Analyst Recommendations subsequent to Stock Price Jumps: Are they informative?

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Key Words: Analyst Recommendations, Stock Price Jumps, Market Reactions

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Despite the unfavorable assertions often made by general public or media that stock analysts are inherently biased, it is fairly well established in the literature that analyst recommendations have added value.[1] Recent studies attempt to further explore what might be the source of this added value, and suggest the following two alternative possibilities: ability to access private information or ability to interpret publicly available information. The empirical evidence so far seems to offer mixed results.

For example, Ivkovic and Jegadeesh (2004) examine the impact of recommendation revisions surrounding earnings announcements and find that price reactions to recommendation revisions are weaker in the period following the announcement than prior to the announcement, especially for upgrades. They conclude that analysts' abilities are more related with access to private information rather than interpretation of public information.

On the other hand, Asquith, Mikhailb, and Au (2005) examine the strength of the written arguments made in each analyst report to support an opinion, and find that this variable has information content even when recommendations are made contemporaneously with other important corporate events, including security issues or mergers and divestitures. Based on this finding, they argue that at least part of analyst's ability is related with interpretation of public information. Park and Pincus (2000) examine earnings announcements that are followed by analysts' recommendation revisions within five days, and find that consensus analyst recommendation revisions have information content beyond earnings surprises, consistent with the view that value of analyst recommendations lies in their expertise to process and interpret public information.

A common characteristic of above approach is that all of them rely on some pre-defined corporate announcements – for example, earnings announcements - as information events. This is likely constrained by the availability of the event dates, such as earnings announcement dates

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

from standard data sources like Compustat or IBES. As documented in the literature, there are a variety of corporate events that convey significant information about firm value. For example, merger and acquisition, spin-off, 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. In addition, the company itself is by no means the sole source of information relevant for stock price. For example, economy wide or industry wide information as well as information about competitors may well affect the stock prices.[2] By construction, these information events cannot be captured by some pre-defined corporate events, and they would be excluded in empirical tests designed to evaluate analysts' ability to process and interpret public information. Moreover, even with all corporate events identified, it is difficult to determine whether certain events contain significant information relevant to stock prices.

In this paper, we attempt to overcome such shortcomings in assessing analyst's information processing ability by examining the effect of analyst revisions conditional on generic "informational events" instead of some pre-defined specific events. Our approach is to identify jumps in stock prices econometrically and interpret these jumps as generic "informational events" that have significant impact on stock prices. Jumps represent large discontinuous changes in stock prices which are typically triggered by substantial information or liquidity shocks. We extend statistical method of 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.

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[2] For example, on October 28, 1999, McDonald's stock price jumped 7.84% following positive macro economic outlook without any firm-specific news. See Jiang and Yao (2007) for a list of days with price relevant information for McDonalds.

Motivated by existing literature, we postulate and empirically test various competing hypotheses on the relation between stock price jumps and analyst recommendation revisions. Our results show that jumps in stock prices are more likely to trigger analyst revisions. The conditional probability of analyst issuing a revision subsequent to a stock price jump is significantly higher than its unconditional probability of issuing a revision. Cross-sectionally, we find that analyst with more experience are more likely to exhibit this tendency, but no evidence that broker reputation is related with this behanior.

In addition, we also find that there tends to be a higher probability of issuing upgrade (downgrade) following positive (negative) stock price jumps. Specifically, compared with unconditional probability of analyst issuing recommendation revision, the probability of issuing an upgrade (downgrade) revision conditional on positive (negative) stock price jumps is roughly two (three) times higher.

To further examine whether revisions following jumps are driven by additional information possessed by analysts or reasons unrelated to information, we examine market reactions to analyst revisions under different scenarios. The results suggest that both upgrades following positive jumps and downgrades following negative jumps contain significant information about future stock returns. Market reactions to these revisions are at least as strong as or even stronger than revisions not following stock price jumps especially for upgrades following positive jumps and for longer horizons. Overall, these results suggest that recommendation revisions made in the same direction as the recent jumps are at least as or more informative as those not following stock price jumps. These results are robust to controlling for potential post-jump drift effects.

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

I. Hypotheses

Stock recommendations are the final product of analysts' research and hence incorporate all information available to the analyst that may be relevant for stock prices as well as analyst's skill in processing these pieces of information. The nature of available information could be quite different across stocks and analysts. Some may be private signals acquired only by certain analysts, while others may be superior interpretation of publicly available information.

Motivated by existing literature, we test various competing hypotheses on the relation between analyst recommendation revisions and stock price jumps. If analyst's recommendations are purely driven by random arrivals of private signals, then we would expect recommendation revisions to be randomly issued as well. That is, the probability of revising a recommendation should not depend on recent price movements, especially those large ones such as jumps. This constitutes the null hypothesis of our analysis.

H0: The probability of analyst issuing a recommendation revision and the direction of recommendation revision are independent of past information shocks, as proxied by jumps in stock prices.

The null hypothesis has strong and testable implications. Under the null hypothesis, the probability of analyst issuing a recommendation revision conditional on recent jumps in stock prices is expected to be the same as unconditional probability of analyst issuing a recommendation revision. In addition, the probability of analyst issuing an upgrade or downgrade revision is independent of whether recent jump in stock prices is positive or negative.

The first alternative of the above hypothesis is that analyst recommendation revisions are related to past information shocks. We postulate the alternative hypotheses under two premises: one is that analyst recommendation revision is driven by further information possessed by analysts, and other is that analyst recommendation revision is due to reasons other than information on firms' future cash flows. In particular, for revisions driven by information, analyst are expected to issue upgrade (downgrade) following negative (positive) price jumps if they possess conflicting information as past information shocks and upgrade (downgrade) following positive (negative) price jumps if they possess conforming information with past information shocks. As noted earlier, our clarification of information driven revisions has a broader interpretation than pure private information. That is, the information possessed by analysts may not be purely private in nature. Specifically, the value of the analysts also may lie in their superior ability to process publicly available information, which is likely to be reflected in price jumps or some generic "information events". In general, if an analyst believes that recent jump in stocks price is the result of market misreaction to certain information, he/she may issue recommendation with clarifying statement interpreting the information content. For example, if analysts view that market overreacts to information shocks, then they would revise against the direction of the jump. Belief of overreaction can also cause analysts to revise their recommendations for pure valuation concerns. [3] On the other hand, if analysts think that the market initially underreacts to past information shocks, then the revision would be more likely to be in the same direction as the jump. In these cases, it is likely that the probability of analyst issuing a recommendation revision may directly depend on recent jump in stock prices.

The second alternative to the null hypotheses is that analyst recommendations may be influenced by stock price jumps for reasons other than information. For example, analysts may simply be extrapolating recent price changes, especially the large ones such as jumps. This is

[3] For example, analysts may have high or low price targets for certain stocks, and make upgrades (downgrades) after substantial prices drops (increases). On April 2, 2009, Cisco stock price jumps to $18.14 at close. On April 6, 2009, the stock was downgraded to neutral from conviction buy at Goldman Sachs after reaching the broker's $18 price target. The analyst issued the following statement: "We maintain a positive long-term view, as Cisco's execution and balance sheet position it well to benefit from favorable secular trends in IP networking, which we expect to drive 15% long-term earnings growth. However, with Cisco now trading at 17 times our estimated calendar 2010 EPS, we view our growth expectation as largely priced in." The stock closes down at $17.53 on that day.

similar to the behavior of a positive feedback trader or a noise trader. In this case, recommendation revisions also tend to move in the same direction as recent jump in stock prices.

Another possibility is that analyst revisions may be influenced by the company's business or investment relation with the firm. To improve a firm's credit rating and appeal to investors, analysts may be obligated to issue upward-biased revisions. This may be one of the potential reasons that analyst recommendations are predominantly biased towards "buys" or "strong buys". The motivation could be stronger especially following negative jump in stock prices.

On the other hand, passive investors subject to loss aversion in prospect theory may influence analysts to issue downgrades. This is particularly true following negative jumps. Suppose there was a negative jump in stock price and there is equal probability of either a recovery or a further price drop. And analysts are concerned about making a wrong call. Consider the first scenario where the analyst issues a downgrade and stock price recovers. Although analyst made a wrong call, the penalty may not be that severe since there is a gain. However, if the analyst issues an upgrade and stock price drops even further, the penalty for this wrong call could be substantial. Knowing this, the analyst may prefer to issue a downgrade following a negative jump to minimize the penalty for a wrong call. This effect would be less pronounced following positive jumps since there is a buffer obtained through this gain (i.e. house money effect). Hence, we are more likely to observe downgrades following negative jumps than following positive jumps or no jumps.[4]

The following hypotheses summarize both information driven and non-information driven recommendation revisions as alternatives of the null hypothesis:

[4] This explanation is broadly consistent with how the media typically criticizes directional forecasts that prove to be wrong ex post. Analysts who previously provided rosy forecasts are often criticized in subsequent down markets, while analysts who previously provided pessimistic forecasts are rarely criticized in subsequent up markets.

H1: The probability of issuing a recommendation revision will be higher when preceded by a stock price jump.

H1a-1 (Conflicting information or buck the trend) Recommendation revisions subsequent to price jumps are more likely to be in the opposite direction of the preceding jump

H1a-2 (Conforming information or feedback effect): Recommendation revisions subsequent to price jumps are more likely to be in the same direction of the preceding jump

H1b-1 (Upward-biased revision due to obligations): Analysts are more likely to issue upgrades following stock price jumps, especially negative jumps.

H1b-2 (Avoidance of a wrong call under loss aversion): Analysts are more likely to issue downgrades following stock price jumps, especially negative jumps.

There can be additional cross-sectional predictions based on broker reputation and analyst's experience. For example, analysts from reputable brokerages or more experienced analysts may have better ability to interpret the information contained recent prices. If so, then these analysts are more likely to revise recommendation following stock price jumps than analysts from less reputable brokerages or with less experience.

There are directional implications as well. On one hand, analysts from smaller brokerage firms or new analysts have incentive to issue recommendation revision against the market trend. This behavior has the potential of enhancing the visibility of analysts (Prendergast and Stole, 1996). On the other hand, new analysts may fear going against the recent price change due to various career concerns, Chevalier and Ellison (1999). This leads to our next set of hypotheses.

H1c: Analysts from more reputable brokerages or with more experience are more likely to issue revisions following recent price jumps.

H1c-1: Analysts from less reputable brokerages or with less experience are more likely to issue revisions in the opposite direction of the recent price jumps.

H1c-2: Analysts from less reputable brokerages or with less experience are less likely to issue revisions in the opposite direction of the recent price jumps.

As mentioned earlier, the probabilities of analysts issuing recommendation revisions conditional on recent price jumps allow us to test whether analyst recommendations are purely driven by random arrivals of private information or not. Furthermore, the probabilities of issuing upgrades or downgrade conditional on the direction of recent price jumps allows us to distinguish sub-hypotheses under H1a. Specifically, under H1a-1 it is expected that analysts tend to issue updates (downgrades) after negative (positive) shocks, whereas it is the opposite under H1a-2.

However, the conditional probabilities of issuing revision cannot clearly distinguish between information-driven revisions versus non-information driven revisions. To further distinguish between these hypotheses, we rely on post-event market reactions. If analyst revisions following jumps are driven by information, then analysts are expected to contain significant information about future stock returns. On the other hand, if they are not driven by information but other reasons, then analyst revisions will not have any predictive power of future stock returns. Thus, in our analysis we rely on market reactions to revisions that are preceded by jumps to distinguish among information versus non-information hypotheses.

H2a (Information): Market reactions to revisions following jumps would be stronger than revisions not following jumps.

H2b (Non-Information): Market reactions to revisions following jumps are weaker than revisions not following jumps.

If H2-1 (Information hypothesis) is supported, then we can further refine it based on the direction of jumps and revisions. If the revisions are mainly based on conflicting information, then subsequent revisions that go against the price change will yield stronger market reactions. On the other hand, if the revisions are based more on conforming information, then market would react more strongly to the revisions made in the same direction as the recent jump.

H2a-1 (conflicting information): Market reaction would be stronger for revisions made in the opposite direction as the recent price jumps than those made in the same direction.

H2a-2 (conforming information): Market reaction would be stronger for revisions made in the same direction as the recent price jumps than those made in the opposite direction.

II. Identifying Stock Price Jumps

Jumps represent 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.[5]

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

[5] 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).

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 (2007) 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 jump test. The "variance swap" approach builds on the idea that in the absence of jumps, the accumulated difference between the simple return and the log return – called "swap variance" - captures one half of the integrated variance in the continuous time limit. By comparing swap variance with realized variance, we can detect jumps. As we elaborate in Appendix A, 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 swap variance 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. The details of this procedure are provided in Appendix A.

III. Data and Sample

We obtain recommendations data from IBES Detailed file to create our revision dataset and stock returns data from CRSP to create the stock price jump dataset. 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,

(c) Stock return data should be available from CRSP on the revision date.

We impose these criteria since our primary focus is on how analysts revise their recommendations following stock price jumps. 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 3,555 in 2006. 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 260 in 2006. The median number of analysts in a brokerage is 9. The last three columns in table I present the number of firms 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 indicate 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 per year for an average stock there are two negative jumps per year.

IV. Empirical Results

1. Stock Price Jumps around Recommendation Revisions

Figure 1 present frequency 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 subsequent revisions. In both panels, day 0 refers to the recommendation revision date and the event window is from -10 to +10 trading days.[6]

The results from panel A indicate that there is a sharp increase in the frequency of stock price jumps from five trading days before the revision date. This suggests that 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 revision suggests that analyst revisions may help to resolve information uncertainty.

[6] 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.

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. That is, upgrades are more often preceded by positive jumps, while downgrades are more often preceded by negative jumps. These results are largely consistent with predictions of H1a-2 (conforming information or feedback effect hypothesis that recommendation revisions subsequent to price jumps are more likely to be in the same direction of the jump.

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 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 results in 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. And this increasing trend is being driven by revisions that are made in the same direction as the preceding jumps. We conjecture that this trend might be related with various regulatory changes that took place since 2000.

2. Recommendation Revisions subsequent to Stock Price Jumps

Our first research question is whether recommendation revisions are influenced by preceding stock price jumps. Although the results from the previous subsection are suggestive of the idea that recommendations are influenced by stock price jumps, the analysis was quite incomplete in the sense that it was conditioned on recommendation revisions.

To formally test whether recommendations are influenced by recent price jumps, we compute the probabilities of issuing a recommendation revision both unconditionally and conditional on a preceding stock price jump. The estimation procedure is as follows.

For each calendar day *t* during our sample period, we define (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 preceding stock priced jump as follows ($\Pr_t(rev \mid jump)$). These probabilities are computed 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 prices during the past 10 trading days of day *t*[7],

$N_{\mathrm{rev},t}$: 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 on day *t* and a stock price jump during the past 10 trading days of day *t*.

The above probabilities are useful to directly test the implications of the null hypothesis: the probability of analyst issuing revisions is not affected by recent jumps in stock prices. To further distinguish between H1a -1 (conflicting information or buck the trend) vs. H1a-2

[7] To avoid potential confounding effect from revisions and jumps made simultaneously on the same day, we identify jumps from day -1 of the revision to day -10, excluding day 0, i.e. the revision date. If there are multiple jumps during this 10 day window, we take the most recent jump.

(conforming information or feedback effect), we estimate both unconditional and conditional probabilities of upgrades and downgrades as follows.[8]

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

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

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

where $N_{\text{up},t}$: number of upgrades on day *t*,

$N_{\text{posi},t}$: number of stocks that experienced a positive jump in stock prices during the past 10 trading days of day *t*,

$N_{(\text{posi} \cap \text{up}),t}$: number of stocks that experienced both an upgrade on day *t* and a positive jump during the past 10 trading days of day *t*,

$N_{\text{nega},t}$: number of stocks that experienced a negative jump in stock prices during the past 10 trading days of day *t*,

$N_{(\text{nega} \cap \text{up}),t}$: number of stocks that experienced both an upgrade on day *t* and a negative jump during the past 10 trading days of day *t*.

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

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

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

[8] 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.

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

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 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 within past 10 trading days. These numbers indicate that roughly a quarter of all stocks in CRSP universe experience a jump within the past 10 trading days at a given point in time.

The next two columns present the unconditional probability of a recommendation revision and the probability conditional on a stock price jump occurring within the past 10 days. The results indicate that probability of issuing a recommendation revision conditional on a recent price jump is larger than the unconditional probability for every single year in our sample period which strongly rejects the null hypothesis (H0). Over the full sample period, the unconditional probability of a revision on a given day is 1.67% on average, while this probability increases to 2.8% when there is a jump during the past 10 days, and this difference is statistically significant with a t-stat of 4.72.[9] This finding suggests that analyst recommendations are not purely driven by random arrivals of private information, but at least partly being driven by recent jumps in stock prices (as proxy of information shock) due to (1) further private information possessed by analysts, (2) further interpretation of public information by analysts, or (3) other reasons not related to information.

To distinguish between H1a1-1 (conflicting information or buck the trend) vs. H1a-2 (conforming information or feedback effect), we next examine the conditional probabilities incorporating directions of both jumps and subsequent revisions.

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

The last six columns of table III report the conditional and unconditional probabilities separately for upgrades and downgrades conditional on both positive and negative jumps. For both upgrades and downgrades, the revisions are more likely to be in the same direction as the preceding stock price jump, confirming H1a-2 and rejecting H1a-1. These results suggest that analysts on average (1) provide private information conforming with recent information shocks, or (2) think that the initial jumps do not fully incorporate all of the available public information and thus further reinforce its effect on stock prices, or (3) exhibit an extrapolative or positive feedback behavior.

But, there is also a clear difference between upgrades and downgrades regarding the magnitude of the conditional probabilities. First, the probability of an upgrade conditional on negative jumps is the smallest among all four conditional probabilities. On the other hand, the probability of a downgrade conditional on a negative jump is overwhelmingly larger than both unconditional probabilities and probabilities conditional on a positive jump. These results reject H1b-1 (upward-biased revision due to obligations): in favor of H1b-2 (avoidance of a wrong call under loss aversion):

Panel B of table III replicates above analysts using medians of daily probabilities rather than average 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 should also note that the conditional probabilities of revisions in the opposite direction of the price jumps are no longer significantly different from unconditional probabilities, providing further support for H1a-2 (conforming information or feedback effect).

3. The Effect of Broker Reputation and Analyst Experience on Revisions following Jumps

Previous literature on broker reputation and analyst experience suggest potential cross-sectional differences in analyst's behavior. Analysts with less experience or employed by less prestigious brokerages may be more likely to issue revisions that go against the current price movements to increase their visibility (H1c-1) or less likely to exhibit this behavior due to various career concerns (H1c-2). On the other hand, more experienced analysts or those employed by more reputable brokerages may have better ability in interpreting information available from stock price jumps leading them to revise more frequently subsequent to jumps (H1c).

To test these implications, we compute the conditional probabilities based on the direction of the jumps and subsequent revisions for a two different sets of sub-groups. We first split the sample into analysts from large brokers and those from small brokers. Large brokers are defined as top 20 brokers based on the number of analysts employed for each year during the sample period. Our second split sample is based on analysts experience. We classify analysts as being "new" if they first appeared in IBES recommendations database less than three years before as of the revision date. All other analysts are defined as "old". For each of these sub-groups, we compute the conditional probabilities in a similar manner as we did for table III. For example, to calculate $\Pr_t(up \mid (+)\, jump)$ for new analysts, we first obtain number of stocks for a given day that experienced both an upgrade from a new analyst and a positive jump during the past 10 trading days, and then divide this quantity by number of stocks that experienced a positive jump i during the past 10 trading

Table IV reports the averages of these conditional probabilities for each of the sub-groups. Panel A reports results fro sub-groups formed by broker reputation and panel B reports the corresponding numbers for –subgroups formed by analyst experience. Because we require at least three years of data to define an "old" analyst, we restrict the sample period to start from 1997 in panel B.

The results from panel A indicate that broker reputation does not have much influence over analyst's tendency to revise recommendations subsequent to price jumps. The conditional probabilities of issuing revisions subsequent to jumps are not significantly different between the two groups. On the other hand, the results from panel B suggest that analyst experience matters when revising their recommendation subsequent to jumps. Specifically, old analysts much more likely to issue revisions subsequent to jumps regardless of the direction of the jumpand the revision.[10] These results indicate that more experienced analysts may possess better abilities in interpreting information contained in the recent price jumps, confirming H1c, but reject the hypothesis that analysts may go against recent price movements to increase their visibility (B1c-1).

4. Market Reactions to Recommendation Revisions subsequent to Price Jumps

The analysis in the previous sub-section has shown that analyst recommendations are clearly influenced by large changes in recent stock prices and that revisions are more likely to be in the same direction as the jumps. But, it is still not clear why they would exhibit such a pattern. One possibility is that analysts revise recommendations based on acquired private information. Or, they are rationally processing public information contained the recent jumps and as a result of this information processing, revise their recommendations. On the other hand, analysts may be surprised by the recent price shock and exhibit extrapolative behavior or overreaction in revising their recommendations, similar to a positive feedback trader. Or, analysts may fear the (reputational) penalty for a wrong call especially there is a negative shock, leading them to issue more downgrades.

The key question of our analysis is whether analyst recommendation revisions are driven by information, or reasons other than information. To disentangle these alternative stories, we rely on market price reactions to recommendation revisions subsequent to price jumps. The basic idea is that if market participants value analysts' private information or the information processing abilities of analysts subsequent to large changes in stock prices, then market reactions to recommendation revisions in periods subsequent to big price jumps should be at least as

[10] The results are robust to using medians of daily conditional probabilities in place of averages.

significant as market reactions to those without preceding jumps. On the other hand, if the market participants do not value analyst revisions immediately following big price changes either due to their simple extrapolative behavior or tendency to avoid a wrong call in down markets, then market reactions to revisions following jumps could be significantly smaller than market reactions to those without preceding jumps.

To implement these tests, we first calculate cumulative abnormal buy-and-hold market-adjusted returns following each recommendation and then compare them across those with preceding jumps and those without jumps. The event window in our analysis is defined as a combination of recommendation revision data (t) and a preceding jump in stock price (t-τ), i.e., [t-τ, t]. That is, our event window is defined as a joint event of analyst recommendation revision and recent jump in stock price. As specified earlier, 1≤τ ≤10 in our analysis. To explore the value of analyst revisions, we examine post-event price dirft and compare with market reaction to revisions that are not preceded by jumps.

Specifically, after a recommendation revision for stock *i* on date *t,* we compute *H*-day buy-and-hold abnormal returns $ABR_i(t,t+H)$ 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.

Before presenting the post-event stock returns, we first document the average market reactions to analyst revisions as well as post jump drifts in stock prices. This is because the post-event stock prices reflect not only (a) the effect of analyst revision on day t, but also (b) potential post-jump drift in stock prices. Table V reports market reactions to analyst revisions for both upgrades and downgrades as well as potential post-jump drift in stock prices for both positive jumps and negative jumps. Since jump occurs on average 5 days (the average value of the distance between the jump and the revision) before the end of our event window, the post-jump drift in stock prices is calculated from 5 days after jump in stock price. We compute serial-correlation consistent Hansen and Hodrick 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.

Results in Table V 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 consistent with the extant literature that examines the impact of analysts' recommendations on stock prices.[11]

Interestingly, there is only a significant post-jump drift after positive jumps in stock prices. The average return drift remains significant even 5 days after positive jumps and gradually increases and remains significant up to 126 trading days. On the other hand, while the average return drift 5 days after negative jumps is mostly negative, the magnitude of average returns is much smaller and statistically insignificant. The results provide some interesting patterns in post-jump stock returns. More importantly, they suggest that in our analysis it is important to control for post-jump effect, in particular for positive jumps, in order to obtain meaningful inference.

Table VI presents abnormal stock returns over various horizons following our joint event of stock price jump and analyst recommendation revision, which is our test sample We report the results separately for four separate sub-groups based on the direction of the jump and subsequent revision.[12] 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"

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

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

presents cumulative abnormal returns over 21 trading days, or roughly one calendar month, after the revision

We also report the abnormal returns for our two sets of benchmarks. The benchmarks are constructed as complementary to our joint event, i.e., the combination of stock price jumps and analyst revisions. The first benchmark is the analyst revision preceded by no jumps in stock price during the past 10 days. This benchmark offers a test for the significance of jump effect on market reactions to analyst revisions following jumps. In particular, if market reactions to analyst revisions following jumps are as strong as analyst revisions without recent jumps in stock price, then we cannot reject the hypothesis that analyst revisions following jumps are as informative as other revisions. The second benchmark is jumps in stock prices not followed by analyst revisions. Stock returns after these jumps are not affected by analyst revision and thus provides a clean sample to measure any potential post-jump drift in stock prices. As discussed earlier, since the end date of our event window is on average 5 days (the average number of days between the jump and the revision) after the jump, only the post-jump drift after 5 days of the jump occurrence is relevant to our study.

The results from Panel A of Table VI suggest that analyst recommendations in general are followed by significant market reactions even after made subsequent to a stock price jump. Upgrades made subsequent to both positive jumps and negative jumps are followed by positive market reactions, and downgrades following both positive and negative jumps are followed by negative market reactions at least up to one month.

However, there are substantial differences based on whether the revision was made in the same or opposite direction as the recent price change. Specifically, upgrades and downgrades made in the same direction as the recent price jump incur stronger market reactions than those that are made in the opposite direction. For example, upgrades following positive stock price jumps show a significant 9.47% abnormal return over 6 months horizon, while returns for upgrades following negative jumps diminish over time and become insignificant over long horizon. We observe similar patterns for downgrades as well.

Overall, these results seem to be consistent with the hypothesis that analyst recommendation following stock price jumps are based on information rather than non-information, supporting H2a (information hypothesis) and rejecting H2b (non-information hypothesis). In addition, the nature of the information conveyed by the analysts are more likely to be conforming rather than conflicting, since market reactions are stronger for revisions made in the same directions as the jumps. Hence, we reject H2a-1 (conflicting information) in favor of H2a-2 (conforming information).

However, as we observe from the 5th and 6th rows of panel A, analyst revisions with no preceding jumps are also followed by substantial market returns in the direction of the revisions. Stock price following positive jumps also exhibit a large positive drift, although negative jumps do not exhibit such a drift.

In panel B of table VI, we report the differences in abnormal returns between our test sample, and the appropriate benchmark returns. For each of the four test groups, we compare their returns with two benchmark returns. For example, positive jumps followed by upgrades are compared first with upgrades with no preceding jumps and then with positive jumps with no subsequent revisions.

The results from panel B indicate that for upgrades following positive jumps, the returns are significantly larger than both benchmarks. For example, abnormal returns following upgrades made subsequent to positive jumps are on average 5.05% points larger than upgrades with no preceding jumps and 3.99% points larger than positive jumps with no subsequent revisions.

For the other three groups within the test sample (i.e. downgrades following positive jumps, upgrades following negative jumps and downgrades following negative jumps), the results are mixed. Specifically, all of the three groups exhibit a stronger market reaction compared with the second benchmark (i.e. jumps with no subsequent revisions), but a weaker market reaction compared with the first benchmark (i.e. revisions with no preceding jumps). Overall, these results suggest that analyst recommendation have added value even made after a stock price jump, and the information seems to be the most valuable for upgrades following positive jumps.

As further robustness checks, in Table VII we pool upgrades and downgrades together in a regression framework to examine the extent to which different combinations of revisions and jumps (based on the directions) affect the market reactions. Specifically, we fit the following regression model:

$$ABR(t,t+H) = a_H + b_H \times I + c_H \times D\_positive\_up + d_H \times D\_negative\_up$$
$$+ e_H \times D\_positive\_down + f_H \times D\_negative\_down + \varepsilon \qquad (11)$$

where $ABR(t,t+H)$ is the *H*-period abnormal return (in %) following the revision date, *t* is the recommendation revision date, and *I* is the indicator variable for upgrades ($I = +1$) and downgrades($I = -1$).

D_positive_up, D_negative_up, D_positive_down, and *D_negative_down* are all dummy variables that capture the directional relationship between the jump and the revision. For example, *D_positive_down* would be one if the revision is a downgrade preceded by positive jump and zero otherwise.

Panel A of table VII presents the results using the pooled OLS approach, while panel B present the results based on Fama-MacBeth approach where the coefficients and *t*-stats are based on time-series averages and standard errors from quarterly cross-sectional regressions.

The results from both panels are consistent with the results from the previous Table VI. First, upgrades following positive jumps amplifies the positive market reactions almost doubles abnormal returns over longer horizons, Second, downgrades following negative jumps do not exhibit significant differences with the baseline case (i.e. downgrades with no preceding jumps) after two months. On the other hand, upgrades following negative jumps are followed by smaller returns while downgrades following positive jumps are followed by larger returns, mitigating the magnitudes of the market reactions.

The results reported in Table VI and VII clearly indicate a significant effect of previous jumps on market reaction to subsequent analyst revisions. Analyst recommendations made in same direction as the recent price jump seems to have added value, especially for upgrades following positive jumps.

V. Conclusion

The source of valued added by stock analysts is one of the key research questions in analysts literature. Researchers have so far suggested two potential possibilities; ability to access private information and ability interpret publicly available information.

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 not only firm specific but also economy-wide or industry-wide, or competitor specific information. Our main research questions are whether analyst revisions are often preceded or influenced by significant events proxied by stock price jumps, and whether such events have any impact on market reaction to analyst revisions.

First, we find that probability of issuing a revision is roughly two times higher for upgrades following positive jumps and close to three times higher for downgrades following negative jumps than unconditional probabilities of issuing revision. In addition, analysts with more experience are more likely to exhibit this tendency. These finding suggest that analysts seem to be influenced by prior stock price jumps either due to conforming information or feedback effect.

To disentangle these alternative explanations based on information vs. non-information, we resort to market reactions. We find that market reactions to analyst revisions differ significantly depending on the relationship between the direction of the revision and the direction of the preceding jumps. Specifically, we find that recommendation revisions made in the same directions as the recent jumps exhibit stronger market reactions compared to those revisions with no preceding jumps. This effect is more pronounced for upgrades following positive jumps and over longer horizons. On the other hand, revisions made in the opposite direction as the recent jumps generally exhibit weaker market reactions than those revisions with no preceding jumps.

Overall, these results suggest that analyst recommendations contain additional information about future stock returns even when they are made after stock price jumps, We also found the effect was the strongest for upgrades following positive jumps. Exploring why analysts might behave differently in issuing upgrades versus downgrades would be an interesting topic for future research.

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Appendix A: Jump Test and Jump Identification

The idea of the swap variance 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 $t_0 = 0, t_N = T$. So, define the realized variance 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 "Swap Variance" 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:

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

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 $\mu_p = 2^{\mu/2}\Gamma\left[{(p+1)}/{2}\right]\Big/\sqrt{\pi}$. 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 time interval. We proceed to identify those days where stock price jumps. The following sequential procedure is used to identify jumps. Let $\{r_{t_1}, r_{t_2}, ..., t_{t_N}\}$ be daily returns over the interval $[t_1, t_N]$. Then 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 the interval $[t_1, t_N]$, if the just test does not reject the null hypothesis of no jumps. We move to the next period, 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 $\{r_{t_1}, ..., r_{t_i}, r_{median}, r_{t_{i+1}}, ..., t_{t_N}\}$ and record the test statistic JS_i for i = 1, …N.
- **<u>Step 3:</u>** Construct the series $JS_0 - JS_i$ for i = 1, …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.

Table I

Sample Descriptive Statistics

This table presents the 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 covered by the sample, the table shows 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 that experienced a jump, a positive jump, or a negative jump, respectively. Stock price jumps are identified using "swap variance" 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 the summary statistics of stock price jumps identified during the sample period. Stock price jumps are identified using "swap variance" 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 occurrences per firm for each year in our sample. The sample period is from November 1993 to December 2007.

Year	Positive Jumps				Negative Jumps			
	Jump Size per Day		Occurence per Firm		Jump Size per Day		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 Recommendation Revisions following Stock Price Jumps

This table presents the averages (Panel A) and medians (Panel B) of the daily probabilities of recommendation revisions conditional on prior 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 during the past 10 days ($N_{jump,t}$), separately for positive jumps ($N_{posi,t}$) and negative jumps ($N_{nega,t}$), before analyst recommendation revisions. Finally, we locate all those stocks that experienced both revisions on that day and jumps within past 10 days 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	0.2197	0.0031	0.0069	0.0017	0.0033	0.0036	0.0015	0.0061	0.0023
1994	252	3,270	0.2240	0.0133	0.0216	0.0066	0.0110	0.0081	0.0068	0.0174	0.0089
1995	252	3,322	0.2775	0.0175	0.0274	0.0074	0.0122	0.0091	0.0102	0.0255	0.0133
1996	254	3,421	0.2807	0.0149	0.0243	0.0073	0.0129	0.0093	0.0077	0.0216	0.0094
1997	253	3,558	0.3182	0.0144	0.0219	0.0065	0.0097	0.0081	0.0080	0.0214	0.0091
1998	252	3,645	0.2987	0.0167	0.0246	0.0073	0.0115	0.0067	0.0096	0.0228	0.0114
1999	252	3,594	0.3153	0.0162	0.0255	0.0082	0.0142	0.0080	0.0082	0.0206	0.0099
2000	252	3,489	0.2810	0.0152	0.0234	0.0068	0.0108	0.0068	0.0086	0.0235	0.0097
2001	248	3,374	0.2931	0.0165	0.0219	0.0068	0.0096	0.0083	0.0099	0.0212	0.0091
2002	252	3,342	0.2344	0.0238	0.0313	0.0082	0.0115	0.0108	0.0162	0.0323	0.0127
2003	252	3,345	0.2823	0.0199	0.0314	0.0091	0.0169	0.0116	0.0112	0.0284	0.0125
2004	252	3,417	0.2560	0.0178	0.0334	0.0086	0.0174	0.0129	0.0094	0.0317	0.0123
2005	252	3,519	0.2364	0.0165	0.0357	0.0084	0.0209	0.0132	0.0084	0.0282	0.0144
2006	251	3,580	0.2369	0.0166	0.0355	0.0077	0.0183	0.0145	0.0091	0.0313	0.0146
2007	251	3,725	0.1937	0.0165	0.0383	0.0083	0.0203	0.0143	0.0085	0.0286	0.0168
All	3,568	3,467	0.2658	0.0167	0.0280	0.0076	0.0140	0.0100	0.0093	0.0251	0.0116
t-stat (against unconditional probabilities)					4.72		4.71	2.62		7.94	1.88
t-stat (between conditional probabilities)				Pr(Up|(+)Jump) vs. Pr(Down|{+)Jump) 1.52				Pr(Up|(-)Jump) vs. Pr(Down|{-)Jump) : 7.47			

Table III - *continued*

Panel B: Medians of Daily Probabilities

	N	$\sum N_{all,t}$/	Pr(Jump)	Pr(Rev)		Pr(Up)			Pr(Down)		
	(trading	N		uncon-	conditional	uncon-	conditional on		uncon-	conditional on	
	days)			ditional	on Jump	ditional	(+) Jump	(-) Jump	ditional	(-) Jump	(+) Jump
1993	43	3,142	0.2149	0.0025	0.0056	0.0010	0.0022	0.0000	0.0010	0.0034	0.0000
1994	252	3,295	0.2224	0.0124	0.0198	0.0060	0.0087	0.0065	0.0061	0.0155	0.0075
1995	252	3,315	0.2710	0.0162	0.0251	0.0069	0.0105	0.0070	0.0091	0.0223	0.0109
1996	254	3,426	0.2826	0.0141	0.0233	0.0068	0.0117	0.0084	0.0072	0.0188	0.0086
1997	253	3,564	0.3080	0.0139	0.0204	0.0060	0.0088	0.0062	0.0078	0.0191	0.0081
1998	252	3,646	0.3012	0.0161	0.0227	0.0068	0.0102	0.0054	0.0091	0.0199	0.0100
1999	252	3,592	0.2903	0.0154	0.0244	0.0078	0.0131	0.0069	0.0076	0.0190	0.0089
2000	252	3,482	0.2831	0.0142	0.0224	0.0063	0.0101	0.0060	0.0080	0.0214	0.0085
2001	248	3,368	0.2622	0.0148	0.0187	0.0059	0.0072	0.0065	0.0090	0.0203	0.0070
2002	252	3,340	0.2394	0.0176	0.0268	0.0072	0.0096	0.0093	0.0105	0.0262	0.0080
2003	252	3,347	0.2753	0.0185	0.0288	0.0084	0.0155	0.0095	0.0103	0.0252	0.0112
2004	252	3,416	0.2612	0.0174	0.0311	0.0078	0.0161	0.0109	0.0088	0.0279	0.0116
2005	252	3,526	0.2366	0.0159	0.0335	0.0080	0.0185	0.0114	0.0080	0.0243	0.0138
2006	251	3,586	0.2358	0.0158	0.0329	0.0071	0.0151	0.0133	0.0085	0.0278	0.0130
2007	251	3,742	0.1989	0.0162	0.0340	0.0077	0.0176	0.0116	0.0082	0.0237	0.0159
All	3,568	3,471	0.2581	0.0155	0.0254	0.0069	0.0118	0.0079	0.0083	0.0216	0.0098
t-stat (against unconditional probabilities)					4.66		4.13	1.35		7.85	1.44

t-stat (between conditional probabilities) Pr(Up|(+)Jump) vs. Pr(Down|{+)Jump) 1.44 Pr(Up|(-)Jump) vs. Pr(Down|{-)Jump) : 7.36

Table IV

Probabilities of Recommendation Revisions following Stock Price Jumps: Brokerage Reputation and Analyst Experience

This table presents the averages of the daily probabilities of recommendation revisions conditional on prior stock price jumps. Panel A reports results separately for large vs. small brokerages while panel B reports the corresponding numbers for new vs. old analysts. Large brokerages are top 20 brokerages based on the number of analysts employed for each year during the sample period. New analysts are those who first appeared in the IBES recommendation s dataset less than three years before as of the revision date. The conditional probabilities are calculated in the same manner as in table III, The t-stats for the differences between the two groups of analysts are reported in the last row of each panel, and are based on time-series averages and standard errors.

Panel A: Averages of Daily Probabilities by Broker Reputation

	Pr(Rev|Jump)		Pr(Up|(+)Jump)		Pr(Up|(-)Jump)		Pr(Down|(-)Jump)		Pr(Down|(+)Jump)	
	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large
1993	0.0030	0.0067	0.0007	0.0038	0.0020	0.0032	0.0036	0.0051	0.0009	0.0023
1994	0.0092	0.0129	0.0038	0.0075	0.0036	0.0047	0.0081	0.0098	0.0042	0.0048
1995	0.0106	0.0172	0.0044	0.0079	0.0036	0.0055	0.0107	0.0153	0.0050	0.0084
1996	0.0107	0.0144	0.0051	0.0080	0.0039	0.0054	0.0097	0.0132	0.0045	0.0051
1997	0.0104	0.0120	0.0043	0.0055	0.0038	0.0044	0.0098	0.0125	0.0047	0.0045
1998	0.0126	0.0132	0.0053	0.0064	0.0034	0.0034	0.0119	0.0125	0.0060	0.0057
1999	0.0136	0.0133	0.0065	0.0080	0.0047	0.0035	0.0117	0.0112	0.0056	0.0047
2000	0.0126	0.0121	0.0055	0.0054	0.0038	0.0032	0.0125	0.0133	0.0055	0.0046
2001	0.0106	0.0127	0.0042	0.0057	0.0037	0.0047	0.0105	0.0125	0.0044	0.0051
2002	0.0163	0.0173	0.0067	0.0053	0.0063	0.0048	0.0157	0.0198	0.0057	0.0073
2003	0.0177	0.0154	0.0091	0.0085	0.0066	0.0051	0.0168	0.0139	0.0071	0.0057
2004	0.0209	0.0148	0.0104	0.0078	0.0081	0.0052	0.0201	0.0148	0.0080	0.0050
2005	0.0228	0.0150	0.0127	0.0091	0.0085	0.0049	0.0181	0.0123	0.0094	0.0057
2006	0.0216	0.0157	0.0106	0.0081	0.0094	0.0053	0.0197	0.0141	0.0085	0.0066
2007	0.0237	0.0167	0.0118	0.0091	0.0090	0.0056	0.0183	0.0124	0.0104	0.0072
All	0.0151	0.0144	0.0071	0.0073	0.0056	0.0047	0.0137	0.0133	0.0063	0.0057
t-stat (small vs. large)		-0.28		0.34		-1.18		-0.19		-0.67

Table IV - *continued*

Panel B: Averages of Daily Probabilities by Analyst Experience

	Pr(Rev|Jump)		Pr(Up|(+)Jump)		Pr(Up|(-)Jump)		Pr(Down|(-)Jump)		Pr(Down|(+)Jump)	
	New	Old	New	Old	New	Old	New	Old	New	Old
1997	0.0094	0.0131	0.0042	0.0056	0.0033	0.0049	0.0090	0.0133	0.0039	0.0054
1998	0.0097	0.0161	0.0041	0.0077	0.0027	0.0041	0.0092	0.0152	0.0043	0.0074
1999	0.0105	0.0163	0.0056	0.0090	0.0034	0.0047	0.0092	0.0136	0.0039	0.0064
2000	0.0085	0.0164	0.0035	0.0075	0.0022	0.0048	0.0098	0.0164	0.0032	0.0068
2001	0.0080	0.0151	0.0033	0.0065	0.0023	0.0061	0.0082	0.0148	0.0034	0.0062
2002	0.0109	0.0223	0.0039	0.0080	0.0037	0.0074	0.0110	0.0241	0.0046	0.0086
2003	0.0103	0.0225	0.0054	0.0120	0.0036	0.0082	0.0093	0.0213	0.0041	0.0086
2004	0.0107	0.0245	0.0048	0.0133	0.0041	0.0090	0.0109	0.0233	0.0043	0.0085
2005	0.0116	0.0258	0.0064	0.0152	0.0039	0.0095	0.0090	0.0209	0.0049	0.0101
2006	0.0106	0.0265	0.0054	0.0133	0.0042	0.0104	0.0094	0.0241	0.0044	0.0106
2007	0.0101	0.0298	0.0049	0.0159	0.0032	0.0114	0.0082	0.0218	0.0048	0.0127
All	0.0100	0.0208	0.0047	0.0104	0.0033	0.0073	0.0094	0.0190	0.0041	0.0083
t-stat (young vs. old)		6.28		4.96		4.98		7.20		6.09

Table V

Cumulative Market-Adjusted Returns following Recommendation Revisions Stock Price Jumps

This table presents the cumulative abnormal returns (in %) following recommendation revisions and stock price jumps in event time. We characterize each revision as an upgrade or a downgrade by comparing the revised recommendation with the previous active recommendation for the stock by the revising analyst. Stock price jumps are also classified as either a positive jump or a negative jump. Stock price jumps are identified using "swap variance" test developed in Jiang and Oomen (2008) at the 5% critical level. The abnormal return is the raw return minus the CRSP value-weighted index return. Day 0 is the event date and the other days in the column headings are the number of trading days from the event date. For recommendations, the event date is the revision date. For jumps, the event date is five trading days after the jump date, reflecting an average interval between the jump and the revision for our test sample. 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 standard errors that take into account of both heteroskedasticity and serial correlation. The sample period is from November 1993 to December 2007.

Event Date		Number of Observations	Number of Trading Days sincer Event Date					
			0	1	2	21	42	126
Revision date	Upgrades	97,709	**2.05%**	**2.39%**	**2.49%**	**3.41%**	**3.71%**	**4.88%**
	Downgrades	125,194	**-3.01%**	**-3.24%**	**-3.34%**	**-3.79%**	**-3.98%**	**-4.28%**
5 trading days after jump	Positive Jumps	268,386	**0.14%**	**0.24%**	**0.35%**	**2.42%**	**4.06%**	**5.45%**
	Negative Jumps	152,868	-0.01%	0.00%	-0.04%	-0.38%	-0.77%	-1.09%

Table VI

Cumulative Market-Adjusted Returns: Test Sample vs. Benchmarks

This table presents the cumulative abnormal returns (in %) for the test sample and the benchmarks. The test sample consists of recommendation revisions preceded by stock price jumps within past 10 trading days. We construct four groups of test sample based on the direction of the jump and subsequent revisions. If there are multiple jumps within the past 10 days, we take the most recent one prior to the revision. We provide two benchmarks for comparison against the test sample. The first benchmark consists of upgrades and downgrades that are not preceded by stock price jumps. The second benchmark consists of stock price jumps not followed by recommendation revisions. For the test sample and the first benchmark, the event date is the revision date. For the second benchmark, the event date is five trading days after the jump date, reflecting an average interval between the jump and the revision for our test sample. Stock price jumps are identified using "swap variance" test developed in Jiang and Oomen (2008) at the 5% critical level. The abnormal return is the raw return minus the CRSP value-weighted index return. Panel A reports the average returns for the test sample and the benchmarks, while panel B reports the differences in average returns between various combinations of test sample and the benchmark. The numbers 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 standard errors that take into account of both heteroskedasticity and serial correlation. The sample period is from November 1993 to December 2007.

Panel A: Average Returns for Each Group

	Jump	Revision	Event Date	Number of Observations	Number of Trading Days since Event Date					
					0	1	2	21	42	126
Test Sample	+	up	Revision Date	10,904	**2.24%**	**2.56%**	**2.72%**	**5.59%**	**7.50%**	**9.47%**
	+	down	Revision Date	11,700	**-1.29%**	**-1.37%**	**-1.38%**	-0.16%	0.64%	1.41%
	-	up	Revision Date	5,937	**2.10%**	**2.34%**	**2.26%**	**2.10%**	**1.75%**	2.43%
	-	down	Revision Date	12,641	**-2.89%**	**-3.02%**	**-3.19%**	**-3.57%**	**-4.21%**	**-5.25%**
Benchmark 1	none	up	Revision Date	80,868	**2.02%**	**2.38%**	**2.47%**	**3.21%**	**3.35%**	**4.44%**
	none	down	Revision Date	100,853	**-3.23%**	**-3.49%**	**-3.59%**	**-4.25%**	**-4.48%**	**-4.75%**
Benchmark 2	+	none	5 trading days	246,598	**0.14%**	**0.22%**	**0.33%**	**2.41%**	**4.07%**	**5.48%**
	-	none	following jumps	136,974	0.01%	0.04%	0.01%	-0.33%	-0.71%	-0.95%

Table VI - *continued*

Panel B: Differences in Average Returns between the Test Sample and Benchmarks

Test Sample		Benchmark		Number of Trading Days since Event Date					
Jump	Revision	Jump	Revision	0	1	2	21	42	126
+	up	none	up	**0.22%**	0.18%	**0.24%**	**2.38%**	**4.15%**	**5.04%**
+	up	+	none	**2.11%**	**2.34%**	**2.39%**	**3.19%**	**3.43%**	**3.99%**
+	down	none	down	**1.94%**	**2.12%**	**2.20%**	**4.09%**	**5.12%**	**6.16%**
+	down	+	none	**-1.42%**	**-1.59%**	**-1.71%**	**-2.57%**	**-3.43%**	**-4.07%**
-	up	none	up	0.08%	-0.04%	-0.21%	**-1.11%**	**-1.60%**	**-2.01%**
-	up	-	none	**2.09%**	**2.30%**	**2.26%**	**2.43%**	**2.46%**	**3.38%**
-	down	none	down	**0.34%**	**0.46%**	**0.40%**	0.68%	0.26%	-0.51%
-	down	-	none	**-2.90%**	**-3.06%**	**-3.20%**	**-3.24%**	**-3.51%**	**-4.30%**

Table VII
Cumulative Market-Adjusted Returns: Multivariate Analysis

This table reports the estimates of the following regression:

$$ABR(t,t+H) = a_H + b_H \times I + c_H \times D\_positive\_up + d_H \times D\_negative\_up + e_H \times D\_positive\_down + f_H \times D\_negative\_down + \varepsilon$$

where t is the forecast revision date, $ABR(t,t+H)$ is the H-period abnormal return (in %) following the revision date, I is the indicator variable for upgrades (I = +1) and downgrades(I = -1), *D_positive_up* is a dummy if the revision is an upgrade preceded by a positive jump, *D_negative_up* is a dummy if the revision is an upgrade preceded by negative jump, *D_positive_down* is a dummy if the revision is a downgrade preceded by positive jump, and *D_negative_down* is a dummy if the revision is a downgrade preceded by negative jump. Panel A reports results from a pooled OLS specification while panel B reports the results from Fama-MacBeth approach where the coefficients and t-stats are based on time-series averages and standard errors from quarterly cross-sectional regressions. The sample period is from November 1993 to December 2007.

Panel A: Pooled OLS

		Explanatory Variables												
Number of Trading Days	N	I_revision (=-1, 1)		positive jump & upgrade (=1,0)		negative jump & upgrade (=1,0)		positive jump & downgrade(=1,0)		negative jump & downgrade (=1,0)		Constant		R^2
		coeff	t-stat	coeff	t-stat	coeff	t-stat	coeff	t-stat	coeff	t-stat	coeff	t-stat	
0	222,903	2.62%	141.58	0.22%	2.78	0.08%	0.75	1.94%	25.30	0.34%	4.57	-0.60%	-32.54	0.10
1	222,856	2.93%	140.27	0.18%	2.04	-0.04%	-0.33	2.12%	24.48	0.46%	5.56	-0.56%	-26.59	0.09
2	222,825	3.03%	137.76	0.24%	2.57	-0.21%	-1.66	2.20%	24.22	0.40%	4.52	-0.56%	-25.36	0.09
21	221,222	3.73%	98.62	2.38%	14.60	-1.11%	-5.18	4.09%	26.12	0.68%	4.48	-0.52%	-13.66	0.05
42	218,463	3.91%	77.92	4.15%	19.21	-1.60%	-5.57	5.12%	24.43	0.26%	1.31	-0.57%	-11.27	0.04
126	206,427	4.59%	49.77	5.04%	12.70	-2.01%	-3.80	6.16%	15.25	-0.51%	-1.38	-0.16%	-1.68	0.02

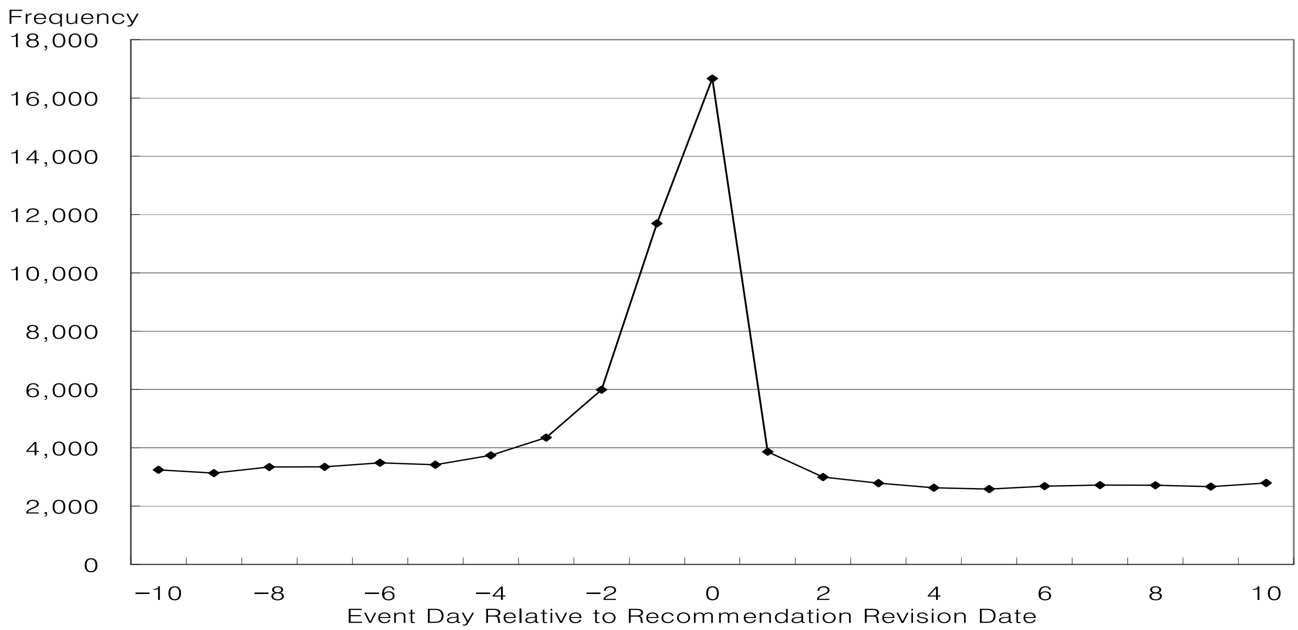
Panel B: Fama MacBeth (time-series standard errors of coefficients from quarterly crosssectional regressions)

		Explanatory Variables												
		coeff	t-stat	coeff	t-stat	coeff	t-stat	coeff	t-stat	coeff	t-stat	coeff	t-stat	
0	222,903	2.55%	17.76	0.22%	2.22	0.04%	0.32	1.88%	10.76	0.44%	2.97	-0.61%	-7.92	0.10
1	222,856	2.86%	17.81	0.22%	1.93	-0.03%	-0.22	2.08%	10.72	0.60%	4.08	-0.57%	-7.06	0.10
2	222,825	2.97%	18.07	0.30%	2.34	-0.18%	-1.20	2.19%	10.43	0.56%	3.86	-0.57%	-6.87	0.10
21	221,222	3.71%	18.63	2.29%	8.79	-0.92%	-2.74	4.00%	13.53	0.78%	2.39	-0.49%	-2.31	0.06
42	218,463	3.97%	19.10	3.80%	9.82	-1.49%	-3.13	5.05%	11.56	0.34%	1.00	-0.62%	-1.81	0.05
126	206,346	4.82%	17.82	5.48%	6.81	-2.38%	-2.95	6.40%	10.32	-0.81%	-1.06	-0.42%	-0.57	0.03

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

This figure plots frequencies of recommendation revisions with stock price jumps around the revision date. Stock price jumps are identified using "swap variance" 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

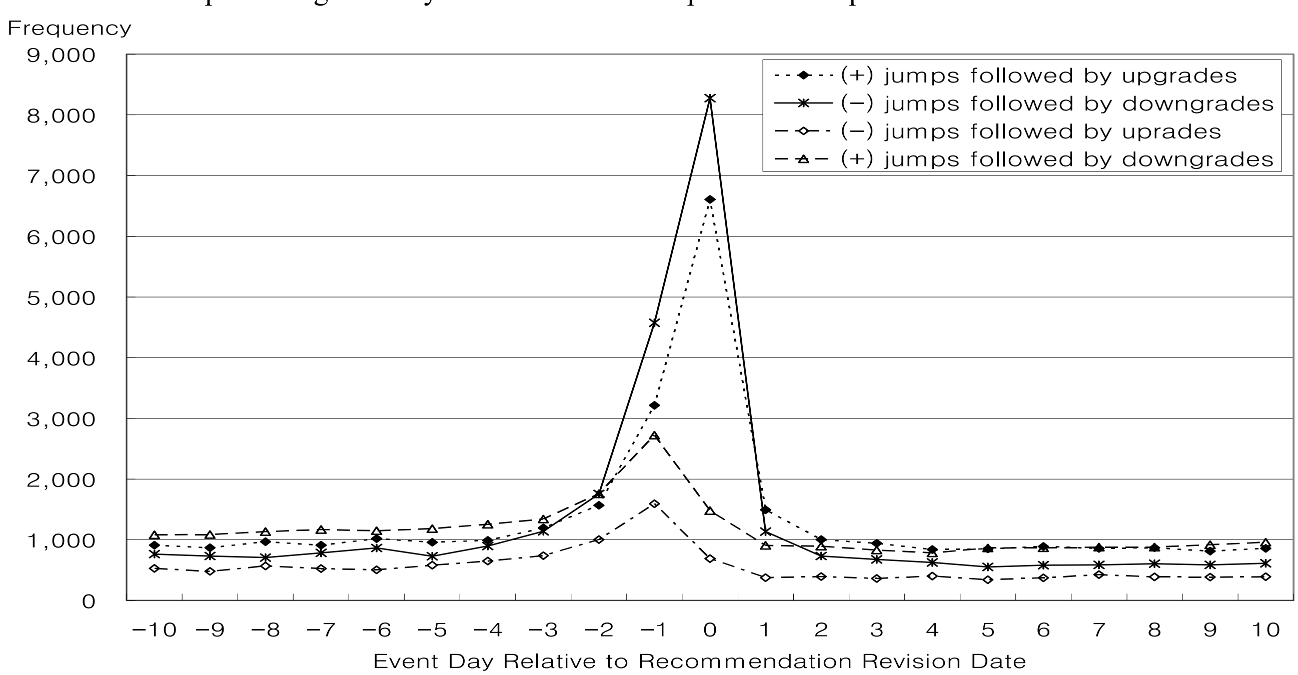
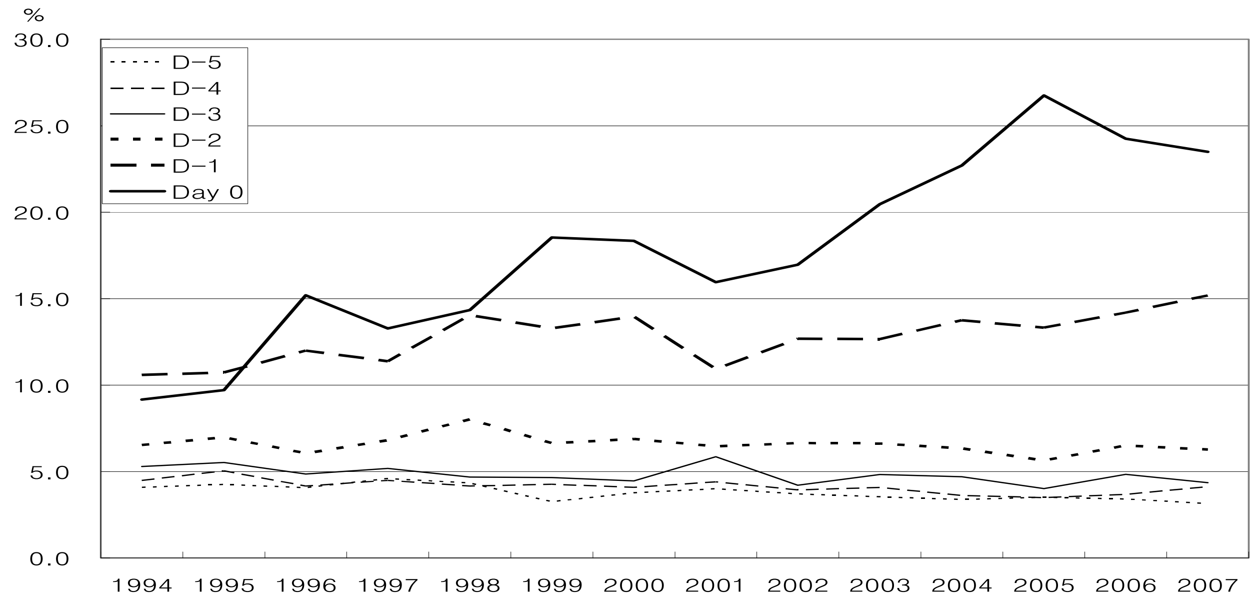


Figure 2. Relative Frequencies of Recommendation Revisions with Stock Price Jumps over Time

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 "swap variance" 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