Evaluating Analysts' Value:
Evidence from Recommendations around Stock Price Jumps

George J. Jiang and Woojin Kim☆

May 2010

Abstract

Recent literature documents that analyst recommendation revisions tend to coincide with important corporate events, but offers mixed evidence on whether such recommendations have added value. In this paper, we use large discontinuous stock price changes, known as *jumps*, to proxy for significant corporate "events" and reexamine the potential value of analyst revision. Consistent with the literature, we find that analysts issue recommendation revisions more frequently on days with jumps in stock prices. These *contemporaneous* revisions, although accounting for only 10% of the revision sample, explain up to a half (a third) of the initial market reactions for downgrades (upgrades). Nevertheless, when focusing on revisions made *after* stock price jumps, we still find that these revisions contain significant price information. The added value is most pronounced for upgrades following positive jumps, with an average of abnormal 4.5% return over 6-month horizon.

Key Words: Analyst Recommendations, Information Processing Ability, Stock Price Jumps, Corporate Event, Market Reactions

---

☆ George Jiang is from the Eller College of Management, University of Arizona, Tucson, AZ 85721, USA. Woojin Kim is from Korea University Business School, Seoul 136-701, South Korea. We would like to thank Chang-Soo Kim, Joonghyuk Kim, Chang-Gyun Park, and other seminar participants at 4th CAFM Meeting (Seoul, 2009), Joint Conference Allied Korea Finance Associations (Dogo, 2009), Korea University, Korea Institute of Finance (KIF), Seoul National University, SKKU Graduate School of Business, and Texas A&M University for helpful comments.

Evaluating Analysts' Value:
Evidence from Recommendations around Stock Price Jumps

May 2010

Abstract

Recent literature documents that analyst recommendation revisions tend to coincide with important corporate events, but offers mixed evidence on whether such recommendations have added value. In this paper, we use large discontinuous stock price changes, known as *jumps*, to proxy for significant corporate "events" and reexamine the potential value of analyst revision. Consistent with the literature, we find that analysts issue recommendation revisions more frequently on days with jumps in stock prices. These *contemporaneous* revisions, although accounting for only 10% of the revision sample, explain up to a half (a third) of the initial market reactions for downgrades (upgrades). Nevertheless, when focusing on revisions made *after* stock price jumps, we still find that these revisions contain significant price information. The added value is most pronounced for upgrades following positive jumps, with an average of abnormal 4.5% return over 6-month horizon.

Key Words: Analyst Recommendations, Information Processing Ability, Stock Price Jumps, Corporate Event, Market Reactions

The information processing ability of stock analysts is one of the contentious debates in finance literature. Anecdotal evidence that led to the 2003 Global Settlement between SEC, State of New York and large brokerages suggests that analysts are inherently biased due to conflicts of interests.[1] Academic studies also document analysts' tendency to issue favorable reports both in terms of earnings forecasts and recommendations.[2] Despite these findings in the literature and the assertions often made by the public media, it is fairly well accepted by the academics that analyst recommendations have added value once investors focus on the revisions of recommendations (i.e. upgrades or downgrades) rather than just recommendations.[3]

However, more recent research challenges the view that analyst recommendations provide incremental value. Specifically, these studies provide that a vast majority of recommendations coincide with important corporate events. For example, 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. Similarly, Asquith, Mikhailb, and Au (2005) document that half of the analyst reports are released simultaneously with important firm-specific activities, including security issues or mergers and divestitures.

One way to test whether analysts provide additional value above and beyond the information contained in the confounding/contemporaneous corporate event is to examine whether recommendations made subsequent to such major corporate events still have information content. Another approach is to measure the relative strength of the opinion contained in the analyst report conditional on a corporate event and test whether it has incremental value. The empirical evidence so far, however, seems to offer mixed results.

---

[1] A Fortune article at the time states that the information provided by analysts is "so dishonest and fraught with conflicts of interest that it has become worthless." See Gimein (2002).

[2] For optimistic biases in earnings forecasts, see Fried and Givoly (1982), Brown, Foster and Noreen (1985), Ali, Klein and Rosenfeld (1992), and Kang, O'Brien and Sivaramakrishnan (1994). For biases in recommendations, see Jegadeesh, Kim, Krishe and Lee (2004), Lin and McNichols (1998), Michaely and Womack (1999), and Jegadeesh and Kim (2006).

[3] For example, see Stickel (1995), Womack (1996), Barber, Lehavy, McNichols and Trueman (2001), Boni and Womack (2004), Jegadeesh et al. (2004), and Jegadeesh and Kim (2006, 2009), among many others.

For example, Park and Pincus (2000) examine analysts' recommendation revisions during a five-day window after earnings announcements, and find that consensus analyst recommendation revisions have information content beyond original earnings surprises. Asquith, Mikhailb, and Au (2005) resort to the second approach and find that relative strength of the written arguments to support an opinion in a report has information content even when recommendations are made contemporaneously with other important corporate events.

On the other hand, Ivkovic and Jegadeesh (2004) examine the impact of recommendation revisions surrounding earnings announcements and find that revisions made after earnings announcement are less informative compared to those made prior to the announcement. In particular, there are no significant market reactions to either upgrade or downgrade revisions made by the analysts during the week after earnings announcements. Similarly, Altinkilic and Hansen (2009) show that intraday return immediately following the announcement time of the recommendation revision is quite small and thus conclude that analyst recommendations have no additional information above and beyond those contained in the original corporate event.

We argue that most existing studies are subject to two common limitations, both of which likely limit the power of empirical analysis. First of all, all existing studies rely on some pre-defined corporate announcements – for example, earnings announcements - as informational events. This is likely constrained by the availability of corporate event dates from standard data sources like Compustat, IBES or SDC Platinum. As documented in the literature, there are a variety of corporate events that contain significant information about firm value, such as management guidance of earnings or firm performance in general, profit warning, or early announcement of earnings, etc. These events can all induce confounding information in analyst recommendations. Exhausting all these events to examine the effect of analyst recommendations presents a formidable, if not impossible, task.[4] Secondly, even with all corporate event dates

[4] In addition, the source of significant shocks to a firm's stock price may go beyond specific corporate events. For example, economy wide or industry wide information as well as

identified, it is not necessarily that all events contain significant information relevant to stock prices. Excluding these events in empirical analysis may artificially underestimate the information content of analyst recommendation revisions.

In this paper, we attempt to overcome such limitations and examine the information content of analyst recommendations conditional on *significant* corporate events. In addition, these events are *generic* information events rather than some pre-defined specific events. Our approach is to identify large discontinuous changes, known as *jumps*, in stock prices and interpret these jumps as "significant events". Jumps represent unexpected large changes in stock prices which are typically triggered by substantial information or liquidity shocks. [5]

The idea of linking large price changes with information events has been suggested and utilized in the previous literature (for example, Ryan and Taffler (2004) and Conrad, Cornell, Landsman, and Roundtree (2004)). These studies typically rely on some arbitrary cut-offs from in-sample stock return distribution to identify large price changes. Our approach relies on a robust statistical method to identify unexpected large price changes in stock prices. Specifically, we extend the statistical method of "variance swap" jump test proposed in a recent work by Jiang and Oomen (2008) to detect jumps in daily stock prices. The method is model-free in the sense that it does not rely on any assumptions on the stock return process and also is robust to market microstructure noises in stock prices. Compared to previous studies, our study offers a more robust approach to identify significant information events for the purpose of our study of the information content of analyst recommendations.

---

information about competitors may well affect the stock prices. These informational events can also cause analysts to revise their recommendations.

[5] Jiang and Yao (2009) examine how often corporate events/news are associated with jumps in daily stock prices. Based on all identified jumps for stocks in the Dow Jones Industrial Average index during the period of July 2003 to June 2005, they find that almost all jumps are linked to specific corporate information events. The detailed distribution of the types of corporate events is outlined in Appnedix 2. On the other hand, Ryan and Taffler (2004) report that less than 2/3 of large price changes in their sample can be attributed to specific corporate events.

A further advantage of our study is that with identified jumps, we can classify certain information event as "good" or "bad" news based on whether the information shocks are "positive" or "negative". Existing studies have documented that the information content may be asymmetric between upgrades versus downgrades. For example, Ivkovic and Jegadeesh (2004) find that there is a sharp increase in the information content of recommendation upgrades in the week before earnings announcement, but no similar increase for recommendation downgrades. Jegadeesh and Kim (2009) show that investors discount the information contained in revisions that move towards the prevailing consensus much more so for downgrades than for upgrades. Our analysis can extend existing studies by examining the informativeness of recommendation upgrades and downgrades interacted with "good" or "bad" news, respectively.

The research questions we attempt to answer in this study are straightforward. First, we explore the extent to which analysts' decision to issue recommendation revisions and the value they create are influenced by jumps in stock prices. If a substantial portion of the initial market reaction documented in the extant literature can be attributed to simultaneous jumps, we should exercise much more care in interpreting the magnitude of the value that analysts actually create. Second, under the premise that revisions made *after* observing such price jumps are less likely a simple reaction to corporate events, we ask whether such revisions still provide incremental value above and beyond the information already reflected in the preceding jumps.

Our results show that both the analysts' tendency to issue a recommendation revision and market reactions to such revisions are strongly influenced by contemporaneous jumps.[6] The probability of analyst issuing a revision coupled with a simultaneous stock price jump is 2.5 times as high as unconditional probability of issuing a revision. 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

[6] We note that some jumps may be triggered by analyst revisions themselves. That is, analyst revision may be the "information event" associated with jumps in stock prices. Nevertheless, the percentage of jumps triggered by analyst revision alone appears to be small. In the aforementioned study by Jiang and Yao (2009), they find that the number of jumps triggered by analyst revisions alone only accounts for 6.5% of the total number of jumps triggered by corporate events/news.

negative (positive) stock price jump. Specifically, compared with the unconditional probability of analyst issuing a recommendation revision on any given day, the probability of a downgrade (upgrade) issued simultaneously with a negative (positive) stock price jump is 6.7 (3.5) times higher.

Although market reactions to upgrades and downgrades in our sample are quite comparable to the magnitudes reported in earlier studies, our findings indicate that the initial market reactions are substantially reduced once we exclude those revisions with simultaneous jumps, despite they only account for 10% of the revision sample. Specifically, average market-adjusted cumulative buy-and-hold return following all downgrades (upgrades) is -3.3% (2.5%) over two days while the corresponding number after excluding those revisions conditional on simultaneous jumps is only -1.8% (1.7%). These findings suggest that we should exercise much more care in interpreting the magnitude of the value that analysts provide.

To address the second question of whether analyst revisions have added value, we focus on recommendation revisions made *after* observing a jump in stock prices. These revisions are unlikely a simple loading on the information contained in corporate events. As we have noted above, some jumps may be triggered by analyst revisions and reflect information contained in analyst revision. By excluding revisions with simultaneous jumps in all of our subsequent analyses, our results on the added value of analysts' revisions tend to be on the conservative side.

The results suggest that over a two-day window, recommendation revisions contain incremental information regardless of the direction of the revision or direction of the preceding jump. Over a longer event window – up to 6 months – though, only revisions made in the same direction as the preceding jumps continue to provide additional value, and this effect is more pronounced for upgrades following positive jumps. For example, the cumulative market-adjusted return over 126 trading days (or 6 months) after an upgrade following positive jump is as high as 7.87%, while the corresponding return for upgrades with no preceding jumps is 3.34%. These results are robust to controlling for potential post-jump price drift, liquidity shocks or economy-wide shocks, as well as clustering of jumps in calendar time

Overall, recommendation revisions are more likely when there is a stock price jump and this explains a large portion of initial market reactions reported in the previous literature. This cautions us about a potential overstatement of analysts' ability. On the other hand, revisions made *after* observing such a jump still has incremental value – especially upgrades following positive jumps. This cautions us about a potential understatement of analysts' ability. In short, our study shows that while analysts may not provide as much additional value as we had previously thought, they do contain significant information about future stock returns above and beyond public information contained in corporate events.

The remainder of the paper is organized as follows. Section I explains how we identify stock price jumps. Section II describes the data and Section III presents the empirical results. Section IV concludes the paper.

I. Identifying Stock Price Jumps

Jumps represent unexpected large discontinuous changes in stock prices. Under a general asset return process, stock price changes can be characterized as smooth and continuous changes in the form of diffusion or sudden and 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.[7]

Various statistical tests have been proposed in recent literature to detect whether there are jumps in asset prices. 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

[7] See, for example, Andersen, Benzoni, and Lund (2002), Bakshi, Cao, and Chen (1997), Bates (2000), Chernov, Gallant, Ghysels, and Tauchen. (2003), Eraker, Johannes, and Polson (2003), Johannes (2004), and Pan (2002).

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 (2007) 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.

In this paper, we employ the variance swap approach by Jiang and Oomen (2008) for testing 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, 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 is model-free in the sense that it does not rely on any assumptions on the stock return process. Other than desirable finite sample properties in size, it 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 stock return observations 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. The identified stock price jumps are used in our analysis as a proxy for generic information event. Details of this procedure are provided in the Appendix 1.

II. Data and Sample

Our revision dataset is created based on recommendations data from IBES Detailed file and daily stock returns data is from CRSP. IBES recommendations data are available only since 1993, so we set our sample period from November 1993 to December 2007.

On the recommendation data, we impose the following criterion.

(a) There should be at least one analyst who issues a recommendation for the stock and revises the recommendation during the sample period,

(b) The analyst code should be available on IBES, and

(c) 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 market reacts to such revisions. Therefore, 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 analyst's identity.

We apply the variance swap approach as described in the previous section on daily returns obtained from the universe of CRSP stocks to detect price jumps. Our baseline jump data is based on 5% critical level.

The first seven columns in Table I 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 3,981 in 1998. The small sample size in 1993 largely reflects that IBES coverage is incomplete in its first year. The median number of analysts following a firm over the entire sample period is two. The number of brokerages in 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 five. The last three columns in Table I present the number of firms in CRSP that experienced at least one jump during each year in our sample period. These numbers suggest that roughly 70% of all CRSP firms experience at least one jump per year on average.

Table II presents summary statistics of stock price jumps for each year during the sample period. The first four columns report summaries for positive jumps, while the next four 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. 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[8], indicating that the identified jumps in individual stock prices are not only statistically significant discontinuous changes but also economically significant large returns. The frequencies of jumps suggest that for every three positive jumps for an average stock each year there are two negative jumps.

III. Empirical Results

1. Stock Price Jumps around Recommendation Revisions

Figure 1 presents the number of recommendation revisions with stock price jumps around the revision date. Panel A reports price jumps around all revisions, while panel B reports results separately for sub-samples categorized by the direction of the jumps and revisions. In both panels, day 0 refers to the recommendation revision date and the event window is from -10 to +10 trading days.[9]

The results from panel A indicate that there is a large number of revisions with stock price jumps occurring 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. The decrease of jumps after

[8] For example, mean 3-day market adjusted returns for the large positive (negative) return group is between 3.5% and 5.5% (-3% and -4.5%) in Conrad et al. (2006).

[9] Multiple jumps within the event window are counted as separate jumps, whereas multiple revisions in the same direction on the same day are counted as one observation of recommendation revision for this analysis.

revision suggests that analyst revisions may help to resolve information uncertainty or, in general, analyst revisions lag other corporate information events.

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 surrounding each recommendation revision date using a 21-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 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 results in Panel A of Figure 2 indicate that there has been an increasing trend in the relative frequencies of recommendation revisions that occur simultaneously with the stock price jumps. Other than the simultaneous 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 simultaneous revisions and jumps is largely being driven by revisions that are made in the same direction as the preceding jumps.

2. Recommendation Revisions with Simultaneous Stock Price Jumps

Our first research question is whether recommendation revisions occur more frequently on days with jumps in stock prices. Since analyst revision itself only account for a small percentage of corporate events that trigger jumps (see Jiang and Yao (2009), we interpret recommendation revisions occurred on days with jumps as largely being influenced by jumps. Although the results from the previous subsection are suggestive of the idea that recommendations are influenced by stock price jumps, the analysis was only conditioned on recommendation revisions as in Altinkilic and Hansen (2009).

To formally test whether recommendations are influenced by simultaneous price jumps, we compute the probabilities of analysts issuing a recommendation revision both unconditionally and conditional on a simultaneous stock price jump. 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 simultaneous stock price jump ($\Pr_t(rev \mid jump)$) as follows.

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

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

$$\Pr_t(rev \mid jump) = \frac{N_{(jump \cap rev),t}}{N_{jump,t}} \qquad (3)$$

where $N_{\mathrm{all},t}$: number of stocks with valid prices from CRSP on day *t,*

$N_{\mathrm{jump},t}$: number of stocks that experienced a jump in stock price on day *t*,

$N_{\mathrm{rev},t}$: number of stocks with recommendation revisions on *day t,*

$N_{(\mathrm{jump} \cap \mathrm{rev}),t}$: 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 simultaneous jump as follows.[10]

[10] We characterize each revision as an upgrade or a downgrade by comparing the revised recommendation with the previous recommendation for the same stock by the same analyst. Multiple upgrades (or downgrades) for a single stock on a given day are counted as one observation for this analysis.

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

$$\Pr_t(up \mid (+)\, jump) = \frac{N_{(posi \cap up),t}}{N_{posi,t}} \quad (5)$$

$$\Pr_t(up \mid (-)\, jump) = \frac{N_{(nega \cap up),t}}{N_{nega,t}} \quad (6)$$

where $N_{\mathrm{up},t}$: number of stocks with upgrades on day t,

$N_{\mathrm{posi},t}$: number of stocks that experienced a positive jump in stock price on day t,

$N_{(\mathrm{posi} \cap \mathrm{up}),t}$: number of stocks that experienced both an upgrade and a positive jump on day t,

$N_{\mathrm{nega},t}$: number of stocks that experienced a negative jump in stock price on day t,

$N_{(\mathrm{nega} \cap \mathrm{up}),t}$: number of stocks that experienced both an upgrade and a negative jump on day t.

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

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

$$\Pr_t(down \mid (-)\, jump) = \frac{N_{(nega \cap down),t}}{N_{nega,t}} \quad (8)$$

$$\Pr_t(down \mid (+)\, jump) = \frac{N_{(posi \cap down),t}}{N_{posi,t}} \quad (9)$$

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

Panel A of Table III 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 for each 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 all stocks in 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 issuing a recommendation revision conditional on a simultaneous 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%, while this probability increases to 4.26% when there is a jump on the same day, and this difference is statistically significant with a t-stat of 4.10.[11]

We next examine the conditional probabilities incorporating directions of both jumps and contemporaneous revisions. The last six columns of Table III 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, but much less likely to be in the opposite direction. These results suggest that at least a portion of the value that analysts create could simply be driven by loading on a simultaneous announcement of an important corporate event as recent studies suggest (e.g. Asquith, Mikhailb, and Au (2005) and Altinkilic and Hansen (2009)).

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 unconditional probability while the corresponding number for downgrades issued together with a negative jump amounts up to 6.7 times as high as the unconditional probability. Taken together, these numbers imply that probability of issuing a downgrade conditional on a negative jump is more than twice as large as

[11] *t*-stats are obtained from the time series averages and standard errors of the annual cross-sectional means.

the probability of an upgrade conditional on a positive jump. The results suggest that analysts are more likely to load on contemporaneous news when the content is bad rather than good.

Panel B of Table III 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 single year during the sample period, strongly suggesting that analysts are quite reluctant in issuing revisions that go against the current large movement in prices.

3. Market Reactions to Recommendation Revisions: The Effect of Contemporaneous Jumps

Although it is widely accepted ever since Stickel (1995) and Womack (1996) that analyst create value by providing useful information to investors, more recent studies point out that this effect may reflect some underlying important corporate event that analysts simply load on by issuing recommendations at the same time. For example, Altinkilic and Hansen (2009) document that 80% of the recommendation revisions are made in response to some corporate events such as earnings or investment announcements. They examine intraday return immediately following the exact time of the recommendation revision and find that the magnitude of the minute by minute market reaction is quite small, leading them to conclude that analyst recommendations have no additional information.

In this section, we examine the extent to which previously documented market reactions are influenced by contemporaneous stock price jumps. If a non-trivial portion of the initial market reaction can be attributed to simultaneous jumps, then it would be supportive of the recent criticisms on the added value of the analysts.

We compute *H*-day cumulative buy-and-hold abnormal returns $ABR_i(t, t+H)$ following a recommendation revision for stock *i* on date *t*, as follows:

$$ABR_i(t,t+H) = \prod_{\tau=t}^{t+H}(1+R_{i,\tau}) - \prod_{\tau=t}^{t+H}(1+R_{m,\tau}) \qquad (10)$$

where, $R_{i,\tau}$ and $R_{m,\tau}$ are the return 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.

We first calculate the averages of this quantity for all recommendation revisions, and then compare them between those accompanied by simultaneous jumps on the same day and those that are not accompanied by such jumps. Table IV 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 from the revision date. For instance, the entries under the column heading "21" presents 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 IV show that there are significant market reactions to both upgrades and downgrades. Market reactions to upgrades (downgrades) are significantly positive (negative) on 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 quite consistent with the extant literature that examines the impact of analysts' recommendations on stock prices.[12]

However, when we partition the revision sample to those with simultaneous jumps and those without such jumps, we observe a marked difference. Once we exclude revisions made simultaneously with jumps that are likely to be confounded by underlying corporate events, the magnitude of the initial market reaction drops by roughly a half (a third) for downgrades

[12] For example, Womack (1996), Jegadeesh, Kim, Krische and Lee (2004) and Jegadeesh and Kim (2006, 2009).

(upgrades). This indicates that a substantial portion of the initial market reaction is largely being driven by contemporaneous jumps in stock prices, although they only account for 8% (11%) of all upgrades (downgrades). These findings are consistent with the recent criticism that the incremental value that analysts create could perhaps be overestimated. On the flip side, the remaining revisions without simultaneous jumps are still followed by significant - albeit smaller – market reactions, indicating that revisions that are made independently without simultaneous jumps still has value.

4. Market Reactions to Recommendation Revisions *after* Stock Price Jumps

The results of the previous section shows that revisions without simultaneous jumps that are less likely to be confounded by underlying corporate events still has investment value. This interpretation follows from the presumption that all important corporate events would be reflected in stock price jumps. However, it could well be the case that there are corporate events that are substantial enough to generate contemporaneous recommendation revisions but not substantial enough to trigger jumps. If so, then revisions without simultaneous jumps may still be contaminated by potential confounding corporate event. That is, 1.31% (-1/47%) initial return for upgrades (downgrades) after excluding simultaneous jumps may still reflect some underlying corporate event.

To address this concern, we focus on recommendation revisions made *after* observing such a jump. These revisions should be relatively free from other corporate events since it would be less likely to have more than one important corporate event within a short event window. For example, if a new product development was the underlying corporate event that triggered a jump, then it would be less likely for the firm to announce another important piece of information within a few days.[13] Since the information from underlying corporate event would be already

[13] As part of robustness check in Section III.5, we further restrict our sample by excluding revisions that are followed by stock price jumps.

reflected in jumps, market reactions to revisions made *after* observing such jumps would provide a cleaner test of whether analysts create additional value above and beyond the information contained in the underlying corporate event.

In Table V, we further separate revisions without simultaneous jumps into those that had jumps within the past 10 trading days and those that had no preceding jumps over the past 10 trading days and report subsequent market reactions.[14] We also distinguish between positive and negative jumps to examine whether the direction of the preceding jumps has any effect on subsequent revisions.

The results from Table V indicate that analyst recommendations made after observing stock price jumps are still followed by significant market reactions in general. Over a short horizon - up to two days - recommendation revisions contain incremental information regardless of the direction of the revision or direction of the preceding jump. For example, two-day abnormal returns following upgrades subsequent to a positive (negative) jump is 1.33% (1.26%), while the corresponding numbers following downgrades is -0.81% (-1.37%), which are all statistically significant. Although the magnitude of these returns are smaller than those following revisions without preceding jumps, we should be careful in directly comparing them since the latter may well be contaminated by some underlying corporate event. .

Over a longer event window – up to 6 months – however, only revisions made in the same direction as the preceding jumps continue to provide additional value. And this effect is more pronounced for upgrades following positive jumps than for downgrades following negative jumps. For example, the cumulative market-adjusted return over 126 days after an upgrade following positive jump is as high as 7.87%, while the corresponding return for upgrades with no preceding jumps is 3.34%. These results show that analysts provide incremental information beyond that contained in the underlying corporate event especially for upgrades following

[14] If there are multiple jumps within the past 10 trading days, we take the most recent jump prior to the revision.

positive jumps, and thus suggests that recent criticism on analysts' added value might be too harsh.

5. Robustness Checks

The analyses so far suggest that analysts provide valuable information to the investors even when recommendation revisions are made after observing conspicuous jumps in stock prices. However, there is a possibility that this value 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 price drift following stock price jumps and compare them between those that are followed by recommendation revisions and those that are not. Specifically, for all stock price jumps, we identify whether there was a recommendation revision on the following day. Then, we calculate cumulative abnormal buy-and-hold returns from one day after the jump for various horizons. In other words, we assign day 0 to jump date and day 1 to revision date and calculate returns since day 1 for the two groups. The returns for the group that are not followed by recommendation revisions would provide benchmark price drift subsequent to jumps that are independent of recommendation revisions. Panel A of Table VI reports the results of this analysis.

The results indicate that positive stock price jumps are followed by substantial price drift while negative jumps are not. For all positive stock price jumps, 6 month cumulative abnormal return since one day after the jump (i.e. excluding the jump return) amounts up to 5.07%. This suggests that at least a part of the additional value that analysts create is being driven by an inherent characteristic of jumps. This is broadly consistent with Jegadeesh, Kim, Krische, and Lee (2004) who find that consensus recommendation levels have investment value only when combined with certain favorable characteristics of the stock such as high book to market or positive momentum.

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 6 month returns are higher for jumps followed by revisions. Specifically, the difference between the 6 month returns is 2.39% and is statistically significant. This suggests that although a large portion of the market reaction to recommendation revision can be explained by price drift following jumps, analysts seem to have the ability to pick those with larger price drift.

In panel B of Table VI, as further robustness check we repeat the above analysis for jumps followed by a revision on the 6th day after the jump. To avoid any confounding effect, we exclude all jumps that are followed by another jump or a revision within 5 days of the jump. Here, we calculate returns starting 6 days after the jump and compare them across the groups. The results are similar to those reported in panel A in that market reaction to upgrades following positive jumps exhibit higher returns compared to price drift without any subsequent jumps. We also note that initial return on day 0 is smaller for subsequently upgraded stocks, which suggests that analysts may have the ability to pick out stocks with underreaction.

In our next set of robustness tests, we repeat the baseline analysis in Table V by further restricting our sample of revisions to those that are not immediately followed by stock price jumps (within 10 trading days of the revision to be specific). This is to ensure that the revisions are not confounded by information contained in subsequent corporate events. Panel A of Table VII reports the results of this analysis. The magnitudes of market reactions to revisions made in the same direction of the preceding jumps are slightly smaller than those reported in Table V, but the main interpretations still remains valid. That is, short-term reactions to revisions are statistically significant regardless of the direction of the preceding jumps, and longer term reactions to upgrades following positive jumps exhibit the largest magnitude. These results suggest that analyst revisions are not simply picking up the effect of subsequent jumps.

In a similar spirit, we next control for potential clustering of jumps in calendar time. By focusing on jumps that are not adjacent to each other, we can examine analysts' value after observing a *single* underlying corporate event. Specifically, we exclude those revisions preceded by jumps where there are other jumps within plus and minus 10 days of the jump.[15] If there is an additional jump immediately following a previous jump, this could reflect another underlying corporate event that could confound the results.

The results reported in panel B of Table VII suggest that close to a half of all revisions that are made in the same direction as the preceding jumps are dropped as a result of this filter. This suggests that stock price jumps frequently occur right next to each other, i.e., jumps tend to be clustered. Nevertheless, the results are largely similar to those reported in Table V. For example, day 0 (day 126) return for upgrades made subsequent to positive jumps is 0.74% (7.14%) in Table VII, while the corresponding numbers reported in Table V are 0.82% (7.87%). These findings indicate that our results are not being driven by multiple underlying corporate events.

In our next robustness check, we try to control for potential liquidity shocks. As mentioned earlier, 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 days. This is based on the main distinction that jumps triggered by information shocks tend to have permanent price effect, whereas those triggered by liquidity shocks tend to be transitory. Specifically, if more than 75% of jump return is reversed over the next 5 trading days, then the jump is believed to be driven by liquidity shock and thus excluded from our sample.

Our final robustness check tests whether the main results are being driven by market-wide shocks (rather than firm-specific shocks) in any material way. To address this issue, we use the following procedure to identify those days that are potentially affected by market-wide information shocks. For each calendar day during our sample period, we calculate the ratio of

[15] By construction, a part of observations excluded through this filter overlaps with those excluded in panel A of Table VII.

number of stocks with positive jumps against the number of stocks with negative jumps. We then sort all days in our sample into ten 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.[16]

The results based on these sub-samples are reported in panel C and D of Table VII. The results are quite consistent with those in Table V. In fact, after removing those jumps potentially driven by liquidity shocks or market-wide information shocks, the patterns seem even stronger. Specifically, the returns following upgrades made in the same direction as the preceding jumps exhibit larger magnitudes than those reported in Table V.

IV. Conclusion

The extent of value added by stock analysts is one of the key research questions in analyst literature. Existing results have so far reached mixed conclusions. Previous studies generally rely on pre-defined corporate announcements as potential information events. In this paper, we focus on stock price jumps as potential information event that is comprehensive enough to capture various forms of significant corporate event. Our main research questions focus on the extent to which market reactions to recommendation revisions are influenced by contemporaneous jumps in stock prices and whether revision made after observing such jumps still has investment value.

First, we find that the probability of issuing a revision is 3.5 times higher for upgrades conditional on simultaneous positive jumps and 6.7 times higher for downgrades conditional on simultaneous negative jumps than unconditional probabilities of issuing upgrades or downgrades.

[16] We also tried an alternative way of identifying days with market-wide information. Specifically, we applied our jump test directly to CRSP value weighted index returns. However, this approach identified only 7 days with negative market-wide jumps and 11 days with positive market-wide jumps in our sample period. Excluding revisions on these days in our analysis has virtually no effect on our results.

These findings suggest that analysts are strongly influenced by contemporaneous stock price jumps.

We also find that market reactions to analyst revisions are substantially influenced by these contemporaneous jumps. Although revisions made contemporaneously with jumps only account for roughly 10% of the sample, they explain up to a half (a third) of the initial market reactions to downgrades (upgrades). These results suggest that the magnitude of the analysts' value reported in extant previous literature could have been overstated once we control for potential underlying corporate event, consistent with the recent arguments by Altinkilic and Hansen (2009).

However, when we examine market reactions to recommendation revisions made *after* observing such stock price jumps, we still find significant market reaction. This effect is most pronounced for upgrades following positive price jumps, which is partly being driven by price drift following jumps.

Overall, these results suggest that analyst recommendations contain additional information about future stock returns, but the value they create may not be as large as the existing literature suggests. This study also highlights the importance of controlling for potential underlying corporate event when implementing analyst research in the future.

References

Aït-Sahalia, Y., 2002, Telling From Discrete Data Whether the Underlying Continuous-Time Model is a Diffusion, *Journal of Finance* 57, 2075–2112.

Aït-Sahalia, Y., and J. Jacod, 2007, Testing for Jumps in a Discretely Observed Process, *Annals of Statistics*, forthcoming.

Ali, A., A. Klein, and J. Rosenfeld, 1992, Analysts' Use of Information about Permanent and Transitory Earnings Components in Forecasting Annual EPS, *The Accounting Review,* 183-98.

Altınkılıc, O., and R.S. Hansen, 2009, On the information role of stock recommendation revisions, *Journal of Accounting and Economics*, forthcoming.

Andersen, T. G., L. Benzoni, and J. Lund, 2002, An Empirical Investigation of Continuous-Time Equity Return Models. *Journal of Finance* 57, 1239–1284.

Andersen, T. G., T. Bollerslev, P. Frederiksen, and M. Nielsen, 2007, "Continuous-Time Models, Realized Volatilities, and Testable Distributional Implications for Daily Stock Returns," *Journal of Applied Econometrics*, forthcoming.

Asquith, P., Mikhail, M.B., and A.S. Au, 2005, Information Content of Equity Analyst Rerports, *Journal of Financial Economics* 75, 245-282.

Bakshi, G., C. Cao, and Z. Chen, 1997, Empirical Performance of Alternative Option Pricing Model. *Journal of Finance* 52, 2003–2049.

Barber, Brad, Reuven Lehavy, Maureen McNichols, and Brett Trueman, 2001, Can investors profit from the prophets? Security analyst recommendations and stock returns, *Journal of Finance* 56, 531-563.

Barndorff-Nielsen, O. E., and N. Shephard, 2006, Econometrics of Testing for Jumps in Financial Economics Using Bipower Variation, *Journal of Financial Econometrics* 4, 1-30.

Bates, D. S., 2000, Post-87 Crash Fears in the S&P 500 Futures Option Market, *Journal of Econometrics* 94, 181–238.

Boni, Leslie, and Kent L. Womack, 2004, Analysts, Industries, and Price Momentum, *Tuck School of Business Working Paper* No. 03-12.

Brown, P., G. Foster, and E. Noreen, 1985, Security analyst multi-year earnings forecasts and the capital market, Sarasota, FL: American Accounting Association.

Carr, P., and L. Wu, 2003, What Type of Process Underlies Options? A Simple Robust Test, *Journal of Finance* 58, 2581–2610.

Chernov, M., A. R. Gallant, E. Ghysels, and G. Tauchen, 2003, Alternative Models for Stock Price Dynamics, *Journal of Econometrics* 116, 225–257.

Conrad, J.S., Cornell, B., Landsman, W.R., and B. Roundtree, 2006. How do analyst recommendations respond to major news? *Journal of Financial and Quantitative Analysis* 41, 25–49.

Eraker, B., M. Johannes, and N. Polson, 2003, The Impact of Jumps in Equity Index Volatility and Returns, *Journal of Finance* 58, 1269–1300.

Fried, D., and D. Givoly, 1982, Financial analysts' forecasts of earnings, *Journal of Accounting and Economics* 4, 85-107.

Gimein, M., 2002. Elliot Spitzer THE ENFORCER, Fortune (September 16), 77–84.

Hansen, L., and R. Hodrick. 1980. Forward Exchange Rates as Optimal Predictors of Future Spot Rates: An Econometric Analysis. *Journal of Political Economy* 88, 829–853.

Ivkovich, Z., and N. Jegadeesh, 2004. The timing and value of foreast and recommendation revisions. *Journal of Financial Economics* 73, 433-463.

Jegadeesh, Narasimhan, Joonghyuk Kim, Susan D. Krische, and Charles M.C. Lee, 2004. Analyzing the analysts: When do recommendations add value? *Journal of Finance* 59, 1083-1124.

Jegadeesh, Narasimhan, and Woojin Kim, 2006. Value of analyst recommendations: International evidence. *Journal of Financial Markets* 9, 274-309.

Jegadeesh, Narasimhan, and Woojin Kim, 2009. Do Analysts Herd? An Analysis of Recommendations and Market Reactions, *Review of Financial Studies,* forthcoming.

Jiang, George J., and Roel C.A. Oomen, 2008. "Testing for Jumps When Asset Prices are Observed with Noise -- A "variance swap" Approach," *Journal of Econometrics*, 144, 352-370.

Jiang, George J., and Tong Yao, 2009, Stock Price Jumps and Cross-Sectional Return Predictability, *Working Paper*.

Johannes, M., 2004, The statistical and economic role of jumps in continuous-time interest rate models, *Journal of Finance* 59, 227–260.

Kang, S., J O'Brien, and K. Sivaramakrishnan, 1994, Analysts' Interim Earnings Forecasts: Evidence on the Forecasting Process. *Journal of Accounting Research*, 103-12.

Lee, S. S. and P. A. Mykland, 2008, "Jumps in Financial Markets: A New Nonparametric Test and Jump Dynamics," *Review of Financial Studies*, 21, 2535-2563.

Lin, H.W., and M.F. McNichols, 1998. Underwriting relationships, analysts' earnings forecasts and investment recommendations. *Journal of Accounting and Economics* 25, 101–127.

Michaely, R., and K. Womack, 1999. Conflict of interest and the credibility of underwriter analyst recommendations, *Review of Financial Studies* 12, 653–686.

Neuberger, A., 1994, The Log Contract: A New Instrument to Hedge Volatility. *Journal of Portfolio Management* 20, 74-80.

Pan, J., 2002, The Jump-Risk Premia Implicit in Options: Evidence from an Integrated Time-Series Study, *Journal of Financial Economics* 63, 3–50.

Park, C.W., and M. Pincus, 2000, Market Reactions to Changes in Analyst Consensus Recommendations Following Quarterly Earnings Announcements, Working Paper

Ryan, P, and R.J. Taffler, 2004, Are economically significant stock returns and trading volumes driven by firm-specific news releases? *Journal of Business Finance & Accounting* 31, 49-82.

Stickel, Scott E., 1995, The anatomy of the performance of buy and sell recommendations, *Financial Analysts Journal* 51, 25-39.

Womack, Kent, 1996, Do brokerage analysts' recommendations have investment value? *Journal of Finance,* 51, 137-167.

Appendix 1: Jump Test and Jump Identification

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

$$d\ln S_t = a_t dt + \sqrt{V_t}dW_t + J_t dq_t \tag{1}$$

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 there is no functional form restriction on the drift, the diffusion, and the jump components. Applying Itô's lemma to (1) and then integrating over time, it can be shown that:

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

where $V_{(0,r)} = \int_0^r V_t dt$ 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 $\{S_{t_0}, S_{t_1}, ..., S_{t_N}\}$ be stock prices observed over the period [0, T] where $t_0 = 0, t_N = T$. Realized variance is defined as:

$$RV_N = \sum_{i=1}^{N} r_i^2 \tag{3}$$

where $r_{t_i} = \ln\left[\frac{S_{t_i}}{S_{t_{i-1}}}\right]$ is the continuously compounded logarithmic return, and the variance swap in the discretized version of the left hand side of (2) is defined as:

$$SWV_N = 2\sum_{i=1}^{N}(R_i - r_i) = 2\sum_{i=1}^{N} R_i - 2\ln(S_T / S_0) \tag{4}$$

where $R_{t_i} = \frac{S_{t_i}}{S_{t_{i-1}}} - 1$ 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:

$$\frac{V_{(0,T)}N}{\sqrt{\Omega_{SWV}}}\left(1-\frac{RV_N}{SWV_N}\right) \xrightarrow{d} \mathbf{N}(0,1) \tag{5}$$

where N is the number of observation sampled between 0 and T, $\Omega_{SWV} = \frac{1}{9}\mu_6 X_{(0,T)}$,

$X_{(0,T)} = \int_0^r V_u^3 du$ and $\mu_p = 2^{\mu/2}\Gamma\left[\left.(p+1)\middle/2\right.\right]\Big/\sqrt{\pi}$. To implement the test statistic in (5), we obtain consistent estimators of $V_{(0,T)}$ and $X_{(0,T)}$. Barndorff-Nielsen and Shephard (2004) show that BPV_N is a consistent estimator of $V_{(0,T)}$:

$$\operatorname*{plim}_{N\to\infty} BPV_N = V_{(0,T)} \tag{6}$$

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

$$BPV_N = \frac{1}{\mu_1^2}\sum_{i=1}^{N-1}|r_i||r_{i+1}| \tag{7}$$

Furthermore, to obtain a feasible version of the test statistic given in (5) we obtain a consistent estimator of Ω_{SwV} based on $\hat{\Omega}_{SwV} = \frac{1}{9}\mu_6 \frac{N^3\mu_{6/p}^{-p}}{N-p+1}\sum_{i=0}^{N-p}\prod_{k=1}^{p}|r_{i+k}|^{6/p}$ with $p = 6$.

Once the above jump test rejects the null hypothesis of no jumps in a given quarter. We proceed to identify those days where 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:

- **<u>Step1:</u>** Assume that we have performed a jump test using return or price 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 rejected the null hypothesis of no jumps, we record the jump test statistic JS_0 and proceed to step 2.
- **<u>Step 2:</u>** 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 $\{r_{t_1}, \ldots, r_{t_i}, r_{median}, r_{t_{i+1}}, \ldots, t_{t_N}\}$ and record the test statistic JS_i for $i = 1, \ldots N$.
- **<u>Step 3:</u>** 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 price changes.

- **Step 4:** Replace the identified jump observation by r_{median} and start again from step1 by considering the new sample.

The above procedure continues until all jumps are identified. Andersen, Bollerslev, Frederiksen and Nielsen (2007) propose a similar procedure for identifying intraday jump returns. The main difference is that instead of using the median of 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 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 autocovariance of observed stock returns and 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 identified jump return must be more than twice the tick size. We find that this restriction has virtually no effect on identified jumps.

Appendix 2: Corporate Events associated with Jump

The table below reports the relative frequencies of certain corporate events manually identified by Jiang and Yao (2009) for detected jumps of all stocks in the Dow Jones Industrial Average index during the period of July 2003 to June 2005. All jumps except one were matched to an information event.

	Types of Corporate Events matched with Jumps	Relative Frequency
1.	Earnings announcement	24.5%
2.	Management earnings guidance	14.5%
3.	Product development, market share	11.0%
4.	Industry news, competitor news	9.5%
5.	Litigation	9.0%
6.	M&A, spinoff	8.5%
7.	Macroeconomic news (Fed FOMC, unemployment, geopolitical, etc.)	7.0%
8.	Analyst forecasts and recommendations	6.5%
9.	Management change	3.5%
10.	Repurchase	1.5%
11.	Dividend changes	1.5%

Table I

Descriptive Statistics of Analyst Revisions and Stock Price Jumps

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, 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 "variance swap" test developed in Jiang and Oomen (2008) at the 5% critical level. The sample period is from November 1993 to December 2007.

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	1,730	1,332	938
1994	2,747	1,460	131	11.69	5	2.67	2	5,367	4,626	4,120
1995	3,195	1,738	134	13.49	6	3.04	2	6,110	5,728	4,058
1996	3,417	1,915	160	12.67	5	2.72	2	6,551	6,088	4,600
1997	3,746	2,183	187	12.36	6	2.62	2	7,300	6,773	5,244
1998	3,981	2,573	209	12.84	5	2.92	2	7,086	6,427	5,631
1999	3,816	2,824	200	15.02	7	3.09	2	7,170	6,615	5,430
2000	3,575	2,742	196	15.13	6	3.09	2	6,566	5,988	5,002
2001	3,232	2,671	171	16.26	7	3.33	2	6,203	5,620	4,939
2002	3,465	2,866	185	16.00	6	4.48	3	5,308	4,603	4,307
2003	3,335	2,727	234	12.12	4	3.82	3	5,620	5,287	3,835
2004	3,387	2,836	267	11.11	3	3.60	2	5,497	4,992	4,132
2005	3,479	2,882	275	10.93	3	3.35	2	5,342	4,758	4,071
2006	3,555	2,871	260	11.48	4	3.34	2	5,413	5,068	3,864
2007	3,549	2,887	251	11.97	4	3.29	3	5,176	4,444	4,175
All Years	9,830	8,844	556	12.73	5	3.23	2	15,928	15,637	15,052

Table II

Summary Statistics for Stock Price Jumps

This table presents summary statistics of stock price jumps identified during the sample period. Stock price jumps are identified using "variance swap" test developed in Jiang and Oomen (2008) at the 5% critical level. The first four columns report the results for positive jumps and the next four columns report those for negative jumps. Within each category, we report the means and medians 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.

Year	Positive Jumps				Negative Jumps			
	Daily Jump Size		Occurence per Firm		Daily Jump Size		Occurence per Firm	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
1993	0.102	0.077	1.7	1	-0.112	-0.080	1.6	1
1994	0.106	0.079	3.0	3	-0.117	-0.081	2.4	2
1995	0.100	0.073	3.7	3	-0.126	-0.090	2.1	2
1996	0.105	0.079	3.5	3	-0.124	-0.089	2.1	2
1997	0.103	0.079	3.7	3	-0.130	-0.094	2.3	2
1998	0.141	0.104	3.3	3	-0.144	-0.104	2.6	2
1999	0.151	0.118	3.7	3	-0.130	-0.095	2.4	2
2000	0.156	0.120	3.3	3	-0.170	-0.128	2.4	2
2001	0.147	0.110	3.5	3	-0.153	-0.112	2.6	2
2002	0.131	0.093	3.1	3	-0.150	-0.106	2.6	2
2003	0.107	0.077	4.2	4	-0.113	-0.082	2.1	2
2004	0.090	0.065	3.6	3	-0.095	-0.067	2.4	2
2005	0.088	0.065	3.3	3	-0.091	-0.064	2.5	2
2006	0.080	0.059	3.6	3	-0.096	-0.069	2.2	2
2007	0.095	0.072	2.8	2	-0.095	-0.065	2.5	2
All Years	0.116	0.084	3.4	3	-0.126	-0.089	2.4	2

Table III

Probabilities of Issuing Recommendation Revisions on Days with Stock Price Jumps

This table presents the averages (Panel A) and medians (Panel B) of the daily probabilities of recommendation revisions with simultaneous stock price jumps. For each calendar day t during our sample period, we identify the number of stocks with valid prices from CRSP ($N_{all,t}$) and the number of stocks with recommendation revisions ($N_{rev,t}$) separately for upgrades ($N_{up,t}$) and downgrades ($N_{down,t}$). We also identify stocks that experienced a jump in stock prices on the recommendation revision date ($N_{jump,t}$), separately for positive jumps ($N_{posi,t}$) and negative jumps ($N_{nega,t}$). Finally, we locate all those stocks that experienced both revision and jump on the same day and calculate the number of stocks for each pair of jump-revision categories ($N_{(jump \cap rev),t}$, $N_{(posi \cap up),t}$, $N_{(posi \cap down),t}$, $N_{(nega \cap up),t}$, $N_{(nega \cap down),t}$). Then for each calendar day we calculate the following probabilities:

$$\Pr_t(jump) = \frac{N_{jump,t}}{N_{all,t}}, \quad \Pr_t(rev) = \frac{N_{rev,t}}{N_{all,t}}, \quad \Pr_t(rev \mid jump) = \frac{N_{(jump \cap rev),t}}{N_{jump,t}}, \quad \Pr_t(up) = \frac{N_{up,t}}{N_{all,t}}, \quad \Pr_t(up \mid (+)\,jump) = \frac{N_{(posi \cap up),t}}{N_{posi,t}},$$

$$\Pr_t(up \mid (-)\,jump) = \frac{N_{(nega \cap up),t}}{N_{nega,t}}, \quad \Pr_t(down) = \frac{N_{down,t}}{N_{all,t}}, \; \Pr_t(down \mid (-)\,jump) = \frac{N_{(nega \cap down),t}}{N_{nega,t}}, \; \Pr_t(down \mid (+)\,jump) = \frac{N_{(posi \cap down),t}}{N_{posi,t}}.$$

The t-stats for the differences between unconditional probabilities and conditional probabilities are obtained from time-series averages and standard errors.

Panel A: Averages of Daily Probabilities

	N (trading days)	$\sum N_{all,t}$ / N	Pr(Jump)	Pr(Rev) uncon-ditional	Pr(Rev) conditional on Jump	Pr(Up) uncon-ditional	Pr(Up) conditional on (+) Jump	Pr(Up) conditional on (-) Jump	Pr(Down) uncon-ditional	Pr(Down) conditional on (-) Jump	Pr(Down) conditional on (+) Jump
1993	43	3,143	0.0277	0.0031	0.0038	0.0017	0.0019	0.0000	0.0015	0.0061	0.0003
1994	252	3,270	0.0287	0.0133	0.0159	0.0066	0.0085	0.0030	0.0068	0.0204	0.0030
1995	252	3,322	0.0355	0.0175	0.0216	0.0074	0.0104	0.0039	0.0102	0.0325	0.0050
1996	254	3,421	0.0359	0.0149	0.0291	0.0073	0.0180	0.0037	0.0077	0.0455	0.0038
1997	253	3,558	0.0409	0.0144	0.0236	0.0065	0.0128	0.0022	0.0080	0.0411	0.0034
1998	252	3,645	0.0390	0.0167	0.0281	0.0073	0.0126	0.0022	0.0096	0.0458	0.0044
1999	252	3,594	0.0416	0.0162	0.0368	0.0082	0.0227	0.0032	0.0082	0.0513	0.0055
2000	252	3,489	0.0363	0.0152	0.0351	0.0068	0.0163	0.0034	0.0086	0.0580	0.0039
2001	248	3,374	0.0384	0.0165	0.0308	0.0068	0.0140	0.0052	0.0099	0.0479	0.0043
2002	252	3,342	0.0304	0.0238	0.0420	0.0082	0.0196	0.0052	0.0162	0.0592	0.0050
2003	252	3,345	0.0361	0.0199	0.0515	0.0091	0.0356	0.0057	0.0112	0.0753	0.0071
2004	252	3,417	0.0323	0.0178	0.0638	0.0086	0.0441	0.0062	0.0094	0.1022	0.0060
2005	252	3,519	0.0292	0.0165	0.0783	0.0084	0.0582	0.0096	0.0084	0.1011	0.0102
2006	251	3,580	0.0296	0.0166	0.0717	0.0077	0.0514	0.0080	0.0091	0.1040	0.0107
2007	251	3,725	0.0244	0.0165	0.0753	0.0083	0.0540	0.0062	0.0085	0.0950	0.0128
All	3,568	3,467	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

Table III - *continued*

Panel B: Medians of Daily Probabilities

	N (trading days)	Median $N_{all,t}$	Pr(Jump)	Pr(Rev) uncon-ditional	Pr(Rev) conditional on Jump	Pr(Up) uncon-ditional	Pr(Up) conditional on (+) Jump	Pr(Up) conditional on (-) Jump	Pr(Down) uncon-ditional	Pr(Down) conditional on (-) Jump	Pr(Down) conditional on (+) Jump
1993	43	3,142	0.0264	0.0025	0.0000	0.0010	0.0000	0.0000	0.0010	0.0000	0.0000
1994	252	3,295	0.0266	0.0124	0.0130	0.0060	0.0000	0.0000	0.0061	0.0000	0.0000
1995	252	3,315	0.0339	0.0162	0.0188	0.0069	0.0099	0.0000	0.0091	0.0294	0.0000
1996	254	3,426	0.0340	0.0141	0.0274	0.0068	0.0152	0.0000	0.0072	0.0370	0.0000
1997	253	3,564	0.0368	0.0139	0.0196	0.0060	0.0108	0.0000	0.0078	0.0313	0.0000
1998	252	3,646	0.0356	0.0161	0.0262	0.0068	0.0099	0.0000	0.0091	0.0405	0.0000
1999	252	3,592	0.0378	0.0154	0.0361	0.0078	0.0189	0.0000	0.0076	0.0463	0.0000
2000	252	3,482	0.0337	0.0142	0.0316	0.0063	0.0132	0.0000	0.0080	0.0486	0.0000
2001	248	3,368	0.0312	0.0148	0.0268	0.0059	0.0105	0.0000	0.0090	0.0400	0.0000
2002	252	3,340	0.0286	0.0176	0.0400	0.0072	0.0153	0.0000	0.0105	0.0513	0.0000
2003	252	3,347	0.0326	0.0185	0.0474	0.0084	0.0303	0.0000	0.0103	0.0625	0.0000
2004	252	3,416	0.0291	0.0174	0.0575	0.0078	0.0388	0.0000	0.0088	0.0866	0.0000
2005	252	3,526	0.0267	0.0159	0.0755	0.0080	0.0529	0.0000	0.0080	0.0909	0.0000
2006	251	3,586	0.0265	0.0158	0.0667	0.0071	0.0465	0.0000	0.0085	0.0930	0.0000
2007	251	3,742	0.0220	0.0162	0.0714	0.0077	0.0492	0.0000	0.0082	0.0855	0.0000
All	3,568	3,471	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

Table IV

Cumulative Market-Adjusted Returns: Revisions with Simultaneous Jumps vs. Revisions without Jumps

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 simultaneous stock price jumps and those that are not. Stock price jumps are identified using "variance swap" test developed in Jiang and Oomen (2008) at the 5% critical level and classified as either a positive jump or a negative jump. 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 the other days in the column headings are the number of trading days from the revision date. The average returns reported in bold face are statistically significant at least at the five percent level (absolute value of *t*-statistics greater than 1.96). 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.

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%*
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%*

* Standard errors could not be determined because the serial correlation-consistent estimate of variance was negative.

Table V

Cumulative Market-Adjusted Returns: Revisions Made *After* Observing Stock Price Jumps

This table presents the cumulative abnormal returns following recommendation revisions that are not accompanied by simultaneous stock price jumps. Within upgrades and downgrades, we further classify them into revisions that had no jumps, positive jumps, or negative jumps in stock prices over the past 10 days leading up to the revision date. Stock price jumps are identified using "variance swap" test developed in Jiang and Ooman (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 the other days in the column headings are the number of trading days after the revision date. The average returns reported in bold face are statistically significant at least at the five percent level (absolute value of *t*-statistics greater than 1.96). 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.

Recommendation Revision		Number of Observations	Number of Trading Days after Revision Date					
			0	1	2	21	42	126
Upgrades	All	89,443	**1.31%**	**1.63%**	**1.74%**	**2.46%**	**2.65%**	**3.64%**
(without	No jump wihin past 10 days	75,358	**1.39%**	**1.72%**	**1.82%**	**2.36%**	**2.39%**	**3.34%**
simlutaneous	Positive jump within past 10 days	8,996	**0.82%**	**1.11%**	**1.33%**	**4.28%**	**6.11%**	**7.87%**
jumps)	(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	All	111,664	**-1.47%**	**-1.70%**	**-1.81%**	**-2.25%**	**-2.38%**	**-2.45%**
(without	No jump wihin past 10 days	90,646	**-1.61%**	**-1.87%**	**-1.97%**	**-2.61%**	**-2.79%**	**-2.85%**
simlutaneous	Positive jump within past 10 days	10,436	**-0.77%**	**-0.82%**	**-0.81%**	**0.50%**	**1.40%**	**2.76%**
jumps)	(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%

Table VI

Price Drift Following Stock Price Jumps

This table presents the cumulative abnormal returns following positive and negative stock price jumps after excluding those jumps that are accompanied by simultaneous recommendation revisions. Within positive and negative jumps, we further classify them into jumps that are followed by subsequent revisions and those that are not. Subsequent revisions are defined as those issued one day after the jump in panel A, and 6 days after the jump in panel B. In panel B, we further exclude all jumps that are followed by either a subsequent jump or a revision within 5 days. If there are both upgrades and downgrades on the same day, we classify them as no revision. Stock price jumps are identified using "variance swap" test developed in Jiang and Ooman (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 jump date. The average returns reported in bold face are statistically significant at least at the five percent level (absolute value of *t*-statistics greater than 1.96). 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.

Panel A: Subsequent Revision One Day after the Jump

		Number of	Day 0	Cumulative Abnormal Market-Adjusted Return since Day 1				
	Stock Price Jumps	Observations	Return	1	1-2	1-21	1-42	1-126
Positive	All	257,955	**12.73%**	**-0.10%**	**-0.24%**	**1.66%**	**3.43%**	**5.07%**
Jumps	No Revision in Day 1	254,022	**12.74%**	**-0.10%**	**-0.24%**	**1.65%**	**3.42%**	**5.06%**
	Upgrade in Day 1	2,081	**11.08%**	**0.65%**	**0.89%**	**4.09%**	**5.95%**	**7.45%**
	Upgrade - No Revision			**0.75%**	**1.13%**	**2.43%**	**2.53%**	**2.39%**
	Downgrade in Day 1	1,852	**13.10%**	**-0.99%**	**-1.21%**	0.07%	0.89%	2.37%
	Downgrade - No Revision			**-0.89%**	**-0.96%**	**-1.58%**	**-2.53%**	**-2.69%**
Negative	All	142,388	**-10.39%**	**1.64%**	**1.94%**	**1.61%**	1.17%	0.92%
Jumps	No Revision in Day 1	139,086	**-10.25%**	**1.68%**	**1.99%**	**1.67%**	1.24%	1.02%
	Upgrade in Day 1	814	**-12.07%**	**1.48%**	**1.65%**	**1.74%**	0.41%	0.38%
	Upgrade - No Revision			-0.20%	-0.34%	0.06%	-0.84%	-0.64%*
	Downgrade in Day 1	2,488	**-17.28%**	**-0.55%**	**-0.97%**	**-2.15%**	**-2.90%**	**-4.32%**
	Downgrade - No Revision			**-2.23%**	**-2.96%**	**-3.82%**	**-4.14%**	-5.34%*

* Standard errors could not be determined because the serial correlation-consistent estimate of variance was negative.

Table VI - *continued*

Panel B: Subsequent Revision Six Days after the Jump

	Stock Price Jumps	Number of Observations	Day 0 Return	Cumulative Abnormal Market-Adjusted Return since Day 6		
				6-21	6-42	6-126
Positive	All (no-jump,no-revision for next 5 days)	187,948	**12.58%**	**2.28%**	**3.82%**	**5.38%**
Jumps	No Revision in Day 6	186,988	**12.60%**	**2.28%**	**3.82%**	**5.37%**
	Upgrade in Day 6	430	**8.62%**	**3.64%**	**5.59%**	**8.57%**
	Upgrade - No Revision			**1.36%**	1.77%	**3.20%**
	Downgrade in Day 6	530	**8.89%**	0.73%	**2.15%**	**4.24%**
	Downgrade - No Revision			**-1.55%**	-1.67%	-1.13%*
Negative	All (no-jump,no-revision for next 5 days)	97,127	**-10.07%**	0.03%	-0.92%	-1.21%
Jumps	No Revision in Day 6	96,684	**-10.07%**	0.04%	-0.91%	-1.19%
	Upgrade in Day 6	179	**-8.17%**	0.68%	-0.90%	0.15%
	Upgrade - No Revision			0.65%	0.01%	**1.35%**
	Downgrade in Day 6	264	**-10.56%**	**-1.96%**	**-4.08%**	**-6.79%**
	Downgrade - No Revision			**-1.99%**	**-3.17%**	-5.59%*

* Standard errors could not be determined because the serial correlation-consistent estimate of variance was negative.

Table VII

Robustness Checks

This table presents the cumulative abnormal returns following recommendation revisions after excluding certain subset of the revisions. In Panel A, we exclude those revisions that are immediately followed by a subsequent jump within 10 trading days of the revision. In panel B, we exclude those revisions preceded by jumps that are preceded or followed by other jumps within plus and minus 10 days. In panel C, we exclude those revisions preceded by jumps that reverse within 5 trading days. Reversals are defined as jumps where more than 75% of the jump return is reversed over the next four trading days. In panel D, we exclude revisions made on days when there was a potential market-wide information shock. Days with potential market-wide shocks are defined as calendar days when the number of stocks with positive jumps relative to negative jumps is in the (below) the top (bottom) decile. As in Table V, we also exclude all revisions that are accompanied by simultaneous stock price jumps. Within upgrades and downgrades, we further classify them into revisions that had no jumps, positive jumps, or negative jumps in stock prices during the past 10 days leading up to the revision date. Stock price jumps are identified using "variance swap" test developed in Jiang and Ooman (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 the other days in the column headings are the number of trading days from the revision date. The average returns reported in bold face are statistically significant at least at the five percent level (absolute value of *t*-statistics greater than 1.96). 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 VII - *continued*

Panel A: Excluding Revisions immediately followed by Subsequent Jumps

Recommendation Revision		Number of Observations	Number of Trading Days after Revision Date 0	1	2	21	42	126
Upgrades	All	80,246	**1.37%**	**1.63%**	**1.70%**	**2.11%**	**2.15%**	**3.19%**
(without	No jump wihin past 10 days	69,721	**1.43%**	**1.71%**	**1.78%**	**2.10%**	**2.00%**	**2.98%**
simlutaneous	Positive jump within past 10 days	6,655	**0.84%**	**0.92%**	**0.97%**	**3.01%**	**4.74%**	**6.83%**
jumps)	(Positive) Jump - No Jump		**-0.59%**	**-0.79%**	**-0.81%**	**0.91%**	**2.73%**	**3.86%**
	Negative jump within past 10 days	3,870	**1.22%**	**1.45%**	**1.41%**	**0.75%**	0.23%	0.70%
	(Negative) Jump - No Jump		**-0.21%**	**-0.26%**	**-0.37%**	**-1.35%**	**-1.78%**	**-2.28%**
Downgrades	All	100,642	**-1.50%**	**-1.72%**	**-1.82%**	**-2.42%**	**-2.67%**	**-2.77%**
(without	No jump wihin past 10 days	84,000	**-1.63%**	**-1.87%**	**-1.97%**	**-2.68%**	**-2.99%**	**-3.09%**
simlutaneous	Positive jump within past 10 days	8,237	**-0.78%**	**-0.97%**	**-1.04%**	**-0.52%**	0.26%	1.47%
jumps)	(Positive) Jump - No Jump		**0.85%**	**0.90%**	**0.92%**	**2.16%**	**3.26%**	**4.56%**
	Negative jump within past 10 days	8,405	**-0.93%**	**-0.99%**	**-1.16%**	**-1.66%**	**-2.22%**	-3.11%
	(Negative) Jump - No Jump		**0.70%**	**0.88%**	**0.81%**	**1.02%**	0.77%	-0.02%

Table VII - *continued*

Panel B: Excluding Revisions following Jumps with Adjacent Jumps

Recommendation Revision		Number of Observations	Number of Trading Days after Revision Date 0	1	2	21	42	126
Upgrades	All	83,013	**1.35%**	**1.66%**	**1.75%**	**2.36%**	**2.48%**	**3.46%**
(without	No jump wihin past 10 days	75,358	**1.39%**	**1.72%**	**1.82%**	**2.36%**	**2.39%**	**3.34%**
simlutaneous	Positive jump within past 10 days	4,679	**0.74%**	**0.89%**	**0.98%**	**3.66%**	**5.57%**	**7.14%**
jumps)	(Positive) Jump - No Jump		**-0.65%**	**-0.83%**	**-0.83%**	**1.30%**	**3.19%**	**3.81%**
	Negative jump within past 10 days	2,976	**1.21%**	**1.42%**	**1.36%**	0.38%	-0.14%	0.66%
	(Negative) Jump - No Jump		**-0.18%**	**-0.30%**	**-0.45%**	**-1.98%**	**-2.53%**	-2.68%*
Downgrades	All	102,830	**-1.50%**	**-1.74%**	**-1.85%**	**-2.41%**	**-2.57%**	**-2.62%**
(without	No jump wihin past 10 days	90,646	**-1.61%**	**-1.87%**	**-1.97%**	**-2.61%**	**-2.79%**	**-2.85%**
simlutaneous	Positive jump within past 10 days	5,624	**-0.71%**	**-0.86%**	**-0.88%**	0.24%	**1.07%**	**2.67%**
jumps)	(Positive) Jump - No Jump		**0.90%**	**1.01%**	**1.09%**	**2.84%**	**3.86%**	**5.52%**
	Negative jump within past 10 days	6,560	**-0.70%**	**-0.77%**	**-0.98%**	**-1.96%**	**-2.50%**	-3.24%
	(Negative) Jump - No Jump		**0.91%**	**1.09%**	**0.99%**	0.64%	0.29%	-0.39%

* Standard errors could not be determined because the serial correlation-consistent estimate of variance was negative.

Table VII - ***continued***

Panel C: Excluding Revisions following Jumps Related with Liquidity Shocks

Recommendation Revision		Number of Observations	Number of Trading Days after Revision Date					
			0	1	2	21	42	126
Upgrades	All	88,116	**1.32%**	**1.64%**	**1.74%**	**2.46%**	**2.63%**	**3.62%**
(without	No jump wihin past 10 days	75,358	**1.39%**	**1.72%**	**1.82%**	**2.36%**	**2.39%**	**3.34%**
simlutaneous	Positive jump within past 10 days	8,292	**0.89%**	**1.24%**	**1.53%**	**4.57%**	**6.36%**	**8.05%**
jumps)	(Positive) Jump - No Jump		**-0.50%**	**-0.48%**	**-0.29%**	**2.21%**	**3.97%**	**4.71%**
	Negative jump within past 10 days	4,466	**0.92%**	**0.99%**	**0.85%**	0.15%	-0.31%	0.03%
	(Negative) Jump - No Jump		**-0.46%**	**-0.73%**	**-0.96%**	**-2.21%**	**-2.69%**	**-3.31%**
Downgrades	All	109,895	**-1.47%**	**-1.70%**	**-1.81%**	**-2.27%**	**-2.41%**	**-2.48%**
(without	No jump wihin past 10 days	90,646	**-1.61%**	**-1.87%**	**-1.97%**	**-2.61%**	**-2.79%**	**-2.85%**
simlutaneous	Positive jump within past 10 days	9,219	**-0.60%**	**-0.51%**	**-0.43%**	0.92%	**1.86%**	**3.42%**
jumps)	(Positive) Jump - No Jump		**1.01%**	**1.35%**	**1.54%**	**3.53%**	**4.65%**	**6.27%**
	Negative jump within past 10 days	10,030	**-1.05%**	**-1.32%**	**-1.61%**	**-2.21%**	**-2.83%**	**-3.81%**
	(Negative) Jump - No Jump		**0.56%**	**0.55%**	**0.37%**	0.40%	-0.04%	-0.96%

Table VII - *continued*

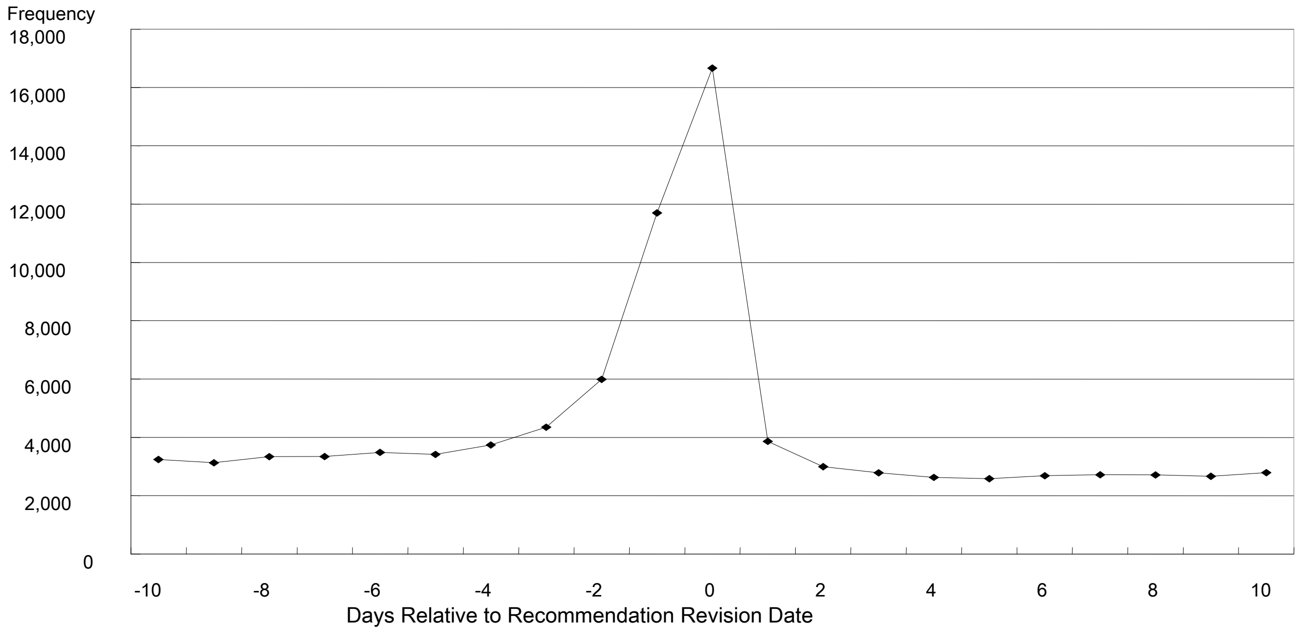
Panel D: Excluding Revisions following Jumps Related with Market Wide Information

Recommendation Revision		Number of Observations	Number of Trading Days after Revision Date 0	1	2	21	42	126
Upgrades	All	85,617	**1.33%**	**1.65%**	**1.75%**	**2.44%**	**2.58%**	**3.61%**
(without	No jump wihin past 10 days	75,358	**1.39%**	**1.72%**	**1.82%**	**2.36%**	**2.39%**	**3.34%**
simlutaneous	Positive jump within past 10 days	6,789	**0.80%**	**1.09%**	**1.30%**	**4.21%**	**6.12%**	**8.34%**
jumps)	(Positive) Jump - No Jump		**-0.59%**	**-0.63%**	**-0.51%**	**1.85%**	**3.73%**	**5.00%**
	Negative jump within past 10 days	3,470	**0.98%**	**1.18%**	**1.16%**	0.58%	-0.16%	0.24%
	(Negative) Jump - No Jump		**-0.41%**	**-0.54%**	**-0.66%**	**-1.78%**	**-2.54%**	**-3.09%**
Downgrades	All	106,334	**-1.50%**	**-1.74%**	**-1.84%**	**-2.36%**	**-2.51%**	**-2.59%**
(without	No jump wihin past 10 days	90,646	**-1.61%**	**-1.87%**	**-1.97%**	**-2.61%**	**-2.79%**	**-2.85%**
simlutaneous	Positive jump within past 10 days	7,728	**-0.74%**	**-0.75%**	**-0.74%**	0.45%	**1.48%**	**3.15%**
jumps)	(Positive) Jump - No Jump		**0.87%**	**1.12%**	**1.23%**	**3.06%**	**4.27%**	**6.00%**
	Negative jump within past 10 days	7,960	**-0.96%**	**-1.21%**	**-1.36%**	**-2.22%**	**-3.09%**	**-4.43%**
	(Negative) Jump - No Jump		**0.65%**	**0.66%**	**0.62%**	0.38%	-0.30%	-1.58%

Figure 1. Number of Recommendation Revisions with Stock Price Jumps around the Revision Date

This figure plots the number of recommendation revisions with stock price jumps around the revision date. Stock price jumps are identified using "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; i.e. 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 A; Stock Price Jumps around All Revisions



Panel B: Sub-samples Categorized by the Direction of Jumps and Subsequent Revisions

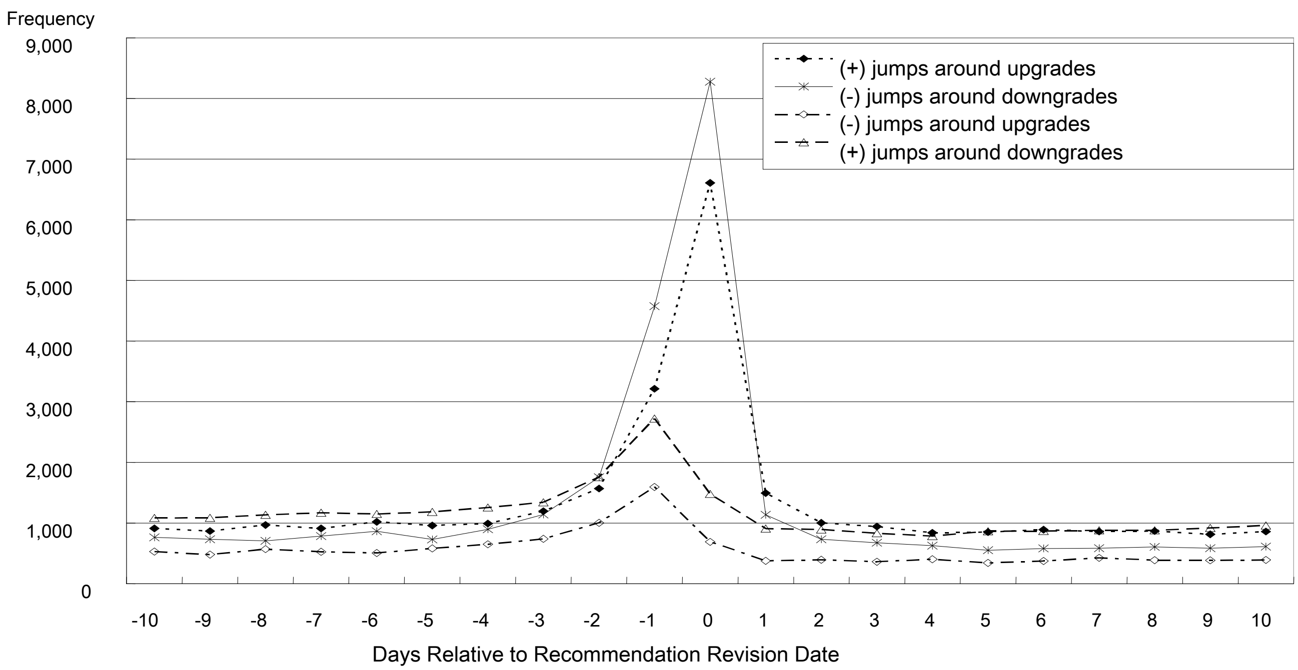
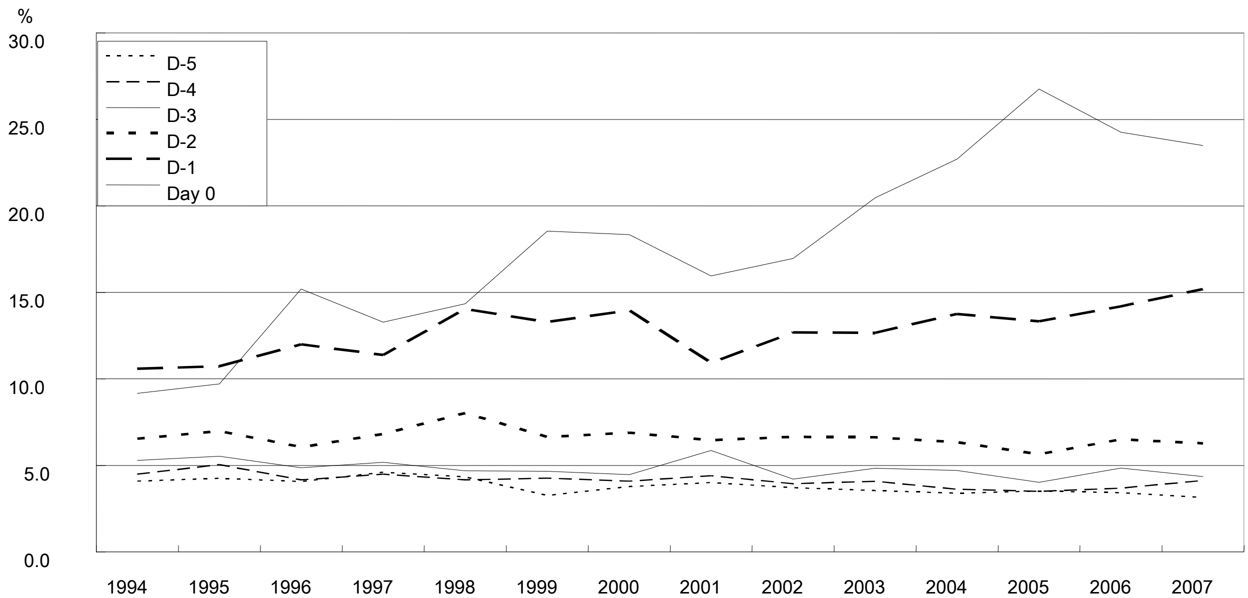


Figure 2. Relative Frequencies of Recommendation Revisions with Stock Price Jumps over Time

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.

Panel A; All Revisions



Panel B; Sub-samples Categorized by the Direction of Jumps and Subsequent Revisions