Are analysts' recommendations informative? Intraday evidence on the impact of time stamp delays

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Abstract:

We demonstrate that time stamps reported in $I/B/E/S$ for analysts' recommendations released during trading hours are systematically delayed. Using newswire-reported time stamps, we find 30-minute returns of 1.83% (-2.10%) for upgrades (downgrades), but for this subset of recommendations we find corresponding returns of -0.07% (-0.09%) using $I/B/E/S$-reported time stamps. We also examine the information content of recommendations relative to management guidance and earnings announcements. Our evidence suggests that analysts' recommendations are the most important information disclosure channel examined.

Keywords: analysts' recommendation, time stamp delays, earnings announcements, management guidance, high-frequency data, jump detection

JEL classification: G24

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1. *Introduction*

A large body of academic research suggests that sell-side analysts play an important role in the price discovery process. In a seminal paper, Womack (1996) documents that recommendation changes generate a large and statistically significant three-day announcement period return, on average. This finding has been replicated in dozens of subsequent studies.[1] However, recent papers by Altinkilic and Hansen (2009) and Altinkilic, Balashov, and Hansen (2010) challenge the view that analysts are important information intermediaries. Using intraday returns centered on recommendation revisions during trading hours, they find revisions are associated with insignificant price reactions. They conclude that analysts "piggyback" by releasing recommendations soon after other news that materially impacts the stock price. Similarly, Loh and Stulz (2011) find that after purging out recommendations that fall in a three-day window around confounding firm-specific news releases, average 2-day abnormal returns around revisions drop dramatically.

In light of these conflicting findings, we reexamine the information content of analysts' recommendations. We focus our analysis on high frequency data because it enables us to pin down the immediate impact of real-time information on stock prices, which is not feasible using daily data.[2] Furthermore, intraday analysis allows us to compare our results directly against Altinkilic and Hansen (2009).

Ivkovic and Jegadeesh (2004) show that recommendations are often released around the same time as earnings announcements, which oftentimes coincide with management guidance.

[1] See Michaely and Womack (2005) and Ramnath, Rock, and Shane (2008) for surveys of this literature.

[2] For instance, Andersen, Bollerslev, Diebold and Vega (2003), Balduzzi, Elton and Green (2001), Ederington and Lee (1993), Harvey and Huang (1991), and Jiang, Lo and Verdelhan (2011) focus on the impact of macroeconomic news releases on volatilities or jumps in the US Treasury or foreign exchange markets. Busse and Green (2002) examine the stock price response to analyst opinions on the financial television network CNBC. All of these papers show that the bulk of the adjustment usually occurs within minutes of the announcement.

Therefore, we control for these announcements in our analysis. Recommendations and earnings announcement data are obtained from *I/B/E/S*, while management guidance data is obtained from *First Call*.

Because our study relies on the accuracy of an event's timing, we manually check the announcement times reported by *I/B/E/S* and *First Call* against three newswire sources: *Dow Jones News Retrieval*, *Reuters*, and *Lexis-Nexis*. Of the recommendations released during trading hours that we are able to match to newswires, we adjust approximately 56% to an earlier time period. Similarly, 58% of guidance and 83% of earnings announcements are adjusted to an earlier time period. We find that the average time stamp delay for recommendations is approximately 2.4 hours and the majority of recommendations with delayed announcement times occur before the market opens.

Using the time stamps reported in *I/B/E/S* during trading hours for the subset of recommendations where we are able to find an earlier time stamp, we find upgrades (downgrades) generate an average 30-minute return of -0.07% (-0.09%). These insignificant returns are consistent with the findings in Altinkilic and Hansen (2009). After correcting for time stamp delays for these recommendations, we find that upgrades (downgrades) generate an average 30-minute return of 1.83% (-2.10%). Thus, it is critical that time stamps be verified against newswires when conducting an intraday event study as failure to do so can lead one to falsely conclude that analysts are uninformative.

Loh and Stulz (2011) argue that recommendation changes could have a statistically significant impact in the aggregate even though no individual recommendation change is influential enough to generate a statistically significant price reaction. Thus, it may not be appropriate to use average stock price reactions to evaluate the price impact of individual analyst recommendation changes. We address this concern by using an intraday jump detection technique and linking jumps to individual news releases.

We apply Lee and Mykland's (2008) nonparametric jump detection test to identify jumps using stock prices sampled at a 15-minute frequency. We find that after removing jumps that may be contaminated with overlapping news events, 25% of analyst recommendations, 16% of earnings announcements, and 10% of management guidance announcements are associated with jumps. To put this in perspective, we observe unconditional jumps in 0.44% of all 15-minute intervals. Thus, jumps are extremely rare events and the fact that a significant portion of their occurrences coincide with recommendation releases strongly indicates that individual recommendations are influential. Furthermore, we find that analysts' recommendations are more likely to surprise the market than either earnings announcements or management guidance. With respect to economic significance, logistic regression results suggest that when an analyst upgrades a stock, the odds of observing a jump increase by about 19 times.

Our results provide several contributions to the literature on sell-side analysts. First, we provide a resolution to the conflict on the value of recommendations raised in Altinkilic and Hansen (2009) by demonstrating that their findings are driven by the use of systematically delayed time stamps. Second, our results reinforce Ljungqvist, Malloy, and Marsten (2009) who argue that researchers should not take the integrity of historical data for granted. Because time stamps obtained from newswires are more accurate than those reported in *I/B/E/S* or *First Call* for daytime announcements, our findings indicate that this does not merely introduce noise, but can lead to incorrect inferences. Finally, we compare the relative information content of three of the most common types of information disclosures (analyst recommendations, management guidance, and earnings announcements). Existing studies such as Loh and Stulz (2011) and Altinkilic and Hansen (2009) examine analyst recommendations in isolation. Our multivariate framework enables us to come to the conclusion that analysts are more influential than earnings announcements or management guidance.

2. Data

2.1 Sample selection

Our sample consists of stocks listed on the NYSE for the six-year period between January 2002 and December 2007. We focus only on NYSE stocks to ensure that differences in trading structures across exchanges do not impact our results. We begin the sample period in January 2002 for two reasons. First, the NYSE fully implemented decimal pricing in 2001. Thus, by beginning the sample in 2002, we maintain a uniform quoting system across the sample period. Second, Chuk, Matsumoto, and Miller (2009) present evidence that the *Thomson First Call Company Issued Guidance* (*CIG*) database becomes reasonably complete following Regulation Fair Disclosure, which was adopted in August 2000.

We require that firms in our sample have complete and consecutive records on the CRSP daily file throughout our sample period. Consequently, we exclude firms that were delisted or experienced trading halts. We further require firms to have a CRSP share code of 10 or 11. This eliminates REITS, ADRs, and closed-end funds from the sample. Finally, we require that firms have at least one analyst recommendation and one management issued guidance forecast over the 2002 to 2007 period. After imposing these criteria, the final dataset contains 537 firms.

2.2 Intraday price data

We gather intraday stock prices from the NYSE TAQ database. We apply the standard filters used in the microstructure literature to our intraday dataset. We exclude trades that are reported outside the normal trading hours (9:30am - 4:00pm), exclude the opening prices on each day and apply a filter to remove any bid-ask bounce effects.[3] We also eliminate trades that are associated with inactive trading days. This refers to days when the database contains less than one trade per hour for a given stock.

2.3 Recommendations, management guidance, and earnings announcements

We collect earnings announcements and analyst recommendations from *Institutional Brokers' Estimate System* (*I/B/E/S*). Management guidance data are obtained from *Thomson First Call's Company Issued Guidance* (*CIG*) database. For each firm in our sample, we capture the reported date and time of all announcements over the sample period. Announcement times are reported to the nearest minute and we refer to this as the *I/B/E/S*-reported time stamp.[4] We define daytime announcements as those occurring on trading days between 9:30am and 4:00pm. Recommendations released on non-trading days or during non-trading hours are classified as occurring during the overnight period.

Following Altinkilic and Hansen (2009), we focus on recommendation revisions and eliminate initiations and reiterations. Kadan, Madureira, Wang and Zach (2009) find that many brokerage houses moved from a five-tier rating system to a three-tier rating system in 2002. Therefore, we eliminate these mechanical recommendation changes from the sample as they are unlikely to contain information.

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[3] To filter out bid-ask bounce effects, we remove cases where there are two consecutive returns, each being more than 5 standard deviations from the mean, and with opposite signs.

[4] Ljungqvist, Malloy, and Marston (2009) report that there are a significant number of additions, deletions, alterations and anonymizations found between snapshots of the *I/B/E/S* recommendation history on different dates. According to Wharton Research Data Services, *I/B/E/S* has corrected these issues as of September 2007.

3. Are analysts' recommendations informative?

3.1 Descriptive statistics

Table 1 provides descriptive statistics for our sample of announcements. Panel A shows the distribution of recommendations, earnings announcements, and management guidance by year as reported in *I/B/E/S* and *First Call.* We report the percentage of overnight announcements in parentheses. Recommendations are evenly distributed during the 2002 through 2007 time period. The percentage of recommendations that occur overnight was approximately 39% in 2002 and then rose to approximately 75% over the 2003 to 2007 period. Our fraction of overnight recommendations is higher than the 61% documented in Altinkilic and Hansen (2009). In conversations with *I/B/E/S*, the large increase in the fraction of overnight recommendations was due to the introduction of a new data collection tool. This allowed *I/B/E/S* to collect research PDFs around the clock. Prior to this tool, *I/B/E/S* relied more heavily on batch files from contributors submitting recommendation revisions. Announcement times corresponded to the receipt of those files rather than the time the reports were announced. Earnings announcements and management guidance are equally distributed through our sample period, with more than 80% occurring overnight.

[Insert Table 1 here]

Panel B of Table 1 summarizes the extent to which analysts' recommendations overlap with management guidance and earnings announcements. Ivkovic and Jegadeesh (2004) find that a significant fraction of analyst recommendations are concentrated in the days following earnings announcements. We find that the percentage of upgrades and downgrades that are released within a three-day window (-1, +1) of earnings and guidance are 26% and 29%, respectively. From a three-day to narrower windows, the percentage of recommendations overlapping with guidance and earnings announcements falls. The probability of daytime recommendations occurring during the same 30-minute interval as earnings or guidance is zero.

Panel C of Table 1 provides analyst coverage descriptive statistics. The average firm receives 5.1 revisions from 3.6 analysts per year. The average rating is 2.5 on a 5-point scale. The average analyst has 7.9 years of experience and 17.6% of analysts are all-stars as defined by *Institutional Investor's* annual all-star Research Team poll.[5]

3.2 Returns to analyst recommendations

Table 2 reports announcement period logarithmic returns centered on the recommendation time stamp reported in *I/B/E/S*. We separate announcements with time stamps during trading hours from those with time stamps during the overnight period. The announcement period return for the overnight interval is computed using close-to-open prices. Following Altinkilic and Hansen (2009), the daytime announcement period return is the 30-minute return centered on the recommendation. It is computed using the nearest observed prices at two sampling points: 15-minutes before and 15-minutes after the recommendation time stamp.[6] When prices are not observed within +/-5 minutes of each sampling point, the observation is removed from the analysis to avoid liquidity-related issues. Table 2 separately reports returns to recommendation revisions where there are no confounding events. Since daytime recommendations are not confounded within the same 30-minute interval (Table 1, Panel B), we only report results for the overnight period excluding simultaneous announcements of earnings or guidance.

[5] All-stars include analysts that make the first through third team or runner-up in their industry.

[6] The sampling period in Altinkilic and Hansen (2009) is the 40 minutes centered on the announcement time. However, they compute the announcement period return using the mean transaction price in the first and last 10 minutes of the announcement period. Consequently, their computation yields the 30-minute announcement period return centered on the recommendation revision. Unlike their study, we do not need to rely on mean transaction prices for return computations because our sample period starts in 2002 when TAQ data became relatively more liquid. Nevertheless, we verify our main results using the sampling method identical to Altinkilic and Hansen (2009).

[Insert Table 2 here]

For the full sample of upgrades, the average announcement period return is 1.41%, which is both statistically and economically significant. Over 75% of upgrades result in a positive return. During the overnight period, the return is 1.83%, and after excluding confounding events the return is 1.72%. For daytime upgrades, however, the 30-minute return is much smaller at 0.22%. For downgrades, we find similar results. The average announcement period return is -1.14% for all downgrades, which is statistically and economically significant. Most downgrades elicit a negative response (73%). The overall return is driven by overnight downgrades, which have an average market reaction of -1.49% compared to -0.25% for daytime downgrades.

The results in Table 2 for daytime recommendations are generally consistent with Altinkilic and Hansen (2009). That is, using a similar method, they find that average 30-minute returns centered on the reported time stamp for daytime recommendation revisions are economically small. They report 0.03% for daytime upgrade recommendations and -0.03% for daytime downgrade recommendations (Table 3, page 23). More importantly, they show most of the reaction occurs before the recommendation revision announcement time. This finding leads them to conclude that recommendations only appear to be informative when viewed at the daily level because they piggyback on other confounding news events.

3.3 Are time stamps reported in I/B/E/S accurate?

A critical assumption made in the return analysis presented in Table 2 is that the time stamp is accurately reported by I/B/E/S. If a significant fraction of time stamps are delayed, then centering our analysis on these reported announcement times may lead to false conclusions regarding the price impact of recommendations. For instance, if reported announcement time stamps are systematically delayed, then price reactions would likely occur prior to the announcement window.

In order to quantify the accuracy of the reported time stamps, we compare samples of recommendations, management guidance, and earnings announcements as reported by *I/B/E/S* and *First Call* to those hand-collected from searching the newswires. We construct a randomly selected sample of 400 observations for each announcement type: 200 drawn from daytime announcements and 200 drawn from overnight announcements. We employ the following news sources: *Dow Jones News Retrieval*, *Reuters*, and *Lexis-Nexis*. In untabled results, we find that differences between the reported time stamps and those obtained through the newswires are immaterial for the overnight period. That is, we find that delayed overnight announcements always fall within the overnight period. Because we do not observe trades during the overnight period, the impact of overnight announcements, regardless of their actual timing, can only be determined from close-to-open prices. On the other hand, we find that a substantial portion of the reported daytime time stamps are delayed for all three types of announcements.

Based on the above findings, we searched the newswires for all daytime announcements reported by *I/B/E/S* and *First Call*. Since we employ various news sources, we retain the earliest reported time stamp. We refer to these hand-collected times stamps as the newswire time stamps. We then replace any reported time stamps that are delayed with the corresponding newswire time stamp. We report the results on this procedure in Table 3.

[Insert Table 3 about here]

For each type of information disclosure, we report: 1) the number of time stamps we hand-checked; 2) the percentage we were able to match; 3) conditional on finding a match, the percentage where we found an earlier time stamp; and 4) conditional on finding an earlier time stamp, the percentage that we adjusted to the overnight interval.

Panel A of Table 3 presents the newswire search results for analyst recommendations. We are able to match 15.6% of recommendation revisions to newswire stories in 2002. Our match rate increases to 27.3% in 2004, but then declines significantly between 2005 and 2007. For recommendations where we were able to find a match, the newswire time stamp was earlier than the time reported by *I/B/E/S* for a significant fraction of the observations. Of those recommendations for which the newswire time stamp was earlier, we find that 61% were disclosed overnight.

Panel B of Table 3 presents the results for earnings announcements. Compared to analyst recommendations, we are able to match a greater proportion of *I/B/E/S*-reported earnings announcements to the newswires. We find close to 85% of earnings announcements. In 2002, we find an earlier time stamp for almost all of the daytime announcements. However, the accuracy of *I/B/E/S* improves through time. In 2007, we find an earlier time stamp in 67.7% of the cases. Similar to analysts' recommendations, a significant fraction of those earnings announcements adjusted earlier actually occurred during the overnight period.

In Panel C of Table 3, we report results for management guidance. Like earnings announcements, we are able to match a majority of management guidance announcements reported by *First Call* with announcements from the newswires. We again find that a significant fraction of the reported guidance announcements have a delayed time stamp and are released during the overnight period.

3.4 The impact of time stamp delay on our results

Panel A of Table 4 compares the newswire time stamp to the reported *I/B/E/S* time stamp for the sample of 305 recommendations that were adjusted to an earlier time period based on our search of the newswires.[7] For all recommendations, we find that the average delay is 2.4 hours, with a median delay of 1.3 hours. The reported delay is slightly larger for upgrades than for downgrades.[8]

Panel B of Table 4 compares the 30-minute market reactions of analyst recommendations using *I/B/E/S*-reported time stamps to those using newswire-corrected time stamps. To clearly see the impact of time stamp delay, we consider only the observations where we were able to match the reported announcements to the newswires. Similar to Table 2, the market reaction using *I/B/E/S*-reported time stamps is economically small. For daytime upgrades, the 30-minute return is -0.07% and -0.09% for daytime downgrades. The results are similar if we exclude contemporaneous earnings announcements or management guidance. We find the market response is statistically and economically significant when we adjust the announcement time to the newswire time stamp. Upgrades generate a 1.83% market return and downgrades exhibit a -2.10% return. Both of these returns are significantly different from the returns using the *I/B/E/S*-reported time stamp. These results indicate that time stamp delay can lead to erroneous inferences and likely explains the results in Altinkilic and Hansen (2009). Further, note that these returns are similar to the 1.83% and -1.49% returns we reported in Table 2 for overnight upgrades and downgrades, respectively.

[Insert Table 4 about here]

In Figure 1, we further examine returns surrounding the release of the recommendations using the *I/B/E/S*-reported time stamps and the newswire time stamps. We plot cumulative 15-minute returns from 90 minutes before to 90 minutes after the announcement times. Each interval represents a 15-minute window. Time 0 corresponds to the announcement time. We do

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7 From Panel A of Table 3, we adjust the time stamps of 305 recommendations (3,993 recommendations checked × 13.55% found × 56.37% adjusted earlier).

8 For time stamps that are adjusted before the market open, we measure the reported delay relative to 9:30am. For instance, if *I/B/E/S* reports a time stamp at 10:30am, but we find a newswire time stamp at 8:30am, we measure the delay as 1 hour. Without truncation, the average delay is 3.7 hours with a median of 1.6 hours.

not observe a significant stock price reaction around the $I/B/E/S$-reported time stamp. The stock price reaction appears to take place before the recommendation release. This is consistent with the piggybacking hypothesis of Altinkilic and Hansen (2009), which suggests that analysts appear informative because they issue their recommendation changes following news. However, once the corrected newswire time stamps are considered, we observe a large and statistically significant price reaction around the announcement period. The results in Figure 1 provide strong evidence against the piggybacking hypothesis and further confirm our finding that when the correct time stamps are used, recommendations are on average informative.

[Insert Figure 1 about here]

3.5 When do daytime recommendations usually occur?

Table 3 shows that we are not able to match the full sample of daytime earnings announcements, guidance, and recommendations to the newswires despite employing various news sources. This problem is most acute for recommendations where the match rate is only 15.6%. As we indicated previously, the results in Table 3 show that a significant portion of the announcements that we matched against the newswires occurred during the overnight period. We conjecture that the bulk of the sample of unmatched daytime recommendations also likely occurred during the overnight period.

To test the above conjecture, we examine the overnight return focusing on the day of those unmatched daytime recommendation releases. If the unmatched recommendations were actually released before trading hours, overnight returns should be significantly different from zero. On the other hand, if the firm's overnight period is information-free, the average overnight return is expected to be approximately zero.

Table 5 reports OLS regression results where the overnight return is the dependent variable. The sample contains one observation for each firm per day over the 2002 to 2007 sample period. The independent variables are indicator variables. *Overnight upgrade* is an indicator variable that equals one when a recommendation upgrade is released during the overnight period. The indicator variable *Overnight downgrade* is defined similarly. Thus, the coefficients on *Overnight upgrade* and *Overnight downgrade* capture the announcement period return of recommendation upgrades and downgrades that are released overnight.

To test for the possibility that the unmatched recommendations were released prior to the market open, we create daily indicator variables that are equal to one when there are daytime revisions that could not be found on the newswires. We term these *Unmatched daytime upgrades* and *Unmatched daytime downgrades*. For instance, if $I/B/E/S$ reports a recommendation upgrade at 10:11am that we could not match to the newswires, *Unmatched daytime upgrade* takes the value of one (zero otherwise) for that observation. A positive and significant coefficient on *Unmatched daytime upgrade* would indicate that these unmatched recommendations were likely released before the market opens. *Unmatched daytime downgrade* is an indicator variable for daytime downgrades that we could not match to the newswires, and a negative and significant coefficient can be similarly interpreted.

[Insert Table 5 here]

We report results for two observation samples. In the first model, we consider all observations. Table 5 shows that the intercept of the model is -0.04 indicating that the average overnight return on days without recommendation releases is not statistically different from zero. As expected, the coefficient on overnight events, *Overnight upgrade* (*Overnight downgrade*), are positive (negative) and highly significant, indicating that recommendation revisions announced before the market open have a significant market impact when trading begins. The magnitudes of their coefficients are consistent with the announcement period returns around overnight revisions reported in Table 2. For example, the coefficient on upgrade is 1.82%, which is comparable to the 1.83% documented in Table 2 for overnight upgrades.

The coefficients of the variables of interest, *Unmatched daytime upgrade* and *Unmatched daytime downgrade* are smaller in magnitude than *Overnight upgrade* and *Overnight downgrade*, but they are nonetheless statistically and economically significant (0.82% and -0.84% for upgrades and downgrades, respectively). This finding supports our conjecture that the reported daytime recommendation announcements that we could not verify with the newswires are likely delayed and are often released before the market opens.

The second model of Table 5 looks at the impact of non-confounded recommendation revisions on the overnight period return. We eliminate observations if there is an earnings announcement or management guidance announcement on the day of the revision. The results are quantitatively similar to those using all observations and further support the view that daytime analyst recommendations are systematically delayed and are likely released before the market opens.

4. Do recommendations generate influential intraday price reactions?

Using average announcement period returns, we provide intraday evidence supporting the conventional view that analysts' recommendations are on average informative. However, Loh and Stulz (2011) argue that using average returns could overstate the actual impact of analysts. They suggest that the average stock price reaction to analyst recommendations could be statistically significant even if no recommendation causes an economically meaningful stock price reaction. For example, they find that after purging out confounding events, only 12% of analyst recommendations result in significant cumulative abnormal returns in the two days surrounding recommendation releases.

In this section, we examine whether individual analyst recommendations induce visible market reactions. By focusing on intraday price changes, the problem of incorrectly concluding that recommendations are influential is substantially mitigated because we can better distinguish their impact from that of other information events that may occur on the same day, but often at different times.

Consistent with a rich literature that shows stock returns consist of a jump and a smooth component, we assume that smoothly evolving price changes are caused by normal trading activities, while sudden price jumps are caused by the arrival of new and surprising information.[9] For our study, we define recommendations that have a noticeable impact as those that can generate large intraday price changes, i.e. "jumps". Subsequently, we employ a multivariate analysis to link various information events to jumps in stock returns. This in turn addresses the information content of recommendations relative to earnings announcements and management guidance.

4.1 Detecting jumps and their descriptive statistics

A number of nonparametric jump detection methods have been developed in recent years.[10] We use the method proposed by Lee and Mykland (2008) because this approach offers greater detection power with intraday data allowing us to identify intraday jumps more precisely.

We use a 15-minute sampling frequency for detecting jumps. Lee and Mykland (2008) present evidence that the likelihood of making a Type I or Type II error increases when sampling at lower frequencies, such as on a daily basis, but is essentially zero when sampling at a frequency of 15 minutes. Although it is ideal to sample at higher frequencies to obtain more precise

[9] For example, see Merton (1976) and Maheu and McCurdy (2004).
[10] For instance, see Barndorff-Nielsen and Shephard (2006), Jiang and Oomen (2008), Lee and Mykland (2008), Andersen, Bollerslev, and Dobrev (2007), and Ait-Sahalia and Jacod (2009).

empirical results, sampling too frequently eliminates a large portion of mid- and small-sized stocks from our sample due to infrequent trading. For robustness, we also repeat the analyses by sampling at a 30-minute interval and obtain similar results.

In order to detect jumps at the 15-minute interval, we start by constructing our sample of discretely sampled stock prices. We search for the trade that is closest to each discrete time point (9:30am, 9:45am, 10:00am, etc.). If no trade is reported within +/- 5 minutes of each sampling point, we interpolate for the price by using the two neighboring observations. When interpolation is not possible due to illiquidity, we leave the price corresponding to this trade interval blank. We then exclude these blank trade intervals from our jump detection analysis. By focusing on 15-minute windows, we effectively partition each day into 27 distinct windows, the overnight period plus 26, 15-minute windows during the trading day between 9:30am and 4:00pm.

[Insert Figure 2 here]

Figure 2 illustrates the intuition behind the development of the jump detection test by Lee and Mykland (2008). First, we assume that n_j is the number of observed stock prices for firm j over our sample period. At each 15-minute time interval t_{i-1} to t_i, we calculate the logarithmic stock return of firm j defined as $R_j(i) = \log\left(S_j(t_i)/S_j(t_{i-1})\right)$, where $S_j(t_i)$ is the stock price of firm j at time t_i. If $R_j(i)$ is extremely large relative to the instantaneous volatility, $\sigma_j(t_i)$, then we say that a jump in the stock price of firm j is detected between time t_{i-1} and t_i. The instantaneous volatility $\sigma_j(t_i)$ is computed using the past K=156 return observations. Appendix A provides details for computing $\sigma_j(t_i)$, and choosing the window size K, as well as the rejection criteria for detecting jumps.

In the example highlighted in Figure 2, a jump is detected during the 9:45am to 10:00am interval. Therefore, we set the jump indicator variable equal to one during this interval. The jump indicator variable is set to zero for each interval without a jump. We use jump indicator variables to proxy for unusual price impact of information events. This metric captures the surprise component of information events on stocks prices in both positive and negative directions. For our purposes, this feature is particularly appealing because we do not need to interpret the information content of earnings announcements or management guidance, which are oftentimes ambiguous.[11]

[Insert Table 6 here]

Table 6 provides descriptive statistics from applying the Lee and Mykland (2008) method using 15-minute returns. On average, a firm experiences about 27 jumps per year. This implies that jumps are extremely rare events because we observe about 6,804 (27 × 252) 15-minute returns per firm each year. The absolute value of the 15-minute jump return is 3.01%, which is economically large. The one-hour return preceding a jump is -6 basis points and the post-jump one-hour return is 0 basis points. Thus, we do not observe return reversal before or after jumps confirming that they are associated with permanent stock price adjustments. Approximately 41% of jumps occur overnight and about half are positive jumps. Conditional on observing a jump, the probability that a firm will experience multiple jumps in a single trading day is 7.6%. Results from applying the jump detection method to 30-minute returns are qualitatively similar.

4.2 Univariate analysis of jump probability

In this subsection, we perform a univariate analysis to illustrate the impact of using high frequency data. Panel A of Table 7 summarizes jump detection statistics from applying different approaches. The number of observations increases tremendously once we move from lower to

[11] Although squared or absolute returns can also be used to measure (directionally independent) price impact, they often capture the usual innovation from a volatility component, which could be solely due to normal uncertainty of the market. In other words, they are not likely to be associated with visible market reactions, which we are interested in studying in this section. The jump detection test used in this study allows us to identify unusual price impact even in the presence of persistent stochastic volatility.

higher frequency data. We define the detection rate as the percentage of observations where jumps are detected (Number of jumps / Number of observations). With 2-day returns, jumps are detected in 7.6% of the observations, while we detect jumps in 0.44% of the observations at both the 30-minute and 15-minute sampling frequencies. This finding follows from the fact that we apply a much more conservative criterion for detecting jumps than Loh and Stulz (2011).[12]

[Insert Table 7 here]

In Panel B, we present evidence on the likelihood of observing a jump during the same interval that information is disclosed. For 2-day returns, 19.5% of recommendations are associated with jumps, while 29.4% of earnings announcements and 30.8% of guidance are associated with jumps. At the 15-minute horizon, 28.3% of recommendations, 36.3% of earnings announcements, and 39.1% of guidance announcements are associated with jumps. Compared with results at the 2-day and 30-minute horizons, the results with 15-minute returns indicate higher jump likelihoods for all announcements types. This finding is consistent with simulation studies in Lee and Mykland (2008), which show that the power of their jump detection method increases with sampling frequency.

The jump probabilities that we report in Panel B provide a simple analysis of the impact of each information event. These values, however, do not take into account the probability that two or more events may arrive contemporaneously in the same interval, and hence, they cannot be used to infer the relative importance of one event against another. For instance, when a jump is observed during the same interval as an earnings announcement and the release of management guidance, it is impossible to conclude whether the observed jump is due to the earnings announcement, management guidance, or both. In order to quantify the impact of

[12] Loh and Stulz (2011) classify outliers if the absolute value of the 2-day cumulative adjusted return (CAR) exceeds $1.96 \times \sqrt{2} \times \sigma_{\varepsilon}$, where σ_{ε}, the idiosyncratic volatility, is the standard deviation of residuals from a daily time-series regression of past three month firm returns against market returns, and the Fama-French factors.

contemporaneous news arrivals on jump probabilities, we remove jumps that occur in the same interval as two or more information events. The results are reported in Panel C.

Panel C shows that after excluding contemporaneous jumps, the percentage of recommendations associated with jumps at the 15-minute horizon falls slightly to 25.0% from the 28.3% documented in Panel B. On the other hand, the percentage of earnings announcements and guidance that are associated with jumps decreases significantly once we remove contemporaneous jumps. When contemporaneous jumps are excluded, earnings announcements are associated with jumps in 16.3% of the cases, while management guidance is associated with jumps in only 10.5% of the observations. At the 2-day return horizon, the percentage of recommendations associated with jumps is 14.2%, which is in line with the 12% documented by Loh and Stulz (2011).[13]

The results in Panel C of Table 7 indicate that the issue of contemporaneous information arrivals can be quite severe for earnings announcements and management guidance even at the intraday level. Therefore, it is difficult to conclude on the relative importance of various events based on a univariate analysis of price reactions around information event times. By considering jumps that are associated with earnings, for example, we may overestimate the importance of earnings because some of these jumps may in fact be due to other contemporaneous news arrivals. On the other hand, if we exclude jumps that are associated with the joint arrival of earnings and other news, we run the risk of underestimating the importance of earnings because we may be eliminating observations that truly represent the impact of earnings news. In the next subsection, we discuss a method to test for the impact of various information disclosures in a multivariate setting where simultaneous information releases are taken into account.

[13] We also studied the likelihood of jumps conditioned on when a recommendation was released with respect to earnings announcements and management guidance. Recommendations issued in the three days prior to an earnings announcement were twice as likely to cause a jump as those issued in the three days following earnings and guidance announcements. This result is consistent with the empirical findings of Ivkovic and Jegadeesh (2004).

4.3 Multivariate logistic regressions

In this subsection, we consider the relative importance of earnings announcements, management guidance, and recommendations by estimating a multivariate logistic regression model. It allows us to investigate the jump intensity or the likelihood of large price changes as a function of individual information releases. The method that we use is an extension of Lee (2010) to panel data. More specifically, we estimate the following model for the likelihood of a jump in firm j's stock price between time t_i and t_{i-1}:

$$\lambda_j(i) = \left(1 + exp\left(-(\alpha + \alpha_j + \boldsymbol{X}_j(\mathrm{i})\boldsymbol{\theta})\right) \right)^{-1} \tag{1}$$

where $\lambda_j(i)$ is the probability that the jump indicator variable for firm j is equal to 1 between t_i and t_{i-1}. The parameter α denotes the intercept, and $\boldsymbol{\theta}$ denotes the effect parameter. We control for firm-level fixed effects in all the regressions with α_j that is specific to firm j. To save space, we do not report these firm-level fixed effect estimates in our table.

The independent variables are denoted by $\boldsymbol{X}_j(\mathrm{i})$, which consist of various event indicator functions for firm j between periods t_i and t_{i-1}. We generate a time series of indicator functions representing the timing of various information releases at a sampling frequency of 15 minutes. For example, the indicator function for earnings announcements released by firm j at time t_i takes the value of one if earnings was released between t_i and t_{i-1} (zero otherwise). Indicator functions for the other information variables are generated similarly. When we have *M* number of information variables, $\boldsymbol{X}_j(\mathrm{i}) = \left[X_{j,1}(\mathrm{i}), X_{j,2}(\mathrm{i}), \ldots, X_{j,M}(\mathrm{i})\right]$, the effect parameter $\boldsymbol{\theta}$ in equation (1) is a $M \times 1$ vector of regression coefficients.

We estimate the jump intensity model as in equation (1) using a panel dataset (possibly unbalanced) that includes data from all firms and all time periods simultaneously. Therefore, the independent variables for each firm j can be thought of as the following large matrix $\boldsymbol{X}_j$ that consists of vectors $\boldsymbol{X}_j(\mathrm{i})$ for $i = 1, .., n_j$, where n_j is the number of observation periods for firm j:

$$\boldsymbol{X}_j = \begin{pmatrix} 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{pmatrix}$$

……….

Earnings indicator

Downgrade indicator

Upgrade indicator

The estimation results are reported in Table 8. We present results from five different models. We consider all observations in models (1) through (3), while models (4) and (5) separately consider daytime and overnight observations. For the daytime observation model, we exclude the overnight window that corresponds to the window from 4:00pm on the previous day to 9:30am on the current day. Conversely, the overnight observation model considers only the observations from that overnight window. Rather than considering one indicator variable for all recommendations, we include separate indicator variables for upgrades and downgrades.

[Insert Table 8 here]

When considering all observations, we include an indicator variable, *Overnight Indicator*, to control for the differential fixed effect between overnight and trading hours observations. The first model includes only the indicator variables specific to analyst recommendations. The coefficients on *Upgrade* and *Downgrade* are each positive and significant, indicating that the arrival of a recommendation revision increases the likelihood of observing a jump for a corresponding stock. The *Overnight Indicator* is positive and significant, indicating that jumps are likely to occur at the market open.

In model (2), we introduce the indicator variables for earnings announcements and management guidance in addition to the analyst-related variables. The coefficients on these variables are also positive and significant, which indicate that their releases are associated with a jump. The magnitude of the coefficients suggests that upgrades are most strongly associated with jumps, followed by downgrades, earnings announcements, and management guidance.

In model (3), we include a control variable, *Market-wide event*, which takes the value of one if there was a jump in the S&P 500 futures index (zero otherwise). The purpose of this indicator is to control for cases where an event at the macroeconomic level causes a significant number of stocks to jump at the same time. We obtain high frequency S&P 500 futures data (S&P500 E-mini) from TickData. The S&P500 E-mini is the S&P 500 futures contract that is traded electronically and continuously around the clock. Therefore, any significant market-wide shocks during either trading hours or overnight should show up as jumps in the S&P 500 future prices. We apply the same 15-minute sampling frequency to the S&P 500 futures price data as we do for equity prices. Table 8 shows that while the coefficient on *Market-wide event* is positive and significant, its inclusion does not impact the other variables or the relative ranking of firm-specific events.

In models (4) and (5) of Table 8, we separately consider observations that belong to the daytime and overnight windows. The results are similar to those reported for all observations. All of the coefficients remain positive and highly significant. Recommendation upgrades and downgrades remain the most important determinants of jumps.

The estimated coefficient θ_m for the information event m represents the change in the log of the odds of observing a jump conditional on a unit change in the independent variable.

Since all of our independent variables consist of indicator functions, each regression coefficient θ_m in Table 8 represents the change in the log of the odds of observing a jump when only an event m occurs, *ceteris paribus*. That is,

$$\theta_m = \log\left(\frac{odds^m}{odds}\right), \tag{2}$$

where $odds^m$ is the odds of observing a jump conditional on an event m ocurring, and $odds$ is the odds of observing a jump in the absence of event m occurring.

In our context, the odds ratio is defined as the probability of observing a jump over the probability of not observing a jump. Table 7 shows that the nonparametric jump detection rate in our sample is 0.44%, which suggests the odds of observing a jump in our full sample is very rare. However, the results in Table 8 show that when relevant news about a firm's fundamentals is released, the odds of observing a jump increase significantly. For instance, the 2.97 coefficient on upgrade in the regression model (1) suggests that the odds of observing a jump increase by $exp(2.97) =$19.5 times when a recommendation upgrade is released. Other coefficients can be interpreted similarly. Thus, our estimates are not only statistically significant, but they also represent an economically large effect.[14]

4.4 The impact of remaining time stamp errors

Table 3 indicates that we were not able to match all the $I/B/E/S$-reported daytime announcements to the newswires. Although we corrected the time stamps that we were able to match, our independent variables are not completely free from time stamp errors. In this

[14] One possible concern about the regressions in Table 8 is that they do not examine the direction of jumps. In the case of upgrades and downgrades there is an unambiguous signal as to the direction in which the stock price should move. In unreported results, we separately run regressions of positive and negative jumps. We indeed find that upgrades increase the likelihood of positive jumps, but not negative jumps. Conversely, downgrades increase the likelihood of negative jumps, but not positive jumps.

subsection, we investigate how the remaining time stamp errors may impact our conclusions on the value of analyst recommendations.

We first approximate the remaining error rate in our sample of daytime announcement time stamps. Table 3 shows that we were able to find only 13.55% of $I/B/E/S$-reported recommendations in the newswires. This implies that the remaining 86.45% of daytime recommendation time stamps are not verified, and hence subject to potential errors. In order to approximate the expected error rate, we assume that the error rate for these unmatched recommendation releases is the same as those found in the newswires, i.e. 56.37%. Based on this assumption, we expect the overall error rate in our daytime analyst recommendations to be approximately 86.45% x 56.37% = 48.73%. Applying the same logic to the earnings and management guidance data, we estimate that the remaining error rate in our daytime earnings and management guidance data are approximately 12.57% and 15.41%, respectively.

The analysis above shows that once the announcement data are corrected using newswire searches, the time stamps for analyst recommendations are likely to remain the most erroneous. We study the bias that the higher rate of time stamp error on recommendation data may create in our logistic regression results using Monte Carlo simulation experiments. In unreported results, we find that a higher time stamp error rate produces more negative bias in the coefficient estimates in Table 7. Since we show time stamp errors are likely to be the most severe for analyst recommendations, we would most likely understate the true impact of analyst recommendations relative to earnings announcements and guidance. Therefore, analysts are likely to be even more influential than our results imply.

4.5 The impact of confounding events on multivariate logistic regressions

Ivkovic and Jegadeesh (2004) find that recommendations often occur around earnings announcements, which often coincide with management guidance. While focusing on intraday data diminishes the percentage of recommendations confounded by earnings and guidance, it does not completely eliminate the issue of confounding events. Table 1 of Panel B shows that 4% of upgrades and 5.5% of downgrades overlap with earnings or guidance in the overnight period. Table 6 shows that the problem of confounding information arrivals can affect the outcomes even at the intraday level.

We investigate how robust our multivariate analysis is to the presence of confounding events by conducting simulation experiments. The simulation is designed to generate data from models that accommodate real market conditions, particularly with multiple intraday information events that are possibly confounded. To save space, the details of the model employed for this simulation and results are discussed in Appendix B. The overall results indicate that our method is robust to varying degrees of confounding information arrivals. Therefore, their presence does not seriously impact our findings.

5. Concluding remarks

We demonstrate that the time stamp reported in two widely used databases, *First Call* and *I/B/E/S,* are typically delayed during daytime trading hours. We demonstrate that for intraday studies, such systematic delays can have serious implications. For instance, in a subset of recommendations where we find an earlier time stamp on the newswires, we show that market reactions around the *I/B/E/S*-reported time stamps are insignificant, but when we correct the time stamps using newswire searches they become economically and statistically significant.

Our findings are in stark contrast to Altinkilic and Hansen (2009), who conclude that analyst recommendations have little value. They argue that analysts update their recommendations after the release of publicly announced news so they appear informative. Our results suggest that their findings are due to the use of time stamps that are systematically delayed relative to the actual announcement times. Thus, it is essential for researchers to compare time stamps obtained from data vendors with those reported on the newswires when using intraday data to measure announcement effects.

After showing that analysts are informative on average, we also examine whether individual recommendations are influential in the presence of firms' own corporate information disclosures. Our multivariate framework allows us to estimate the relative importance of analyst recommendations, earnings announcements, and management guidance in corresponding stock markets. These events are among the most studied in finance and accounting, but typically are analyzed independently. Because they are often issued on the same day, it is difficult to determine the relative importance of each event on a daily basis. Our method using intraday data overcomes this problem. We find that analyst recommendation revisions are the most important and influential information disclosure channel examined.

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Figure 1. Intraday price reaction to recommendation changes.
This figure shows cumulative returns surrounding the release of recommendation upgrades and downgrades. We examine market reactions around daytime announcements. "Downgrade: *I/B/E/S*" and "Upgrade: *I/B/E/S*" refer to the results from using the time stamps as reported on *I/B/E/S*. "Downgrade: Newswire" and "Upgrade: Newswire" refer to the results from using the time stamps that we corrected using the newswires. Time 0 corresponds to the announcement time. Each interval represents a 15-minute window. Time -1 corresponds to the 15 minute window before the announcement, while +1 corresponds to the 15 minute window after the announcement. All other windows are similarly defined.

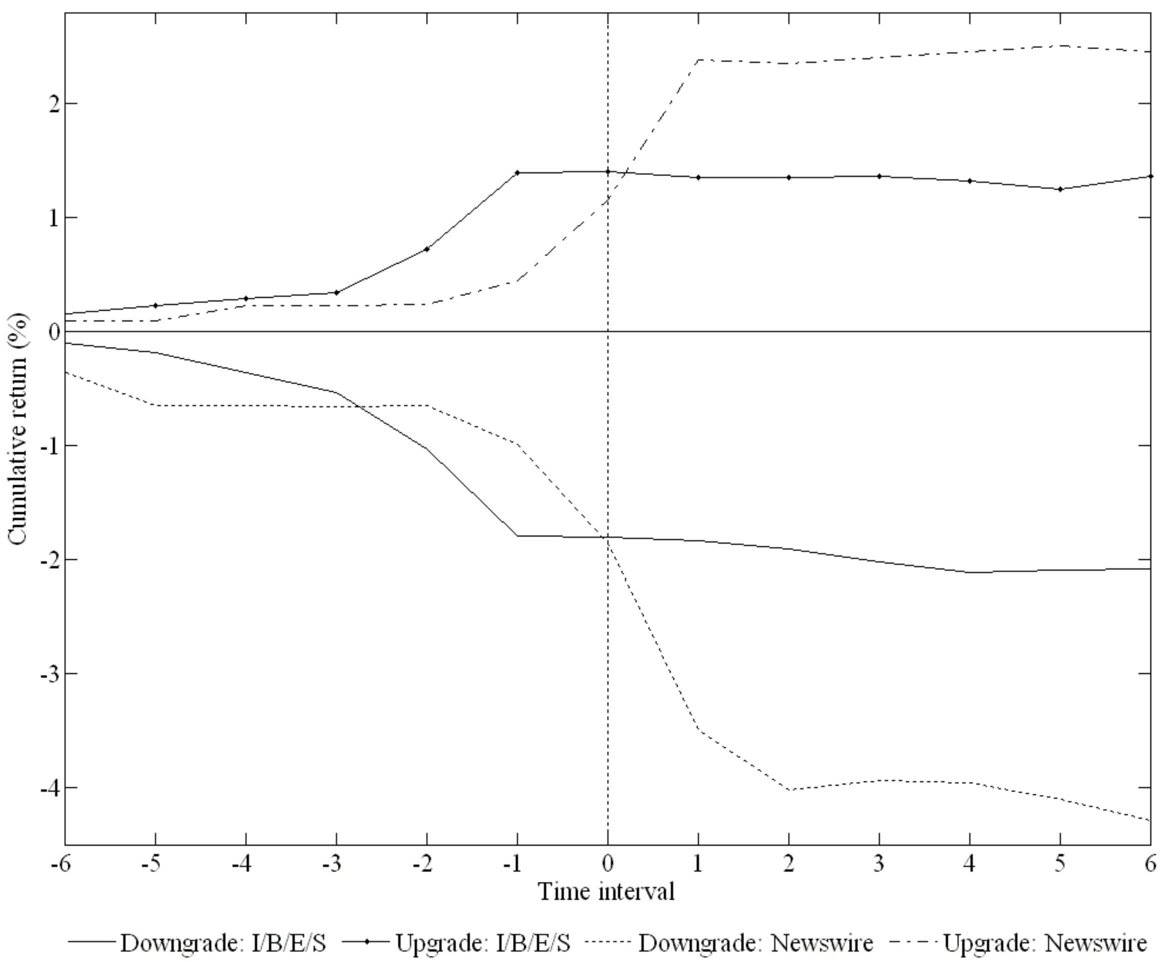

Figure 2. Time line and the jump detection method

This figure illustrates the intuition behind the jump detection test used in this paper. The asterisk represents the discrete observed stock price path. According to this figure, a jump occurs between 9:45am and 10:00am. We partition the time horizon during the trading day into 15-minute intervals. We retrieve the stock price from the NYSE TAQ database that is closest to each interval mark. We then apply the Lee and Mykland (2008) test to detect whether the return over each 15-minute interval can be characterized as a jump. The intuition behind this test is to compare the logarithmic return over each interval to its instantaneous volatility that is computed using the past K=156 return observations. See Appendix A for details of the statistical jump detection threshold. If a jump is detected, we set the jump indicator variable for that return interval equal to one (zero otherwise). Overnight refers to the closing period from day *t*-1 to the opening period on day *t*.

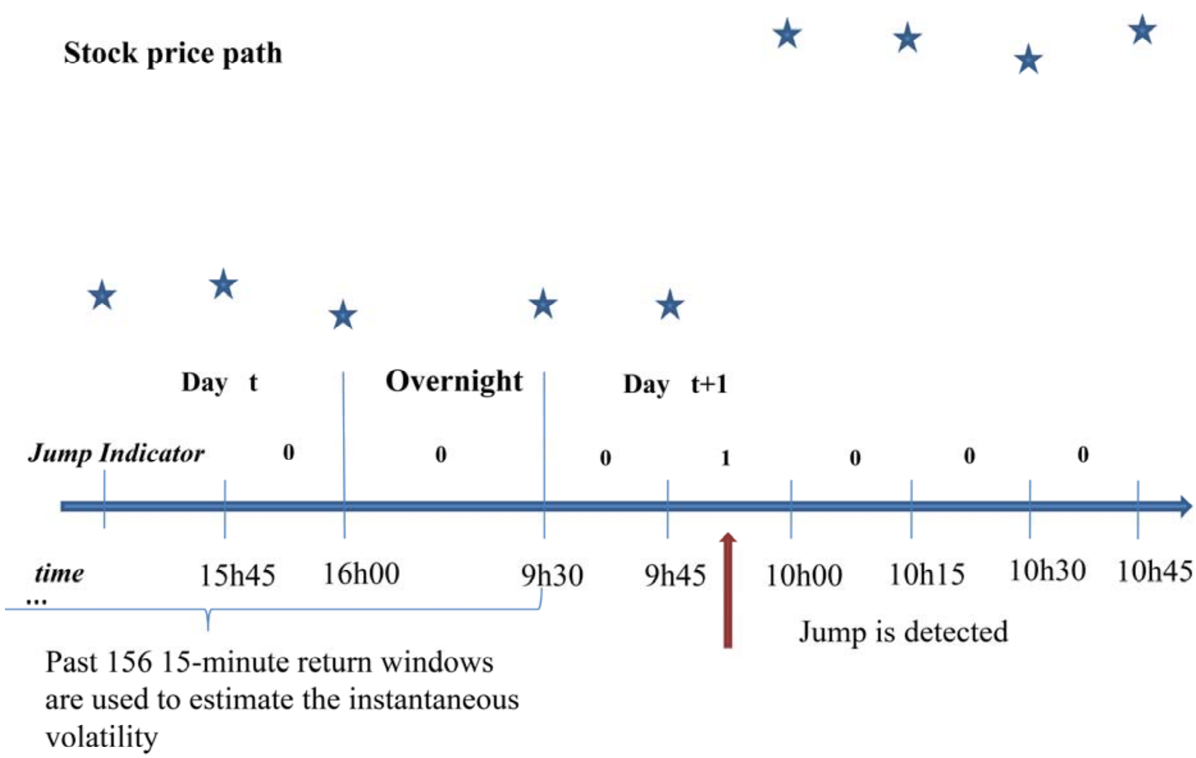

Table 1. Sample descriptive statistics

This table presents descriptive statistics for our sample of analyst recommendations, earnings announcements, and management guidance. The data are from 2002 through 2007. Recommendations and earnings announcement data are obtained from *I/B/E/S* and management guidance data are from *First Call*. Panel A provides a distribution of the sample by year as reported in *I/B/E/S* and *First Call*. The percentage of announcements occurring during the overnight hours is given in parentheses. We classify announcements as occurring during the overnight period if the time stamp is between 4:00pm and 9:30am. Panel B provides statistics on the contemporaneous announcement of guidance or earnings around recommendation revisions. Panel C presents statistics on analyst coverage. Recommendation level is the average rating based on a 5-point scale with 1 being the highest rating. Experience is the average number of years an analyst has been making recommendations. Star status is the percentage of recommendations that are issued by an all-star analyst. All-stars are defined by *Institutional Investor's* annual all-star Research Team poll.

Panel A: Analyst recommendations, earnings, and guidance by year as reported by *I/B/E/S* and *First Call*

Year	Upgrades	Downgrades	Earnings	Guidance
2002	940	1,280	2,118	1,511
	(39.36%)	(39.14%)	(74.65%)	(83.85%)
2003	1,011	1,270	2,123	1,386
	(75.17%)	(71.89%)	(82.62%)	(87.66%)
2004	987	1,004	2,123	1,542
	(71.53%)	(74.30%)	(88.88%)	(87.16%)
2005	966	859	2,120	1,456
	(78.05%)	(76.48%)	(90.94%)	(89.22%)
2006	905	1,089	2,125	1,475
	(77.90%)	(75.85%)	(91.95%)	(87.66%)
2007	1,138	1,057	2,024	1,358
	(74.17%)	(69.16%)	(92.98%)	(81.00%)
Total	5,947	6,559	12,633	8,728
	(69.60%)	(66.69%)	(86.96%)	(86.14%)

Panel B. Percentage of recommendation revisions confounded by announcements of earnings and guidance

	Upgrades	Downgrades
Three-day window	25.81%	29.00%
Same day	9.77%	13.19%
Same overnight period	4.04%	5.50%
Same 30-minute daytime interval	0.02%	0.00%

Panel C. Analyst coverage statistics

	Mean	Median	Std. Deviation
Recommendations per stock per year	5.09	4.00	4.37
Analysts issuing recommendations per stock per year	3.55	3.00	2.60
Recommendation level	2.46	3.00	1.07
Experience	7.91	7.33	4.12
Star status	17.60%	NA	NA

Table 2. Announcement period returns to recommendation revisions
This table reports distributional statistics for 30-minute returns centered on the time stamp as reported in $I/B/E/S$. We classify announcements as occurring either during the overnight or daytime periods. Time stamps reported between 9:30am and 4:00pm on the same trading day are classified as Daytime. Time stamps reported between 4:00pm today and 9:30am the next day are classified as Overnight. The return for these overnight observations is the close-to-open return. The label "excluding confounding events" indicates observations where there are no confounding events, i.e. earnings announcement or management guidance, released within 15-minutes of the recommendation. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels respectively

	N	Mean	Std. Dev	10th	Median	90th	% positive
Upgrade revisions							
All upgrades	5,487	1.41***	2.26	-0.41	0.87***	3.95	76.22
Overnight	4,052	1.83***	2.43	-0.25	1.41***	4.52	82.60
Overnight - excluding confounding events	3,839	1.72***	2.20	-0.24	1.36***	4.16	82.39
Daytime	1,435	0.22***	1.01	-0.69	0.11***	1.19	58.19
Downgrade revisions							
All downgrades	5,898	-1.14***	2.66	-3.40	-0.48***	0.56	27.23
Overnight	4,209	-1.49***	2.99	-4.08	-0.84***	0.51	22.64
Overnight - excluding confounding events	3,924	-1.25***	2.50	-3.52	-0.78***	0.49	23.11
Daytime	1,689	-0.25***	1.17	-1.28	-0.09***	0.67	38.66

Table 3. Daytime *I/B/E/S* and *First Call* time stamps versus newswire stamps

We assess the accuracy of the time-stamped data provided by *I/B/E/S* and *First Call*. We consider only daytime observations where the reported time stamp is between 9:30am and 4:00pm. For each observation, we search *Lexis-Nexis*, *Reuters*, and *Dow Jones News Retrieval* for the earliest release of the announcement. We classify announcements as occurring during the overnight period if the time stamp is between 4:00pm and 9:30am. Panels A, B, and C provide results for analyst recommendations, earnings announcements, and management guidance, respectively. The "% Found" represents the fraction of observations that we were able to find from searching the newswires. If the time stamp is found and appeared to be delayed, we replace them using those from newswire. The fraction of time stamps found that is delayed is reported under "Of those found % adjusted earlier". The last column "Of those adjusted earlier % adjusted to overnight" represents the fraction of delayed time stamps that were adjusted to the overnight window, prior to the market opens.

Panel A: Analyst recommendations

Year	# Hand Checked	% Found	Of those found % adjusted earlier	Of those adjusted earlier % adjusted to overnight
2002	1,349	15.57%	72.37%	70.39%
2003	608	14.97%	52.74%	77.08%
2004	539	27.27%	29.93%	75.00%
2005	414	11.35%	70.23%	9.09%
2006	463	4.32%	100.00%	25.00%
2007	620	4.19%	30.80%	12.50%
Overall	3,993	13.55%	56.37%	60.98%

Panel B: Earnings announcements

Year	# Hand Checked	% Found	Of those found % adjusted earlier	Of those adjusted earlier % adjusted to overnight
2002	537	89.39%	96.25%	82.03%
2003	369	84.01%	88.39%	76.64%
2004	236	81.36%	69.27%	69.17%
2005	192	81.25%	69.23%	56.48%
2006	171	86.55%	71.62%	48.11%
2007	142	78.17%	66.67%	31.08%
Overall	1,647	84.82%	82.82%	70.52%

Panel C: Management guidance

Year	# Hand Checked	% Found	Of those found % adjusted earlier	Of those adjusted earlier % adjusted to overnight
2002	244	70.90%	56.65%	61.22%
2003	171	80.12%	54.74%	60.00%
2004	198	80.30%	57.23%	49.45%
2005	157	81.53%	42.19%	25.93%
2006	182	71.43%	50.77%	31.82%
2007	258	62.02%	80.00%	67.19%
Overall	1,210	73.31%	57.72%	52.92%

Table 4. The impact of time stamp corrections

This table compares *I/B/E/S*-reported time stamps with those obtained from the newswires. Panel A reports descriptive statistics on the difference between these two time stamps in hours. Panel B reports 30-minute returns centered on the time stamp. P-value for difference is the p-value for the difference between the returns generated using the *I/B/E/S*-reported time stamp and the newswire time stamp.

Panel A: Time stamp difference in hours between *I/B/E/S* and the newswires

	N	Mean	Std. Deviation	10th	Median	90th
All recommendations	305	2.38	3.51	0.48	1.30	5.01
Upgrades	140	2.87	4.69	0.50	1.43	5.64
Downgrades	165	1.96	1.94	0.47	1.25	4.45

Panel B: 30-minute returns surrounding *I/B/E/S* and newswire time stamps

	N	Mean	Std. Dev	10th	Median	90th	% positive
Upgrades:							
I/B/E/S-reported time	136	-0.07%	1.08%	-1.29%	0.04%	0.87%	52.21%
Newswire-reported time	112	1.83%***	2.95%	-0.60%	1.50%***	5.13%	81.25%
P-value for difference		0.01			0.01		
Downgrades:							
I/B/E/S-reported time	150	-0.09%	1.28%	-1.20%	0.00%	0.94%	46.67%
Newswire-reported time	124	-2.10%***	2.83%	-6.61%	-1.22%***	0.38%	18.55%
P-value for difference		0.01			0.01		

Table 5. When do unmatched daytime recommendations occur?

This table presents ordinary least squares regression results with the overnight return as the dependent variable. *Overnight upgrade* (*Overnight downgrade*) is an indicator variable that takes the value of one when a recommendation upgrade (downgrade) is released overnight. We refer to daytime recommendations from $I/B/E/S$ that we could not verify with the newswires as "unmatched." For instance, *Unmatched daytime upgrade* is an indicator variable that takes the value of one if there is a daytime recommendation upgrade on $I/B/E/S$ that we could not match with the newswires on that day (zero otherwise). In model (1), we consider all observations. In model (2), we exclude days where there is either an earnings announcement or release of management guidance. Firm fixed effects are included in each regression. P-values are reported in parentheses.

	All observations	Excluding confounding events
	(1)	(2)
Intercept	-0.04	-0.04
	(0.19)	(0.19)
Overnight events		
Overnight upgrade	1.82	1.68
	(0.00)	(0.00)
Overnight downgrade	-1.57	-1.29
	(0.00)	(0.00)
Unmatched daytime events		
Unmatched daytime upgrade	0.82	0.80
	(0.00)	(0.00)
Unmatched daytime downgrade	-0.84	-0.71
	(0.00)	(0.00)
Number of Obs.	786,200	785,869
Firm Fixed Effects	Yes	Yes

Table 6. Jump descriptive statistics

This table reports descriptive statistics for jumps. Jumps were detected using the Lee and Mykland (2008) method to our data from 2002 to 2007 using 15-minute returns that are computed from discretely sampled stock prices at each discrete time point (9:30am, 9:45am, 10:0am etc.). See the text for details of the sampling method. The row labeled "Absolute value of jump return" reports the average magnitude of the return associated with each jump. We report returns 1 hour prior and post of the interval when a jump is detected. The row labeled "% jumps at open" represents the fraction of jumps that occur during the overnight window (i.e. close-to-open). "% positive jumps" refer to the fraction of jumps that are associated with positive returns. Finally, the last row labeled "% of days with multiple jumps" reports the fraction of days, conditional on observing a jump, that a firm experiences multiple jumps in a single day.

Variable	Mean	Std. Deviation	10^{th} Percentile	Median	90^{th} Percentile
# jumps per stock per year	26.93	9.18	16.00	27.00	38.00
Absolute value of jump return (%)	3.01	3.01	0.96	1.90	4.56
Prior 1 hour jump return (%)	-0.06	1.51	-1.23	0.00	1.11
Post 1 hour jump return (%)	0.00	1.92	-1.72	0.00	1.74
% jumps at open	41.07				
% positive jumps	50.53				
% of days with multiple jumps	7.59				

Table 7. Univariate estimates of jump probability

This table presents descriptive statistics of jump probabilities computed using the methods described in Loh and Stulz (2011) and Lee and Mykland (2008). Loh and Stulz (2011) classify returns as being influential when a 2-day return around the announcement date is abnormally large. The Lee and Mykland (2008) approach is implemented using both 15- and 30-minute returns. The univariate jump probability is defined as the percentage of jumps occurring when a particular type of announcement is released. Panel A reports the detection rate for each approach, which is defined as the number of jumps divided by the number of observations. Panel B reports the likelihood of a jump conditional on the announcement of earnings, recommendations, or guidance. In Panel C, we exclude jumps where two or more events occur in the same window.

	Loh and Stulz (2011)	**Nonparametric Jump**	
	2-day return	30-minute return	15-minute return
Panel A: Jump detection statistics			
Number of observations	764,042	10,042,726	19,663,802
Number of jumps	58,325	43,879	86,576
Detection rate	7.63%	0.44%	0.44%
Panel B: Univariate jump probabilities using all jumps			
Recommendations associated with jumps	19.54%	23.76%	28.27%
Earnings associated with jumps	29.40%	31.66%	36.28%
Guidance associated with jumps	30.82%	35.85%	39.13%
Panel C: Univariate jump probabilities excluding contemporaneous jumps			
Recommendations associated with jumps	14.20%	20.82%	24.95%
Earnings associated with jumps	13.25%	13.27%	16.33%
Guidance associated with jumps	7.61%	9.49%	10.45%

Table 8. Logistic regressions of jump likelihood

This table shows the results from a logistic regression where the dependent variable takes the value of one if there was a jump in a given 15-minute time interval (zero otherwise). The independent variables are all indicator variables designed to capture various events including analyst recommendations, earnings announcements, management guidance, market-wide events, and the timing of the announcement for non-trading hours (*Overnight indicator*). We use jumps in the S&P500 E-mini futures contract to proxy for market-wide events. In models (1)-(3) we report results based on all observations, while models (4) and (5) report results based on daytime and overnight observations, respectively. Firm fixed effects are included in each specification. P-values are reported in parentheses. See Appendix A for a complete description of how jumps are detected.

	All observations			Daytime	Overnight
	(1)	(2)	(3)	(4)	(5)
Parameter estimates					
Intercept	-5.93	-5.93	-5.94	-5.94	-3.40
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Upgrade	2.94	2.97	2.98	2.23	2.89
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Downgrade	2.56	2.53	2.54	2.47	2.43
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Earnings announcement		2.08	2.10	2.01	2.16
		(0.01)	(0.01)	(0.01)	(0.01)
Guidance		1.53	1.53	1.75	1.48
		(0.01)	(0.01)	(0.01)	(0.01)
Market-wide event			1.04	1.18	0.98
			(0.01)	(0.01)	(0.01)
Overnight indicator	2.77	2.63	2.59		
	(0.01)	(0.01)	(0.01)		
Number of Obs.		19,663,802		18,777,602	786,200
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes

Appendix A: Lee and Mykland (2008) test

We denote n_j to be the number of observed stock prices for firm j over our time horizon. At each 15-minute time interval t_{i-1} to t_i, we calculate the logarithmic stock return of firm j defined as $R_j(i) = \log\left(S_j(t_i)/S_j(t_{i-1})\right)$, where $S_j(t_i)$ is the stock price of firm j at time t_i. If $R_j(i)$ is extremely large relative to the instantaneous volatility, $\sigma_j(t_i)$, then we say that a jump in the stock price of firm j is detected between time t_{i-1} to t_i. The instantaneous volatility is estimated by the scaled bipower variation defined as in:

$$\widehat{\sigma_j}(t_i)^2 \stackrel{\text{def}}{=} \frac{1}{K-2} \sum_{m=i-K+2}^{i-1} \left|\log\left(S_j(t_m)/S_j(t_{m-1})\right)\right| \left|\log\left(S_j(t_{m-1})/S_j(t_{m-2})\right)\right|,$$

where *K* is the size of the rolling window. The first K-1 observations in the window are used to measure the instantaneous volatility. Thus, the instantaneous volatility at time t_i is computed using the past return windows from time t_{i-K+2} to t_{i-1}, and the last observation in the window is compared to the estimated volatility. For 15-minute intervals, we follow the recommendation of Lee and Mykland (2008) and set *K* equal to 156.

More formally, to test at time t_i whether there was a jump in the stock price of firm j from t_{i-1} to t_i, we use the test statistic $L_j(i)$ defined as in:

$$L_j(i) \stackrel{\text{def}}{=} \frac{\log\left(S_j(t_i)/S_j(t_{i-1})\right)}{\widehat{\sigma_j}(t_i)}. \tag{A.1}$$

Lee and Mykland (2008) derive the asymptotic distribution of this test statistic $L_j(i)$ and suggest the following rejection criteria for the null hypothesis that there is no jump in the stock price of firm j over the interval t_{i-1} to t_i:

$$\frac{L_j(i) - C_{n_j}}{S_{n_j}} > 4.6001, \tag{A.2}$$

where $$C_{n_j} = \frac{(2\log n_j)^{1/2}}{c} - \frac{\log\pi + \log(\log n_j)}{2c(2\log n_j)^{1/2}} \quad ; \quad S_{n_j} = \frac{1}{c(2\log n_j)^{1/2}} \quad ; \quad c \sim 0.7979$$

and n_j is the total number of observed stock prices of firm j during the sample period. The threshold 4.6001 in equation (A.2) refers to the 1% significance level according to a Gumbel distribution, which is the limiting distribution of maximums of our jump test statistics under the null hypothesis of no jump. This conservative choice of rejection criteria reduces the chance of spuriously detecting jumps. If the condition in equation (A.2) is met, we reject the null hypothesis of no jump in the return of stock j and claim the presence of jump over the interval t_{i-1} to t_i. See the Appendix B for the asset pricing model for this method.

Appendix B: The impact of confounding events in multivariate logistic regression

We provide simulation evidence showing the robustness of our multivariate logistic regression performed in Section 4 to the presence of confounding information events. Results in Table B1 are based on the average of 1,000 simulation runs. In order to see how confounding events may influence our results, we generate 15-minute returns over a 5-year period from a general continuous-time asset pricing model that accommodates various empirical evidence such as the presence of price jumps, stochastic volatility, and stochastic jump intensity, among others. The model follows a jump diffusion process with stochastic jump intensity depending on information releases. We assume that prices are observed between 9:30am and 4:00pm to mimic our data from New York Stock Exchange (NYSE).

Specifically, for each firm j, we assume that the evolution of its asset price $S_j(t)$ at time t is represented by the following equations:

$$d\log S_j(t) = \mu_j(t)dt + \sigma_j(t)dW_j(t) + Y_j(t)J_j(t), \qquad \text{(B.1)}$$

Where $W_j(t)$ is a standard Brownian motion and $J_j(t)$ is a Poisson counting process with stochastic jump intensity, or equivalently jump probability, $\lambda_j(t)$, which depends on information covariates. Price and information data for firm j are assumed to be observed only at discrete times $t_0 < t_1 < \cdots < t_{n_j}$. This article sets observation times to be equally spaced such as at 15 minutes: $\Delta t = t_{i-1} - t_i$.

For simplicity, we suppose in this simulation study that there are two independent variables that are possibly confounded. The stochastic jump intensity model is

$$\lambda_j(i) = \left(\ 1 + exp\left(-\left(\alpha + \theta_1 X_{j,1}(\mathrm{i}) + \ \theta_2 X_{j,2}(\mathrm{i})\right)\right) \ \right)^{-1}, \tag{B.2}$$

where the first and second information covariates $X_{j,1}(\mathrm{i})$ and $X_{j,2}(\mathrm{i})$ are quarterly event timing indicators and α is the intercept. Their impact parameters are set at θ_1 = 3 and θ_2 = 2.5, respectively. In estimating the jump intensity model $\lambda_j(t)$, we set our dependent variable to takes the value of one if a jump in stock price of firm j is detected in a 15-minute time interval and zero otherwise according to the method in Lee and Mykland (2008).

Conditions for this type of models are general enough to cover almost all continuous-time models with nonlinear drift, stochastic volatility, and stochastic jumps used in the asset pricing literature. The related assumptions can also be found in Lee (2011).

The confounding rates of the two event indicators are set at three different levels as listed in Table B1. We first note that even when the error rate is equal to zero, we expect a small bias in our estimates due to the discretizing error in the continuous-time model. Nevertheless, the results show that while the coefficients can be slightly biased, the significance levels and ranking of the parameters remain intact. Thus, our results are robust to confounding events.

Table B1. Impact of confounding announcements

This table shows the impact of confounding information events on our multivariate analysis performed in Section 4. The dependent variable for the logistic regression takes the value of one if a jump is detected in a 15-minute time interval and zero otherwise according to the method in Lee and Mykland (2008). The stochastic jump intensity model is described in equation (B.2) where both $X_{j,1}(t)$ and $X_{j,2}(t)$ are observed at discrete 15-minute time intervals. All the information variables are set to be time-series indicators that capture the timing of different information events to mimic our analysis. We report the averaged parameter estimates and associated p-values in parentheses.

Parameter	Confounding Event Rate		
	0%	25%	50%
$\alpha = -4.00$	-4.05	-4.05	-4.05
	(0.00)	(0.00)	(0.00)
$\theta_1 = 3.00$	2.88	2.83	2.86
	(0.01)	(0.01)	(0.01)
$\theta_2 = 2.5$	2.35	2.13	2.16
	(0.03)	(0.04)	(0.04)