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Are Analysts' Forecasts Informative to the General Public?

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Contrary to the common view that analysts are important information agents, intraday returns evidence shows that announcements of analysts' forecast revisions release little new information, on average. Further cross-sectional evidence from returns around the announcements confirms that revisions are virtually information free. Daily announcement returns used in the literature appear to overstate the analyst's role as information agent, because forecast announcements are often issued directly after reports of significant news about the followed firm. The evidence reveals a sequential relationship between events and news and forecast revisions indicative of analyst piggybacking, not prophecy. These new findings about the most sought-after analyst reports broaden significantly the evidence indicating that price reactions to analysts' reports reveal little new information.

Key words: analysts' forecasts; financial analysts; financial markets; investment banking; market efficiency; security analysts
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1. Introduction

Security analysts' forecasts of corporate earnings play important economic roles. They provide a reliable benchmark for firms' expected future earnings and related cash flows that aid the resource allocation decisions of various market participants. Because forecast accuracy, which is rewarded highly in the market for analysts, is regularly revealed when earnings are realized, forecasts bond analysts to staying abreast of followed firms' foreseeable performance. Forecasts therefore aid the monitoring of top management, the shaping of analysts' career paths and wealth, and the signaling of brokerage firm research quality.[1] This paper examines yet another forecast role, supplying new information to brokerage firm clients. Academic researchers and practitioners often suggest that analysts are information agents who revise their forecasts to communicate new information that they discover by processing public information about the firm. Large and significant stock price reactions around forecast announcements agree with the information agent view.[2]

Of primary interest is the hypothesis that analysts tend to piggyback their reports on public information from recent events and news about the firm, while delivering little incremental information. By piggybacking we mean that analysts convert public information into a forecast revision, which is not very informative beyond the information itself. Forecasts are commonly updated based on significant events and other new public information that multiday returns used in earlier research often credit to analysts' information, thus overstating analysts' output, on average. Using intraday stock returns around forecast revisions to measure analysts' information can isolate investor reactions to the forecasts from the reactions to other news. New findings reveal that forecasts release little new information and that analysts piggyback forecasts on recent public information. To our knowledge, this is the first study that examines intraday stock returns around forecast revisions.

[1] See Trueman (1994), Mikhail et al. (1999), Healy and Palepu (2001), Lim (2001), Hong and Kubik (2003), Asquith et al. (2005), Jackson (2005), and Groysberg et al. (2011).

[2] See Lys and Sohn (1990), Stickle (1992), Francis and Soffer (1997), Brav and Lehavy (2003), Gleason and Lee (2003), Ivkovic and Jegadeesh (2004), and Asquith et al. (2005).

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New evidence establishes that analysts' forecasts often follow recent events and news. The time soon before the forecast announcement is searched for new public information that could overstate analysts' information when using multiday returns. Surprising findings show that the vast majority of forecasts follow recent events and news. For example, over 55% of daytime forecasts and 51% of nighttime forecasts follow a recent key event. A key event in this study is an earnings or guidance report found in common commercial sources (e.g., Center for Research in Security Prices, Compustat, or First Call Historical Database (FC)). For the remaining forecasts that have no key event, searches of Dow Jones & Company Factiva (Factiva) for several distinct samples reveal Factiva events in 90% of the cases, including reports of earnings, guidance, investment projects, restructurings, and other news. This new evidence validates that forecasts frequently track notable public information about the firm, suggesting that lengthy announcement period returns could overstate analysts' information.

To assess analyst information, the announcement return, R(ann), is examined first. R(ann) is measured over a window of four 10-minute intervals around the forecast announcement, where nontrading nighttime (or weekend or holiday) periods are folded into one interval. The narrow 40-minute window helps isolate the measured forecast return from reactions to recent news. For forecasts with no key event, the daytime mean announcement returns are clearly muted indicating that little information is supplied to the general public. They average 2 basis points (bps) for revisions upward and 0 bps for revisions downward. For nighttime forecasts, which in real time have a significantly longer announcement window exposure to public information, the mean announcement returns are 18 bps and 3 bps, respectively. These returns are below transaction costs. Further results show that when there is no key event and no Factiva event, the forecast announcement has little information.

Our result that forecasts do not appear to have a significant impact is a surprise in light of the large body of evidence indicating they are informative, and the common belief that analysts are information agents in securities markets. Three plausible reinterpretations are investigated that could reconcile the information agent view with the finding of little new information from forecasts. One reinterpretation is that while most analysts are usually uninformed, some analysts are informed in particular cases. A key case is forecasts that are associated with extreme return reactions, which could be driven by a subset of informed analysts. Findings show that 60% of the extreme return cases are crowded with key events. This coincides with more piggybacking when returns are more extreme. Factiva events are searched for samples of the other 40% of the extreme return forecasts that have no key event. The pattern is again surprising, as nearly all of these forecasts follow significant public information. Thus, the tight temporal linkage between events and news and forecast revisions most likely exemplifies not analyst prescience but analyst piggybacking.

Another vital case is forecasts from superior analysts, that is, the bold, the first movers, the accurate, and those employed by reputable brokerage firms. This case is expanded to include forecasts for widely followed stocks, which could be more informative because their stock prices may adjust most quickly to new information.[3] Gleason and Lee (2003) and Clement and Tse (2005) find that bold forecasts are more informed, Hong and Kubik (2003) find that accurate forecasts are better informed, Cooper et al. (2001) find that first-mover forecasts are more informative, and Stickel (1992) finds greater price impacts for reputable brokerage forecasts. The mean announcement reactions for superior forecast traits do not contain high price responses different from the reactions for all other revisions. These forecast types do not seem to provide new information. However, further new findings show that these traits occur at times when the preannouncement return is larger in absolute value, which will make the forecasts appear more informed when using multiday returns. Additional results show that analysts can follow events swiftly with their forecast revisions, confirming their responsiveness, as implied by piggybacking. These findings have implications for a number of studies on analysts' traits, especially those examining the traits in conjunction with the cross-sectional return reactions around forecast revisions.

The second reinterpretation is that the weakly informed announcements are not informative because investors have already anticipated most of analysts' information, which should thus be evident in the prereturn, R(pre), not the R(ann). Forecasts could be leaked or tipped to clients before they are announced, or FC time stamps could be late. However, we know of no evidence of the kind of widespread leaking presumed in this reinterpretation. Note that anticipation also assumes that savvy investors trade promptly before the announcement based on the leaked information. R(pre) is examined for evidence of anticipation evidence. While R(pre) agrees with anticipation on average, it is also inundated with events and news. Many tests of the R(pre) cross section fail to provide consistent evidence that agrees with analysts' new information. At the least, these new findings suggest

[3] See Brennan and Subrahmanyam (1995), Hong et al. (2000), and Gleason and Lee (2003).

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that, on average, analysts are not informative to the general public, a substantial departure from the information agent view.

In the third and last reinterpretation, analysts' forecasts convey new information on time, but investors react slowly to integrate the information into stock price. Pervasive delay is plausibly a secondary concern to the extent that brokerage clients and vigilant arbitrageurs are savvy enough to trade promptly on any new information. Although the postreturn, R(post), average drifts modestly with the revisions, barely half of the return signs agree with the revision direction. Nor is R(post) different for any superior forecast type. Average R(post) is similar for revisions in the daytime and nighttime, yet investors have far more time to react to nighttime forecast announcements. These findings disagree with much analyst information in the postreturn and thus with the delay notion. Further cross-section tests show that revisions are correlated with familiar predictors of return drift (e.g., postearnings or post-guidance announcement drift (PEAD and PGAD)). This evidence of comovement between forecasts and drift predictors coincides with analysts also combining return prediction into their forecasts. This can give the appearance of delayed reaction to new forecast information, even when analysts are uninformed. When the influence of return predictors is controlled, the correlation between postreturns and forecasts weakens sizably; there is no strong evidence that post-forecast drift agrees with the forecasts, contrary to the delay notion.

We underscore two clarifications about our interpretations. First, we do not interpret our results as implying that analysts do not add value. The large annual research expenditures by many competitive brokerage firms provide convincing evidence of analysts' added value. Further evidence appears when analysts initiate coverage, which agrees with analysts raising investor awareness about followed stocks.[4] Second, our findings are not sufficient to support the broad conclusion that analysts never supply new information. The findings do not rule out the innovative interpretation that analysts convey new information, not in their report, but through selective leaks to some market participants who reap most of the rents from the research. They could hold back such information from typical participants such as retail investors who use the publicly released forecast revisions. A central contribution of this study is to show that forecast announcements are not a regular source of useful new information for public customers. This has implications for a wide range of studies on the value of analysts' outputs, including those that analyze cross-sectional variation in market reactions to analysts forecast revisions.

[4] See Bhushan (1989), Hayes (1998), Altınkılıç and Hansen (2000), and Irvine et al. (2007).

2. Public News and Intraday Stock Return Behavior Around the Forecasts

The data used in the empirical tests are drawn from the population of 6,360,415 quarterly and annual earnings forecasts found on the FC for 1997 through 2007 (Table 1). Daily Trade and Quote (TAQ) file stock returns posted every 10 minutes, based on the FC forecast announcement time, are examined. This method follows Altınkılıç and Hansen (2009) who use narrow return windows. Because the FC population is too large for intraday analyses, a random sample of 250,000 revisions is drawn using SAS Procedure SURVEYSELECT, which draws a corresponding sample from the population while preserving the population's analyst following frequencies. This yields the TAQ sample of 197,052 revisions. As rows 8–12 of Table 1 show, the mean annual following proportions are similar for each level in all three samples. Most forecasts have a prior forecast and over 97% have a prior earnings announcement by the followed firm.

The sample spans three reform eras. In period 1, before Regulation Fair Disclosure (Reg FD) (January 1997 through October 2000), management could selectively disclose information to analysts and institutional investors. Studies find that some analyst information could have come from firm managers before Reg FD took effect (see Bailey et al. 2003, Cohen et al. 2010). Period 3 follows the Global Research Analysts Settlement (GRAS) from December 2002 through 2007. Period 2 is between Reg FD and GRAS. The population and sample proportions are similar within each era.

Batch forecasts are not real time and are aggregate forecasts of varying frequency (e.g., weekly) or FC *systime*, and are thus not used. Womack (1996) and Green (2006) find that in earlier sample years, report delay is rare. In early communications, FC (the original company) notes it directly transmits its research to all institutional clients, and investors learn of the reports promptly. For example, Brav and Lehavy (2003) detail FC coding of analyst reports in real time (see also Green 2006, Christophe et al. 2009). Sample revision representations are similar to those in the population. It is thus unlikely that the findings are influenced by the sampling method.

2.1. Returns Around the Forecast Announcements and Forecast Volume

TAQ trade-by-trade prices are first converted into a series of 10-minute interval prices. The opening (closing) price (P_{open} (P_{close})) is the price before 9:35 (after

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Table 1 Population and Samples

		FC population			Replicated sample			TAQ sample		
Row	Item	All	Daytime	Nighttime	All	Daytime	Nighttime	All	Daytime	Nighttime
1	Forecasts	6,360,415	2,399,595	3,960,820	250,000	94,462	155,538	197,052	74,060	122,992
	(percent of all)	(100.0)	(37.7)	(62.3)	(100.0)	(37.8)	(62.4)	(100.0)	(37.6)	(62.4)
2	Q I earnings	16.0	16.0	17.3	16.4	16.3	17.4	17.2	16.3	17.4
3	Q II earnings	12.6	12.3	13.5	13.0	12.7	13.8	13.5	12.8	13.7
4	Q III earnings	10.3	10.1	10.7	10.6	10.3	10.9	10.9	10.4	11.2
5	Q IV earnings	8.0	7.9	8.1	8.3	8.2	8.5	8.5	8.3	8.6
6	FY 1 earnings	19.6	19.6	19.6	20.2	20.2	20.2	20.6	20.0	20.8
7	FY 2 earnings	14.9	14.9	14.9	15.2	15.4	15.1	14.9	15.1	14.6
8	0–25 yearly	7.6	8.8	6.9	7.5	8.9	6.6	7.7	9.1	6.9
9	25–50 yearly	8.6	9.7	8.0	8.6	9.7	7.9	8.8	9.9	7.8
10	50–100 yearly	15.3	16.5	14.6	15.5	16.6	14.9	15.2	16.6	14.9
11	100–200 yearly	23.2	23.1	23.2	23.2	23.1	23.2	23.2	23.1	23.2
12	Over 200 yearly	45.2	41.9	47.2	45.1	41.7	47.3	45.1	41.7	47.3
13	Prior forecast	73.9	74.1	73.8	74.6	74.7	76.6	75.2	75.2	76.5
14	Prior earnings	97.7	97.8	97.8	98.8	98.0	99.8	98.9	98.1	99.4
15	Before Reg FD	26.8	31.5	20.2	26.6	31.5	20.1	26.9	31.8	19.7
16	After GRAS	49.4	43.7	57.8	49.7	43.6	57.9	50.0	43.9	62.8
17	Top brokerage	54.7	41.8	61.6	54.5	41.7	61.8	54.6	41.5	62.5

Notes. Reported are selected statistics for the population of 6,360,415 analyst earnings forecasts found in the FC for 1997 through 2007, for a random sample of 250,000 from those forecasts, and for forecasts from the random sample found on Daily TAQ. Revisions are in the daytime if made on a trading day from 9:30 to 16:00 and in the nighttime otherwise. The replicated sample of 250,000 forecasts is obtained using the SAS Procedure SURVEYSELECT, which creates a sequence of random numbers without repetitions and draws the corresponding sample of observations from the population. Daytime forecasts are made on a trading day between 9:30 and 16:00. All row entries are expressed as a percent of the row 1 number of forecasts. Row 1 is the number of forecasts followed in parentheses by the fraction of the corresponding row 1 number of all forecasts. Rows 2–7 are the fractions of forecasts of earnings at the end of one of the next four quarters (Q I to Q IV) and the next two fiscal year-ends (FY 1 and FY 2). Rows 8–12 report the mean annual fraction of forecasts by levels of analyst following. Rows 13 and 14 are the fraction of forecasts with a prior forecast by the same brokerage house and a prior earnings report, over the prior two years, respectively. Rows 15 and 16 are the fraction of forecasts made prior to the October 2000 enactment of Reg FD and after the December 2002 news of GRAS, respectively. Row 17 is the fraction of forecasts by analysts employed at one of the top 20 brokerage firms, those with the most revisions in the sample period.

15:55) that is nearest to the 9:30 opening (16:00 closing) time or the mean price in the first (last) second of trading. Remaining interval prices are formed at times ending in 0 ($P_{9:40}, \ldots, P_{15:40}, P_{15:50}$) using the nearest TAQ price within ±5 minutes of the interval time. For brevity, nighttimes, weekends, and holidays (i.e., nontrading hours), are collectively called nights. Because intraday prices do not exist during nights, each night is treated as a 10-minute interval with prices formed from its P_{close} and P_{open}. For each forecast 10-minute interval returns are identified around the announcement interval which starts with price p_0 and ends with price p_1. The announcement window has four of the intervals; the announcement period return is $\text{R(ann)} = p_3/p_{-1} - 1$. Both the prereturn, $\text{R(pre)} = p_{-1}/p_{-81} - 1$, and the postreturn, $\text{R(post)} = p_{83}/p_3 - 1$, have 80 intervals and thus span two calendar days (Figure 1, panel (A)). Also considered at times is the all-in return, $\text{R(all)} = p_{83}/p_{-81} - 1$.

When R(ann) contains a night return interval it is exposed to 18 hours of real time (and more for weekends and holidays), from 16:00 to 9:30 plus the 10 minutes before and 20 minutes after announcement. The exposure is information enriched since most earnings reports are released in the night. There may be a selection effect if the long information exposure attracts piggybacking analysts, causing more nighttime forecasts. We call these phenomena nighttime bias. Indicative of the bias, nighttime forecasts are more plentiful and have more big news. Forecasts are therefore separated into nighttime forecasts, those with a night interval in the announcement window, and daytime forecasts whose entire announcement window is in trading hours (Figure 1, panel (B)). To the extent nighttime news is partially absorbed in opening prices, it also impacts morning returns, an effect we call morning bias. Another notable pattern is that while each forecast has two nights in the pre- and postperiods, for daytime forecasts, the nights are dispersed over the 80 pre- and postperiod intervals. For nighttime forecasts, the nights cluster around 40 and 80 intervals from the announcement window (hence, at one and two days).

On a typical trading day hourly forecast volume rises significantly after 6:00 A.M. and the prior low volume since midnight, peaking around the market opening. Just over 40% of the forecasts are from 6:00 A.M. and 11:00 A.M. (Figure 1, panel (C)). Early morning forecasts are a significant majority (63%) of all forecasts and could contain morning bias. Weekend and holiday nighttime forecast volume is very light, less than 1% of all forecasts (Figure 1, panel (D)).

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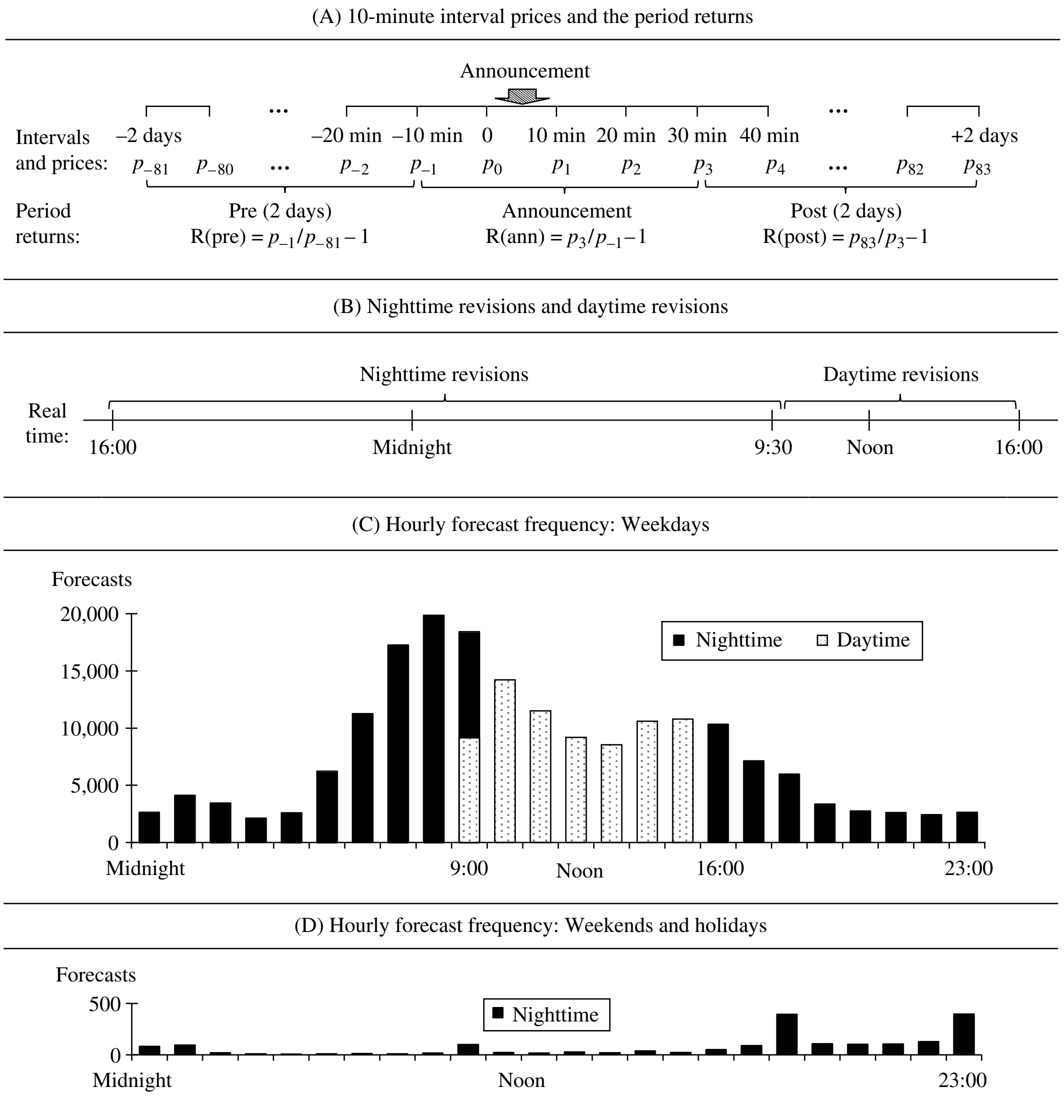
Figure 1 **Forecast Event Time, Period Returns, and Intraday Frequencies**



Notes. Panel (A) reports relative forecast–event time 10-minute interval prices based on 10-minute intraday prices built from the Daily TAQ trade-by-trade prices. Intraday prices are formed at each 10-minute interval ending in 0 ($P_{9:40}, \ldots, P_{15:50}$) by selecting the nearest TAQ price within ±5 minutes of the interval time. The starting price in the 10-minute announcement interval is p_0. Relative prices p_{-81} to p_{-1} (p_1 to p_{83}) are start prices in the prior (subsequent) 10-minute intervals. Panel B shows the classification of revision time to nighttime and daytime revisions. Panel C (D) reports intraday hourly frequency of forecasts issued on weekdays (weekends and holidays).

2.2. Evidence of Events and News Ahead of the Forecast Announcement

Consider next the presence of recent events and news that could be allied with forecast announcements. Enough events prior to the forecasts is distinct evidence that agrees with piggybacking that is not entangled with concerns over causality; the forecasts do not cause the events and news. The findings could also reveal how promptly analysts respond to events and news.

Consider first the key events. For daytime revisions, 44% of the up and 45% of the down forecasts follow a key event in days −3 to 0. Key events are more common before nighttime revisions, agreeing with nighttime bias (Table 2, panel (A)).

More evidence of fresh events and news is provided by Factiva for the Table 2 forecasts that do not follow a key event. Four random samples are drawn from the revisions with no key event: 150 up and 150 down daytime revisions, and 150 up and 150 down nighttime revisions. A Factiva event is present for 86% to 91% of the revisions in these samples (Table 2, panel (B)). Most common is earnings news, then new business, then other news. This agrees with analysts quickly issuing reports that recast the news.

Piggybacking suggests that events and news could be especially common when forecasts ally with more

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Table 2 Frequency (%) of Key Events and Factiva Events for Different Revision Samples

	Daytime		Nighttime	
Event	Revision up	Revision down	Revision up	Revision down
Panel A: Key events overall				
Sample size	32,564 (100%)	31,496 (100%)	50,664 (100%)	62,859 (100%)
Key event	14,275 (44%)	18,509 (45%)	25,761 (51%)	29,779 (48%)
No key event	18,289 (56%)	22,987 (55%)	24,903 (49%)	33,080 (52%)
Panel B: Factiva events in random $N = 150$ samples from corresponding panel (A) columns, which had no key event				
Sample size	150 (100%)	150 (100%)	150 (100%)	150 (100%)
Earnings and guidance	65 (43%)	76 (51%)	77 (51%)	74 (49%)
Financing	16 (11%)	15 (10%)	13 (9%)	14 (9%)
New business	50 (33%)	34 (23%)	48 (32%)	34 (23%)
Other news	27 (18%)	29 (19%)	39 (26%)	42 (28%)
Total with events	134 (89%)	136 (91%)	132 (86%)	135 (90%)
Panel C: Key events for $N = 1,500$ forecasts with the most extreme prereturns				
Sample size	1,500 (100%)	1,500 (100%)	1,500 (100%)	1,500 (100%)
Earnings report	824 (55%)	662 (44%)	1,183 (79%)	1,232 (82%)
Guidance report	39 (3%)	137 (9%)	118 (10%)	105 (7%)
Total with key event	863 (58%)	799 (53%)	1,301 (88%)	1,337 (90%)
Panel D: Factiva events in random $N = 150$ samples from corresponding panel (C) columns, which had no key event				
Sample size	150 (100%)	150 (100%)	150 (100%)	150 (100%)
Earnings and guidance	47 (32%)	67 (44%)	53 (35%)	84 (56%)
Financing	6 (4%)	4 (3%)	11 (7%)	8 (5%)
New business	52 (34%)	28 (19%)	51 (33%)	29 (19%)
Other news	40 (26%)	47 (30%)	33 (22%)	28 (18%)
Total with events	145 (96%)	147 (97%)	148 (98%)	148 (98%)

Panel E: Factiva news in two samples of $N = 100$ for most recommended and forecasted stocks with no key event

Event	100 most recommended	100 most forecasted
Sample size	100 (100%)	100 (100%)
Earnings and guidance	6 (6%)	96 (96%)
Hot stocks	17 (17%)	60 (60%)
Investment projects	14 (14%)	14 (14%)
Mergers and acquisitions	73 (73%)	8 (8%)
Other	26 (26%)	27 (27%)
Total with events	91 (91%)	100 (100%)

Notes. Daytime forecasts have their entire 40-minute announcement window in trading hours; nighttime forecasts have a night interval in the announcement window. Panels (B) and (D): Factiva event sorts follow Asquith et al. (2005) and Altınkılıç and Hansen (2009). *Earnings news*: Earnings and guidance announcements. *Financing news:* Altered borrowing base, boosted debt reserves, debt financing, debt rating change, dividend change, private placement, stock repurchase, and stock split. *New business*: Asset sale, Food and Drug approval, merger, new client, new contract, new products, new projects, new strategic plan, product withdrawal or delay, sale of stake in another company, and stakeholder holding change. *Other news*: Accounting issue, CEO talk, Chapter 11 discussion, foreign stock market–related, governance action, industry wrap-up, insider trading, lawsuit, management change, award recipient, 52-week high and low (Dow Jones), and big movers. Panels (C) and (D): Daytime (nighttime) revisions extreme return revisions are from the prereturns (announcement returns). Panel (D) report types are described above for panel (C). Panel (E): *Earnings and guidance*: Earnings, sales, guidance, conference call reports. *Hot stock*: Big movers, hot stocks, and brokerage report stocks. *Investment projects*: New products, projects, strategic plans, deal closings, and workforce cuts. *Mergers and acquisitions*: Merger, acquisition, and alliances.

extreme stock returns. Although mean returns for these revisions could reflect analysts' new information, piggybacking suggests that more analysts will be attracted to revise their forecast after key events with more extreme returns. Key event frequency for forecasts associated with the most extreme returns is examined for 1,500 up and 1,500 down daytime revisions, and similarly for nighttime revisions. For daytime forecasts with extreme prereturns, a key event is present for 58% of the up revisions and 53% of the down revisions (Table 2, panel (C)). For the nighttime extreme return revisions, a key event is present for a striking 88% of the up and 90% of the down revisions.

Further evidence of event piggybacking can be identified from a search for Factiva events for the extreme return forecasts that do not have a key event. Four samples of 150 forecasts are drawn from each of the above four ($N = 1,500$) extreme return samples that do not have an event. On average, 97% of revisions in each sample has at least one significant Factiva event (Table 2, panel (D)). Earnings news is most common, then new business, then other news.

A fifth check for close links between forecasts, events, and news is performed for 100 of the most widely followed stocks and 100 of the most recommended stocks, for those forecasts that have no key

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event over relative days −2 to 0. The search reveals a very high rate of Factiva events, as these revisions follow earnings-related news reported in the media over 90% of the time (Table 2, panel (E)).

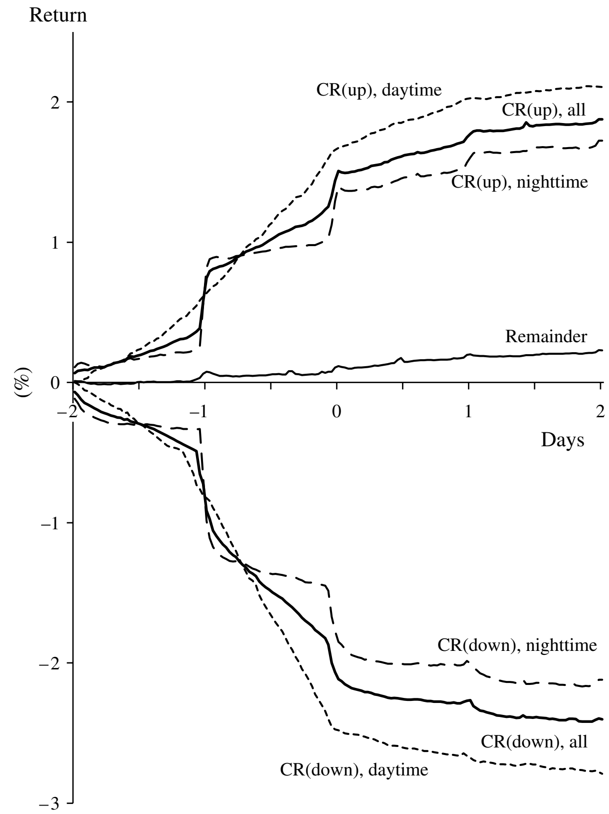
2.3. Stock Return Behavior

Given the evidence of ample events and news in the preperiod, consider the key issue of assessing analysts' new information reflected in stock prices around the forecasts. Figure 2 reports mean cumulative returns over the four trading days around the revision announcements.[5] For the figure, revisions are sorted into three groups: Up revisions exceed +5%, down revisions are below −5%, and the remainder have absolute change under +5%, relative to the previous brokerage forecast. Up revisions follow positive prereturns and down revisions follow negative prereturns, on average. These patterns agree with revisions tracking preperiod stock returns and the events that drive them. It also agrees with anticipation of analysts' information. Distinct jumps in mean returns in the direction of the respective forecasts are evident, and are driven by clustered nighttime jumps for the nighttime revisions, with the largest jump the night before the announcement night. Recall that all of the nighttime forecasts' announcement windows contain one night. Thus, the two nights before and the two nights after the announcement of all of these forecasts are also clustered together. Their nighttime return jumps, particularly the night prior to the announcement night, agree with nighttime bias as analyst track night returns and news.

For all revisions, the up revision mean announcement return of +26 bps is statistically and economically significantly positive, as are the mean pre- and postreturns (Table 3). The down revision mean announcement return (−28 bps) and mean pre- and postreturns are significantly negative. The all-in returns show that when informativeness is measured using a surrounding multiday return, analyst revisions appear to release economically large information, averaging over 1.5%.

Although the announcement period returns agree with modest information release, on average, the averages are driven largely by nighttime revision returns. The respective daytime mean announcement reactions are an economically small +4 bps and −4 bps, or a half penny on a $10 dollar stock; for nighttime they are larger: ±50 bps, or 6¢ on a $10 dollar stock (Table 3). The returns are not driven by a few particular months because they are confirmed in the

Figure 2 **Mean Cumulative 10-Minute Returns (CR) on the Four Trading Days Centered on the Forecast Revision Announcement**



Notes. Shown are returns around up and down forecast revisions during daytime and nighttime, cumulated over 10-minute intervals from 80 before to 80 after (each two days) the interval 0 forecast announcement. A revision is up (down) if it is above (below) 5%; otherwise, it is in the remainder.

130 within-month mean returns. The results are similar for the firm-days sample, in which similar same day revisions are counted as one observation. They are alike across quarterly and yearly earnings forecast horizons (Table 3). In all cases, the nighttime revision announcement period return is relatively large. Moreover, the percent of forecasts associated with announcement returns greater than 1% (0.5%) in absolute value is 45.7% (66.0%) in the nighttime and 15.0% (38.4%) in the daytime (not reported). These results show that the nighttime forecast is associated with bigger news, on average. Moreover, 62% of the forecasts are in the nighttime (Table 1), which could partly reflect a selection effect in which bigger night news attracts piggybacking analysts.

The return findings include other evidence of piggybacking. When the announcement window is extended back an hour, R(ann −1 hr) $= p_3/p_{-7} - 1$, piggybacking predicts that the longer return expands in the direction of the forecast due to other events and news. The daytime back-extended mean returns

[5] For revision i the interval t cumulative return is $\mathrm{CR}_{it} = p_{it}/p_{i-81}$. Risk-adjusted returns are not examined because the return intervals are short, so the impacts of expected returns are small and can be ignored (see Fama 1998). In unreported results, we document that our findings are robust to using market adjusted returns.

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Table 3 Percentage Returns Around Revision Announcements

	Revision up					Revision down				
Sample	Number	R(pre)	R(ann)	R(post)	R(all)	Number	R(pre)	R(ann)	R(post)	R(all)
				Panel A: All revisions						
All	83,228	0.98[1]	0.26[1]	0.34[1]	1.57[1]	104,355	−1.19[1]	−0.28[1]	−0.10[1]	−1.56[1]
All daytime	32,564	1.23[1]	0.04[1]	0.35[1]	1.62[1]	41,496	−1.57[1]	−0.04[1]	−0.13[1]	−1.74[1]
All nighttime	50,664	0.73[1]	0.47[1]	0.32[1]	1.52[1]	62,859	−0.80[1]	−0.51[1]	−0.06[1]	−1.37[1]
				Panel B: Daytime revisions						
Monthly means	130	1.13[1]	0.04[3]	0.36[2]	1.53[1]	130	−1.57[1]	−0.04[2]	−0.14[1]	−1.75[1]
Firm-days	27,963	1.17[1]	0.04[1]	0.36[1]	1.56[1]	35,962	−1.45[1]	−0.04[1]	−0.12[1]	−1.61[1]
Q I earnings	4,860	1.37[1]	0.04[1]	0.35[1]	1.76[1]	7,937	−1.45[1]	0.06[1]	0.13[1]	−1.65[1]
Q II earnings	4,062	1.27[1]	0.03[2]	0.33[1]	1.50[1]	4,452	−1.27[1]	−0.03[2]	−0.18[1]	−1.32[1]
FY 1 earnings	7,150	1.42[1]	0.04[1]	0.43[1]	1.89[1]	7,855	−1.84[1]	−0.06[1]	−0.22[1]	−2.12[1]
FY 2 earnings	5,171	1.35[1]	0.05[2]	0.33[1]	1.73[1]	5,821	−1.76[1]	−0.04[2]	−0.21[1]	−2.00[1]
Before Reg FD	8,679	1.10[1]	0.04[1]	0.20[1]	1.35[1]	11,824	−1.57[1]	−0.04[1]	−0.10[2]	−1.71[1]
FD to GRAS	5,102	0.90[1]	0.02	0.45[2]	1.38[1]	8,571	−1.88[1]	−0.05[1]	−0.11[1]	−2.04[1]
After GRAS	18,783	1.37[1]	0.05[1]	0.40[1]	1.81[1]	21,101	−1.45[1]	−0.04[1]	−0.15[1]	−1.63[1]
				Panel C: Nighttime revisions						
Monthly means	130	0.70[1]	0.42[3]	0.30[2]	1.42[1]	130	−0.89[1]	−0.35[2]	−0.07[1]	−1.31[1]
Firm-days	39,159	0.66[1]	0.41[1]	0.34[1]	1.41[1]	49,547	−0.76[1]	−0.35[1]	−0.07[1]	−1.18[1]
Q I earnings	7,668	0.89[1]	0.43[1]	0.41[1]	1.73[1]	12,052	−0.86[1]	−0.31[1]	−0.03	−0.99[1]
Q II earnings	6,452	0.67[1]	0.32[2]	0.29[1]	1.30[1]	9,146	−0.89[1]	−0.37[2]	−0.07[3]	−1.32[1]
FY 1 earnings	11,542	0.88[1]	0.46[1]	0.33[1]	1.67[1]	12,085	−1.08[1]	−0.55[1]	−0.13[1]	−1.76[1]
FY 2 earnings	8,301	0.88[1]	0.46[2]	0.30[1]	1.64[1]	8,890	−0.92[1]	−0.44[2]	−0.12[1]	−1.48[1]
Before Reg FD	9,347	0.68[1]	0.47[1]	0.16[1]	1.31[1]	12,228	−0.86[1]	−0.39[1]	−0.11[2]	−1.06[1]
FD to GRAS	6,669	0.49[1]	0.39[1]	0.34[2]	1.21[1]	12,254	−1.36[1]	−0.58[1]	−0.01	−1.93[1]
After GRAS	35,204	0.81[1]	0.40[1]	0.35[1]	1.57[1]	39,036	−0.72[1]	−0.47[1]	−0.09[1]	−1.28[1]

Notes. Reported are three mean percentage returns: R(ann), from 10 minutes before through 20 minutes after the 10-minute announcement interval; R(pre), over two trading days before the announcement return; and R(post), over the two trading days after the announcement return. Revisions are in daytime if made on a trading day from 9:30 to 16:00 and are in nighttime if otherwise. Also reported is their cumulative sum, R(all). Up (down) revisions are forecasts above (below) the analyst's prior forecast. Monthly means is the mean of the 130 monthly returns. Firm-days treat similar forecasts changes on the same day as one, Q I (Q II) forecast is for one (two) quarter ahead earnings, and FY 1 (FY 2) is for one (two) fiscal year ahead earnings. Before Reg FD are forecasts made prior to the October 2000 enactment of Reg FD, after GRAS are forecasts after the December 2002 news of the GRAS, and FD to GRAS are forecasts between the two reforms.

[1] [(2, 3)]Indicates statistical significance at the 1% (5%, 10%) level for two-sided student t-statistic.

are a significant 23 bps larger for up revisions and 25 bps smaller for down revisions (Table 4, panel (A)). However, after deleting the early morning revisions the returns shrink to +6 bps and −4 bps, respectively. This agrees with revisions tightly following other news, especially near the start of the day after bigger news nights. Anticipation of analysts' information could also explain the larger back-extended returns. The nighttime announcement return could also be driven by nighttime bias. In agreement, weekend all-in returns and announcement returns are more modest than those on weeknights (Table 4, panel (B)).

Further piggybacking evidence may be found in the preperiod returns. Key event revisions drive much of the daytime prereturns as their all-in mean returns, +2.03% and −3.34%, are over 50% larger than in the no-key-event case; 1.29% and −0.45%, respectively. Also, nighttime prereturns expand significantly when there is a key event, as do announcement returns, reflecting the longer announcement window exposure to real time. The all-in mean returns for the respective no-key-event forecasts are significantly smaller in absolute value, and their announcement returns are small and inconsistent, +18 bps and +3 bps. Overall, the presence of a key event accounts for much of the mean returns. We again see a close relationship between events in the preperiod and the forecasts, and how most of the multiday return before the forecast is linked to these other events.

Panels (C) and (D) of Table 4 report return behavior for the no-key-event sample forecasts in Table 2 panel (B), when a Factiva event is present, and when there is no Factiva event. Note that a Factiva event is present for over 80% of these no-key-event forecasts. R(pre) typically reacts to Factiva events in the direction of the forecast, which also agrees with piggybacking on the event news. R(ann) is generally small and insignificant in the daytime, whereas for nighttime it is significantly different from zero in the direction of the revision given Factiva events. This pattern of relatively greater agreement between forecasts and R(ann) in the night than in the day also agrees with nighttime bias. For these samples there is little reaction to forecasts when there is no key event or media news.

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Table 4 Key Events, Short Windows, and Weekends

Revision direction:	Revision up					Revision down				
Item:	Number	R(pre)	R(ann)	R(post)	R(all)	Number	R(pre)	R(ann)	R(post)	R(all)
				Panel A: Daytime revisions						
All daytime	32,564	1.23[1]	0.04[1]	0.35[1]	1.62[1]	41,496	−1.57[1]	−0.04[1]	−0.13[1]	−1.74[1]
All daytime+	22,111	1.26[1]	0.03[1]	0.35[1]	1.65[1]	28,368	−1.59[1]	−0.02[1]	−0.17[1]	−1.78[1]
+1 hour	32,564	1.23[1]	0.07[1]	0.32[1]	1.62[1]	41,496	−1.58[1]	−0.04[1]	−0.12[1]	−1.75[1]
−1 hour	32,564	1.04[1]	0.23[1]	0.35[1]	1.62[1]	41,496	−1.37[1]	−0.25[1]	−0.13[1]	−1.75[1]
−1 hour+	22,211	1.23[1]	0.06[1]	0.35[1]	1.65[1]	28,368	−1.58[1]	−0.04[1]	−0.17[1]	−1.78[1]
No key event	18,289	0.88[1]	0.03[1]	0.39[1]	1.29[1]	22,987	−0.42[1]	−0.01[3]	−0.02[1]	−0.45[1]
No key event+	12,342	0.84[1]	0.02[2]	0.38[1]	1.24[1]	15,589	−0.43[1]	−0.00	−0.05	−0.49[1]
Has key event	14,275	1.67[1]	0.05[1]	0.31[1]	2.03[1]	18,509	−3.01[1]	−0.08[1]	−0.25[1]	−3.34[1]
Has key event+	4,493	1.41[1]	0.04[2]	0.23[1]	1.68[1]	12,662	−3.02[1]	−0.04[1]	−0.31[1]	−3.38[1]
				Panel B: Nighttime revisions						
All nighttime	50,664	0.73[1]	0.47[1]	0.32[1]	1.52[1]	62,859	−0.80[1]	−0.51[1]	−0.06[1]	−1.37[1]
Weeknight	45,052	0.74[1]	0.49[1]	0.31[1]	1.54[1]	55,053	−0.78[1]	−0.56[1]	−0.04[1]	−1.38[1]
Weekends, holidays	5,612	0.55[1]	0.28[1]	0.33[1]	1.16[1]	7,806	−0.81[1]	−0.13[1]	−0.21[1]	−1.15[1]
No key event	24,903	0.48[1]	0.18[1]	0.27[1]	0.92[1]	33,080	−0.30[1]	0.03[1]	0.03[3]	−0.24[1]
Has key event	25,761	1.01[1]	0.71[1]	0.38[1]	2.10[1]	29,779	−1.35[1]	−1.12[1]	−0.17[1]	−2.64[1]
				Panel C: Daytime revisions: Factiva events when no key event for Table 2, panel (B) samples						
Factiva event	124	0.90[1]	0.02	−0.31[3]	0.61[1]	126	−1.48[1]	−0.05	0.09	−1.44[1]
No Factiva event	26	0.18	−0.09	1.20[3]	1.29[3]	24	−0.31	0.01	−0.14	−0.44
				Panel D: Nighttime revisions: Factiva events when no key event for Table 2, panel (B) samples						
Factiva event	137	0.29	0.46[1]	−0.01	0.74[1]	132	−0.78[1]	−0.38[2]	−0.13	−1.29[1]
No Factiva event	13	0.21	0.02	−0.06	0.18	18	−0.83[3]	0.01	0.74	−0.08

Notes. Reported are three mean percentage returns, R(ann), R(pre), and R(post), and their cumulative sum, R(all), for up (down). Revisions are in daytime if made on a trading day from 9:30 to 16:00 and are in nighttime otherwise. An extended announcement period −1 (+1) hour indicates the period starts (ends) six 10-minute intervals before (after) the announcement interval. Weeknights are Monday through Thursday nights and extend to the next day's open, and the weekend is from the Friday close through the Monday open. The revision is associated with a key event if the followed firm announces either earnings or earnings guidance, as found in commercial data sets, on or within one day before the revision announcement day. Otherwise, there is no key event. The samples used in panels (C) and (D) are described in Table 2.

[+] Indicates that revisions announced before 11:00 are removed from the computations.

[1 (2, 3)] Indicates statistical significance at the 1% (5%, 10%) level for two-sided student *t*-statistic.

A concern is that the announcement window is too short. This could censor price reactions to new information, biasing average R(ann) toward zero. Yet studies report that investors react within 15 minutes and often faster to real-time news releases, like announcements of dividends, earnings, equity offerings, and stock recommendations.[6] The likelihood of speedy investor reaction is compelling in the case of revisions because savvy investors know analysts' reports occur repeatedly, allowing investors to learn to trade quickly and profit from new information. Still, to check for shortness bias the daytime announcement interval is extended forward one full hour (the postreturn interval is correspondingly shortened); R(ann +1 hr) $= p_7/p_{-1} - 1$. If significant shortness bias is present, the extended return will increase significantly, revealing announcement reaction censoring. However, the mean extended announcement return grows by at most +3 bps for the up revisions and does not change for the down revisions (Table 4).

3. Special, Informed Analysts

We next consider possible reinterpretations that could reconcile the findings with the information agent view. The small mean forecast announcement reaction can be reconciled with analysts as information agents if only a subset of forecasts are informed, which are not common enough to have measurable impact on the average announcement return. Four types of informed forecasts are examined.

Hypothesis 1. *Special forecasts are more informed than others.*

One possible informed forecast type is issued by analysts with superior traits that enhance their skill for finding new information. Four superior traits are examined. First are bold forecasts, which are intended to reflect analysts' greater confidence in their own abilities. A bold forecast is defined as above both the analyst's prior forecast and the prevailing consensus forecast for the firm, or below the two. Gleason and Lee (2003) and Clement and Tse (2005) conclude that bold forecasts convey more information than other forecasts. To distinguish bolder forecasts, the focus is on the relatively high and low bold. Note also

[6] See Busse and Green (2002) and Chordia et al. (2008).

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Table 5 Percentage Revision Returns for Superior Revisions

	Bold		Mover		Accuracy		Top broker		Wide follow	
Return	High	Low	First	Later	High	Low	Yes	No	Yes	No
					Panel A: Daytime revisions up					
R(pre)	$1.49^{1,a}$	1.08^{1}	$1.16^{1,a}$	1.64^{1}	$1.30^{1,c}$	1.21^{1}	$1.13^{1,b}$	1.25^{1}	$1.13^{1,b}$	1.25^{1}
R(ann)	0.04^{1}	0.04^{1}	0.04^{1}	0.05^{1}	0.07^{1}	0.03^{1}	0.04^{1}	0.04^{1}	0.04^{1}	0.04^{1}
R(post)	$0.41^{1,b}$	0.32^{1}	0.34^{1}	0.29^{1}	0.38^{1}	0.34^{1}	$0.25^{1,b}$	0.38^{1}	0.25^{1}	0.38^{1}
R(all)	$1.95^{1,a}$	1.44^{1}	$1.54^{1,a}$	1.98^{1}	$1.75^{1,a}$	1.58^{1}	1.42^{1}	1.67^{1}	1.42^{1}	1.67^{1}
Contrarian	40.3	46.4	44.0	42.8	42.6	44.4	43.5	43.9	43.5	43.9
					Panel B: Daytime revisions down					
R(pre)	$-3.14^{1,a}$	-0.51^{1}	$-1.45^{1,b}$	-2.36^{1}	$-1.34^{1,a}$	-1.64^{1}	$-1.28^{1,a}$	-1.64^{1}	$-1.28^{1,a}$	-1.64^{1}
R(ann)	$-0.08^{1,a}$	-0.01^{1}	-0.04^{1}	-0.05^{1}	-0.04^{1}	-0.04^{1}	-0.05^{1}	-0.04^{1}	-0.05^{1}	-0.04^{1}
R(post)	$-0.27^{1,a}$	-0.02	-0.12^{1}	-0.13^{1}	-0.12^{1}	-0.13^{1}	$-0.19^{1,c}$	-0.11^{1}	-0.19^{1}	-0.11^{1}
R(all)	$-3.49^{1,a}$	-0.55^{1}	$-1.62^{1,a}$	-2.54^{1}	$-1.50^{1,a}$	-1.81^{1}	-1.53^{1}	-1.79^{1}	-1.53^{1}	-1.79^{1}
Contrarian	35.9	47.4	43.7^{x}	40.1	44.1	43.0	44.0	43.0	44.0	43.0
					Panel C: Nighttime revisions up					
R(pre)	$0.82^{1,b}$	0.71^{1}	$0.71^{1,b}$	0.81^{1}	0.77^{1}	0.72^{1}	$0.70^{1,c}$	0.78^{1}	$0.70^{1,c}$	0.78^{1}
R(ann)	$0.62^{1,a}$	0.36^{1}	$0.45^{1,b}$	0.55^{1}	0.46^{1}	0.47^{1}	0.46^{1}	0.50^{1}	0.46^{1}	0.50^{1}
R(post)	$0.37^{1,c}$	0.29^{1}	0.34^{1}	0.26^{1}	0.36^{1}	0.31^{1}	0.33^{1}	0.32^{1}	0.33^{1}	0.32^{1}
R(all)	$1.81^{1,a}$	1.36^{1}	$1.50^{1,a}$	1.62^{1}	1.59^{1}	1.50^{1}	$1.49^{1,c}$	1.60^{1}	1.49^{1}	1.60^{1}
Contrarian	43.6^{x}	47.8	45.5	48.2	45.4	46.3	46.4	45.3	46.4	45.3
					Panel D: Nighttime revisions down					
R(pre)	$-1.52^{1,a}$	-0.32^{1}	$-0.74^{1,a}$	-1.07^{1}	$-0.68^{1,a}$	-0.84^{1}	$-0.75^{1,c}$	-0.82^{1}	$-0.75^{1,c}$	-0.82^{1}
R(ann)	$-0.94^{1,a}$	-0.22^{1}	$-0.40^{1,a}$	-0.96^{1}	-0.49^{1}	-0.52^{1}	-0.51^{1}	-0.51^{1}	-0.51^{1}	-0.51^{1}
R(post)	$-0.19^{1,a}$	0.02	-0.06^{1}	-0.07^{2}	-0.06^{3}	-0.06^{3}	-0.00^{c}	-0.09^{1}	-0.00	-0.09^{1}
R(all)	$-2.65^{1,a}$	-0.52^{1}	$-1.20^{1,a}$	-2.09^{1}	$-1.23^{1,a}$	-1.42^{1}	$-1.26^{1,a}$	-1.43^{1}	-1.26^{1}	-1.43^{1}
Contrarian	39.6	53.1	44.6	45.3	44.9	44.6	44.9	44.6	44.9	44.6

Notes. Reported are mean percentage returns, R(ann), R(pre), and R(post), and their cumulative sum, R(all), for the daytime and nighttime samples from Table 1, by four forecast traits and analyst following. Revisions are in daytime hours if made on a trading day from 9:30 to 16:00 and are in nighttime hours otherwise. High (low) bold forecasts are the top (bottom) third of forecasts sorted by boldness. First-mover forecasts are the first forecast on the revision day, and others move later in the day. High (low) accuracy forecasts are in the top (bottom) 35% of forecasts sorted by forecast accuracy, measured following Hong and Kubik (2003), the absolute difference between the forecast for firm and its realized earnings, deflated by stock price five days before the forecast. Top brokerage forecasts are from one of the top 20 brokerage firms: Citigroup, CS, Morgan Stanley, Lehman Brothers, UBS, Goldman Sachs, J.P. Morgan, Banc of America, Merrill Lynch, Deutsche Bank, Bear Stearns, CIBC, A.G. Edwards, RBC Capital, Piper Jaffray, Raymond James, Wachovia, FBR & Co., Robert Baird, and Jefferies. Widely followed are the top third of firms in number of forecasts by different brokers in the quarter before the revision. Percent contrarian is the fraction of forecasts in opposite direction of R(pre).

[1 (2, 3)]Indicates statistical significance at the 1% (5%, 10%) level for two-sided student t-statistic.

[x]Indicates that contrarian for the first category is statistically significantly different from contrarian for the second category, at the 1% level for two-sided student t-statistic.

[a (b, c)]Indicates statistical significance different from the mean return in the alternate category for the trait, at the 1% (5%, 10%) level for two-sided student t-statistic.

that because bold forecasts are often mechanically tied with large prereturns, by construction they can also indicate piggybacking. For example, analysts' forecasts piggyback on striking news, such as a large positive earnings surprise, aiding forecasts to move above the consensus forecast and their prior forecast. Thus, evidence of boldness may not faithfully confirm or reject the information hypothesis. High and low bold forecasts show no significant announcement impacts (Table 5).

Superior information discovery has also been associated with the first forecast that is issued with others at the same proximate time in the semiconductor and restaurant industries (Cooper et al. 2001). However, this result is not expected by piggybacking. When there is larger price reaction to other events and news, each analyst is more inclined to piggyback on the news and the events, updating her forecast. Thus, piggybacking suggests greater price reactions will be associated with multiple revisions, and weaker news with one revision. First-mover announcements also contain little information (Table 5).

Studies report that the best-informed analysts have greater forecast accuracy based on association between accuracy and greater multiday stock returns around forecasts.[7] However, this finding can also be explained by piggybacking. To improve forecast accuracy, rational analysts are inclined to update outstanding forecasts to reflect changes in expected earnings and reduce possible forecast errors, all else the same. Thus, entirely independent of analysts' information and forecasting abilities, there is a natural

[7] See Stickel (1992), Clement (1999), Mikhail et al. (1999), Cooper et al. (2001), Gleason and Lee (2003), Hong and Kubik (2003), Clement and Tse (2005), and Jackson (2005).

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association between piggybacking and accuracy. The accuracy test focuses on the most accurate forecasts, that is, those in the top accuracy quartile. Accuracy appears to have little announcement return impact (Table 5).

Another possible superior forecast is one by analysts at reputable brokerage firms. Stickel (1992), Clement (1999), Malloy (2005), and Cowen et al. (2006) report that reputable brokerage firms provide more accurate forecasts. Reputable brokerages are defined as the top 20 brokerage firms ranked by forecasting frequency. Reputable brokerage forecast announcements are not found to be more informative than those by other brokerage firms (Table 5).

In a fourth case, superior information is associated with forecasts for widely followed firms, as stock prices adjust more quickly to new information for these firms. In the information agent view, this suggests that more new information is reflected in forecast announcement reactions for widely held firms. Contrary to the information agent view, the data show that wide following is not associated with a greater average announcement return.

Note also that if superior revisions accelerate investor reaction, reduced underreaction to their news should result in larger announcement returns. Yet no significant evidence shows that superior revision announcements release more information, in daytime or nighttime, whether up or down (Table 5).

All else the same, larger return reactions should be evident among forecasts that provide new information. This suggests that larger reactions could reflect new information (e.g., Loh and Stulz 2011). However, earlier results show that 60% of the revisions associated with extreme returns are also linked with key events. Factiva searches also show that significant events are present for almost all of the other 40% of the forecasts. Thus, extreme returns do not faithfully identify whether the forecast is informed or instead associated with a powerful event.

4. Anticipation of Analysts' Information

Another plausible explanation for little information in average R(ann) is that investors learn of analysts' information beforehand. Analysts might leak or tip their information to clients who trade on it quickly before the forecast is announced. The time stamps may not correspond to the time the analyst's clients were told of the revision, so the announcement window is late. Report announcement times could be innately sluggish, allowing public release of the new information before the formal announcement. Such cases explain the lack of price reaction to forecast announcements occurs because the information is already absorbed in R(pre) and not because analysts provide little information. We call these cases anticipation.

Hypothesis 2. *Analysts' information is anticipated in the prereturn.*

Note that the anticipation resolution requires that virtually all analysts' new information is anticipated fully before the forecasts are announced. Otherwise, unanticipated information will be evident in average R(ann), but average R(ann) has little information. The anticipation notion thus foresees that analysts' information is in R(pre). Note further that average R(pre) is not always a reliable statistic for testing the information hypothesis since, as is shown above, analysts often piggyback promptly on preperiod events and news that impact their forecasts.

One set of tests for anticipation focuses on analysts with superior traits and their R(ann) and R(pre). If these analysts excel at finding new information, which we find is not evident in the average R(ann), anticipation predicts their information should be evident in R(pre). Although the R(pre) pattern for bold forecasts seems to agree with anticipation, this evidence does not faithfully confirm anticipation because bold forecasts are likely to piggyback on news that impacts R(pre). But for the other traits the evidence contradicts anticipation, in both daytime and nighttime forecasts. For up revisions high accuracy associates with a more positive R(pre), but with less negative R(pre) for down revisions. First movers have significant absolute average R(pre), but the average is greater for late movers, contrary to first movers being more informed. Absolute average R(pre) is greater for less reputable forecasts, contrary to a positive association with reputation. Another test is suggested by the notion that with anticipation the information should be evident in R(pre) for widely followed stocks, all else the same. Yet daytime up revision average R(pre) is smaller and for down revisions is less negative.

Further tests are suggested by another variation of anticipation, that is, that the information is partially anticipated in the preperiod. However, this predicts that significant new information is often in R(ann), which is not the case. It also predicts less anticipation is prevalent among stocks that have inconsequential R(pre) (e.g., $-1\% < \text{R(pre)} < +1\%$), and thus a more informative average R(ann). Yet, average R(ann) when R(pre) is small is not different from the typical reaction (Table 6).

Contrarian revisions also allow testing for anticipation. When investors wrongly anticipate revision information in the preperiod, their R(ann) should reveal significant reaction that reflects the correction for the wrongly anticipated information, plus inclusion of the correct information. Yet, average R(ann)

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Table 6 Anticipation and Underreaction Tests

Revision direction:	Revision up					Revision down				
Item:	Number (%)	R(pre)	R(ann)	R(post)	R(all)	Number (%)	R(pre)	R(ann)	R(post)	R(all)
				Panel A: Daytime revisions						
$\lvert R(pre)\rvert < 1\%$	7,679	0.02[1]	0.03[1]	0.27[1]	0.32[1]	9,387	−0.01	−0.04[1]	−0.15[1]	−0.19[1]
Fraction trending	56.1	3.02[1]	0.05[1]	0.41[1]	3.49[1]	56.8	−4.68[1]	−0.05[1]	−0.21[1]	−4.95[1]
Fraction contrarian	43.9	−1.07[1]	0.03[1]	0.27[1]	−0.77[1]	43.2	2.51[3]	−0.03[1]	−0.01	2.47[1]
Fraction same	52.1	1.28[2]	0.05[1]	1.79[1]	3.13[1]	52.9	−1.61[1]	−0.05[1]	−2.27[1]	−3.93[1]
Fraction opposite	47.9	1.17[1]	0.03[1]	−1.21[1]	−0.02	47.1	−1.54[1]	−0.03[2]	2.29[1]	0.72[1]
				Panel B: Nighttime revisions						
$\lvert R(pre)\rvert < 1\%$	13,559	0.01[3]	0.38[1]	0.34[1]	0.73[1]	16,414	−0.02[2]	−0.36[2]	−0.09[1]	−0.46[1]
Fraction trending	54.0	2.29[1]	0.41[1]	0.31[1]	3.01[1]	55.4	−3.36[1]	−0.44[1]	−0.06[1]	−3.87[1]
Fraction contrarian	46.0	−1.06[1]	0.41[1]	0.32[1]	−0.33[1]	44.6	2.23[3]	−0.39[1]	−0.09[1]	1.76[1]
Fraction same	52.3	−0.84[1]	−0.47[1]	2.06[1]	0.74[1]	55.4	0.73[1]	0.42[1]	−1.05[1]	0.10[1]
Fraction opposite	47.7	−0.75[1]	−0.54[1]	−2.01[1]	−3.32[1]	47.8	0.73[1]	0.52[1]	1.57[1]	2.22[1]

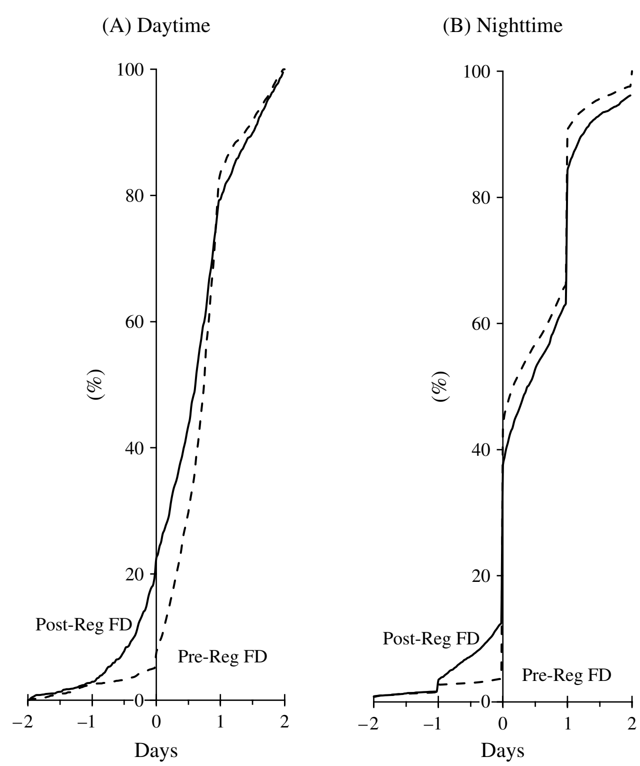
Notes. The samples are described in Table 1. Revisions are in the daytime if made on a trading day from 9:30 to 16:00 and are in the nighttime otherwise. Reported are three mean percentage returns, R(ann), R(pre), and R(post), and their cumulative sum, R(all), for up (down) revisions in the daytime or nighttime, as described in Table 2. $\lvert R(pre)\rvert < 1\%$ indicates $-1\% < R(pre) < +1\%$. A revision is trending (contrarian) if it is in the same (opposite) direction of R(pre). A revision is the same (opposite) if it is in the same (opposite) direction of R(post).
[1] [(2, 3)] Indicates statistical significance at the 1% (5%, 10%) level for two-sided student t-statistic.

for contrarian and trending revisions are under 5 bps in absolute value, in daytime and nighttime, up or down (Table 6).

Another form of anticipation could be present if analysts tend to issue forecasts sluggishly after events or significant returns. For example, practical frictions might delay the release of piggybacking reports even though they are basically completed soon after triggering news or events. In such situations, the bulk of the prerevision price responses will occur too close to the revision time stamp to be attributed to the earlier piggybacking events and news. If piggybacking from start to finish does not happen within 24 hours of the events, large absolute prereturns just before the revisions are less likely to reflect the piggybacked events and news, and could imply that anticipation of analysts' information drives those prereturns. Tests for analyst sluggishness focus on the speed of their forecast responses to earnings reports. Specifically, the cumulative frequency of forecast timing is examined over the four trading days centered on the 10-minute earnings announcement interval, or in its absence the 10-minute guidance interval (two two-day periods of 80 10-minute intervals) identified using the FC earnings announcement time stamp. If forecasts tend to be sluggish and thus respond to the earnings reports after a lengthy delay, the cumulative forecast report frequency should be low and flat and move sluggishly through the earnings announcement day into the following day. If forecasts respond quickly, the cumulative frequency should rise sharply on the earnings announcement day.

Figure 3 reports cumulative forecast frequencies before and after Reg FD, after removing reports of earnings and earnings guidance on relative days −2 or −1. For daytime reports before Reg FD, 22.5% of the forecasts are announced prior to the earnings report. This percentage quickly climbs to 81.7% on the earnings announcement day, leaving 18.3% the next

Figure 3 Cumulative Forecast Frequencies Around Earnings and Guidance Event Announcements



Notes. Shown are frequencies of daytime and nighttime forecasts, cumulated over 10-minute intervals from 80 before to 80 after (each two days) the interval 0 company announcement of earnings or guidance, pre- and post-Reg FD.

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day. Thus, more than 80% of the forecasts are issued promptly within 24 hours of the earnings announcement. After Reg FD, the response rises to 83.6% with only 5.1% issued before the earnings report. Thus, a very large fraction of forecasts is issued within 24 hours after the news, and the majority of those 24 hours are nighttime. For response time to nighttime earnings announcements, the conclusions are qualitatively similar. A huge fraction of forecasts are announced at the open after the earnings report, 93.1% before Reg FD and 95.6% after. This evidence shows that analysts' report announcements are not sluggish after significant events and news.

A concern is that these cross-section results fail to control for other possible effects. In unreported tests, we address this concern in regressions of the R(pre) cross section that include controls for firm size, cumulative return performance over the 120 days before the preperiod, the presence of key events in the preperiod, and fixed effects for sample years, followed firm industries using the Fama and French (1997) industry classifications, and brokerage firm identity. The R(pre) cross-section regression results confirm the above inconsistent and contradictory findings. They are also confirmed in unreported similar regressions of R(sum) = R(pre) + R(ann), which is free of time stamp reliability concern and thus whether analysts' information is in R(ann) or R(pre).

5. Delayed Investor Reaction

The appearance of limited or insufficient announcement information could instead be the result of persistent widespread delayed reaction to timely analyst reports, a scenario that aligns with analysts as providers of new information. Yet reasons for delay could also be a secondary concern to the extent that brokerage clients are likely to include savvy, repeat investors who are poised to jump at the chance to profit from new information. Thus, delayed reactions require the caveat that most brokerage clients are not savvy, despite the opportunities for them to benefit from analysts' new information, month after month.[8]

Hypothesis 3. *Investor reaction to analyst information is delayed.*

5.1. Testing Special Cases

If key events amplify returns and there is underreaction, postreturns should be bigger when key events precede forecast announcement. However, this is not the case for up or down revisions, in daytime or nighttime. Because the nighttime announcement window allows more mulling time than the daytime window, the nighttime return reaction, on average, should be larger. Yet it is not, either for up or down forecasts, when nighttimes with key events are removed (Table 4). Daytime and nighttime postreturns also do not differ significantly for up or down revisions, even after controlling for key events and nighttime bias (Table 4).

Perhaps investors are split—some anticipate analysts' information and others underreact to other analysts' information—thus creating little announcement reaction. Because little information is anticipated for stocks with low prereturns, in the split investor notion there should be more underreaction to forecast announcements for low prereturn stocks and, under the delay scenario, more evidence of analysts' information in the postreturns. However, the postreturns for these revisions are not more informed in the daytime or in the nighttime, whether up or down (Table 6).

Underreaction could resolve the puzzling lack of reaction to contrarian revisions, if revisions are informative. Although investors could wrongly anticipate contrarian revisions, their correction of the wrong anticipation might not show up at the announcement due to delay. This underreaction prediction is not supported by the up and down revisions, in the daytime or nighttime (Table 6).

5.2. Testing the R(post) Cross Section

R(post) appears to drift with the forecasts (Table 2). This could reflect analysts' incremental information. However, it could also reflect piggybacking on postreturn predictors. For example, the mean frequencies of some known drift events during the year before the forecasts are five earnings reports, one guidance report, 122 forecast revisions, and 13 recommendation changes. These events are also common in the quarter before the forecast revision. For the sample, 95% of the forecasts follow an earnings report, and thus PEAD, on average.[9]

The test for new information in R(post) uses a two-step estimation. Step 1 estimates the forecast revision using a linear regression model. The revision model includes revision determinants reported in the literature. UPDATE is the difference between the consensus forecast for firm j and analyst i's most recent forecast, $\text{Update}_{i,j,t} = (f_{conj,t} - f_{i,j,t-1})/p_{j,-5}$. Asquith et al. (2005) and Clement and Tse (2005) show that analysts use other recent forecasts to form their forecasts. The second instrument is the earnings SURPRISE, firm j's recent earnings less analyst i's prior forecast,

[8] In a behavioral view, investors may need time to mull over the report, adjust beliefs, and get more information. See Baker and Wurgler (2002) and the discussion therein.

[9] See Givoly and Lakonishok (1979), Elton et al. (1986), Bernard and Thomas (1989, 1990), Lys and Sohn (1990), Bhushan (1994), Trueman (1994), Womack (1996), Berk et al. (1999), Jegadeesh et al. (2004), and Barber and Odean (2008).

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$\text{Surprise}_{j,t} = (e_{j,t} - f_{i,j,t-1})/p_{j,-5}$. Lys and Sohn (1990) and Chan et al. (1996) show that revisions increase in the surprise. To test for piggybacking, the model includes R(pre) and R(pre) times a key event indicator, represented by KEYEVENT, which is equal to 1 when earnings or guidance is reported in the preperiod and 0 otherwise. Under piggybacking, R(pre) is expected to positively impact the revision, more so when there is a key event.

The step 1 estimation also includes several drift predictors that have been documented in the literature. Vega (2006) and Altınkılıç and Hansen (2009) find that trading predicts drift. To control for scale, stock price inverse five days before the announcement is used, 1/PRICE. Bernard and Thomas (1990) show that long-drift moves with standardized unexpected earning (SUE), which is quarterly earnings, $e_{j,t}$, less the prior eight quarterly mean earnings, $\mu_{j,t}$, relative to the earnings standard deviation, $\sigma_{j,t}$, $\text{SUE}_{j,t} = (e_{j,t} - \mu_{j,t})/\sigma_{j,t}$. Jegadeesh and Titman (1993), Cooper et al. (2001), and Vega (2006) show that return momentum predicts future returns. Returns over 120 days before the preperiod, R(−120 DAYS), are included. Bernard and Thomas (1989, 1990) and Vega (2006) show that momentum is dampened by market value of equity (MVE) (outstanding shares times stock price six days before). Consensus forecast change, $\text{CONCHANGE}_{i,j,t} = (f_{conj,t} - f_{conj,t-1})/p_{j,-5}$, registers other analysts' expected earnings. Brennan and Subrahmanyam (1996) and Chordia et al. (2009) show that long-drift narrows with liquidity. Also used is Amihud's (2002) liquidity measure for 120 days before the preperiod (LIQUIDITY). The estimations also use fixed effects for the forecast horizon, year, month, and day of week, and firm industry using the Fama and French (1997) industry classifications. These coefficient estimates are not reported.

The step 1 revision regression estimates are reported in columns (1) and (2) of Table 7. Most of the predictors impact the forecast revision as expected. The findings show that analysts' forecast revisions rely on public information that is known to predict the postreturn. Predictor piggybacking could improve accuracy, but it can also make the forecast appear to be informed. The forecast also responds significantly to news before the forecast announcement. The

Table 7 Forecast Revision and Postreturn Regressions

Dependent variable:	Forecast revision		R(post)			
Sample:	Daytime	Nighttime	Daytime		Nighttime	
			R(post) negative	R(post) positive	R(post) negative	R(post) positive
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	$1.56^{1}\ e^{-4}$	$1.75^{1}\ e^{-3}$	$-2.44^{2}\ e^{-2}$	$2.56^{1}\ e^{-2}$	$-2.56^{1}\ e^{-2}$	$2.42^{1}\ e^{-2}$
REVISION						
E[REVISION]			1.37^{1}	$6.70^{1}\ e^{-1}$	2.82^{1}	-2.96^{1}
RES[REVISION]			$1.37^{2}\ e^{-1}$	$3.65\ e^{-3}$	$2.31\ e^{-2}$	$8.01\ e^{-3}$
TURNOVER			$-1.62^{1}\ e^{-8}$	$2.78^{1}\ e^{-8}$	$-5.37^{1}\ e^{-9}$	$1.06^{1}\ e^{-8}$
1/PRICE	$-2.80^{1}\ e^{-2}$	$1.71^{1}\ e^{-2}$	$-2.21^{1}\ e^{-2}$	$4.45^{1}\ e^{-2}$	$-2.44^{2}\ e^{-2}$	$2.48^{1}\ e^{-2}$
SUE	$3.58^{1}\ e^{-4}$	$-2.48\ e^{-6}$	$-8.43^{1}\ e^{-4}$	$5.11^{1}\ e^{-4}$	$-1.68^{2}\ e^{-4}$	$2.64^{2}\ e^{-4}$
R(−120 DAYS) ∗ MVE	$2.46^{1}\ e^{-3}$	$1.35^{1}\ e^{-4}$	$-1.83^{1}\ e^{-13}$	$-2.21^{1}\ e^{-13}$	$1.29^{1}\ e^{-13}$	$-1.46^{2}\ e^{-13}$
CONCHANGE	$5.00^{1}\ e^{-2}$	$1.92^{1}\ e^{-2}$	$-8.46^{1}\ e^{-2}$	$6.92^{1}\ e^{-2}$	$-5.77^{2}\ e^{-2}$	$6.41^{1}\ e^{-2}$
LIQUIDITY	$3.49^{1}\ e^{-1}$	$-4.92^{3}\ e^{-14}$	$-6.49\ e^{-2}$	$-6.17^{3}\ e^{-1}$	$-9.54^{2}\ e^{-1}$	$-4.49^{3}\ e^{1}$
UPDATE	$2.83^{1}\ e^{-2}$	$8.96^{1}\ e^{-2}$				
SURPRISE	$3.23^{1}\ e^{-1}$	$-7.63\ e^{-4}$				
R(pre)	$1.63^{1}\ e^{-2}$	$-5.56\ e^{-4}$				
R(pre) ∗ KEYEVENT	$2.76^{1}\ e^{-3}$	$3.61^{1}\ e^{-3}$				
N	62,035	105,634	62,035		112,858	
R-squared	0.176	0.082	0.0054		0.0036	

Notes. Reported are regressions of the earnings forecast revision deflated by stock price and R(post). The samples are described in Table 1. Revisions are in trading hours if made on a trading day from 9:30 to 16:00 and nontrading hours otherwise. Independent variables are as follows: REVISION, the change in the forecast of firm earnings deflated by the stock price five days before the forecast is announced; E[REVISION], the predicted revision measured using columns (3) and (5) model parameters; RES[REVISION], the revision residual from columns (3) and (5) model estimations; TURNOVER, the abnormal share turnover in the preperiod relative to mean turnover the prior 120 days; 1/PRICE, the inverse of stock price before the offer period; SUE, standardized unexpected earnings; R(−120 DAYS), cumulative return over the 120 days before the preperiod; R(−120 DAYS) ∗ MVE, R(−120 DAYS) times the value of outstanding common stock as of five trading days before the revision; CONCHANGE, the change in analysts' consensus forecast for the followed firm just prior to the forecast; LIQUIDITY, Amihud's (2002) liquidity measure for the 120 days before the preperiod; UPDATE, the price-deflated difference between the consensus earnings forecast for firm *j* and analyst *i*'s most recent prior earnings forecast; SURPRISE, the firm's price-deflated recent earnings less analyst prior forecast (from FC); R(pre), return over two trading days before the announcement period; R(pre) ∗ KEYEVENT, R(pre) times the dummy variable equal to 1 when earnings or guidance is reported in the preperiod. All estimations include among the independent variables fixed effects for year, month, weekday, forecast horizon, and Fama and French (1997) industry classifications.

[1 (2, 3)] Indicates statistical significance at the 1% (5%, 10%) level for two-sided student *t*-statistic.

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response is significantly amplified when the news is linked to a key event, for both the daytime and nighttime forecasts. This is consistent with piggybacking.

The step 1 estimated forecast revision model is used to decompose the revision into its predicted component and its residual component, both of which will be used in the step 2 estimation. The step 2 regression estimation focuses on R(post). Following Vega (2006) and Altınkılıç and Hansen (2009), the estimation includes the six drift predictors and the abnormal preperiod turnover relative to mean turnover the prior 120 days (TURNOVER). The model also includes the predicted revision (E[REVISION]), which is estimated from the step 1 parameters, and the residual revision (RES[REVISION]), which is the residual from the step 1 estimation.

Because the expected revision is based on public information before the forecast it captures much of the portion of the analyst's forecast that is based on public news and contains no incremental information from the analyst. If the expected revision acts like the other noted predictors, it should raise positive postreturns and lower negative postreturns. If forecasts also provide analyst incremental information, that information is likely to be captured by the forecast residual. Thus, if the revisions contain analysts' information, the residual is expected to expand the postreturn. There is, however, a caveat: Such an effect could also result from predictors that are omitted from the expected revision built from the step 1 estimation, which could cause spurious positive correlation between the forecast residual and the postreturn.

Consider first daytime forecasts (Table 7, columns (3) and (4)). R(post) is positively impacted by the earnings surprise, momentum, the prereturn, the announcement return, and key events. The prereturn effect dampens with turnover and for larger firms. Nighttime revision estimates are qualitatively similar (Table 7, columns (5) and (6)). Greater R(post) follows a greater earnings surprise, prior returns, turnover, and key events. Short-drift shows a tendency to reverse from the prior three-month return. These results generally agree with findings reported in the literature.

Consider next the incremental forecast information. For the daytime forecasts the predicted forecast positively impacts rising postreturns. A one-standard deviation prediction increase leads to a 16 bp fall (8.5 bp rise) in rising (falling) returns. However, the residual forecast impact is inconsistent as it has no significant impact on the upward returns and a significant effect on the downward returns. Moreover, these effects are economically small; one residual standard deviation raises postreturn bps 4.9 for positive and 3.5 for negative. These effects are noticeably less than the predictors' effects. For nighttime revisions the expected forecast also has significant prediction power. Furthermore, the residual forecast is insignificant in all other cases. This evidence weighs against the conclusion that forecasts supply significantly new incremental information.

6. Conclusion

Intraday stock returns around the public announcement of analyst forecast revisions do not support forecasts in the information role. Many cross-section tests also show that the two day returns before and after forecast announcements do not behave as predicted by analysts' new information. Further new results show that a super majority of forecasts follow events and news, which are often not in machine form, and their impacts are not accounted for in studies that use long announcement return windows. In addition, new evidence shows that sorts across special forecast traits (e.g., bold, accurate, and those from reputable brokerages), do not have informative announcement period returns, but look informed when using mean multiday returns. This suggests that earlier evidence that associates the traits with new information is likely a reflection of their association with other Factiva events and news that impact multiday returns around the forecasts. Thus, the new evidence in this study showing that price reactions to forecasts are not particularly informative is, to our knowledge, the first significant evidence indicating that analysts are not vital information agents in the short run.

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