcement. To test this hypothesis, we re-classify our media-covered sample firms into three subsets: firms with cumulative negative news scores on the day before an announcement, firms with positive news scores and their sample complement (neutral). Figure 20.3 illustrates the CAR up to 10 days after the event. When stocks are upgraded, firms with positive sentiment do not demonstrate positive abnormal returns, except as an initial reaction to the announcement. This is consistent with the hypothesis that positive news encourages individual investors to put in speculative bids; those bids are to be filled by professional traders at an overvalued level. Thus, the subsequent rise upon good news of such stocks is limited. The subset of the sample firms with neutral sentiment score and negative sentiment score do not have this effect. The difference between these two groups is statistically significant. We conjecture that positive sentiment in the news entices individual investors to trade at an overvalued price.

Again, we see an asymmetric result for the sentiment-based subsample analysis on downgrades. Regardless of the sentiment in the pre-event window, the stocks tend to drift downward in tandem. As discussed in subsection 4.3, downward stickiness in analysts' recommendation revisions (Conrad et al. 2006) may be making the sentiment factor trivial.

5 Robustness Checks

Post-earnings announcement drift, initial public offering (IPO) underperformance and delisting bias are well-documented return anomalies and, hence, we need to check that the media effect is not driven by them. These anomalies could lead to a spurious media effect if media coverage is more intense for firms announcing earnings, for IPO stocks or for stocks going through delisting. For example, if media coverage is biased toward bad earnings news, or if returns tend to drift more following bad earnings news compared to good earnings news, then, indeed, the non-media-covered perform better. A no-coverage premium would also result if high-coverage stocks are disproportionally represented by IPO stocks that subsequently underperform. Finally, if the media has a tendency to cover firms going through delisting for negative reasons (e.g. liquidation or takeover), then the delisting bias reported by Shumway (1997) could also lead to a spurious media effect.

To check that our results are not driven by post-earnings announcement drift, IPO underperformance or delisting stocks, we exclude all potentially earnings-related media coverage, all IPO stocks and all delisted stocks during our sample period. Our clean sample comprises 2,415 firm upgrade events and 2,560 firm downgrade events.

Table 20.5 indicates the post-event CAR up to 10 days into the post-announcement period. When stocks are upgraded, as described in Fig. 20.1, significant drift occurs. When we divide our sample into media-covered and non-

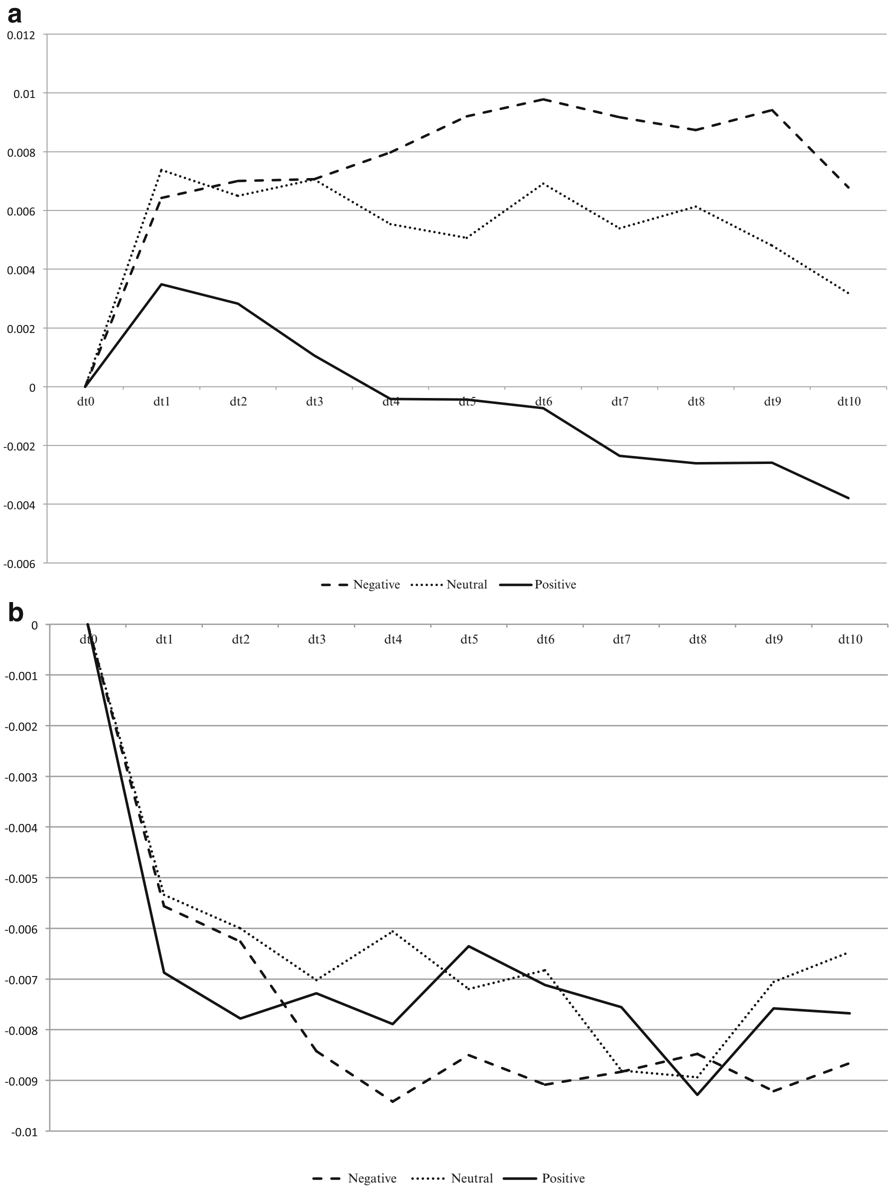

Fig. 20.3 Post-announcement performance by sentiment score. The 'negative', 'neutral' and 'positive' sub-sample sets are created based on the cumulative sentiment score over the 10-day period prior to the announcement date

Table 20.5 Post-event CAR up to 10 days into the post-announcement period

	No media cover	Media cover	Diff	*p-value*	No media cover	Media cover	Diff	*p-value*	Non-negative	Negative	Diff	*p-value*	Non-negative	Negative	Diff	*p-value*
Upgrades																
	Total sample (n = 6,038)				Clean sample (n = 4,605)				Total sample (n = 3,212)				Clean sample (n = 2,321)			
n	3,212	2,826			2,321	2,284			1,532	1,680			1,141	1,180		
CAR1	0.011	0.005	0.006	***0.000***	0.011	0.006	0.005	***0.000***	0.006	0.009	−0.003	***0.001***	0.006	0.009	−0.003	***0.030***
CAR2	0.013	0.005	0.007	***0.000***	0.013	0.006	0.007	***0.000***	0.005	0.010	−0.005	***0.000***	0.006	0.011	−0.005	***0.004***
CAR3	0.013	0.005	0.009	***0.000***	0.014	0.006	0.008	***0.000***	0.003	0.011	−0.008	***0.000***	0.004	0.012	−0.008	***0.000***
CAR4	0.013	0.005	0.009	***0.000***	0.015	0.006	0.009	***0.000***	0.002	0.011	−0.009	***0.000***	0.002	0.013	−0.010	***0.000***
CAR5	0.013	0.004	0.008	***0.000***	0.014	0.006	0.008	***0.000***	0.002	0.010	−0.009	***0.000***	0.002	0.013	−0.010	***0.000***
CAR6	0.013	0.005	0.008	***0.000***	0.014	0.007	0.008	***0.001***	0.002	0.011	−0.009	***0.000***	0.003	0.013	−0.011	***0.000***
CAR7	0.011	0.004	0.008	***0.000***	0.014	0.006	0.008	***0.002***	0.001	0.010	−0.008	***0.000***	0.002	0.013	−0.010	***0.000***
CAR8	0.012	0.003	0.010	***0.000***	0.015	0.006	0.009	***0.000***	0.000	0.010	−0.010	***0.000***	0.001	0.013	−0.012	***0.000***
CAR9	0.012	0.003	0.009	***0.000***	0.014	0.006	0.008	***0.002***	0.000	0.010	−0.010	***0.000***	0.001	0.013	−0.012	***0.000***
CAR10	0.012	0.002	0.009	***0.000***	0.014	0.005	0.008	***0.004***	−0.001	0.009	−0.011	***0.000***	0.001	0.012	−0.011	***0.000***
Downgrades																
	Total sample (n = 6,110)				Clean sample (n = 4,489)				Total sample (n = 3,141)				Clean sample (n = 2,189)			
n	3,141	2,969			2,189	2,300			1,200	1,941			914	1,275		
CAR1	−0.011	−0.006	−0.005	***0.000***	−0.011	−0.006	−0.005	***0.000***	−0.006	−0.009	0.003	***0.027***	−0.005	−0.009	0.004	***0.012***
CAR2	−0.014	−0.007	−0.007	***0.000***	−0.014	−0.007	−0.007	***0.000***	−0.007	−0.011	0.004	***0.007***	−0.006	−0.012	0.005	***0.008***
CAR3	−0.016	−0.009	−0.008	***0.000***	−0.016	−0.009	−0.007	***0.001***	−0.008	−0.013	0.005	***0.011***	−0.009	−0.014	0.005	***0.019***
CAR4	−0.018	−0.010	−0.008	***0.000***	−0.017	−0.010	−0.007	***0.002***	−0.008	−0.015	0.007	***0.001***	−0.008	−0.015	0.006	***0.009***
CAR5	−0.019	−0.010	−0.009	***0.000***	−0.019	−0.010	−0.009	***0.000***	−0.009	−0.016	0.007	***0.002***	−0.010	−0.015	0.006	***0.018***
CAR6	−0.020	−0.010	−0.009	***0.000***	−0.019	−0.010	−0.009	***0.001***	−0.009	−0.016	0.007	***0.008***	−0.010	−0.016	0.005	***0.031***
CAR7	−0.021	−0.012	−0.009	***0.000***	−0.020	−0.012	−0.008	***0.006***	−0.011	−0.017	0.006	***0.020***	−0.012	−0.016	0.004	*0.059*
CAR8	−0.021	−0.011	−0.010	***0.000***	−0.020	−0.010	−0.009	***0.003***	−0.010	−0.018	0.008	***0.005***	−0.011	−0.016	0.005	***0.043***
CAR9	−0.021	−0.011	−0.011	***0.000***	−0.020	−0.010	−0.010	***0.001***	−0.008	−0.018	0.010	***0.001***	−0.009	−0.016	0.008	***0.013***
CAR10	−0.021	−0.009	−0.012	***0.000***	−0.020	−0.008	−0.012	***0.001***	−0.005	−0.017	0.012	***0.000***	−0.005	−0.016	0.011	***0.002***

media-covered firms, we still find the same results. Table 20.5 indicates that the p-values are less than 1 % for CAR1 through CAR10 for both upgrades and downgrades. Statistical significance remains intact, even when we limit our analysis to the clean sample.

We subsequently conduct the same comparison for the sentiment score effect on post-event returns. We observe little difference between our total sample and the clean sample for either upgrades or downgrades.

6 Conclusion

We examine the effect of media coverage and media sentiment on investor behavior surrounding sell-side analysts' rating revisions. First, we find significantly stronger post-announcement drift when the stocks are not covered by the media. On average, stocks that are not featured in the media outperform the benchmark by over 1.35 % in the 3 days after the upgrading announcement and underperform by 1.64 % in the downgrading announcement. Our findings are consistent with the view that new fundamental information has stronger effect when Bayesian updating investors are not exposed to any news.

Second, we find significant return difference among media-covered stocks. For upgraded stocks, those with positive sentiment do not demonstrate positive announcement return. The stocks with high media exposure with positive sentiment are likely to be bought by naïve individual investors. Our result is consistent with the view that such attention-grabbing stocks are overvalued because professional investors sell to naïve investors at overvalued prices.

Finally, we show that the media effect is robust to the well-known post-earnings announcement drift, IPO underperformance and delisting bias anomaly. We provide test results for clean samples, excluding firms that are subject to these three biases, but the results remain intact. Interestingly, media coverage sentiment affects future returns (e.g. Tetlock 2007; Tetlock et al. 2008). The negative correlation between media sentiment score and post-event returns then suggests that that naïve investors, regardless of their fundamental news, long stocks when the media sentiment is positive and short stocks when negative. These observations suggest that the mass media's effect on security pricing stems from its ability to not only disseminate information broadly but also shape opinions or form consensus.

Acknowledgements The authors are thankful for the financial support by the Grant in Aid in Scientific Research (KAKENHI), JST-ERATO Minato Discrete Structure Manipulation System Project and Ishii Memorial Foundation for the Study of Securities Markets.

Addendum: News Effect on Pre-announcement Performance[6]

1. Attention Effect in the Pre-announcement Period

In this subsection, we investigate whether the pre-recommendation returns of firms are affected by the fact that they gained media attention. The relation between media attention and stock returns, if any, gives us a hint about the interaction between investor behavior and stock market returns. Fang and Peress (2009) find return differentials due to media coverage. They examine cross-sectional return patterns and find that media-covered stocks have lower returns than non–media-covered stocks. Chan (2003) examines momentum and reversal patterns following large price moves with and without accompanying news and supports the same findings. In this addendum, we examine pre-announcement price behavior with and without media attention.

Appendix Fig. 20.4 describes the pre-event abnormal returns based on our sub-sample sets. We divide our samples based on media coverage during the 10 business days prior to the announcement date ($dt - 0$). As shown, the media-covered stocks to be upgraded (downgraded) generate greater positive (negative) abnormal returns in the run-up period than their non–media-covered counterparts. This can be interpreted to mean that streaming news conveys fundamental information about stocks and investors update their evaluations as news is disseminated. Interestingly, the media-covered stocks' return pattern reverses in the post-announcement period, as discussed in the main text.

One possible explanation of this reversal is that individual investors trade (long/short) attention-grabbing stocks and thus the stock price at the time of the announcement is overvalued (undervalued) (Barber and Odean (2008)). An alternative plausible explanation is that the media convey some fraction of the fundamental information; therefore, media-covered stocks are traded at a price that already partially discounts the good (bad) news. The latter interpretation is consistent with the work of Tetlock et al. (2008), who argue that the words contained in news stories are not redundant information but, instead, capture otherwise hard-to-quantify aspects of firms' fundamentals. Our conjecture is that both effects are behind the price move. The media not only convey future fundamental information but also affect investor behavior.

One of the characteristics of our data is those made available to us are incomplete. Certain brokerage houses have entered into agreements with their information vendors that preclude their recommendations from being distributed immediately after their release. Consequently, some of the analysts' recommendation information remains in the private domain for a few days before it becomes available to

[6]This addendum has been newly written for this book chapter.

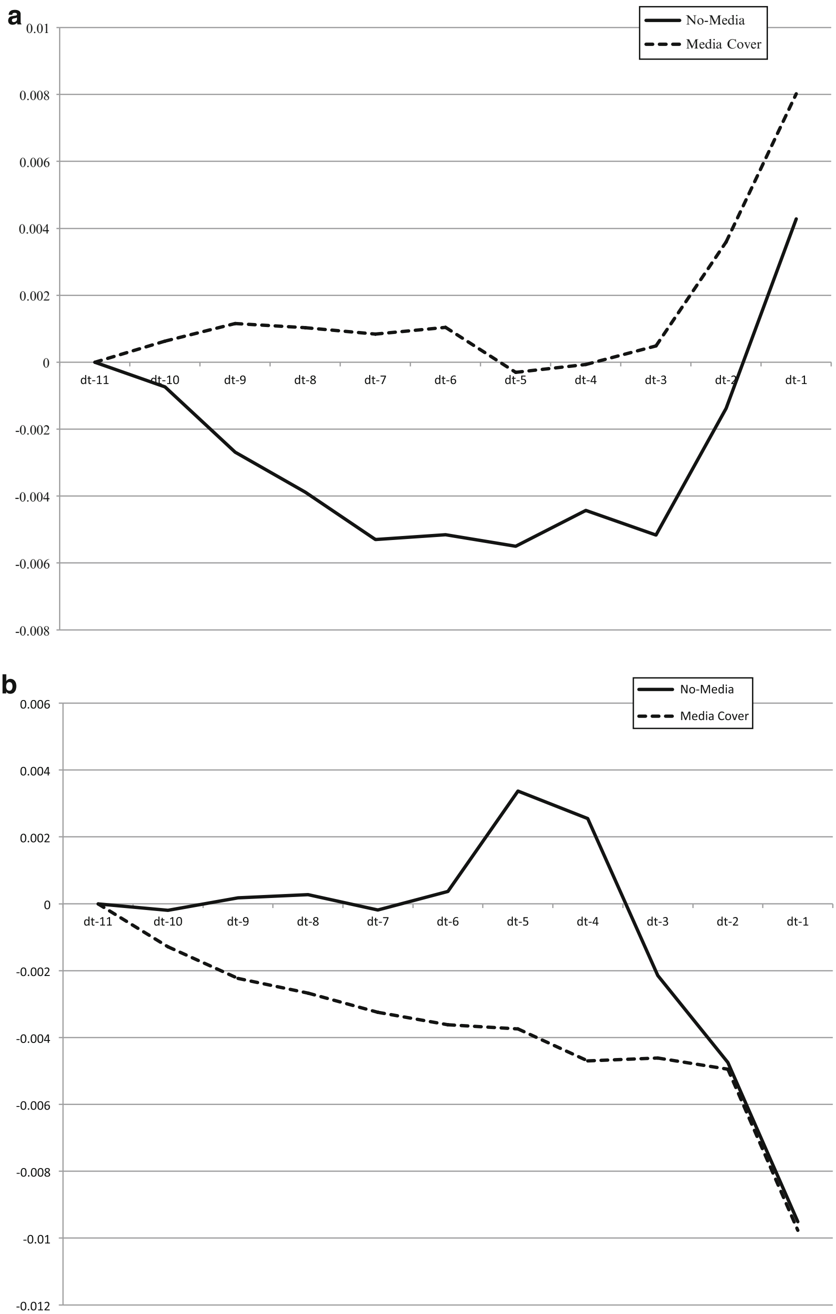

Fig. 20.4 The plot of the cumulative abnormal returns for (**a**) upgrades and (**b**) downgrades prior to the announcement. (*Notes*: The benchmark return is the return of the respective control firm, chosen based on industry, size, and book-to-market ratio. The market starts to react to analysts' upgrades starting three days prior to the announcement date. For downgrades, only media-covered stocks start to react three days prior)

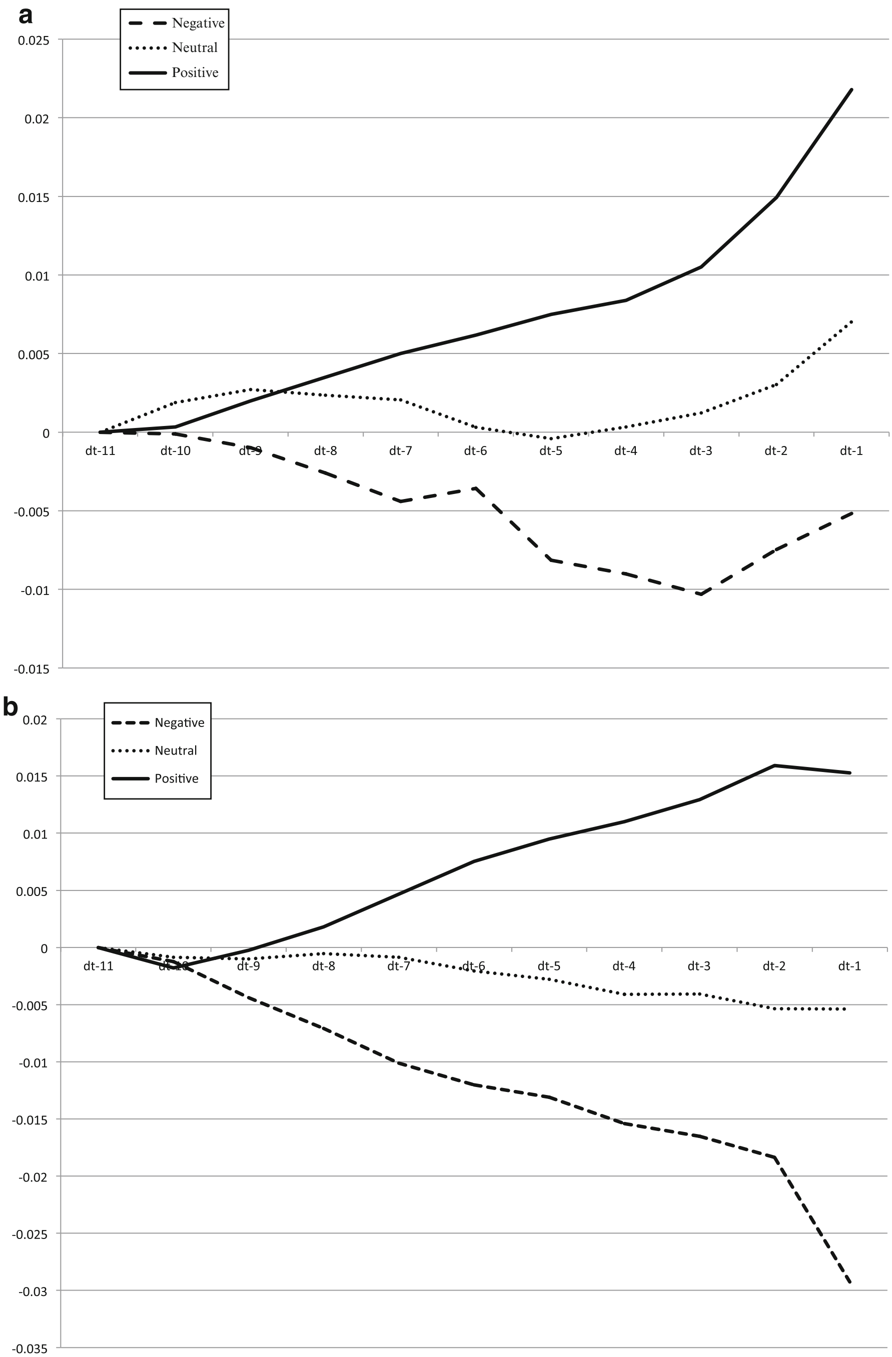

Fig. 20.5 The plot of cumulative abnormal returns for upgrades (**a**) upgrades and (**b**) downgrades prior to the announcement

the public. This enables certain privileged investors to act before others do. The abnormal return spike observed at $dt-2$ is primarily due to this time difference in information dissemination.

2. *Sentiment Effect for Stocks in the Pre-announcement Period*

In this subsection, we focus on media-covered stocks and investigate whether media tone – that is, whether negative, positive, or neutral – affects stock market returns in the pre-announcement period. As discussed in the main text, we use a simple word count method to proxy for the sentiment of streaming news. As shown in Fig. 20.5, positively reported stocks generate positive abnormal returns in the pre-announcement run-up period, while the neutral and negative subsets of the samples do not. This is primarily because investors obtain a fraction of otherwise hard-to-quantify fundamental information in positive news and discount it in the stock prices. In the run-up period, positively reported stocks rise two percentage points above their benchmarks. However, as shown in Fig. 20.2 in the main text, these stocks are the ones that demonstrate little positive abnormal return in the post-announcement period. This can be interpreted as the result of investors having discounted most of the good fundamental information. For downgraded stocks, the positively reported subset does perform well in the run-up period. This indicates that the fraction of fundamental information contained in the news is not relevant to the analysts' downward revision. The fact that the negatively reported subset performs poorly in the run-up period and deteriorates further beyond $dt-2$ is consistent with this irrelevancy conjecture.

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