Appendix 2. Definition of variables

Variable	Definition
Geographic focus (diversification)	$\mathrm{HHI_{GF}} = \left(\frac{\mathrm{Rev\_home}}{\mathrm{REV}}\right)^2 + \left(\frac{\mathrm{Rev\_Europe}}{\mathrm{REV}}\right)^2 + \left(\frac{\mathrm{Rev\_World}}{\mathrm{REV}}\right)^2$, where Rev_home is the revenues generated at home, Rev_Europe the revenues generated in the rest of Europe, Rev_World the revenues generated in the rest of the World, and REV the total revenues generated at home and abroad $\mathrm{Geog\_focus} = \frac{\mathrm{HHI_{GF}}-1/3}{1-1/3}$.
Business focus (diversification)	$\mathrm{HHI_{BF}} = \left(\frac{\mathrm{INT}}{\mathrm{TOR}}\right)^2 + \left(\frac{\mathrm{COM}}{\mathrm{TOR}}\right)^2 + \left(\frac{\mathrm{TRAD}}{\mathrm{TOR}}\right)^2 + \left(\frac{\mathrm{OTI}}{\mathrm{TOR}}\right)^2$, where INT is the net interest revenue, COM the net commission and fee revenue, TRAD the net trading revenue, OTI the all other revenue, and TOR the total operating revenue, equal to the sum of the absolute values of INT, COM, TRAD, and OTI $\mathrm{Bus\_focus} = \frac{\mathrm{HHI_{BF}}-1/4}{1-1/4}$.
Leverage	Book value of total liabilities over the sum of book value of equity and total liabilities
Credit risk	Loan loss provisions over loans
Volatility	The standard deviation of monthly prices over the last 12 months divided by the average of the monthly price over the last 12 months, calculated in June of every year
The dispersion of analysts' earnings forecasts (KV FEPS)	The natural logarithm of the coefficient of variation of analysts' one-year-ahead earnings per share forecasts as reported by I/B/E/S in June of every year
Book to market	Book value of equity capital over market value of equity capital
Momentum	Buy and hold return on the bank's stock over the period: beginning of June ($t-1$) until the end of May (t)

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Evaluating analysts' value: evidence from recommendation revisions around stock price jumps

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Recent studies document that analyst recommendation revisions tend to coincide with important corporate events, but offer mixed evidence on whether these revisions still contain significant information content. In this paper, we use large discontinuous changes, known as *jumps*, in stock prices as proxy for significant events and examine the information content of analyst revisions. We find that although recommendation revisions are more likely to be clustered around stock price jumps, they still contain significant information, especially those issued *prior* to jumps.

Keywords: analyst recommendation revisions; information processing ability; stock price jumps; corporate events; market reactions

JEL Classification: G12; G14; G20; G23

The information processing ability of stock analysts is one of the contentious debates among finance scholars and practitioners. Existing literature in general concludes that analyst recommendation revisions (i.e. upgrades or downgrades) contain significant information. However, more recent studies cast doubt on such conclusions. These studies document that a vast majority of recommendation revisions coincide with important corporate events. For example, Asquith, Mikhail, and Au (2005) document that half of the analyst reports are released concurrently with important firm-specific activities, including security issues or mergers and divestitures. Altinkilic and Hansen (2009) show that 80% of the recommendation revisions are made in response to some corporate events such as earnings announcements or investment project announcements. We note that the observation that most of analysts' reports are released concurrently with important corporate events should be expected and is thus not sufficient evidence to undermine analysts' information processing ability. This is because the main role of analysts is to help investors translate corporate events into investment decisions.

Despite the above challenge, the existing literature is far from being conclusive in regard to whether analyst revisions contain significant information beyond the confounding corporate events. For example, Altinkilic and Hansen (2009) present evidence that the intraday return immediately following the announcement time of revision is quite small. They conclude that analyst revisions have no additional information beyond that contained in the original

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corporate events. On the other hand, Loh and Stulz (2011) explicitly exclude recommendations issued around earnings announcements and management earnings guidance and find that market reactions are still significant, although the magnitude is reduced. Similarly, Park and Pincus (2000) examine analysts' revisions issued over a five-day window after earnings announcements and find that consensus analyst revisions have information content beyond earnings surprises.

The analysis of most existing studies, however, is based on certain pre-defined corporate events. For instance, Ivkovic and Jegadeesh (2004) focus on earnings managements and Loh and Stulz (2011) focus on earnings announcements and management earnings guidance. This is likely constrained by the availability of corporate event dates from standard data sources such as Compustat, Institutional Brokers' Estimate System (IBES) or SDC Platinum. As documented in the literature, there are a number of other corporate events, such as mergers and acquisitions, spinoffs, litigations, and also some economy- or industry-wide events that contain significant information about firm value. These events can all induce confounding information in analyst recommendations. However, exhausting all these events to examine the effect of analyst recommendations is a formidable, if not impossible, task. In addition, even with all corporate event dates identified, it is impossible to measure unexpected information content of all corporate events. Other than earnings announcements where analysts provide forecasts prior to the announcement, there are no readily available *ex ante* measures of market expectation for other corporate events. Since not all corporate events necessarily contain significant unexpected information, excluding revisions on these event dates may underestimate the information content of analyst revisions.

In this paper, we extend existing literature and use large discontinuous changes, known as jumps, in stock prices as proxy for significant information events. That is, we identify jumps in stock prices and examine the information content of analyst revisions after controlling for jumps. The idea of linking large price changes with information events has been utilized in the previous literature (see, for example, Ryan and Taffler (2004); Conrad et al. (2006)). Different from previous studies that rely on certain cutoffs to identify extreme price changes, our study relies on a robust statistical method to identify jumps in stock prices. Specifically, we extend the jump test proposed in Jiang and Oomen (2008) to detect jumps in daily stock prices. The method is based on a general Brownian diffusion process with jumps for stock returns and is also robust to market microstructure noises in stock prices.

In addition, our method also enables us to classify certain information events as 'good' or 'bad' news based on whether the jumps are 'positive' or 'negative'. Existing studies have documented that information content may be asymmetric for upgrades versus downgrades. For example, Ivkovic and Jegadeesh (2004) find that there is a sharp increase in the information content of upgrades in the week before an earnings announcement, but no similar increase for downgrades. Jegadeesh and Kim (2010) show that investors discount the information in revisions that move toward the prevailing consensus much more so for downgrades than for upgrades. Nolte, Nolte, and Vasios (2014) provide evidence that career concerns have a stronger impact on analysts' behavior for negative deviations from the consensus earnings forecast than for positive deviations. Our analysis extends existing studies by examining the informativeness of upgrades and downgrades interacting with 'good' or 'bad' news, respectively.

The research questions we attempt to address in this study are as follows. We first explore the extent to which analysts' decision to issue revisions are linked to jumps in stock prices. We note that the major role of analysts is to interpret information contained in corporate events and disseminate such information in the form of investment decisions. If analyst revisions are mostly triggered by contemporaneous corporate events, we should observe more revisions on days with stock price jumps. More importantly, we next examine whether analyst revisions have added value beyond the confounding events as proxied by jumps. Since revisions made on jump days are potentially contaminated by confounding events, we focus on revisions made both before and after jumps in stock prices. In particular, as noted in Louth et al. (2010), one important aspect of analyst forecasts and revisions is to provide information on the likelihood of a potential jump event. Our approach is similar in spirit to that of Park and Pincus (2000) and Ivkovic and Jegadeesh (2004) who examine the information content of recommendation revisions made around earnings announcements.[1] In addition, we compare these revisions with those unrelated to jumps and test whether revisions made around jumps still contain significant information content.

We find that both the analysts' tendency to issue recommendation revisions and market reactions to revisions are strongly related to jumps in stock prices. The probability of an analyst issuing a revision coupled with a concurrent stock price jump is 2.5 times as high as the unconditional probability of issuing a revision on any given day. In addition, we find that there tends to be a much higher probability that a downgrade (upgrade) is issued on days where there is a negative (positive) stock price jump. Specifically, compared with the unconditional probability of an analyst issuing a downgrade (upgrade) on any given day, the probability of a downgrade (upgrade) issued concurrently with a negative (positive) stock price jump is 6.7 (3.5) times higher. This finding confirms the notion that analysts often release their reports concurrently with important corporate events to convey their updated stock valuation and revise their recommendations for investment decisions.

Our results confirm that the initial market reactions to upgrades and downgrades in our sample are comparable to the magnitudes reported in earlier studies. However, these reactions are largely driven by revisions with concurrent stock price jumps, despite the fact that they only account for about 10% of the revision sample. Specifically, average market-adjusted cumulative three-day buy-and-hold return following all downgrades (upgrades) is -3.3% (2.5%) while the corresponding number after excluding those revisions with concurrent jumps is only -1.8% (1.7%). These findings suggest that without controlling for the effect of confounding corporate events, there may be a potential overestimation of the value provided by analysts.

Our main objective is to test whether analysts provide incremental information above and beyond that contained in confounding corporate events. To do so, we focus on revisions made both before and after stock price jumps. Revisions made prior to jumps could be issued by analysts who have access to private information, while those made after jumps likely reflect analysts' effort to interpret publicly available information. The results based on univariate analyses indicate that short-term market reactions to both pre-jump revisions and post-jump revisions are statistically significant, indicating that these revisions contain significant information content. In addition, our results show that long-term effects of revisions around jumps are more pronounced for upgrades. Moreover, we find that 'lead' analysts as identified following the procedure in Cooper, Day, and Lewis (2001) are more likely to issue revisions on the same day as the jump but less likely to issue revisions following jumps. This suggests that pre-jump revisions and post-jump revisions may have different information content.

To control for potential differences in characteristics at the revision-level, analyst-level, and stock-level, we next implement a multivariate regression where the dependent variable is the three-day buy-and-hold market-adjusted return. In particular, we control for information contained in earnings forecast revisions and target price changes issued by the same analyst. The key explanatory variables include dummies for concurrent revisions, pre-jump revisions, and post-jump revisions. The results indicate that while revisions made concurrently with jumps amplify market reactions to a large extent, those made after jumps mitigate market reactions even after controlling for potential differences in revision characteristics, analyst characteristics, and firm characteristics. Furthermore, we find that market reactions to pre-jump revisions are similar in magnitude as those to revisions that are not associated with any jumps. Finally, our results show that pre-jump revisions are more informative than post-jump revisions.

Overall, our analysis shows that analyst recommendation revisions are more likely to occur on days with stock price jumps, and these revisions explain a large portion of initial market reactions reported in the previous literature. However, there is still significant information content in revisions made both before and after jumps in stock prices – especially those made prior to jumps. Our study provides additional evidence that analyst revisions do contain significant information about future stock returns beyond public information in corporate events.

The remainder of the paper is organized as follows. Section 1 describes the data and the procedure of identifying jumps in stock prices. Section 2 examines how recommendation revisions are clustered around stock price jumps. Section 3 presents univariate analyses of market reactions to revisions issued around jumps in stock prices. Section 4 performs multivariate analyses of market reactions by controlling for various characteristics at the revision-level, analyst-level, and stock-level. Section 5 presents additional robustness checks and Section 6 provides the conclusion.

1. Data and methodology

1.1 *Data*

Data on recommendation revision is obtained from IBES Detail Recommendation file and daily stock returns are obtained from Center for Research in Security Prices (CRSP). IBES recommendations data are only available since 1993, so we set our sample period from November 1993 to December 2007.

For the recommendation data, we impose the following criterion.

(1) There should be at least one analyst who issues a recommendation for the stock and revises the recommendation during the sample period,
(2) The analyst code should be available on IBES, and
(3) Stock return data should be available from CRSP on the revision date.

We impose these criteria since our primary focus is how analysts revise their recommendations around stock price jumps and how the market reacts to such revisions. We do not include recommendations in our sample if an analyst makes only one recommendation for the stock, or it is a reiteration of a previous recommendation, or IBES does not provide any code for the analyst's identity.

We initially start out with 488,098 recommendations from IBES Detail US Recommendations file. After filtering out those recommendations without analyst identifiers, we are left with 471,668 recommendations. To obtain recommendation *revisions*, we locate the most recent recommendation issued by the same analyst for the same covered firm and take the difference in recommendation levels. In this process, the first recommendations issued by an analyst on a given stock, a total of 169,069, are dropped by construction. Since our focus is on changes in recommendations, 68,224 reiterations of previous recommendations are further dropped from our sample. We then merge the recommendation revisions with CRSP to obtain daily returns following recommendation revisions. Our final sample consists of 97,709 upgrades and 125,194 downgrades with valid returns on the revision date.

1.2 *Identifying stock price jumps*

Stock price changes can be characterized as smooth and continuous changes in the form of Brownian diffusion or sudden and large discontinuous changes in the form of jumps. Jumps are typically triggered by substantial information or liquidity shocks. A number of recent empirical studies find that jumps constitute a critical component in asset returns.[2]

Various statistical tests have been proposed in the recent literature to detect whether there are jumps in asset prices.[3] In this paper, we employ the variance swap approach by Jiang and Oomen (2008) to identify jumps. The variance swap approach builds on an intuition long established in the finance literature: in the absence of jumps, the difference between simple return and log return – called 'variance swap' – captures one half of the instantaneous return variance. As such, the variance swap can be perfectly replicated using the log contract (see Neuberger (1994)). However, in the presence of jumps, the replication strategy is imperfect and the replication error, as a function of realized jumps, can be used to identify jumps. As we elaborate in the Appendix, the approach does not rely on any specific stock return model. In addition to possessing desirable finite sample properties in regard to size, the variance swap approach has nice power in detecting infrequent but large changes in stock prices. This feature suits the purpose of our study, as we focus on large changes in stock prices. In addition, the variance swap test also explicitly incorporates market microstructure noise, allowing for serial correlations induced by non-trading effects and bid-ask spreads.

In our empirical analysis, we first apply the jump test to daily return observations of all stocks in the universe of CRSP over each calendar quarter to examine whether stock prices exhibit jumps. If the null hypothesis of no jumps is rejected, we then follow a sequential procedure to determine whether the price change (or return) of a particular day represents a jump. Jumps are identified at the 5% critical level. The identified stock price jumps are used in our analysis as proxy for generic information events.[4] Details of this procedure are provided in the Appendix.

1.3 *Summary statistics*

The first seven columns in Table 1 present the descriptive statistics of analyst recommendation revisions. The number of firms covered in the sample ranges from a low of 328 in 1993 to a high of 3981 in 1998. The small sample size in 1993 largely reflects that IBES coverage is incomplete in its first year. The first recommendation date available from IBES is 29 October 1993, but the first available revision date, which requires a previous recommendation, is 2 November 1993. The median number of analysts following a firm over the entire sample period is 2. The number of brokerages in the database increases from 57 in 1993 to 275 in 2005 before decreasing to 251 in 2007. The median number of analysts in a brokerage is 5. The last three columns in Table 1 present the number of firms in CRSP that have at least one jump during each year in our sample period. It also reports the number of firms with positive jumps versus those with negative jumps. The results show that overall there are more firms with positive jumps than those with negative jumps.

Table 2 presents summary statistics of stock price jumps for each year during the sample period. The first five columns report summaries for positive jumps, while the next five columns present corresponding numbers for negative jumps. For both positive and negative jumps, we observe that the mean and median magnitudes of these jumps are quite substantial. For example, the mean daily jump size is 11.6% for positive jumps and −12.6% for negative jumps.

Table 1. Descriptive statistics of recommendation revisions and stock price jumps.

Year	Number of firms followed	Number of analysts	Number of brokerages	Number of analysts per brokerage		Number of analysts following each firm		Number of firms with jumps		
				Mean	Median	Mean	Median	All	(+) Jumps	(−) Jumps
1993	328	262	57	4.61	3	1.20	1	1730	1332	938
1994	2747	1460	131	11.69	5	2.67	2	5367	4626	4120
1995	3195	1738	134	13.49	6	3.04	2	6110	5728	4058
1996	3417	1915	160	12.67	5	2.72	2	6551	6088	4600
1997	3746	2183	187	12.36	6	2.62	2	7300	6773	5244
1998	3981	2573	209	12.84	5	2.92	2	7086	6427	5631
1999	3816	2824	200	15.02	7	3.09	2	7170	6615	5430
2000	3575	2742	196	15.13	6	3.09	2	6566	5988	5002
2001	3232	2671	171	16.26	7	3.33	2	6203	5620	4939
2002	3465	2866	185	16.00	6	4.48	3	5308	4603	4307
2003	3335	2727	234	12.12	4	3.82	3	5620	5287	3835
2004	3387	2836	267	11.11	3	3.60	2	5497	4992	4132
2005	3479	2882	275	10.93	3	3.35	2	5342	4758	4071
2006	3555	2871	260	11.48	4	3.34	2	5413	5068	3864
2007	3549	2887	251	11.97	4	3.29	3	5176	4444	4175
All years	9830	8844	556	12.73	5	3.23	2	15,928	15,637	15,052

Notes: This table presents descriptive statistics of analyst recommendation revisions and stock price jumps. The recommendation revisions sample includes all firms that have at least two active recommendations from the same analyst in the IBES Detailed US Recommendations database which resulted in either an upgrade or a downgrade, and also have stock return data on recommendation revision dates. For each calendar year of the sample period, the table reports the number of firms followed by analysts, the number of analysts, and the number of brokerage firms. The next four columns present the mean and median numbers of analysts per brokerage firm and the number of analysts following each firm, respectively. The remaining three columns present the number of firms with stock price jumps, positive jumps, and negative jumps, respectively. Stock price jumps are identified using the 'variance swap' test developed in Jiang and Oomen (2008) at the 5% critical level. The sample period is from November 1993 to December 2007.

Table 2. Summary statistics of stock price jumps.

Year	Positive jumps					Negative jumps				
	Jump size per day		Occurrence per firm			Jump size per day		Occurrence per firm		
	Mean	Median	Mean	Median	Maximum	Mean	Median	Mean	Median	Maximum
1993	0.102	0.077	1.7	1	6	−0.112	−0.080	1.6	1	5
1994	0.106	0.079	3.0	3	14	−0.117	−0.081	2.4	2	14
1995	0.100	0.073	3.7	3	16	−0.126	−0.090	2.1	2	11
1996	0.105	0.079	3.5	3	14	−0.124	−0.089	2.1	2	10
1997	0.103	0.079	3.7	3	16	−0.130	−0.094	2.3	2	12
1998	0.141	0.104	3.3	3	16	−0.144	−0.104	2.6	2	16
1999	0.151	0.118	3.7	3	16	−0.130	−0.095	2.4	2	15
2000	0.156	0.120	3.3	3	18	−0.170	−0.128	2.4	2	14
2001	0.147	0.110	3.5	3	15	−0.153	−0.112	2.6	2	13
2002	0.131	0.093	3.1	3	14	−0.150	−0.106	2.6	2	13
2003	0.107	0.077	4.2	4	16	−0.113	−0.082	2.1	2	12
2004	0.090	0.065	3.6	3	13	−0.095	−0.067	2.4	2	12
2005	0.088	0.065	3.3	3	13	−0.091	−0.064	2.5	2	12
2006	0.080	0.059	3.6	3	13	−0.096	−0.069	2.2	2	16
2007	0.095	0.072	2.8	2	12	−0.095	−0.065	2.5	2	12
All years	0.116	0.084	3.4	3	18	−0.126	−0.089	2.4	2	16

Notes: This table presents summary statistics of stock price jumps identified during the sample period. Stock price jumps are identified using the 'variance swap' test developed in Jiang and Oomen (2008) at the 5% critical level. The first four columns report results for positive jumps and the next four columns report those for negative jumps. Within each category, we report the mean and median of daily jump size as well as the number of jumps per firm for each year in our sample. The sample period is from November 1993 to December 2007.

Corresponding median jump sizes are 8.4% and −8.9%, respectively. These numbers are substantially larger than those reported in the previous research based on in-sample tail distributions. For example, average three-day market-adjusted returns for the large positive (negative) return group are between 3.5% and 5.5% (−3% and −4.5%) in Conrad et al. (2006). The frequencies of jumps suggest that for every three positive jumps for an average stock each year there are two negative jumps. The results also show that some stocks experience as many as 18 (16) positive (negative) jumps in a given year. Since the results are based on firms with at least one jump, minimum occurrence per firm is one by construction.

2. Stock price jumps around recommendation revisions

Figure 1 plots the number of stock price jumps around the revision date. Panel A plots price jumps around all revisions, while Panel B plots sub-sample results for positive/negative jumps and upgrades/downgrades. In both panels, day 0 refers to the recommendation revision date and the event window is from −10 to +10 trading days.

The results from Panel A indicate that a large number of revisions are accompanied by concurrent stock price jumps on or around the revision date. In addition, there is a higher frequency of stock price jumps before the revision than after the revision. The larger number of jumps reflects higher intensity of information flow before and on the revision date. This suggests that stock price jumps may trigger the demand for analysts to disseminate information to investors. The decrease of jumps after revision suggests that analyst revisions may help to resolve information uncertainty or, in general, analyst revisions lag other corporate information events.

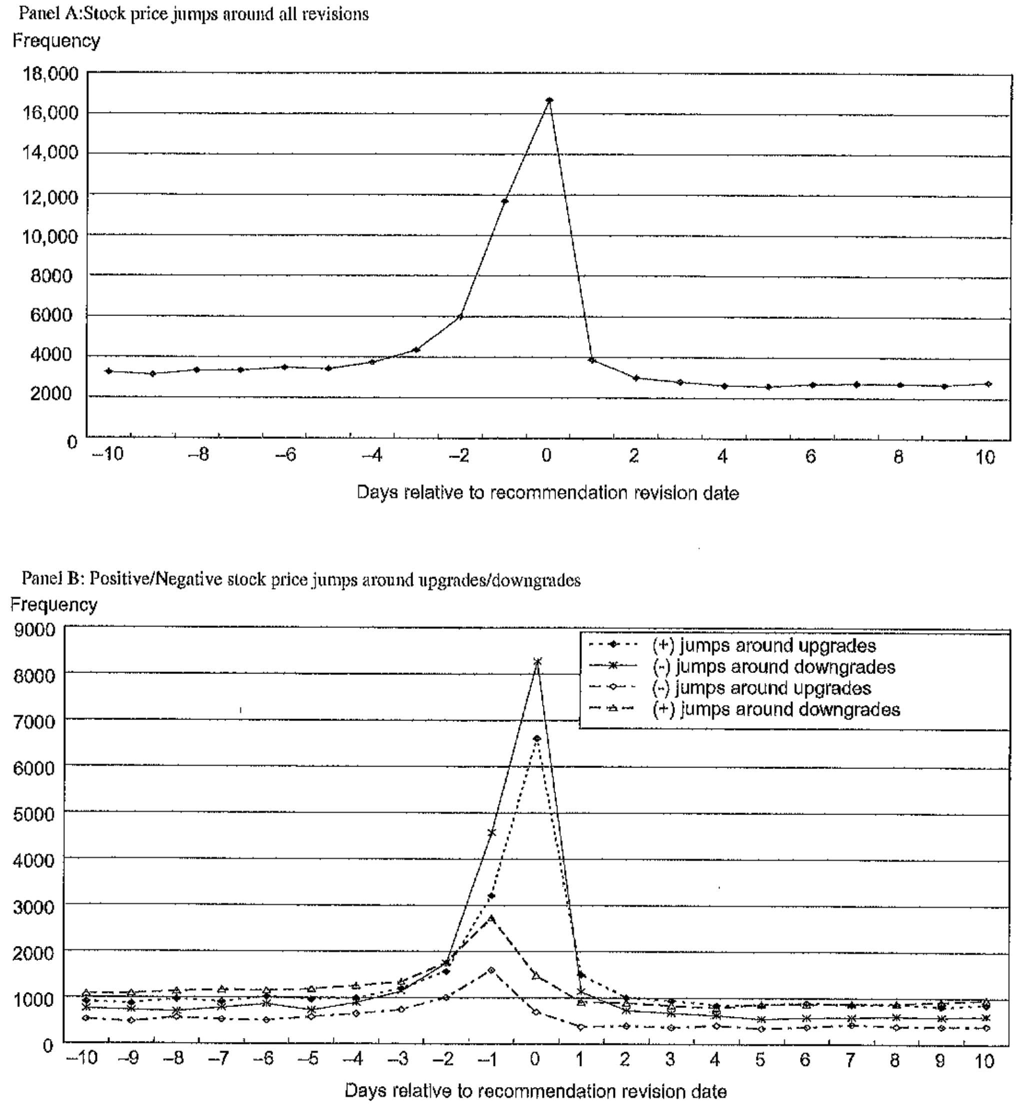

Figure 1. Number of stock price jumps around the recommendation revision date. This figure plots the number of stock price jumps around the recommendation revision date. Stock price jumps are identified using the 'variance swap' test developed in Jiang and Oomen (2008) at the 5% critical level. If there are multiple revisions within the event window, we count them separately. Panel A reports the results for all revisions. Panel B reports separate results based on the direction of the jumps and subsequent recommendation revisions, that is, positive jumps followed by upgrades and negative jumps followed by downgrades as well as negative jumps followed by upgrades and positive jumps followed by downgrades. The sample period is from November 1993 to December 2007.

Panel B provides similar results as in Panel A. In addition, the results from Panel B indicate that revisions are much more likely to be in the same direction as the preceding jumps, consistent with the findings in Altinkilic and Hansen (2009). That is, upgrades are more often preceded by positive jumps, while downgrades are more often preceded by negative jumps.

In Figure 2, we present relative frequencies of recommendation revisions with stock price jumps around the revision date over time. Specifically, we first calculate relative frequencies of stock price jumps around each recommendation revision date using a 21-day window from day -10 to day $+10$. In Panel A, we plot the relative frequencies for each event day from day -5 to day 0 for brevity. In Panel B, we plot the results separately based on the direction of the jump

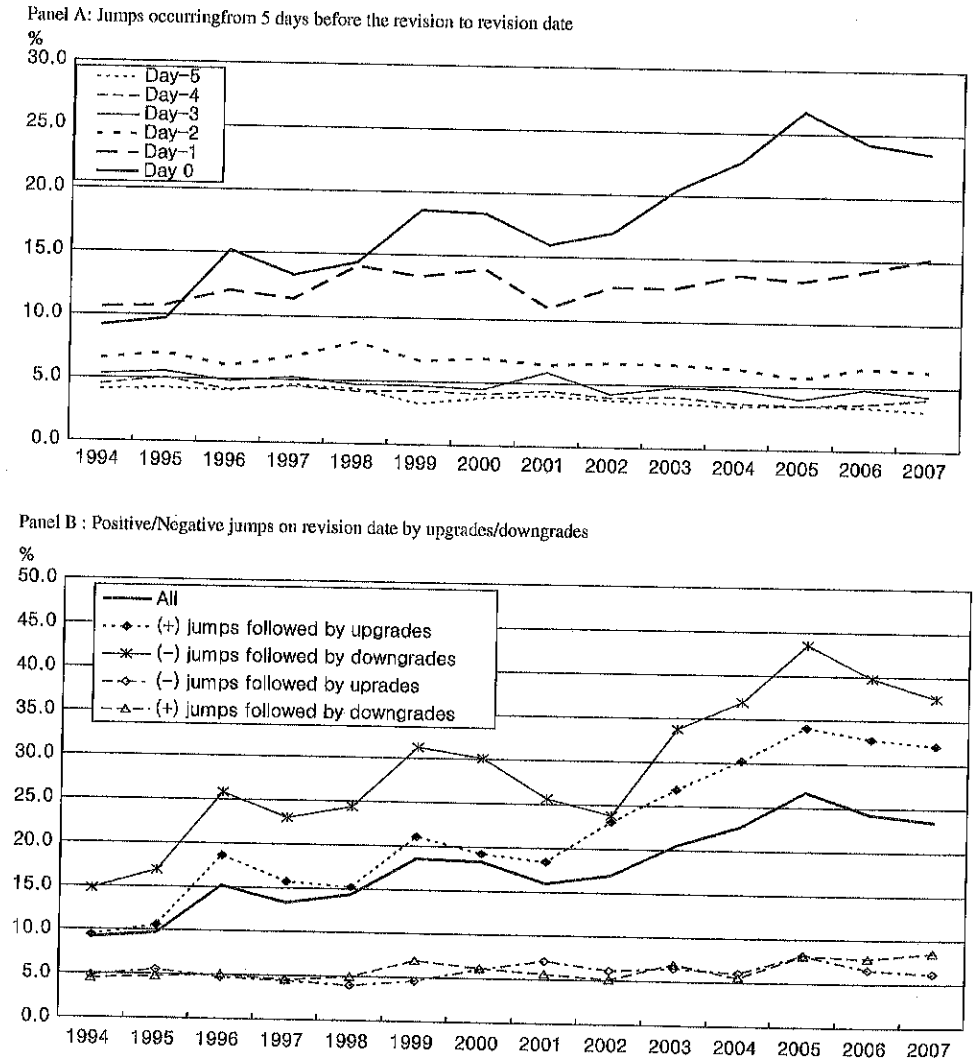

Figure 2. Relative frequencies of recommendation revisions around stock price jumps over time. This figure plots relative frequencies of recommendation revisions with stock price jumps around the revision date for each year during the sample period. Stock price jumps are identified using 'variance swap' test developed in Jiang and Oomen (2008) at the 5% critical level. We calculate relative frequencies for each event day using an 11 day window from day -10 to day $+10$. In Panel A, we report the relative frequencies for each event day from day -5 to day 0 for the sake of brevity. In Panel B, we report the results separately based on the direction of the jump and subsequent revision. For Panel B, we only report the relative frequencies of day 0 (i.e. jump and revision occurring on the same day) for the sake of brevity. The sample period is from November 1993 to December 2007.

and revision. For Panel B, we only plot the relative frequencies of day 0 (i.e. jump and revision occurring on the same day) for brevity.

The results in Panel A of Figure 2 indicate that there has been an increasing trend in the relative frequencies of recommendation revisions that occur concurrently with stock price jumps. Other than the concurrent revisions, the relative frequency of jumps prior to a revision seems to have remained fairly stable over time. The findings in Panel B indicate that the upward trend of concurrent revisions and jumps is largely being driven by revisions that are made in the same direction as the preceding jumps. For example, within the 21-day window around a downgrade, the proportion of negative jumps occurring on day 0 increases from 15% in 1994 to 38% in 2007.

Before addressing our main research question, we first examine how more likely recommendation revisions are issued on days with jumps in stock prices. Although the results from the previous subsection are suggestive of the idea that recommendations tend to occur on days with stock price jumps, the analysis was only conditional on recommendation revision days. To formally test whether recommendations are more likely to occur on days with stock price jumps, we calculate two probabilities, the first is unconditional probability of analysts issuing a recommendation revision on any given day and the second is conditional probability of analysts issuing a recommendation revision on days with stock price jumps. The estimation procedure is as follows.

For each calendar day t during our sample period, we compute (1) unconditional probability of a jump ($\Pr_t$(jump)), (2) unconditional probability of a revision ($\Pr_t$(rev)), and (3) probability of a revision conditional on a concurrent stock price jump ($\Pr_t$(rev|jump)) as follows:

$$\Pr_t(\text{jump}) = \frac{N_{\text{jump},t}}{N_{\text{all},t}}, \tag{1}$$

$$\Pr_t(\text{rev}) = \frac{N_{\text{rev},t}}{N_{\text{all},t}}, \tag{2}$$

$$\Pr_t(\text{rev}|\text{jump}) = \frac{N_{(\text{jump}\cap\text{rev}),t}}{N_{\text{jump},t}}. \tag{3}$$

where $N_{\text{all},t}$ denotes the number of stocks with valid prices from CRSP on day t, $N_{\text{jump},t}$ the number of stocks that experienced a jump in stock price on day t, $N_{\text{rev},t}$ the number of stocks with recommendation revisions on day t, and $N_{(\text{jump}\cap\text{rev}),t}$ the number of stocks that experienced both a recommendation revision and a stock price jump on day t.

We also estimate conditional probabilities of upgrades based on the direction of the concurrent jump as follows:

$$\Pr_t(\text{up}) = \frac{N_{\text{up},t}}{N_{\text{all},t}}, \tag{4}$$

$$\Pr_t(\text{up}|(+)\text{jump}) = \frac{N_{(\text{posi}\cap\text{up}),t}}{N_{\text{posi},t}}, \tag{5}$$

$$\Pr_t(\text{up}|(-)\text{jump}) = \frac{N_{(\text{nega}\cap\text{up}),t}}{N_{\text{nega},t}}. \tag{6}$$

where $N_{\text{up},t}$ denotes the number of stocks with upgrades on day t, $N_{\text{posi},t}$ the number of stocks that experienced a positive jump in stock price on day t, $N_{(\text{posi}\cap\text{up}),t}$ the number of stocks that experienced both upgrade and positive jump on day t, $N_{\text{nega},t}$ the number of stocks that experienced a negative jump in stock price on day t, and $N_{(\text{nega}\cap\text{up}),t}$ the number of stocks that experienced both upgrade and negative jump on day t.

Similar to upgrades, we define and calculate conditional and unconditional probabilities of downgrades as follows:

$$\Pr_t(\text{down}) = \frac{N_{\text{down},t}}{N_{\text{all},t}}, \tag{7}$$

$$\Pr_t(\text{down}|(-)\text{jump}) = \frac{N_{(\text{nega}\cap\text{down}),t}}{N_{\text{nega},t}}, \tag{8}$$

$$\Pr_t(\text{down}|(+)\text{jump}) = \frac{N_{(\text{posi}\cap\text{down}),t}}{N_{\text{posi},t}}. \tag{9}$$

where $N_{\text{down},t}$, $N_{(\text{posi}\cap\text{down}),t}$, and $N_{(\text{nega}\cap\text{down}),t}$ are defined in a similar manner as above.

Panel A of Table 3 reports the averages of these daily probabilities for each year in our sample period, and Panel B reports the corresponding medians. The first column presents the number of trading days in each year, and the second column presents the average number of stocks with valid prices from CRSP on each trading day. The third column presents the average probabilities of a jump occurring on any given date. These numbers indicate that on a given day during our sample period, 3.4% of stocks in the CRSP universe experience a jump.

The next two columns present the unconditional probability of a recommendation revision and the probability conditional on a stock price jump occurring on the same day. The results indicate that the probability of analysts issuing a recommendation revision conditional on a concurrent price jump is larger than the unconditional probability for every single year in our sample period, and the difference between the two has been steadily increasing over time. Over the full sample period, the average unconditional probability of a revision on a given day is 1.67%. The probability of a revision increases to 4.26% when there is a jump on the same day, and the difference is statistically significant with a t-stat of 4.10. The t-stats are obtained from the time series averages and standard errors of the annual cross-sectional means.

We next examined the conditional probabilities incorporating directions of both jumps and contemporaneous revisions. The last six columns of Table 3 report the conditional and unconditional probabilities separately for upgrades and downgrades conditional on positive and negative jumps, respectively. For both upgrades and downgrades, the revisions are much more likely to be in the same direction as the contemporaneous stock price jump and much less likely to be in the opposite direction. As noted earlier, one of the main roles of analysts is to interpret and disseminate information contained in corporate events to the marketplace and investors. Thus, it is expected that analysts often release their reports and revise their recommendations concurrently with important corporate events.

We also observe a clear difference between upgrades and downgrades regarding the magnitude of the conditional probabilities. For example, the probability of an upgrade issued together with a positive jump is 3.5 times higher than the unconditional probability, while the probability of a downgrade issued together with a negative jump amounts to 6.7 times as high as the unconditional probability. Taken together, these numbers imply that the probability of issuing a downgrade conditional on a negative jump is more than twice as large as the probability of an upgrade conditional on a positive jump. The results suggest that analysts are more likely to exploit contemporaneous news when the content of the news is bad than when the content is good.

Table 3. Probabilities of issuing recommendation revisions on days with stock price jumps.

				Pr (rev)		Pr (up)			Pr (down)		
							Conditional on			Conditional on	
	N (trading days)	$\sum N_{\text{all},t}/N$	Pr (jump)	Unconditional	Conditional on jump	Unconditional	(+) Jump	(−) Jump	Unconditional	(−) Jump	(+) Jump
Panel A: Mean of daily probabilities											
1993	43	3143	0.0277	0.0031	0.0038	0.0017	0.0019	0.0000	0.0015	0.0061	0.0003
1994	252	3270	0.0287	0.0133	0.0159	0.0066	0.0085	0.0030	0.0068	0.0204	0.0030
1995	252	3322	0.0355	0.0175	0.0216	0.0074	0.0104	0.0039	0.0102	0.0325	0.0050
1996	254	3421	0.0359	0.0149	0.0291	0.0073	0.0180	0.0037	0.0077	0.0455	0.0038
1997	253	3558	0.0409	0.0144	0.0236	0.0065	0.0128	0.0022	0.0080	0.0411	0.0034
1998	252	3645	0.0390	0.0167	0.0281	0.0073	0.0126	0.0022	0.0096	0.0458	0.0044
1999	252	3594	0.0416	0.0162	0.0368	0.0082	0.0227	0.0032	0.0082	0.0513	0.0055
2000	252	3489	0.0363	0.0152	0.0351	0.0068	0.0163	0.0034	0.0086	0.0580	0.0039
2001	248	3374	0.0384	0.0165	0.0308	0.0068	0.0140	0.0052	0.0099	0.0479	0.0043
2002	252	3342	0.0304	0.0238	0.0420	0.0082	0.0196	0.0052	0.0162	0.0592	0.0050
2003	252	3345	0.0361	0.0199	0.0515	0.0091	0.0356	0.0057	0.0112	0.0753	0.0071
2004	252	3417	0.0323	0.0178	0.0638	0.0086	0.0441	0.0062	0.0094	0.1022	0.0060
2005	252	3519	0.0292	0.0165	0.0783	0.0084	0.0582	0.0096	0.0084	0.1011	0.0102
2006	251	3580	0.0296	0.0166	0.0717	0.0077	0.0514	0.0080	0.0091	0.1040	0.0107
2007	251	3725	0.0244	0.0165	0.0753	0.0083	0.0540	0.0062	0.0085	0.0950	0.0128
All	3568	3467	0.0341	0.0167	0.0426	0.0076	0.0267	0.0048	0.0093	0.0621	0.0060
t-stat (against unconditional probabilities)					4.10		3.80	−3.58		6.32	−2.79
t-stat (between conditional probabilities)				Pr (up|(+)jump) vs. Pr (down|(+)jump): 4.08				Pr (up|(−)jump) vs. Pr (down|(−)jump): 6.89			
Panel B: Medians of daily probabilities											
1993	43	3142	0.0264	0.0025	0.0000	0.0010	0.0000	0.0000	0.0010	0.0000	0.0000
1994	252	3295	0.0266	0.0124	0.0130	0.0060	0.0000	0.0000	0.0061	0.0000	0.0000
1995	252	3315	0.0339	0.0162	0.0188	0.0069	0.0099	0.0000	0.0091	0.0294	0.0000
1996	254	3426	0.0340	0.0141	0.0274	0.0068	0.0152	0.0000	0.0072	0.0370	0.0000
1997	253	3564	0.0368	0.0139	0.0196	0.0060	0.0108	0.0000	0.0078	0.0313	0.0000
1998	252	3646	0.0356	0.0161	0.0262	0.0068	0.0099	0.0000	0.0091	0.0405	0.0000
1999	252	3592	0.0378	0.0154	0.0361	0.0078	0.0189	0.0000	0.0076	0.0463	0.0000
2000	252	3482	0.0337	0.0142	0.0316	0.0063	0.0132	0.0000	0.0080	0.0486	0.0000
2001	248	3368	0.0312	0.0148	0.0268	0.0059	0.0105	0.0000	0.0090	0.0400	0.0000
2002	252	3340	0.0286	0.0176	0.0400	0.0072	0.0153	0.0000	0.0105	0.0513	0.0000
2003	252	3347	0.0326	0.0185	0.0474	0.0084	0.0303	0.0000	0.0103	0.0625	0.0000
2004	252	3416	0.0291	0.0174	0.0575	0.0078	0.0388	0.0000	0.0088	0.0866	0.0000
2005	252	3526	0.0267	0.0159	0.0755	0.0080	0.0529	0.0000	0.0080	0.0909	0.0000
2006	251	3586	0.0265	0.0158	0.0667	0.0071	0.0465	0.0000	0.0085	0.0930	0.0000
2007	251	3742	0.0220	0.0162	0.0714	0.0077	0.0492	0.0000	0.0082	0.0855	0.0000
All	3568	3471	0.0311	0.0155	0.0357	0.0069	0.0182	0.0000	0.0083	0.0476	0.0000
t-stat (against unconditional probabilities)					3.83		3.23	−14.69		5.39	−13.80
t-stat (between conditional probabilities)				Pr (up|(+)jump) vs. Pr (down|(+)jump): 4.71				Pr (up|(−)jump) vs. Pr (down|(−)jump): 6.44			

Notes: This table presents the mean (Panel A) and median (Panel B) probabilities of issuing recommendation revisions on days with stock price jumps. For each calendar day t during our sample period, we identify the number of stocks with valid prices from CRSP ($N_{\text{all},t}$) and the number of stocks with recommendation revisions ($N_{\text{rev},t}$) separately for upgrades ($N_{\text{up},t}$) and downgrades ($N_{\text{down},t}$). We also identify stocks that experience a jump in stock prices on the recommendation revision date ($N_{\text{jump},t}$), separately for positive jumps ($N_{\text{posi},t}$) and negative jumps ($N_{\text{nega},t}$). Finally, we locate all those stocks that experience both revision and jump on the same day and calculate the number of stocks for each pair of jump-revision categories ($N_{(\text{jump}\cap\text{rev}),t}$, $N_{(\text{posi}\cap\text{up}),t}$, $N_{(\text{posi}\cap\text{down}),t}$, $N_{(\text{nega}\cap\text{up}),t}$, $N_{(\text{nega}\cap\text{down}),t}$). Then for each calendar day, we calculate the following probabilities: $\Pr_t(\text{jump}) = (N_{\text{jump},t}/N_{\text{all},t})$, $\Pr_t(\text{rev}) = (N_{\text{rev},t}/N_{\text{all},t})$, $\Pr_t(\text{rev}|\text{jump}) = (N_{(\text{jump}\cap\text{rev}),t}/N_{\text{jump},t})$, $\Pr_t(\text{up}) = (N_{\text{up},t}/N_{\text{all},t})$, $\Pr_t(\text{up}|(+)\text{jump}) = (N_{(\text{posi}\cap\text{up}),t}/N_{\text{posi},t})$, $\Pr_t(\text{up}|(-)\text{jump}) = (N_{(\text{nega}\cap\text{up}),t}/N_{\text{nega},t})$, $\Pr_t(\text{down}) = (N_{\text{down},t}/N_{\text{all},t})$, $\Pr_t(\text{down}|(-)\text{jump}) = (N_{(\text{nega}\cap\text{down}),t}/N_{\text{nega},t})$, $\Pr_t(\text{down}|(+)\text{jump}) = (N_{(\text{posi}\cap\text{down}),t}/N_{\text{posi},t})$. The t-stats for the differences between unconditional probabilities and conditional probabilities are based on time-series averages and standard errors.

Panel B of Table 3 reports medians of daily probabilities during each year in the sample. The results are largely similar to those presented in Panel A, although the magnitudes of the probabilities are a bit smaller. We also note that the median conditional probabilities of revisions in the opposite direction of the contemporaneous price jumps are all zero for every year during the sample period. This implies that revisions are made in the same direction in more than half of the trading days within a calendar year. This strongly suggests that analysts are quite reluctant in issuing revisions that go against the current large movement in stock prices.

3. Market reactions to recommendation revisions: univariate analysis

3.1 *Revisions made concurrently with stock price jumps*

Although earlier studies, such as Stickel (1995) and Womack (1996), show that analysts create value by providing useful information to investors, more recent studies, for example, Asquith, Mikhail, and Au (2005) and Altinkilic and Hansen (2009), challenge such conclusions. They present evidence that analysts tend to issue recommendation revisions concurrently with important corporate events. We argue that such coincidence is expected to some extent since one important function of analysts is to interpret and translate publicly available corporate information into investment advice. Nevertheless, if a non-trivial portion of market reactions to revisions documented in the previous literature is indeed attributed to concurrent jumps, then the magnitude of analysts' value reported in the previous literature is likely inflated. In this section, we examine the extent to which previously documented market reactions may be explained by contemporaneous stock price jumps.

We compute H-day cumulative buy-and-hold abnormal returns $\mathrm{ABR}_i(t, t+H)$ following a recommendation revision for stock i on date t, as follows:

$$\mathrm{ABR}_i(t, t+H) = \prod_{\tau=t}^{t+H}(1 + R_{i,\tau}) - \prod_{\tau=t}^{t+H}(1 + R_{m,\tau}), \tag{10}$$

where $R_{i,\tau}$ and $R_{m,\tau}$ are the returns on stock i and the value-weighted index return, respectively. We compute serial-correlation consistent Hansen and Hodrick (1980) standard error estimates allowing for non-zero serial correlation for up to six months to take into account that the return measurement intervals overlap across longer horizons. Hansen and Hodrick (1980) standard error estimates are robust to both heteroskedasticity and serial correlation induced by overlapping samples.

We first calculate the averages of this quantity for all recommendation revisions, and then compare those accompanied by concurrent jumps on the same day with those that are not accompanied by jumps. Table 4 reports the results of this analysis. Day 0 is the revision date and the other days in the column headings are the number of trading days after the revision date. For instance, the entries under the column heading '21' present cumulative abnormal returns over 21 trading days, or roughly one calendar month, after the revision.

The results in the first and fifth row of Table 4 show that there are significant market reactions to both upgrades and downgrades. Market reactions to upgrades (downgrades) are significantly positive (negative) on the revision date and gradually increase afterward up to 126 trading days, roughly half a year. Specifically, the average abnormal return on the revision date is 2.05% for all upgrades and −3.01% for all downgrades. The abnormal return gradually increases to 4.88% by the end of the sixth month for upgrades and decreases to −4.28% for downgrades. These results are consistent with findings documented in the extant literature (Womack (1996); Jegadeesh et al. (2004); Jegadeesh and Kim (2006, 2010)).

Table 4. Cumulative market-adjusted returns: revisions with concurrent jumps vs. revisions without jumps.

	Recommendation revision	Number of observations	Number of trading days after revision date					
			0	1	2	21	42	126
Upgrades	All	97,709	2.05%	2.39%	2.49%	3.41%	3.71%	4.88%
	No jump on the revision date	89,443	1.31%	1.63%	1.74%	2.46%	2.65%	3.64%
	Jump on the revision date	8,266	10.02%	10.62%	10.61%	13.65%	15.20%	18.23%
	Jump–no jump		8.70%	8.99%	8.87%	11.18%	12.55%	14.58%[a]
Downgrades	All	125,194	−3.01%	−3.24%	−3.34%	−3.79%	−3.98%	−4.28%
	No jump on the revision date	111,664	−1.47%	−1.70%	−1.81%	−2.25%	−2.38%	−2.45%
	Jump on the revision date	13,530	−15.74%	−15.95%	−16.02%	−16.54%	−17.22%	−19.66%
	Jump–no jump		−14.27%	−14.25%	−14.22%	−14.30%	−14.84%	−17.21%[a]

Notes: This table presents the cumulative abnormal returns following recommendation revisions in event time. We characterize each revision as an upgrade or a downgrade by comparing the revised recommendation with the previous recommendation for the stock by the same analyst. Within upgrades and downgrades, we further classify them into revisions that are accompanied by concurrent stock price jumps and those that are not. Stock price jumps are identified using the 'variance swap' test developed in Jiang and Oomen (2008) at the 5% critical level. The abnormal return is the raw buy-and-hold return minus the CRSP value-weighted index return for the corresponding holding period. Day 0 is the recommendation revision date and other numbers in the heading denote the number of trading days after the revision date. The average returns reported in bold face are statistically significant at the 5% level. The t-statistics are computed based on Hansen and Hodrick (1980) standard errors that take into account both heteroskedasticity and serial correlation. The sample period is from November 1993 to December 2007.
[a]Standard errors could not be determined because the serial correlation-consistent estimate of variance was negative.

However, when we partition the revision sample into those with concurrent jumps and those without concurrent jumps, we observe a marked difference. Once we exclude revisions made concurrently with jumps, the magnitude of the initial market reaction drops by roughly a half (a third) for downgrades (upgrades). This indicates that a substantial portion of the initial market reaction is largely driven by contemporaneous jumps in stock prices or confounding corporate events, although these revisions only account for 8% (11%) of all upgrades (downgrades). On the flip side, the remaining revisions without concurrent jumps are still followed by significant – albeit smaller – market reactions, indicating that these revisions still have investment value.

3.2 *Market reactions to revisions around stock price jumps*

The results of the previous subsection show that revisions without concurrent jumps may still provide some investment value. However, it could well be the case that market reactions can be explained by corporate events that are close to analyst revisions, especially for revisions issued right after significant corporate events. To address this concern, we focus on revisions made both before and after jumps in stock prices. We note that it is important to distinguish revisions issued before jumps versus those issued after. This is because recommendation revisions made before jumps could well reflect analysts' access to private information. As pointed out by Louth et al. (2010), one important aspect of analysts' job is to predict the impact of potential jump events.

In Table 5, we further separate revisions without concurrent jumps into those that are followed by jumps within the next 10 trading days and those that had no subsequent jumps over the next 10 trading days. We also distinguish between positive and negative jumps to examine whether the direction of the subsequent jumps has any effect on the information content of pre-jump revisions. If there are multiple jumps within the next 10 trading days, we take the sign of the most adjacent jump after the revision.

The results from Table 5 indicate that there are significant market reactions in general to analyst recommendations made before stock price jumps. For example, the average three-day buy-and-hold abnormal return following upgrades preceding a jump is 2.1% while the corresponding return following downgrades is − 1.64%, both of which are statistically significant. As expected, market reactions are overwhelmingly dominated by the subsequent jumps themselves when the return period overlaps with jumps. For example, 21-day abnormal return following an upgrade is 11.82% when there is a subsequent positive jump within 10 days, but − 9.34% when there is a subsequent negative jump. We observe a similar pattern for downgrades as well.

To further explore this issue, we implement a day-by-day analysis from − 10 days to + 10 days around a jump. For each day during the event window, we identify revisions made on that day, and then track down returns following revisions. In unreported results, we find that market reactions are directly influenced by the jumps when the event period includes jump dates. For example, a three-day return following a downgrade made one day prior to a positive jump is 8.24%, which precisely reflects the magnitude of the jump on the next day. To disentangle the information content of analyst revisions from confounding events, we implement two sets of analyses. First, we examine market reactions to revisions issued *after* observing jumps. By construction, these market reactions are not contaminated by jumps. Second, we examine short-term three-day returns that do not overlap with subsequent jump returns in a multivariate framework in the next section.

In Table 6, we provide results analogous to those reported in Table 5 where we now focus on revisions made *after* observing a jump. The results from Table 6 indicate that market reactions to revisions issued subsequent to jumps are still significant, although the magnitude is

Table 5. Cumulative market-adjusted returns: revisions made before stock price jumps.

	Recommendation revision	Number of observations	Number of trading days after revision date					
			0	1	2	21	42	126
Upgrades (without simultaneous jumps)	All	89,443	1.31%	1.63%	1.74%	2.46%	2.65%	3.64%
	No jump within subsequent 10 days	75,358	1.37%	1.63%	1.70%	2.11%	2.15%	3.19%
	Jump within subsequent 10 days		0.84%	1.66%	2.10%	5.50%	6.98%	7.61%
	Jump–no jump		− 0.53%	0.03%	0.40%	3.39%	4.84%	4.42%
	Positive jump within subsequent 10 days	8,996	0.87%	2.43%	3.53%	11.82%	14.16%	15.25%
	Positive jump–no jump		− 0.50%	0.80%	1.83%	9.71%	12.01%	12.06%
	Negative jump within subsequent 10 days	5,089	0.78%	− 0.15%	− 1.25%	− 9.34%	− 9.94%	− 10.50%
	Negative jump–no jump		− 0.59%	− 1.78%	− 2.95%	− 11.45%	− 12.09%	− 13.69%
Downgrades (without simultaneous jumps)	All	111,664	− 1.47%	− 1.70%	− 1.81%	− 2.25%	− 2.38%	− 2.45%
	No jump within subsequent 10 days	90,646	− 1.50%	− 1.72%	− 1.82%	− 2.42%	− 2.67%	− 2.77%
	Jump within subsequent 10 days		− 1.18%	− 1.51%	− 1.64%	− 0.65%	0.25%	0.42%
	Jump–no jump		0.32%	0.21%	0.19%	1.77%	2.92%	3.19%
	Positive jump within subsequent 10 days	10,436	− 1.00%	− 0.11%	0.75%	9.04%	10.80%	12.63%
	Positive jump–no jump		0.50%	1.61%	2.57%	11.46%	13.47%	15.40%
	Negative jump within subsequent 10 days	10,582	− 1.44%	− 3.42%	− 4.91%	− 13.94%	− 14.22%	− 16.13%
	Negative jump–no jump		0.06%	− 1.70%	− 3.08%	− 11.51%	− 11.55%	− 13.36%

Notes: This table presents the cumulative abnormal returns following recommendation revisions that are not accompanied by concurrent stock price jumps. Within upgrades and downgrades, we further classify them into revisions that lead to positive jumps, negative jumps, or no jumps in stock prices within 10 days following the revision date. Stock price jumps are identified using the 'variance swap' test developed in Jiang and Oomen (2008) at the 5% critical level. If there are multiple jumps within the next 10 days, we take the most adjacent one following the revision. The abnormal return is the raw buy-and-hold return minus the CRSP value-weighted index return for the corresponding holding period. Day 0 is the revision date and other numbers in the heading denote the number of trading days after the revision date. The average returns reported in bold face are statistically significant at the 5% level. We use heteroskedasticity and serial correlation consistent Hansen and Hodrick (1980) standard errors to compute the t-statistics. The sample period is from November 1993 to December 2007.

Table 6. Cumulative market-adjusted returns: revisions made after stock price jumps.

	Recommendation revision	Number of observations	Number of trading days after revision date					
			0	1	2	21	42	126
Upgrades (without simultaneous jumps)	All	89,443	**1.31%**	**1.63%**	**1.74%**	**2.46%**	**2.65%**	**3.64%**
	No jump within past 10 days	75,358	**1.39%**	**1.72%**	**1.82%**	**2.36%**	**2.39%**	**3.34%**
	Jump within past 10 days	14,085	**0.92%**	**1.18%**	**1.31%**	**3.01%**	**4.04%**	**5.29%**
	Jump–no jump		**−0.47%**	**−0.54%**	**−0.51%**	**0.65%**	**1.65%**	**1.96%**
	Positive jump within past 10 days	8,996	**0.82%**	**1.11%**	**1.33%**	**4.28%**	**6.11%**	**7.87%**
	Positive jump–no jump		**−0.57%**	**−0.61%**	**−0.48%**	**1.92%**	**3.73%**	**4.54%**
	Negative jump within past 10 days	5,089	**1.09%**	**1.30%**	**1.26%**	**0.76%**	0.32%	0.65%
	Negative jump–no jump		**−0.30%**	**−0.42%**	**−0.56%**	**−1.60%**	**−2.07%**	**−2.68%**
Downgrades (without simultaneous jumps)	All	111,664	**−1.47%**	**−1.70%**	**−1.81%**	**−2.25%**	**−2.38%**	**−2.45%**
	No jump within past 10 days	90,646	**−1.61%**	**−1.87%**	**−1.97%**	**−2.61%**	**−2.79%**	**−2.85%**
	Jump within past 10 days	21,018	**−0.87%**	**−0.99%**	**−1.09%**	**−0.69%**	−0.59%	−0.63%
	Jump–no jump		**0.74%**	**0.87%**	**0.88%**	**1.92%**	**2.20%**	**2.22%**
	Positive jump within past 10 days	10,436	**−0.77%**	**−0.82%**	**−0.81%**	**0.50%**	**1.40%**	**2.76%**
	Positive jump–no jump		**0.84%**	**1.05%**	**1.16%**	**3.11%**	**4.19%**	**5.61%**
	Negative jump within past 10 days	10,582	**−0.96%**	−1.17%	−1.37%	**−1.87%**	**−2.50%**	−3.54%
	Negative jump–no jump		**0.65%**	**0.70%**	**0.60%**	0.74%	0.29%	−0.69%

Notes: This table presents the cumulative abnormal returns following recommendation revisions that are not accompanied by concurrent stock price jumps. Within upgrades and downgrades, we further classify them into revisions that have no jumps and those that have jumps in stock prices over the past 10 days leading up to the revision date. Revisions following jumps are again categorized by the direction of the jumps. Stock price jumps are identified using the 'variance swap' test developed in Jiang and Oomen (2008) at the 5% critical level. If there are multiple jumps within the past 10 days, we take the most recent one prior to the revision. The abnormal return is the raw buy-and-hold return minus the CRSP value-weighted index return for the corresponding holding period. Day 0 is the revision date and other numbers in the heading denote the number of trading days after the revision date. The average returns reported in bold face are statistically significant at the 5% level. We use heteroskedasticity and serial correlation consistent Hansen and Hodrick (1980) standard errors to compute the t-statistics. The sample period is from November 1993 to December 2007.

smaller than those not following jumps over a short horizon. For example, the average three-day abnormal return following upgrades subsequent to a jump is 1.31%, while the corresponding return following downgrades is − 1.09, both of which are statistically significant. The incremental information provided in post-jump revisions is observed regardless of the direction of the preceding jump.

However, over a six-month event window, upgrades following jumps generate higher returns than upgrades not following jumps. For example, the cumulative market-adjusted return over 126 days after an upgrade following positive jumps is as high as 7.87% and significant, while the corresponding return for downgrades following negative jumps is − 3.54% and insignificant. These results show that analysts provide incremental information beyond that in the underlying corporate event, especially for upgrades following positive jumps.

4. Market reactions to recommendation revisions: multivariate analysis

In our previous univariate analyses, we distinguish between revisions made concurrently with jumps and other revisions in an attempt to disentangle the effect of confounding corporate events. We note that revisions occurring at different points around a jump may be fundamentally different in terms of information content and quality. For example, revisions that come 'too late' or follow corporate events may not have information value equal to that of revisions made before the events. In addition, the relatively weak market reactions to post-jump revisions may reflect that they either contain stale information or are issued by analysts that simply 'herd' on other analysts.[5]

To explore whether post-jump revisions are indeed issued by 'herding' analysts, we examine the relative proportions of recommendation revisions issued by 'lead' analysts following the procedure in Cooper, Day, and Lewis (2001). We categorize each recommendation into four categories: those without any jumps before or after 10 days of a revision, those with concurrent jumps on the revision date, those issued within 10 days following a jump, and those issued within 10 days prior to a jump. Note that the last three categories are not mutually exclusive.

The results are reported in Table 7. Unconditionally, lead analysts issue slightly less than 10% of all recommendation revisions. But when we condition revisions on jumps, there is a conspicuous change in this proportion. Specifically, lead analysts are more likely to issue revisions on days with jumps, but less likely to issue revisions following jumps. This finding suggests that revisions made subsequent to jumps are more likely to be issued by herding analysts and thus have less information content.

To control for inherent differences between revisions made concurrently with jumps and those made after jumps, we run a set of multivariate regressions that explicitly control for various characteristics at the revision-level, analyst-level, and firm-level. The revision characteristics include an indicator for multiple level changes in recommendations, most recent or concurrent changes in earnings forecast as well as target prices within one year of the recommendation revision. The analyst characteristics include whether or not an analyst is a 'lead' analyst as identified in Cooper, Day, and Lewis (2001), and whether or not an analyst belongs to a top 20 broker based on number of analysts employed each year. The firm characteristics are size (market capitalization) and market to book equity.

The key variables include indicator for concurrent revision, the indicator for pre-jump revision, and the indicator for post-jump revision. The multivariate analysis allows us to properly compare revisions made on days with jumps with other types of revisions after controlling for various potential characteristics. We also control for year fixed effects and industry fixed effects (SIC 2

Table 7. Proportion of recommendation revisions issued by 'lead' analysts.

	Revision type					Difference (z-stat)		
		Jumps						
	All	No jumps (A)	Simultaneous (B)	Post-jump (C)	Pre-jump (D)	(B) − (A)	(C) − (A)	(D) − (A)
Downgrade	9.38	9.47	9.99	8.64	9.3	**1.967**	**−3.906**	−0.627
Upgrade	9.49	9.47	10.62	8.79	9.89	**3.419**	**−2.727**	1.421
Total	9.39	9.44	10.16	8.74	9.49	**3.664**	**−4.835**	0.308

Notes: This table presents the proportions of recommendation revisions issued by 'lead' analysts as identified in Cooper, Day, and Lewis (2001). We categorize each recommendation into four categories; those without any jumps before or after 10 days of a revision, those with concurrent jumps on the revision date, those issued within 10 days following a jump, and those issued within 10 days prior to a jump. The last three categories are not mutually exclusive. The last three columns present z-statistics from comparing the proportions of each category. Bold face indicates statistical significance at the 5% level.

digit) in most of our specifications. The standard errors are clustered by both analyst and covered firm, following Petersen (2009).

We report the regression results in Table 8, where the dependent variable is the three-day cumulative buy-and-hold abnormal return. In this analysis, we carefully exclude all revisions that are made within two days prior to a jump since their three-day returns are dominated by the subsequent jump itself. Panel A reports regressions for upgrades while Panel B reports those for downgrades. The first column in both panels reports unconditional mean market reactions following upgrades and downgrades, which largely corresponds to univariate results reported in Table 4.[6]

The results from columns (3) to (7) indicate that revisions made concurrently with jumps amplify market reactions to a large extent, while those made after jumps mitigate market reactions, even after controlling for potential differences in revision characteristics, analyst characteristics, and firm characteristics. Specifically, the coefficient of post-jump revision dummies are significantly negative (positive) for upgrades (downgrades), indicating that the market discounts information contained in revisions made subsequent to jumps relative to revisions unrelated with jumps. This also suggests that differences in market reactions between concurrent revisions and post-jump revisions are not simply picking up inherent differences in analyst or revision characteristics.

We also test whether the combined effect of the post-jump dummy and the constant is statistically different from zero. In unreported results, we find that it is the case in most of the specifications. p-Values for corresponding tests are all less than 0.1% except for columns (3) and (7) in Panel B where the corresponding p-values are 0.0765 and 0.034, respectively. This suggests that post-jump revisions still contain information content, albeit to a lesser degree compared to revisions unrelated to jumps.

Market reactions to revisions made prior to jumps, on the other hand, are not much different from those to revisions that are not related with any jumps. Specifically, the coefficients on pre-jump revision dummies are insignificantly different from zero, once we appropriately control for various revision, analyst, and firm characteristics. This implies that the degree of information content in revisions made prior to jumps is similar to those from revisions that are not related to jumps. When testing the equality of coefficients between pre-jump and post-jump dummies,

Table 8. Multivariate analysis: the effect of concurrent, pre-jump, and post-jump revisions.

	All upgrades						Exclude stale upgrades	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Upgrades								
Constant	0.024***	0.020***	0.018***	0.047***	0.048***	0.058***	0.019***	0.046***
	(50.911)	(9.576)	(9.237)	(18.548)	(15.140)	(13.595)	(8.661)	(12.880)
Simultaneous jump			0.090***	0.087***	0.086***	0.082***	0.091***	0.087***
			(40.989)	(42.093)	(38.684)	(28.346)	(36.921)	(34.423)
Post-jump upgrade			−0.009***	−0.010***	−0.010***	−0.011***	−0.009***	−0.010***
			(−12.707)	(−13.119)	(−12.173)	(−8.991)	(−11.346)	(−10.332)
Pre-jump upgrades			−0.002**	−0.002**	−0.002	−0.001	−0.003**	−0.002
			(−1.997)	(−2.311)	(−1.503)	(−0.693)	(−2.123)	(−1.609)
ln(Market Cap)				−0.004***	−0.004***	−0.006***		−0.004***
				(−18.458)	(−18.764)	(−15.734)		(−16.060)
ln(ME/BE)				0.001***	0.001**	0.001		0.001**
				(2.605)	(1.982)	(1.330)		(2.020)
Multiple level upgrade					0.003***	0.006***		0.003***
					(5.091)	(6.238)		(4.597)
Lead analyst					0.002**	0.002		0.002*
					(2.189)	(1.091)		(1.845)
Top20 broker					0.007***	0.005***		0.007***
					(10.395)	(4.973)		(8.831)
EPS forecast revision					−0.000	0.000		−0.000
					(−0.949)	(0.350)		(−1.091)
Target price revision						0.001		
						(1.181)		
Year/industry FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.000	0.025	0.136	0.146	0.155	0.161	0.132	0.150
N	95,558	91,596	91,596	89,224	66,813	28,549	72,451	52,287

(*Continued*).

Table 8. Continued.

	All downgrades						Exclude stale downgrades	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel B: Downgrades								
Constant	− 0.034***	− 0.031***	− 0.025***	− 0.048***	− 0.051***	− 0.062***	− 0.028***	− 0.056***
	(− 47.881)	(− 7.459)	(− 7.079)	(− 12.871)	(− 11.691)	(− 10.072)	(− 6.901)	(− 11.306)
Simultaneous jump			− 0.143***	− 0.139***	− 0.138***	− 0.124***	− 0.148***	− 0.141***
			(− 48.105)	(− 47.226)	(− 46.559)	(− 34.264)	(− 46.606)	(− 45.415)
Post-jump downgrade			0.019***	0.019***	0.021***	0.023***	0.019***	0.021***
			(19.670)	(20.019)	(19.990)	(15.035)	(18.480)	(18.558)
Pre-jump downgrade			− 0.001	− 0.001	− 0.001	− 0.003	− 0.000	− 0.000
			(− 0.592)	(− 0.539)	(− 0.333)	(− 1.396)	(− 0.041)	(− 0.198)
ln(Market Cap)				0.004***	0.005***	0.005***		0.005***
				(14.557)	(16.454)	(12.177)		(16.271)
ln(ME/BE)				− 0.007***	− 0.008***	− 0.007***		− 0.007***
				(− 9.977)	(− 9.121)	(− 6.024)		(− 7.477)
Multiple level downgrade					− 0.006***	− 0.007***		− 0.006***
					(− 8.422)	(− 6.321)		(− 7.163)
Lead analyst					− 0.002*	− 0.000		− 0.002*
					(− 1.895)	(− 0.236)		(− 1.797)
Top20 broker					− 0.009***	− 0.004***		− 0.009***
					(− 11.116)	(− 3.921)		(− 10.598)
EPS forecast revision					0.000	0.001		0.000
					(0.846)	(1.172)		(0.766)
Target price revision						0.020***		
						(6.143)		
Year/industry FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.000	0.034	0.229	0.229	0.238	0.233	0.245	0.256
N	122,922	117,861	117,861	114,920	86,814	39,548	87,019	63,022

Notes: This table presents the estimation results of multivariate regressions where the dependent variable is the three-day abnormal return following a recommendation revision. We exclude revisions made within two days prior to a jump to avoid contamination by jumps themselves. The key explanatory variables are indicators for concurrent revisions, pre-jump revisions, and post-jump revisions made within 10 trading days of a jump. Control variables are natural log of market capitalization, natural log of market equity to book equity, an indicator for revisions with multiple level changes, a dummy for whether or not an analyst is a 'lead' analyst as identified in Cooper, Day, and Lewis (2001), a dummy for whether or not an analyst belongs to a top 20 broker based on the number of analysts employed in a given year, and most recent or concurrent changes in earnings forecasts and target prices made by the same analyst within one year of the recommendation revision. Panel A reports the results for upgrades, while panel B reports those for downgrades. Columns (1) through (6) report the results for the full sample, and columns (7) and (8) exclude revisions where the previous recommendations are made more than one year ago. The constant term contains the year and industry fixed effect for year 2002 and communications industry (two-digit SIC 48). Standard errors are clustered by both analyst and covered firm, following the approach in Petersen (2009). The sample period is from November 1993 to December 2007. FE, fixed effect. ***, **, * represent statistical significance at 1%, 5%, 10% level, respectively.

we easily reject the equality at the 1% level in all of our specifications, indicating that pre-jump revisions are more informative than post-jump revisions. These findings are similar to those reported in Ivkovic and Jegadeesh (2004) who find that market reactions are stronger for pre-earnings announcement revisions than post-earnings announcement revisions.

In columns (7) and (8) of both Panels A and B, we additionally drop revisions that are more than a year apart from the most recent previous recommendation to address concerns for stale revisions. The median time between revisions is 124 trading days (180 calendar days), roughly 6 months. The results indicate that removing these potential stale revisions do not affect our results.

5. Robustness checks

The analyses so far suggest that analysts provide valuable information to investors not only when recommendation revisions are made before observing conspicuous jumps in stock prices, but also when they are issued after observing jumps. In this subsection, we perform various robustness checks of market reactions to post-jump revisions.

5.1 *Controlling for potential post-jump stock price drift*

It is well known that stock returns exhibit certain statistical patterns. There is a possibility that the value we documented above may be driven by certain properties of jumps themselves rather than analysts' skill. For example, stock price jumps may be followed by a subsequent drift in prices regardless of recommendation revisions. To explore this possibility, we calculate the post-jump stock price drift and control for the effect of post-jump stock price drift in market reactions to recommendation revisions. The returns subsequent to jumps that are not followed by recommendation revisions would provide a benchmark of post-jump stock price drift that is independent of recommendation revisions. In unreported results, we find that positive stock price jumps are followed by substantial price drift while negative jumps are not. The presence of post-jump momentum suggests that at least a part of the additional value that analysts create is being driven by inherent characteristic of jumps. However, when we partition these jumps into those that are followed by a recommendation revision the next day and those that are not, we find that the post-jump cumulative 6-month returns are higher for those jumps followed by revisions. This suggests that although a large portion of the market reaction to recommendation revisions can be explained by the post-jump stock price drift, analysts seem to have the ability to pick those stocks with larger post-jump price drift. We further extend our analysis by excluding all jumps that are followed by another jump or a revision within five days of the jump and find similar results.

5.2 *Excluding revisions followed by jumps or preceded by clustered jumps*

To ensure that analyst revisions are not confounded by information contained in subsequent corporate events, we repeat the baseline analysis in Table 6 by further restricting our sample of revisions to those that are not immediately followed by stock price jumps within 10 trading days. In unreported results, we find that market reactions to revisions made in the same direction of the preceding jumps have slightly smaller magnitude than those reported in Table 6, but remain significant. That is, short-term reactions to revisions are statistically significant regardless of the direction of the preceding jumps, and longer term reactions are most pronounced for upgrades following positive jumps.

In a similar spirit, we next control for potential clustering of jumps in stock prices. That is, we restrict our sample to revisions made after observing a *single* jump. Specifically, we exclude those revisions preceded by jumps where there are other jumps within plus or minus 10 days. These clustered jumps could reflect a sequence of corporate events. In unreported results, we find that the results are largely similar to those reported in Table 6.

5.3 *Controlling for liquidity shocks or market-wide information shocks*

Jumps can be the result of information shocks as well as liquidity shocks. To ensure that jumps in our empirical analysis are triggered by information rather than liquidity shocks, we exclude those jumps whose return is immediately reversed over the next few trading days. Specifically, if more than 75% of the jump return is reversed over the next five trading days, then the jump is believed to be driven by a liquidity shock and is thus excluded from our sample.

We also control for potential effects of market-wide information shocks. For each day during our sample period, we calculate the ratio of number of stocks with positive jumps against the number of stocks with negative jumps. We then sort all days in our sample into 10 deciles according to this ratio. Days in the top and bottom deciles are defined as those potentially influenced by significant market-wide information shocks. We then exclude revisions made on these days and repeat our empirical analysis.[7] In unreported results, we find that the results based on these sub-samples are consistent with those in Table 6. In fact, after removing those jumps potentially driven by liquidity shocks or market-wide information shocks, the patterns are even stronger.

5.4 *Excluding revisions by 'lead' analysts*

In our final robustness check, we exclude those analysts that are more likely to lead other analysts than follow other analysts. The purpose is to examine whether the information content of revisions as documented above is entirely due to a small elite group of so-called 'lead' analysts. Our classification of 'lead' analyst follows Cooper, Day, and Lewis (2001), and is intended to proxy for analysts' ability. Basically, we locate the two most adjacent recommendations issued by different analysts before a given revision and after this revision, respectively. Then we calculate the number of days between these four adjacent recommendations and the revision date. The shorter the distance between a given revision and subsequent revision by a different analyst, and the longer the distance between the previous revision by a different analyst and a given revision, the more likely that the analyst who issued the given revision is a leader rather than a follower. In unreported results, we show that after excluding revisions by 'lead' analysts within top 10 percentile, the cumulative abnormal returns are only slightly lower but remain statistically significant. This is evidence that the information content of analyst recommendation revisions cannot be entirely credited to the 'lead' analysts.

6. Conclusion

The value of analyst revision is one of the key research questions in analyst literature. Existing studies have so far reached mixed conclusions. In this paper, we use jumps as proxy of significant information events and examine the extent to which market reactions to recommendation revisions are related to jumps in stock prices and whether revisions issued around jumps

have investment value beyond confounding corporate events. Our results show that compared to unconditional probabilities of issuing upgrades or downgrades on any given day, the probability of issuing a revision is higher on days with stock price jumps. Although revisions made contemporaneously with jumps only account for roughly 10% of the entire revision sample, they explain up to a half (a third) of the initial market reactions to downgrades (upgrades).

Nevertheless, when we examine market reactions to recommendation revisions issued after stock price jumps, there are still significant market reactions. This effect is more pronounced for upgrades following positive jumps. Our multivariate results indicate that revisions issued concurrently with jumps amplify market reactions to a large extent, while post-jump revisions mitigate market reactions. In addition, pre-jump revisions are similar to revisions unrelated to jumps in terms of the magnitude of market reactions and are more informative than post-jump revisions.

Overall, our results suggest that analyst recommendation revisions contain significant information about future stock returns, but the value they create may not be as large as suggested in the existing literature. This study also highlights the importance of controlling for potentially confounding underlying corporate events when examining the information processing ability of analysts.

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Notes

1. Since some jumps may be triggered by analyst revisions themselves, we note that our estimate of the information content of analyst revisions is on the conservative side. In addition, existing studies have documented evidence of analysts 'tipping' to their own firms before making revisions public, see, for example, Juergens and Lindsey (2009), Christophe, Ferri, and Hsieh (2010), and Anderson and Martinez (2011). This implies that the information content of revisions may be reflected in stock prices prior to the announcement of revisions. As such, we interpret our results as providing a conservative estimate of analysts' investment value.
2. See Andersen, Benzoni, and Lund (2002), Bakshi, Cao, and Chen (1997), Bates (2000), Chernov et al. (2003), Eraker, Johannes, and Polson (2003), Johannes (2004), and Pan (2002), among others.
3. For instance, Aït-Sahalia (2002) exploits the restriction on the transition density of diffusion processes to assess the likelihood of jumps. Carr and Wu (2003) make use of the decay of the time value of an option with respect to the option's maturity. Barndorff-Nielsen and Shephard (2006) propose a bi-power variation (BPV) measure to separate the jump variance and diffusive variance. Lee and Mykland (2008) exploit the properties of BPV and develop a rolling-based nonparametric test of jumps. Aït-Sahalia and Jacod (2009) propose a family of statistical tests of jumps using power variations of returns. Jiang and Oomen (2008) propose a jump test based on the idea of 'variance swap' and explicitly take into account market microstructure noise.
4. For the purpose of our analysis, there are several reasons to use daily data instead of high frequency data as employed by Bradley et al. (2014). First, intraday stock returns are known to subject to severe market microstructure effect. In a recent study, Christensen, Oomen, and Podolskij (forthcoming) show that jumps in financial asset prices are far less frequent as tests based on high frequency data suggest. Many intraday large returns are simply the effect of market microstructure noise or illiquidity as they are often quickly reversed. Second, as Bradley et al. (2014) acknowledge, time stamps provided in I/B/E/S can be delayed by 2.4 hours. The inaccuracy of these time stamps would undermine any empirical design that utilizes high frequency intraday data. Dong et al. (2011) also question

the accuracy of I/B/E/S time stamps. Finally, using daily data allows us to work on a larger sample of stocks over a longer sample period. Compared to Bradley et al. (2014) who focus on NYSE stocks over 2002–2007, our sample cover all stocks in CRSP database over the period of 1993–2007.

5. We would like to thank an anonymous referee for pointing this out.
6. The number of observations and reported market reactions are slightly different between column (1) of Table 8 and those in Table 4 since we drop revisions made within two days prior to a jump in Table 8.
7. We also use an alternative way of identifying days with market-wide information. Specifically, we apply our jump test directly to CRSP value weighted index returns. However, this approach identifies only 18 days with market-wide jumps during our sample period. Excluding revisions on these days has virtually no effect on our results.

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Appendix. Jump test and identification

The idea of the variance swap test is as follows. Assume that stock prices follow a very general martingale process:

$$\mathrm{d}\ln S_t = a_t \mathrm{d}t + \sqrt{V_t}\mathrm{d}W_t + J_t \mathrm{d}q_t, \tag{A1}$$

where S_t is the stock price at time t, a_t is the instantaneous drift, V_t is the instantaneous variance when there are no jumps, J_t represents the jumps in asset prices, W_t is a standard Brownian motion, and q_t is a counting process with finite instantaneous intensity λ_t. The process is general in the sense that since the demeaned asset return process is a local martingale in an efficient market, it can be decomposed into two canonical orthogonal components, namely a purely continuous martingale and a purely discontinuous martingale (see Jacod and Shiryaev (2003, Theorem 4.18)). In addition, there is no functional form restriction on the drift, the diffusion, or the jump components. Applying Itô's lemma to (1) and then integrating over time, it can be shown that

$$2\int_0^T \left[\frac{\mathrm{d}S_t}{S_t} - d\ln S_t\right] = V_{(0,r)} + 2\int_0^T (e^{J_t} - 1 - J_t)\mathrm{d}q_t, \tag{A2}$$

where $V_{(0,r)} = \int_0^r V_t \mathrm{d}t$ is the integrated variance. Equation (2) forms the basis for the jump test. In the absence of jumps, the difference between simple and logarithmic returns captures one half of the integrated variance in the continuous time limit. Let $\{S_{t_0}, S_{t_1}, \ldots, S_{t_N}\}$ be stock prices observed over the period $[0, T]$ where $t_0 = 0$, $t_N = T$. Realized variance is defined as

$$\mathrm{RV}_N = \sum_{i=1}^{N} r_i^2, \tag{A3}$$

where $r_{t_i} = \ln\left[S_{t_i}/S_{t_{i-1}}\right]$ is the continuously compounded logarithmic return, and the variance swap in the discretized version of the left hand side of Equation (A2) is defined as:

$$\mathrm{SWV}_N = 2\sum_{i=1}^{N}(R_i - r_i) = 2\sum_{i=1}^{N} R_i - 2\ln\left(\frac{S_T}{S_0}\right), \tag{A4}$$

where $R_{t_i} = \left(S_{t_i}/S_{t_{i-1}}\right) - 1$ is the simple return, both of which are sampled with step size T/N over the interval [0, T]. Jiang and Oomen (2008) show that:

$$\frac{V_{(0,T)}N}{\sqrt{\Omega_{\mathrm{SWV}}}}\left(1 - \frac{\mathrm{RV}_N}{\mathrm{SWV}_N}\right) \xrightarrow{d} N(0,1), \tag{A5}$$

where N is the number of observation sampled between 0 and T, $\Omega_{\mathrm{SWV}} = (1/9)\mu_6 X_{(0,T)}$, $X_{(0,T)} = \int_0^T V_u^3 du$, and $\mu_p = 2^{p/2}\Gamma\left[(p+1)/2\right]/\sqrt{\pi}$. To implement the test statistic in Equation (A5), we obtain consistent estimators of $V_{(0,T)}$ and $X_{(0,T)}$. Barndorff-Nielsen and Shephard (2006) show that BPV_N is a consistent estimator of $V_{(0,T)}$:

$$\operatorname*{plim}_{N\to\infty} \mathrm{BPV}_N = V_{(0,T)}. \tag{A6}$$

Thus, a consistent estimator of $V_{(0,T)}$ is obtained based on the bi-power variation (BPV):

$$BPV_N = \frac{1}{\mu_1^2}\sum_{i=1}^{N-1}|r_i|\,|r_{i+1}|. \tag{A7}$$

Furthermore, to obtain a feasible version of the test statistic given in Equation (A5), we obtain a consistent estimator of Ω_{SWV} based on $\hat{\Omega}_{\mathrm{SWV}} = (1/9)\mu_6(N^3\mu_{6/p}^{-p}/N - p + 1)\sum_{i=0}^{N-p}\prod_{k=1}^{p}|r_{i+k}|^{6/p}$ with $p = 6$.

Once the above jump test rejects the null hypothesis of no jumps in a given quarter in our empirical analysis, we proceed to identify those days with stock price jumps following a sequential procedure. Let $\{r_{t_1}, r_{t_2}, \ldots, t_{t_N}\}$ be daily returns over the interval $[t_1, t_N]$, the sequential procedure is described in the following steps:

Step 1 Assume that we have performed a jump test using return observations over a quarter $[t_1, t_N]$. If the jump test does not reject the null hypothesis of no jumps, we move to the next quarter, and repeat the procedure from Step 1. If the test rejects the null hypothesis of no jumps, we record the jump test statistic JS_0 and proceed to Step 2.

Step 2 Replace each daily return by the median of the sample (denoted by r_{median}), perform the jump detection test on the series. For example, when ith day's return is replaced, we perform the jump detection test on the series $\{r_{t_1}, \ldots, r_{t_{i-1}}, r_{\mathrm{median}}, r_{t_{i+1}}, \ldots, t_{t_N}\}$ and record the test statistic JS_i for $i = 1, \ldots, N$.

Step 3 Construct the series $JS_0 - JS_i$ for $i = 1, \ldots, N$. Then, the stock price change on day j is identified as a jump if $JS_0 - JS_j$ has the highest value among all days.

Step 4 Replace the identified jump observation by r_{median} and start again from Step 1 with a new sample of stock returns.

The above procedure continues until all jumps are identified. Andersen et al. (2010) propose a similar procedure for identifying intraday jump returns. The main difference is that instead of using the median of the sample to replace each single return in Step 2 of the sequential procedure, they use the mean of remaining $N - 1$ returns.

Finally, daily stock returns contain market microstructure noise. We take this into account in both the jump test and jump identification. Specifically, the jump test is modified with the assumption that stock prices are observed with noise where the standard deviation of the noise is estimated from the autocovariance of observed stock returns and is used to adjust the asymptotic variance of the jump test. Details can be found in Jiang and Oomen (2008). In addition, to ensure that identified jump returns are not the result of bid-ask bounce, we impose additional restrictions. That is, the absolute value of an identified jump return must be more than twice the tick size. We find that this restriction has virtually no effect on identified jumps.