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Following the leader: a study of individual analysts' earnings forecasts ☆

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Abstract

This paper develops and tests procedures for ranking the performance of security analysts based on the timeliness of their earnings forecasts, the abnormal trading volume associated with these forecasts, and forecast accuracy. Our framework provides an objective assessment of analyst quality that differs from the standard approach, which uses survey evidence to rate analysts. We find that lead analysts identified by our measure of forecast timeliness have a greater impact on stock prices than follower analysts. Further, we find that performance rankings based on forecast timeliness are more informative than rankings based on abnormal trading volume and forecast accuracy. We also present evidence that analyst's forecast revisions are correlated with recent stock price performance, suggesting that security analysts use publicly

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available information to revise their earnings forecasts.

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1. Introduction

Full service brokerage firms provide clients with many services in addition to the execution of trades. The most visible of these services is the production of equity research. Most brokerage firms employ a number of analysts with expertise in tracking certain industries and following selected firms within those industries. These analysts produce research reports that include forecasts of future earnings, information about the company's markets and products, and ultimately investment recommendations.

An analyst may have a comparative advantage in analyzing certain stocks based on innate ability, industry-specific human capital, or an underwriting relation between a company and the brokerage firm's investment banking group. Over time, these factors may permit dominant or *lead* analysts to become recognized for the superior value of their earnings forecasts and trading recommendations. To the extent that disclosures by lead analysts have more influence on the decisions of investors, lead analysts will have a greater impact on the prices and trading volume of stocks than other analysts.

The hypothesis that analysts' earnings forecasts and investment recommendations have a significant impact on prices and trading volume is consistent with recent research. Stickel (1992) finds a positive relation between the information contained in earnings forecasts and security returns. He also shows that this reaction is more pronounced for *Institutional Investor* All-Stars than for other analysts. Womack (1996) demonstrates that the subsequent returns on stocks receiving new buy and sell ratings are consistent with analysts' recommendations, thus creating investment value for investors.

Comparative advantages in analyzing particular companies may permit lead analysts to release earnings forecasts that are timelier than forecasts by other analysts. Since brokerage firms' profits depend directly on commission revenues, analyst compensation is based, in part, on the trading volume generated by their research. This gives superior analysts an incentive to release information before other analysts in order to capture trading volume for their firms. But timeliness and volume aren't the superior analyst's only measures of performance. Selection to the roster of an All-Star analyst list, such as those published by *Institutional Investor* and *The Wall Street Journal* can determine compensation.

Since analyst compensation and tenure is also based on forecast accuracy, analysts having lesser ability may delay the release of their forecasts to use information produced by lead analysts to improve forecast accuracy. Thus, forecast revisions by lead analysts may trigger the release of revised forecasts by other analysts.

The clustering of analysts' forecasts following a forecast release by the lead analyst is consistent with the reputation-based herding models of Graham (1999) and Trueman (1994). Graham finds that investment newsletters herd following the release of market timing advice in the *Value Line Investment Survey*. Trueman shows that high quality analysts are more likely to deviate from the consensus, which is consistent with Stickel's (1990) finding that *Institutional Investor* All-Stars are less likely to rely on consensus forecasts than other analysts. Similarly, Lamont (1995) finds that the magnitude of deviations from consensus forecasts increases with a forecaster's age. He argues that analysts with track records have less incentive to herd since their true ability can be inferred more accurately.

This article shows that an ex ante measure of analyst performance can be constructed by exploiting tendency for analysts to herd following the release of earnings forecasts by superior analysts. In particular, we show that lead analysts can be identified by the timeliness their earnings forecasts. We then compare this approach to identifying lead analysts with ex ante performance rankings that are based on abnormal trading volume and forecast accuracy.

Quantitative approaches to identifying lead analysts such as those we explore here differ from those used in the investment community. For example, *Institutional Investor* magazine ranks analysts by polling directors of research and chief investment officers at major money management institutions. The main advantage of a survey is that investment professionals are in the best position to know who does the best job. However, analyst polls may be criticized for rewarding analysts who have been around a long time or who aggressively lobby their customers for votes.

We find that forecast revisions by lead analysts ranked according to the timeliness of their forecasts have a greater release-period impact on stock prices than forecasts by follower analysts. Further, we present evidence that performance rankings based on the timeliness of analysts' forecasts are more informative than performance rankings based on either forecast accuracy or the abnormal trading generated by an analyst's forecasts. Our results also show that analysts' forecast revisions are correlated with recent stock price performance, suggesting that security analysts use publicly available information to update their earnings forecasts.

The measures of performance that we use to identify lead analysts are discussed in Section 2. In addition, we formulate testable hypotheses concerning the relation between excess stock returns and forecast revisions by lead and follower analysts. The statistical measures that we use to identify lead analysts are described in Section 3. Section 4 examines the congruence of these performance measures. In Section 5, we present tests of our hypotheses concerning analyst performance. Section 6 considers whether certain forecast revisions are more informative than others. We conclude the paper in Section 7.

2. Components of analyst performance

This section describes the testable hypotheses that differentiate lead and follower analysts. We identify lead analysts using the timeliness of their forecasts relative to other analysts, the trading volume these forecasts generate, and the accuracy of earnings forecasts. Although we consider forecast timeliness to be the most intuitive criterion for classifying analysts as leaders and followers, the fact that analyst compensation is related to both forecast accuracy and trading volume suggests that these measures may also be useful in classifying analysts as leaders and followers.

2.1. Timeliness

By definition, lead analysts have advantages in collecting and processing information that permit them to release earnings forecasts before competing analysts. The timeliness of their releases may be accentuated by a tendency for other analysts to delay the release of their forecasts to incorporate the information produced by the lead analysts. Thus, the relative timeliness of an analyst's forecasts may be used as a proxy for unobservable advantages in the production of earnings forecasts.

The hypothesis that timeliness is a proxy for superior skill can be tested by regressing excess stock returns on the unexpected or surprise component of the respective forecast revisions by lead and follower analysts. The slope coefficients for these regressions, which we refer to as forecast response coefficients (FRCs), can then be used to compare the value of the incremental information in analysts' earnings forecasts. If lead analysts produce superior earnings forecasts, the unexpected component of their forecasts should have a greater impact on excess stock returns than the corresponding "forecast surprises" for follower analysts. The preceding year is used to classify analysts as leaders and followers in order to eliminate any dependence of our classification procedures on the excess returns associated with forecast revisions. The use of the prior year's data to classify analysts as leaders and followers may be viewed as an "estimation period" used by market participants to infer an analyst's relative ability. We refer to this hypothesis as the Relative Information Content Hypothesis:

Relative Information Content Hypothesis. The FRCs for lead analysts are greater than the corresponding FRCs for follower analysts.

The timeliness hypothesis also suggests that forecasts by lead analysts reflect the discovery and analysis of new information. This implies that lead analysts' forecasts should be independent of excess returns during the pre-release period. By contrast, the inability of follower analysts to produce timely investment research suggests that their forecasts are more likely to rely on public information such as recent corporate disclosures, trends in stock prices, and forecasts by lead analysts. Thus, forecasts by follower analysts may be correlated with excess stock returns during the pre-release period. These arguments suggest the following hypothesis:

Information Creation Hypothesis. Forecast surprises by lead analysts are independent of excess returns during the pre-release period, while forecast surprises by follower analysts are positively related to excess stock returns during the pre-release period.

Since security analysts play an important role in providing investors with information, we examine the speed with which stock prices impound the information contained in analysts' forecast revisions. If security prices quickly adjust to reflect the information in forecast revisions, there should be no excess stock returns during the post-revision period. However, if investors react slowly or overreact, it may be possible to earn excess profits using trading strategies based on forecast revisions. This suggests the following hypothesis:

Zero Trading Profits Hypothesis. Excess stock returns during the post-release period are independent of the surprise component of analysts' forecast revisions.

The potential profits from trading strategies based on analysts' forecast revisions are of both practical and academic interest. However, excess stock returns during the period following forecast revisions must be interpreted with caution. For example, investors may use earnings forecasts by followers to confirm forecasts by lead analysts. Alternatively, if forecasts by lead analysts anticipate important corporate disclosures, post-release excess returns may be triggered by the official announcement.

2.2. Trading volume

To the extent that lead analysts provide information that is not reflected in the prices of the stocks they follow, we should observe an increase in trading volume following the release of their forecasts. By contrast, since forecast revisions by follower analysts tend to be redundant, trading volume is less likely to increase. Therefore, the abnormal trading volume associated with an analyst's forecast revisions provides a natural proxy for the information content of an analyst's forecast revisions.

Measures of analyst performance based on abnormal trading volume avoid one of the potential drawbacks associated with measures of an analyst's timeliness. Although lead analysts tend to produce more timely forecasts, the fact that it takes time to evaluate new information implies that the lead analyst may not always be the first to release a revised forecast. Analyst rankings based on abnormal trading volume avoid this problem by identifying analysts whose forecasts contain valuable information, but who may not consistently release the timeliest forecasts.

The use of abnormal trading volume to measure analyst performance also has disadvantages. For example, abnormal volume may be attributable to either market-wide news or an important corporate announcement. In spite of these potential drawbacks, the classification of analysts using measures of abnormal trading volume is a useful check on the sensitivity of our results to any trade-off between timeliness and information content implicit in the production of forecast revisions. Therefore, we examine each of the hypotheses developed previously for lead analysts identified using the abnormal trading volume associated with their forecast revisions.

2.3. Accuracy

Analysts must provide accurate earnings forecasts on a timely basis if investors are to profit from their research. Consequently, a lead analyst may choose to sacrifice small improvements in accuracy to release information before competing analysts can update their forecasts. The willingness to trade accuracy for timeliness is due to lead analysts' desire to maximize compensation, which can depend on the trading volume generated by their research. Releasing timely forecasts allows the lead analyst to take credit for any increase in trading volume generated by their information. However, since follower analysts can update their forecasts using information released by lead analysts, accuracy differences between lead and follower analysts may not be as large as would be expected given lead analysts' advantages in producing information.

We expect to find a positive relation between forecast accuracy and the market impact of an analyst's forecasts. However, the relation between excess returns and the surprise component of earnings forecasts by accuracy leaders should be weaker than the corresponding relation for lead analysts ranked according to timeliness and trading volume due to potential misclassification problems. These arguments can be summarized by the following hypothesis:

Information Creation/Accuracy Tradeoff Hypothesis. There is no significant difference between the FRCs for lead and follower analysts ranked according to forecast accuracy. Further, the FRCs for lead analysts ranked by timeliness and trading volume are greater than the FRCs for lead analysts ranked by forecast accuracy.

2.4. The congruence between proxies for analyst performance

Each of the performance measures that we have discussed is designed to identify superior analysts based on different objective criteria. To the extent that these measures have validity, they should identify the same set of analysts. Unfortunately, each approach has certain limitations. If the measurement problems associated with one or more of these performance measures are severe, analysts' rankings will differ across performance measures. By contrast, if they provide accurate assessments of the relative value of analysts' forecasts, these rankings should be highly correlated.

We expect the ranking procedures based on timeliness and abnormal trading volume to identify the same set of analysts. However, since follower analysts can easily improve their forecast accuracy by free riding on the forecasts of timely analysts, the correlation between rankings based on ex post forecast accuracy and rankings based on timeliness and trading volume should be very weak. Thus, we examine the hypothesis that:

Ranking Congruence Hypothesis. Rankings of analyst performance by measures of forecast timeliness and abnormal trading volume will be positively correlated, while rankings based on forecast accuracy will be uncorrelated with rankings based on forecast timeliness and abnormal trading volume.

3. Statistical measurement of analyst performance

This Section discusses the data and performance statistics that we use to measure the timeliness, accuracy, and volume impact of an analyst's earnings forecasts. We also discuss the procedures that are used to examine the relation between stock prices and the information content of analysts' forecasts.

We examine earnings forecasts for firms in two industries: (1) high-tech firms that manufacture semiconductors and printed circuit boards and (2) low tech firms in the restaurant industry. Both industries are characterized by intense competition among firms to innovate. However, high-tech firms face rapid technological change, while marketing initiatives and consumer trends drive innovation in the restaurant industry. In both cases, the analysts who follow these industries have the opportunity to create significant value for investors who are unable to accurately gauge relative investment value.

Table 1
Analysis of forecast revisions by high-tech and low-tech analysts

This table summarizes the number of firms, analysts, and forecast revisions included in the high-tech and low-tech samples for the period from January 1, 1993 through March 31, 1995. The number of observations eliminated due to missing stock return, trading volume, or earnings filters, as well as, the number of observations occurring within an n-day window surrounding quarterly earnings report dates are also reported.

	High-tech firms		Low-tech firms		Total	
	Amount	%	Amount	%	Amount	%
Firms	77		79		156	
Analysts	201		157		358	
Forcast revisions:						
Total available	2917		4030		6947	
Lost observations due to						
Missing returns data	2	0.1	6	0.1	8	0.1
Missing returns and volume data	8	0.3	61	1.5	69	1.0
Missing returns and fiscal year-end earnings data	3	0.1	14	0.3	17	0.2
Revisions in n-day window surrounding earnings announcement dates:						
On quarterly anouncement date	69	2.4	190	4.7	259	3.7
Within 1-Day	300	10.3	497	12.3	797	11.5
Within 2-Days	468	16.0	644	16.0	1112	16.0
Within 3-Days	594	20.4	737	18.3	1331	19.2
Within 4-Days	721	24.7	843	20.9	1564	22.5
Within 5-Days	811	27.8	967	24.0	1778	25.6

The industry classifications are based on the Institutional Brokers Estimate System (I/B/E/S) industry grouping codes.[1] The sample includes all annual earnings forecasts reported to I/B/E/S for the period January 1, 1993 through March 31, 1995. The beginning of the sample period in 1993 coincides with the approximate date at which I/B/E/S began to update analysts' forecasts on a daily basis. Prior to this, analysts' forecasts were updated weekly or in some instances monthly. Unfortunately, I/B/E/S cannot identify the exact date that these reporting changes occurred.

Table 1 shows that our sample includes 358 analysts, who made 6,947 earnings forecasts for 156 firms. The 201 high-tech analysts made an average of 37.9 earnings forecasts per firm, which reflects an average of 14.5 forecasts per analyst. The 157 low-tech analysts appear to work much harder. They cover a similar number of firms; yet manage to produce an average of 51.0 forecasts per firm, which represents 25.7 forecasts per analyst.

Stock return and daily trading volume data were obtained from the Interactive Data Corporation Stock Price database. Year-end earnings data were obtained from the I/B/E/S earnings file. We eliminate all observations for

[1] The I/B/E/S industry groupings were as follows: semiconductors (80802), printed circuit boards (80801), and restaurants (40303).

which daily stock returns, daily trading volume, or annual earnings per share data are unavailable. As noted in Table 1, eight observations were eliminated due to missing stock return data, while missing trading volume and earnings per share data respectively eliminated 69 and 17 observations.

We control for the tendency of analysts to revise year-end forecasts following the release of quarterly earnings by eliminating forecast revisions that occur within five days of the quarterly earnings report. Since analysts tend to mechanically adjust their annual forecasts to reflect the surprise contained in quarterly earnings announcements, these forecast revisions are unlikely to contain new information. The severity of this problem is illustrated in Fig. 1, which depicts the clustering of forecast revisions surrounding quarterly earnings reports. Revisions continue after the fiscal year end until the firms release their final earnings numbers.

Table 1 summarizes the number of forecast revisions that occur around the quarterly earnings announcement date. A total of 259 forecast revisions representing 3.7% of the sample were released on the same date as a quarterly

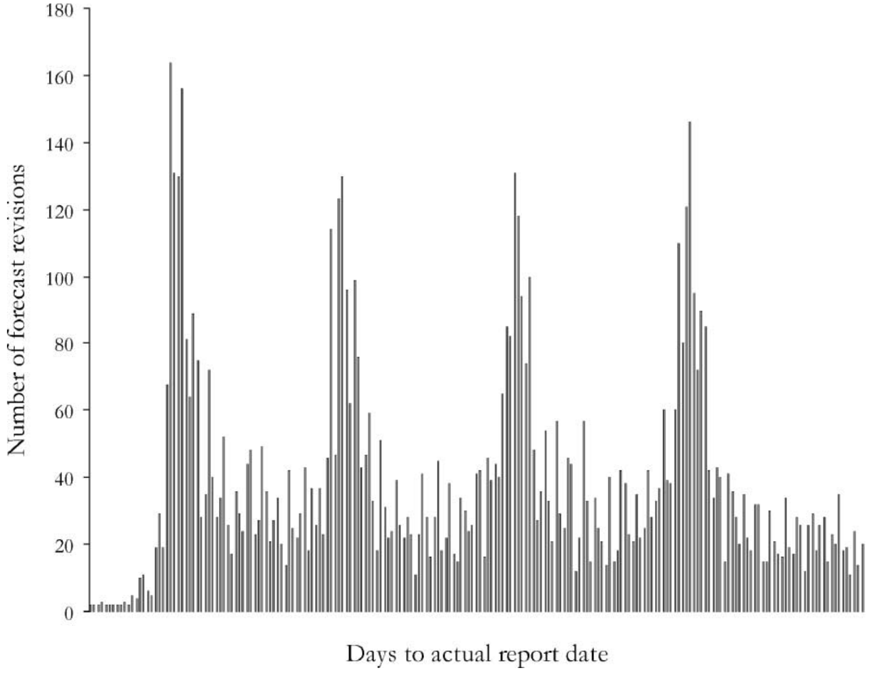

Fig. 1. Forecast revision frequency. This figure cumulates the number of forecast revisions for all sample firms relative to the actual earnings report date. The X-axis is measured as the number of days to the actual report date with the actual earnings report date appearing as the last entry on the right hand side of the chart. We cumulate the number of revisions by non-overlapping, two-day periods for illustration purposes.

earnings report. In addition, 25.6% of the earnings forecasts were released within a five-day window surrounding the quarterly earnings announcements. Following the elimination of these observations, the final sample includes 5,137 earnings forecasts.

The following subsections describe the measures of timeliness, trading volume, and forecast accuracy that we use to classify analysts as leaders and followers. Each of these performance measures is used to identify lead analysts during an estimation period from January 1, 1993 through December 31, 1993. Given the lead analysts identified by each of these performance measures, we test our hypotheses concerning analyst performance using a sample that covers the period from January 1, 1994 through March 31, 1995.

3.1. Analyst timeliness

The hypothesis that follower analysts herd on earnings forecasts by lead analysts is based on the assumption that they free-ride on the information produced by the leader. Consequently, forecast revisions by lead analysts should be followed closely by the forecast revisions of other analysts. To test this hypothesis, we assume that conditional on the release of a forecast revision by a lead analyst, the times until the release of revised forecasts by follower analysts have independent exponential distributions,

$$\frac{1}{\theta_1}e^{-t/\theta_1}, \tag{1}$$

where the expected time until the release of the next forecast revision, θ_1, is the same for each follower analyst.[2] Similarly, conditional on the release of a forecast revision by a follower analyst, the times until the release of forecast revisions by other analysts have independent exponential distributions with expected release times given by θ_0.

Followers who herd will quickly update their forecasts following the release of an earnings forecast by the lead analyst. However, they have no incentive to revise their forecasts in response to forecast revisions by other followers. Consequently, θ_0 must be greater than θ_1.

We identify lead analysts by comparing the expected release times of forecasts by other analysts during the periods preceding and following each analyst's forecast revisions. We estimate these expected release times for

[2] The exponential distribution is commonly used to model arrival times in medical studies of smoking and drug development, as well as the failure rates associated with new and existing equipment. More recently, time series econometricians have applied the exponential distribution to study the behavior of high-frequency stock price data. For example, Engle and Russell (1998) use the exponential distribution to develop their autoregressive conditional duration (ACD) model, which characterizes the arrival process for stock transactions. Lawless and Lawless (1982) provides an excellent textbook treatment of the exponential distribution.

each analyst using the cumulative analyst days required to generate the N forecasts preceding and following each of the K forecasts by that analyst. Let t_{ik}^0 and t_{ik}^1 denote the number of days by which forecast i either precedes or follows the kth forecast by a selected analyst. The cumulative lead-time for the K forecasts by a given analyst is

$$T_0 = \sum_{k=1}^{K} \sum_{i=1}^{N} t_{ik}^0. \tag{2}$$

Similarly, the cumulative follow-time for these K forecasts is,

$$T_1 = \sum_{k=1}^{K} \sum_{i=1}^{N} t_{ik}^1. \tag{3}$$

Our estimates of cumulative lead-times and follow-times for a given analyst exclude any additional forecasts by that analyst during the pre- or post-release periods. When more than one forecast revision is released on a given day, we exclude each of these forecasts from the computations of the cumulative lead- and follow-times for the respective analysts.

The maximum likelihood estimates of the expected forecast arrival times during the pre- and post-release periods ($\hat{\theta}_0$ and $\hat{\theta}_1$) are respectively equal to T_0/N and T_1/N. Since $2T_0/\theta_0$ and $2T_1/\theta_1$ are distributed as $\chi^2_{(2KN)}$ (see Lawless and Lawless, 1982), the test statistic

$$LFR = \frac{2T_0/\theta_0}{2T_1/\theta_1}, \tag{4}$$

is distributed as $F_{(2KN,\,2KN)}$. This implies that we can determine whether an analyst is a leader or a follower using the test statistic,

$$LFR = \frac{T_0}{T_1}. \tag{5}$$

We refer to this test statistic as the leader–follower ratio (LFR). Since a timeliness leader systematically releases forecast revisions before other analysts, a lead analyst has an LFR statistic greater than one.

Fig. 2 illustrates the computation of the LFR ratio for a single forecast by a lead analyst. The earnings forecasts by analysts C and D precede the leader's forecast by a cumulative total of 19 analyst days. By contrast, only three cumulative analyst days are required to generate the forecasts by analysts X and Y following the release of the leader's forecast. The quick response by X and Y is typical of follower analysts. The LFR statistic for this example is 6.33 (i.e., $(10+9)/(1+2)$).

Fig. 3 illustrates the pattern of forecast release dates for a follower analyst. The earnings forecasts by analysts C and D precede the follower's forecast by a cumulative total of three days, and the forecasts by analysts X and Y follow the follower's forecast by a cumulative total of 19 days. The scarcity of forecast

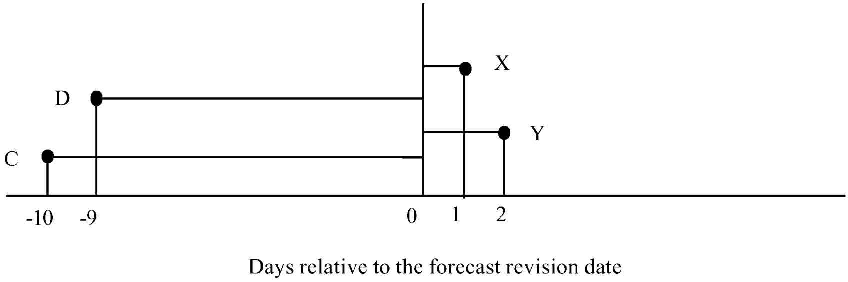

Fig. 2. Forecast revision dates surrounding the forecast revision of a lead analyst. This timeline depicts the forecast revision dates for analyst i and the two most recent forecast revisions before and after analyst i's revision. This situation depicts the hypothesized behavior of a lead analyst. A lead analyst revises a forecast before other analysts and such an action induces others analysts to revise their forecasts. The LFR equals $(10+9)/(1+2) = 6\ 1/3$.

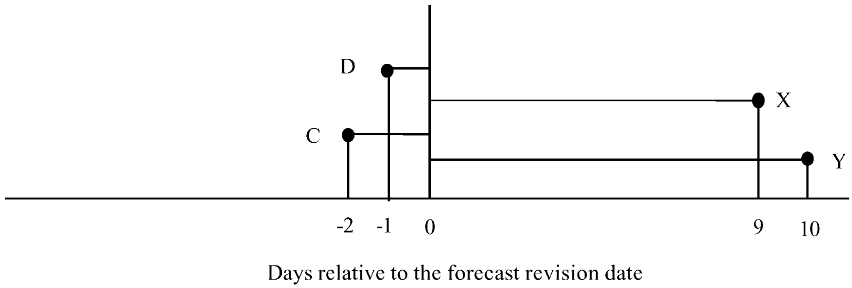

Fig. 3. Forecast revision dates surrounding the forecast revision of a follower analyst. This timeline depicts the forecast revision dates for analyst i and the two most recent forecast revisions before and after analyst i's revision. This situation depicts the hypothesized behavior of a follower. A follower revises a forecast after the lead because the lead analyst's forecasts contain valuable information. The LFR equals $(2+1)/(9+10) = 3/19$.

revisions following the release of the follower's earnings forecast implies that this forecast is not sufficiently informative to cause other analysts to update their own forecasts. As expected, the LFR statistic of 3/19 is less than one.

A firm-specific LFR statistic can be calculated by computing lead and follow times across all forecast revisions for a given analyst on a firm-by-firm basis. Alternatively, an industry-based LFR can be computed by cumulating across all forecasts for the firms that an analyst follows. Since the investment community tends to evaluate analyst performance at the industry level, our results focus on analysts who are identified as industry leaders.[3]

To minimize the possibility that an analyst's ranking is attributable to a single lucky forecast, our rankings of industry leaders include only those

[3] An earlier version of this paper presented results for individual firm leaders as well. These results, which are available on request, are qualitatively similar to our results for industry leaders.

analysts who made at least five forecasts for firms within the industry. After imposing this restriction, all analysts having LFR ratios significant at the 10% level are classified as timeliness leaders. All remaining analysts are classified as followers.

Fig. 4 illustrates the empirical distribution of the leader follower ratios for the low-tech and high-tech analysts. The lighter shaded bars in the foreground depict the sample distribution of the LFRs for low-tech analysts, while the darker shaded bars in the background represent the high-tech analysts. The average LFR for the low-tech sample is 1.17, with a standard deviation of 0.83. Since the LFR is bounded below at zero, the distribution is positively skewed with sample skewness of 4.16. The sample statistics for the high-tech analysts are similar with an average LFR of 1.25, a standard deviation of 1.76, and skewness of 6.77. These sample statistics are consistent with the underlying assumption that the LFR statistic has an F-distribution.

3.2. Trading volume

Analysts may also be classified as leaders using the abnormal trading volume associated with their forecast revisions. Following Michaely and Vila (1996), we estimate abnormal trading volume by expressing daily turnover (trading volume divided by shares outstanding) as a percentage deviation from the

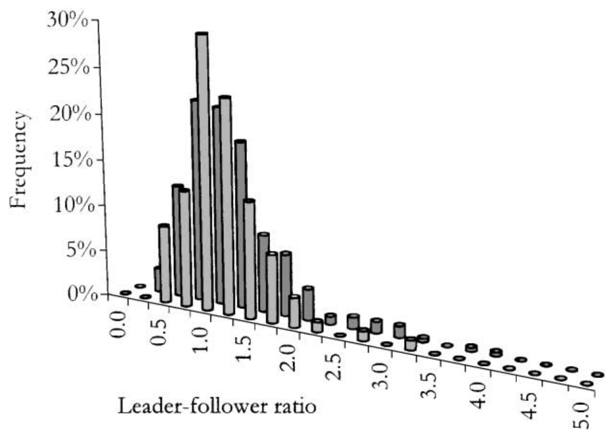

Fig. 4. Distribution of industry-based leader–follower ratios. This figure illustrates the empirical distribution of leader–follower ratios for the low-tech and high-tech analysts. The lighter (darker) shaded bars represent low-tech (high-tech) analysts. The Y-axis is measured as the number of analysts relative to the total number of analysts in a given industry as a percentage for the low-tech and high-tech industries. The leader-follower ratios are organized in bins that start at 0.00 to 0.25 and end with a bin that contains all values greater than 5.0.

average turnover for the periods prior and subsequent to the event window for each forecast revision. The average daily turnover for forecast i is computed using days -81 to -41 and days $+41$ to $+81$ relative to the forecast release date,

$$ATO_i = \frac{\sum_{t\in[-81,-41]\cup[+41,+81]} TO_{it}}{T}, \tag{6}$$

where TO_{it} represents the turnover for security i on day t, and T is the number of days during the pre and post-release periods. For each day during the forecast release period, abnormal volume is computed using the ratio of turnover for day i to the average turnover

$$AV_{it} = \frac{TO_{it}}{ATO_i} - 1, \quad t\in -21, \ldots, +21. \tag{7}$$

We examine the timing of abnormal trading volume relative to the forecast release date by dividing the event window surrounding the forecast release into a two-day release period beginning with the day prior to the reported forecast release, as well as 20-day pre-release and 21-day post-release periods. A 45-day forecast release period permits us to examine abnormal stock price performance for a full month prior and subsequent to the forecast release date, assuring that our results reflect the impact of important corporate disclosures that might either trigger or be anticipated by analysts' forecasts. The event window used to estimate normal daily trading volume permits us to use a four-month period that should not be correlated with any abnormal volume during the four-month period surrounding the forecast release. The cumulative abnormal volume (CAV) within each sub-period is computed by summing the daily abnormal volume,

$$CAV_i = \sum_{t=t_1}^{t_2} AV_{it}, \tag{8}$$

where t_1 and t_2 represent the beginning and ending dates of the applicable sub-period.

Summary statistics for the abnormal trading volume around forecast release dates are reported in Table 2. The average CAV during the forecast release period exceeds trading levels during the pre- and post-release periods. High-tech firms have an average release period CAV of 0.509 compared to pre- and post-release CAVs of 0.408 and 0.299. Similarly, low-tech firms have an average release period CAV of 0.460 compared to pre- and post-release CAVs of 0.216 and 0.151.

It also is of interest to note that the abnormal trading volume is greater in the pre-release period than the post-release period. This likely reflects corporate disclosures or market-wide information that causes analysts to update their earnings forecasts. Alternatively, it may reflect selective

Table 2
Summary statistics for forecast revisions by individual analysts

This table presents summary statistics for a sample of 5,137 earnings forecasts released by analysts for firms in the semiconductor and restaurant industries during the period January 1, 1993 to March 31, 1995. Cumulative abnormal volume is computed as the difference between actual turnover (volume divided by shares outstanding) during a given period and expected turnover based on the average daily turnover, scaled by expected turnover. The average daily turnover is estimated using the two-month periods preceeding and following the event window surrounding the forecast revision. Cumulative excess returns are computed as the difference in the buy-and-hold returns for the relevant common stock and the I/B/E/S Industry Index over the indicated period. The forecast surprise is the current forecast by analyst i net of either a measure of the consensus forecast across all analysts or actual earnings. An event is classified as good news if the forecast surprise based on the 60-day consensus forecast is positive and bad news otherwise.

	High-tech – semiconductors		Low-tech – restaurants	
	Mean	Standard deviation	Mean	Standard deviation
Cumulative abnormal trading volume:				
Prior to forecast revision	0.408	1.002	0.216	0.857
Forecast revision period	0.509	1.857	0.460	3.032
Following forecast revision	0.299	1.024	0.151	0.793
Forecast accuracy:				
Actual earnings	0.795	1.110	0.223	0.375
Percentage forecast error relative to actual earnings	0.755	4.190	0.638	2.200
Forecast surprise:				
60-day consensus forecast	0.019	0.220	0.132	0.329
Previous earnings forecast	0.080	0.246	−0.029	0.087
Stock returns – all events:				
Prior to forecast revision	4.44%	15.51%	−2.01%	12.10%
Forecast revision period	0.19%	3.36%	−0.05%	3.23%
Post-revision period	3.95%	12.78%	−0.44%	10.30%
Stock returns – good news events:				
Prior to forecast revision	6.05%	15.63%	−0.92%	11.52%
Forecast revision period	0.30%	3.40%	0.06%	2.82%
Post-revision period	4.24%	13.13%	0.17%	10.28%
Stock returns – bad news events:				
Prior to forecast revision	2.08%	15.04%	−4.08%	12.89%
Forecast revision period	0.01%	3.31%	−0.26%	3.87%
Post-revision period	3.53%	12.25%	−1.59%	10.24%
Observations:				
All events	2104		3033	
Good news events	1248		1988	
Bad news events	856		1045	

distribution of analysts' forecasts to preferred customers prior to their official release.

We refer to analysts whose forecast revisions are associated with significant abnormal trading volume during the forecast release period as volume leaders. To control for differences in the variability of trading volume over time and across firms, we standardize the abnormal trading volume for each forecast i (AV_{it}) using the standard deviation of the daily turnover for days −81 to −41 and +41 to +81 ($\sigma(TO_i)$).

The Central Limit Theorem implies that the standardized abnormal volume for each day t has a standard normal distribution. Assuming that daily trading volume is independently distributed, the standardized cumulative abnormal volume during the release period for forecast i,

$$SCAV_i = \sum_{t=-1}^{t=0} \frac{TO_{it} - ATO_i}{\sigma(TO_i)}, \tag{9}$$

has a normal distribution with mean zero and standard deviation $\sqrt{t_2 - t_1 + 1}$.

Let $Avg(SCAV_i)$ and $\sigma(SCAV_i)$ denote the sample mean and standard deviation of the analyst's cumulative abnormal volume during the two-day forecast release period and let I denote the number of forecast revisions by an analyst during the estimation period. Then the test statistic TAV is calculated as:

$$TAV = \sqrt{I-1} \times Avg(SCAV_i)/\sigma(SCAV_i) \tag{10}$$

and has a t-distribution with $I-1$ degrees of freedom.

The TAV statistic can be used to rank analysts according to the significance of either their firm-specific or industry-wide trading volume. As with timeliness leaders, we require that volume leaders release five or more forecasts within an industry. Those analysts having TAV statistics significant at the 1% level who also rank in the top decile are classified as volume leaders.

3.3. Forecast accuracy

Timeliness and abnormal volume are indirect measures of the quality of an analyst's research. By contrast, forecast accuracy is an absolute measure of quality. We measure each analyst's forecast accuracy using the average percentage forecast error adjusted for the tendency for analysts to become less optimistic as the earnings announcement draws near. The percentage forecast error for analyst i's forecast of earnings per share at date t is,

$$FE_{it} = \frac{FEPS_{it} - EPS}{|EPS|}, \tag{11}$$

where $FEPS_{it}$ is analyst i's forecast of earnings per share at date t and EPS is the reported earnings level at the end of the forecast horizon.

Table 2 shows that the average mean forecast error is 0.795 for high-tech and 0.223 for low-tech analysts. The average percentage errors also are positive. These findings indicate that the forecasts in our sample are subject to the optimistic bias found previously by Brown et al. (1985), O'Brien 1998, and Butler and Lang (1991).

To control for this bias, we regress FE_{it} on the length of time from the forecast release date to the annual earnings announcement. Since the residual from this regression is free of bias related to the length of the forecast horizon, the absolute value of the regression errors can be used to measure the accuracy of the earnings forecasts in our sample. The forecast accuracy regression is estimated as

$$FE_{it} = b_0 + b_1 T + \varepsilon_{it}, \tag{12}$$

where T is the number of days until the earnings announcement date and ε_{it} is the residual forecast error for analyst i on date t.

Table 3 reports the estimated regression coefficients for high-tech and low-tech analysts. In both cases, the slope coefficient is positive and significant, consistent with the trend in analysts' forecasts found by Chopra (1998). The relative magnitudes of the slope and intercept imply that high-tech and low-tech analysts remain overly optimistic until respectively 80 and 51 days prior to the release of corporate earnings. Since it takes approximately 60 days to audit annual financial statements, the optimistic bias is eliminated close to the fiscal year-end date.

We rank each analyst according to average forecast accuracy during the preceding year

$$Avg(ACC_i) = \sum_{t=1}^{N} |\varepsilon_{it}|/N, \tag{13}$$

where N is the number of forecasts revisions by analyst i. Analysts ranked in the top decile for each industry are classified as industry leaders, subject to the requirement that they make at least five forecast revisions.

3.4. Forecast surprises and consensus forecasts

We expect that lead analysts' provide more information to investors when their earnings forecasts differ significantly from the consensus of their peers. The incremental information content of analysts' forecasts can be estimated by translating each earnings estimate into a forecast surprise relative to a consensus forecast based on the average of the most recent forecasts by analysts who have released earnings estimates during the last 60 days. The exclusion of stale forecasts improves the quality of our consensus estimates by eliminating forecasts from analysts who do not closely follow the stock.

Table 3
Adjustments for horizon-related biases in analyst's earnings forecasts: OLS coefficients for regressions of percentage forecast errors on the length of the forecast horizon

We estimate the following regression model:

$$FE_i = b_0 + b_1 T + \varepsilon_i,$$

where FE_i is the percentage forecast error by analyst i and T is the number of days until the earnings announcement date. Percentage forecast errors are computed as the difference between analysts' earnings forecasts and the actual earnings scaled by the absolute value of actual earnings. The first column reports estimates of the intercept, while the second column reports the estimated coefficients for the number of days remaining until the earnings announcement. The standard errors and the p-values are reported directly below the coefficient estimates. The third columns reports the implicit estimate of the remaining days until the earnings announcement when the optimism bias is eliminated, while the fourth column reports the adjusted R^2. The sample covers the period from January 1, 1993 through December 31, 1993.

	Intercept (b_0)	Days to annual earnings announcement (b_1)	Days remaining in fiscal year when optimism bias is eliminated	Adjusted R^2
High-tech analysts				
Coefficient estimate	−0.7750	0.0098	79.9	0.055
Standard error	0.1818	0.0008		
p-value	0.0001	0.0001		
Low-tech analysts				
Coefficient estimate	−0.2593	0.0051	50.7	0.036
Standard error	0.1236	0.0005		
p-value	0.0360	0.0001		

The information content of an individual forecast may be diminished by wide variation in opinions across analysts. To control for the variability of forecasts across analysts, we scale each forecast surprise by the standard deviation of the forecasts comprising the consensus. The forecast surprise for analyst i at date t is given by

$$FS_{it} = \frac{FEPS_{it} - CF_{t-1}}{\sigma(CF_{t-1})}, \tag{14}$$

where $FEPS_{it}$ is the revised forecast by analyst i on day t, CF_t is the consensus forecast on day t, and $\sigma(CF_t)$ is the standard deviation of the consensus forecast for date t. Scaling forecast revisions by the price per share does not change our conclusions.

Table 2 shows that high-tech analysts increased their earnings forecasts by an average of \$0.08, while low-tech analysts reduced their earnings forecasts by an average of \$0.029. The direction of these revisions is consistent with the trends in prices and earnings during the sample period, which was positive for high-tech firms and negative for low-tech firms. Interestingly, on average high-tech and low-tech analysts respectively increased their earnings estimates relative to the consensus forecast by \$0.019 and \$0.132. This finding is consistent with the hypothesis that the average analyst is reluctant to make downward adjustments in estimates of future earnings.

3.5. Stock price behavior around forecast revision dates

The predictive content of the alternative procedures that we use to rank analyst performance can be compared by examining the relation between excess stock returns and analysts' forecast surprises during the out-of-sample period subsequent to the analysts' classification as leaders and followers. In particular, we examine the relation between analysts' forecast surprises and the cumulative excess returns during the 20-day pre-release period, the two-day forecast release period, and the 21-day post-release period. The cumulative excess returns for each sub-period are computed using the difference between the buy-and-hold return for the company's common stock and the value-weighted I/B/E/S industry index.

Summary statistics for stock returns during each of the three sub-periods surrounding the forecast release date are reported in Table 2. In addition to the mean and standard deviation of the returns for each sub-period, we report summary statistics for stock returns following forecast revisions classified as good news and bad news according to whether the revised forecast is greater or less than the current consensus.

These summary statistics are computed for each industry using raw stock returns, rather than the industry-adjusted returns used in our hypothesis tests. This is done to highlight the differences in industry performance during the sample period. Note that the average returns for high-tech firms are positive during each sub-period, while the average returns for low-tech firms are uniformly negative. In spite of the differential between their average event-period returns, high-tech and low-tech firms receiving good news forecast revisions both outperform firms receiving bad news forecast revisions by approximately 0.30% during the forecast release period.

The average pre-release returns associated with good news and bad news earnings forecasts for high-tech firms are respectively 6.05% and 2.08%. This differential between the average returns for firms that subsequently receive good news and bad news forecasts suggests that forecast revisions by high-tech analysts incorporate information reflected by pre-release changes in the stock price. We find a similar result for low-tech firms, where the average pre-release return for firms that receive good news revisions is –0.92% compared with an average return of –4.08% for firms that receive bad news forecast revisions.

The differential between the average returns for firms receiving good news and bad news earnings forecasts persists during the post-release period. For example, high-tech firms receiving good news forecasts have an average return of 4.24% during the post-release period compared with an average return of 3.53% for firms that receive bad news forecasts. This differential in average returns is more pronounced for low-tech firms, with a differential in the average post-release returns following good news and bad news forecasts of 1.76%. The persistence of the differential returns for good news and bad news firms during the post-release period is consistent with the post-announcement drift that has been observed following corporate earnings announcements (see Rendleman et al., 1982).

4. Tests of the congruence between proxies for analyst performance

Each of the analyst performance measures that we examine has certain advantages and limitations. However, to the extent that these measures are equally useful in identifying superior analysts, there should be significant overlap among the lead analysts identified by each criterion. By contrast, the Ranking Congruence Hypothesis predicts that rankings of analyst performance based on forecast timeliness and abnormal trading volume will be positively correlated, while rankings based on forecast accuracy will be uncorrelated with rankings based on timeliness and abnormal trading volume.

Table 4 summarizes the performance rankings for 358 analysts based on a total of 3,352 forecast revisions during the sample period that we use to classify analysts as leaders and followers. Using the ranking procedures and the criteria described previously, we identify 6 timeliness leaders, 23 volume leaders, and 23 accuracy leaders. Note that the timeliness criterion identifies fewer lead analysts than the alternative ranking procedures.

The differential selectivity evidenced by our measure of analyst timeliness may reflect biases in the proxies that we use to measure abnormal trading volume and forecast accuracy. For example, whereas our measure of timeliness depends only on the timing of an analyst's forecasts relative to forecasts by competing analysts, the abnormal volume statistic depends on economic events that affect trading volume during the reference period used to estimate normal trading volume. Similarly, since we do not have a formal test statistic to identify accuracy leaders, we include all analysts in the top accuracy decile. To the extent that the top decile encompasses "too many" analysts for industries having a large analyst following, we should expect to include relatively more accuracy leaders.

Given the discrepancy in the number of lead analysts identified using each performance measure, it is of interest to examine whether these alternative criteria identify a common group of influential analysts. We address this issue by comparing the number of leaders identified by two or more criterion with the number that would be expected under the null hypothesis that the

Table 4
Industry leaders ranked by timeliness, trading volume, and forecast accuracy

This table reports the number of analysts that are identified as leaders according to performance rankings based on timeliness, trading volume, and forecast accuracy for the sample period from January 1, 1993 through December 31, 1993. Each column represents the number of cases where analysts ranked as leaders according to performance measures based on timeliness, trading volume, and forecast accuracy are also ranked as leaders by each of the alternative ranking procedures. The diagonal elements of this cross-classification matrix represent the number of analysts who are ranked as leaders by only one performance measure.

Ranking approach	Timeliness	Trading volume	Forecast accuracy	Total
Panel A. High-tech leaders (131 analysts)				
Timeliness	1	2	0	3
Trading volume	2	10	1	13
Forecast accuracy	0	1	12	13
Panel B. Low-tech leaders (102 analysts)				
Timeliness	2	1	0	3
Trading volume	1	8	1	10
Forecast accuracy	0	1	9	10

performance rankings for each procedure are independent. For example, given that we find six timeliness and 23 trading volume leaders, the expected number of analysts ranked as leaders by both criterion is one under the null hypothesis (i.e., $233 \times (6/233) \times (23/233) = 0.59$). The fact that three analysts are identified as leaders by both ranking procedures strongly suggests that these performance rankings are not independent.

To formally test the null hypothesis that the analyst rankings generated by alternative performance measures are independent, we use Pearson's Q-statistic to perform a Chi-square test of goodness of fit. The test statistic is given by

$$Q = \sum_{i=1}^{2} \frac{\left(N_i - np_i^0\right)^2}{np_i^0}, \tag{15}$$

where N_i represents the number of analysts identified as leaders by the performance measures under consideration, p_i^0 represents the proportion of leaders that are expected to be jointly identified by the ranking procedures under consideration, and n represents the total number of analysts in the sample ($n = 233$). The Q-statistic is asymptotically distributed as Chi-square with one degree of freedom.

The Q-statistics for timeliness/volume, timeliness/accuracy, and volume/accuracy are respectively 9.85, 0.60, and 0.03. The p-values are respectively 0.002, 0.440, and 0.856. Thus, the proxies for analyst performance based on timeliness and trading volume appear to identify the same group of analysts. By contrast, the analysts identified as accuracy leaders seem to be unrelated to those based on timeliness and trading volume. Both of these results support the Ranking Congruence Hypothesis.

5. Stock price responsiveness to forecast revisions

This section presents evidence that documents the relative information content of earnings forecasts by leader and follower analysts. Our results include regression models that characterize the relation between excess returns and forecast surprises, as well as direct comparisons of the estimated FRCs for leader and follower analysts.

5.1. Forecast revisions and contemporaneous stock prices

The hypothesis that earnings forecasts by lead analysts convey more information than earnings forecasts by follower analysts can be tested by examining the contemporaneous relation between forecast revisions and excess stock returns. In particular, the Relative Information Content Hypothesis predicts that the estimated FRC for lead analysts should be larger than the FRC for follower analysts during the two-day forecast release period. We test this hypothesis by regressing excess returns during the pre-release period on analysts' forecast surprises using the regression specification,

$$XR_t = b_0 + b_1 FSL_t + b_2 FSF_t + \varepsilon_t, \tag{16}$$

where FSL_t is the forecast surprise if an analyst is a leader (and zero otherwise) and FSF_t is the forecast surprise if the analyst is a follower (and zero otherwise).

5.1.1. Timeliness leaders

Table 5 reports the release-period FRCs for high-tech and low-tech analysts. The results show that timeliness leaders in both the high-tech and low-tech industries have significant FRCs. Thus, earnings forecasts by timely analysts have a significant impact on stock prices. Consistent with the Relative Information Content Hypothesis, the FRCs for high-tech and low-tech leaders are respectively 6.9 and 15.8 times larger than the corresponding FRCs for follower analysts. The F-test of the null hypothesis that the FRCs for leaders

Table 5
Release period forecast response coefficients for lead and follower analysts

This table reports release period estimates of the respective forecast response coefficients for lead and follower analysts during the period January 1, 1994 through March 31, 1995 based on the following regression model:

$$XR_t = b_0 + b_1 FSL_t + b_2 FSF_t + \varepsilon_t,$$

where XR_t is the cumulative excess return over the two-day forecast release period, FSL_t is the forecast surprise if an analyst is a leader (and zero otherwise), and FSF_t is the forecast surprise if an analyst is a follower (and zero otherwise). Cumulative excess returns are computed as the difference in the buy-and-hold returns for the relevant common stock and the I/B/E/S industry index over the two-day forecast release period. Each forecast surprise represents the difference between an analyst's current forecast and a consensus earnings forecast this measured as the average of the most recent forecasts by each analyst during the past 60 days. The forecast surprises for lead and follower analysts respectively represent the average forecast surprises for all lead or follower analysts releasing earnings forecasts on a given day. T-statistics are reported in parentheses. We also report an F-statistic for our test of the null hypothesis that the forecast response coefficients for leader and follower analysts are equal.

Independent variables	Timeliness leaders ($\times$ 100)	Volume leaders ($\times$ 100)	Accuracy leaders ($\times$ 100)
Panel A. High-tech firms – semiconductors and printed circuit boards			
Intercept	0.0749	0.0184	0.0943
	(0.606)	(1.406)	(0.763)
Leader forecast surprise	0.0882***	0.0161*	0.0173
	(2.796)	(1.916)	(1.137)
Follower forecast surprise	0.0127*	0.0170*	0.0129*
	(1.831)	(1.812)	(1.844)
F test – leader/follower	5.3649**	0.0046	0.0659
Adjusted R^2	0.0108	0.0061	0.0033
Panel B. Low-tech firms – restaurants			
Intercept	−0.1920*	−0.1647*	−0.1687*
	(−1.870)	(−1.635)	(−1.657)
Leader forecast surprise	0.1453**	0.0066	0.0979
	(1.907)	(0.135)	(1.389)
Follower forecast surprise	0.0092**	0.0070	0.0101***
	(2.359)	(1.516)	(2.601)
F test – leader/follower	1.9825	0.0001	1.5432
Adjusted R^2	0.0073	0.0004	0.0082

***, **, *Denote significance at the 1%, 5%, and 10% levels, respectively.

and followers are equal is rejected for high-tech analysts but not for low-tech analysts.

5.1.2. Trading volume leaders

The FRCs for leaders and followers ranked according to abnormal trading volume are reported in the second column of Table 5. Although the results show that forecast revisions by volume leaders in the high-tech group have a significant impact on stock prices, the FRC for volume leaders in the low-tech group is not statistically significant. The F-test of the null hypothesis that the FRCs for lead and follower analysts are equal cannot be rejected for either the high-tech or low-tech analysts. Thus, the regression results for lead and follower analysts ranked according to abnormal trading volume are not consistent with the Relative Information Content Hypothesis.

The differential information content of earnings forecasts by timeliness leaders and volume leaders may be attributable in part to measurement error in the abnormal trading volume statistic that we use to identify volume leaders. Whereas, the LFR statistic directly measures the timeliness of an analyst's forecasts relative to the timeliness of forecasts by competing analysts, our measure of abnormal trading volume represents an indirect performance comparison based on the trading volume on the release date relative to the trading volume on typical days. Since our estimates of normal daily volume may be biased by the frequency with which firms release information during the estimation period, analyst rankings based on abnormal trading volume may be less informative than rankings based on the LFR statistic, which tends to be unaffected by measurement errors.

The identification of volume leaders is also hampered by the fact that the TAV statistic may mistakenly attribute high levels of trading volume to an analyst whose forecast revisions tend to be released immediately subsequent to significant corporate news releases. This explanation is consistent with the data reported in Table 4, which shows that we identify respectively ten and thirteen volume leaders for the high-tech and low-tech industries. These estimates are obtained by limiting the number of volume leaders to the top ranking deciles for the TAV statistic. Since the decile constraint is binding, the TAV statistic identifies the maximum number of the eligible analysts as volume leaders, which indicates that the TAV statistic is less selective than the LFR statistic. Consequently, the abnormal volume statistic has less power to detect superior analyst performance.

5.1.3. Accuracy leaders

Since it is relatively easy for weak analysts to improve forecast accuracy by mimicking superior analysts, we do not test the Relative Information Content Hypothesis for accuracy leaders. We consider instead the Information Content/Accuracy Tradeoff Hypothesis, which predicts that the estimated

FRC for accuracy leaders and followers should be the same due to potential misclassification problems associated with ranking procedures based on forecast accuracy. This suggests also suggests that the FRCs for timeliness and volume leaders will exceed the FRC for accuracy leaders.

Our tests of the Information Content/Accuracy Tradeoff Hypothesis for accuracy leaders are also reported in Table 5. Consistent with the predictions of this hypothesis, the incremental information contained in forecast revisions by accuracy leaders has no significant impact on stock prices. Further, the F-test indicates that we cannot statistically distinguish between leaders and followers ranked by forecast accuracy.

The Information Content/Accuracy Tradeoff Hypothesis also suggests that the FRCs for timeliness and volume leaders should be larger than the FRC for accuracy leaders. Although a formal statistical test is not implemented, the FRCs for high- and low-tech timeliness leaders respectively are 5.2 and 1.5 times larger than the FRCs for accuracy leaders. Not surprisingly, given the observed limitations of the abnormal volume statistic, the FRCs for trading volume and forecast accuracy leaders are very similar.

5.2. The relation between forecast revisions and past stock prices

This section reports the test results for the Information Creation Hypothesis concerning the relation between forecast revisions and excess stock returns during the pre-release period. This hypothesis argues that forecast revisions by lead analysts provide investors with new information, while forecast revisions by followers simply recycle existing information in updating their forecasts. If the Information Creation Hypothesis is true, there should be no significant correlation between the forecast revisions by lead analysts and stock returns during the pre-release period. By contrast, if follower analysts use public information reflected by recent trends in stock prices to update their earnings estimates, there should be a positive correlation between the forecast revisions by follower analysts and pre-release excess returns.

We test this hypothesis by regressing excess returns during the pre-release period on analysts' forecast surprises using the regression specification,

$$XR_t = b_0 + b_1 FSL_t + b_2 FSF_t + \varepsilon_t, \tag{17}$$

where FSL_t is the forecast surprise if an analyst is a leader (and zero otherwise) and FSF_t is the forecast surprise if the analyst is a follower (and zero otherwise). The regression specification above is not intended to imply that pre-release expected returns anticipate analysts' forecasts. Instead, we use the estimated coefficients from this regression to determine whether or not the information used in updating analysts' forecasts had a significant impact on stock prices during the pre-release period.

The estimated regression coefficients reported in Table 6 suggest that security analysts following firms in high-tech and low-tech industries may use different sources of information to update their earnings forecasts. We find that there is a significant relation between pre-release excess returns and the yet-to-be-released forecast revisions for both leaders and follower analysts in the high-tech industry. This result is robust with respect to the measure of analyst performance used to identify leaders and followers. The significance of the relation between forecast revisions and pre-release excess returns implies that forecast revisions by both lead and follower analysts tend to incorporate information that was available to the market during the pre-release period.

The results for analysts in the low-tech industry differ markedly from the results for high-tech analysts. Consistent with the prediction of the Information Creation Hypothesis, we find that the forecast revisions of timeliness leaders are not significantly related to pre-release returns. By contrast, the forecast revisions of follower analysts are positively correlated with pre-release period excess returns. Thus, our results imply that lead analysts who follow low-tech firms are less reliant on publicly available information in updating their earnings forecasts than are follower analysts.

5.3. The relation between forecast revisions and future stock prices

This section reports the results for tests of the Zero Trading Profits Hypothesis concerning the relation between forecast revisions and excess stock returns during the post-release period. Our tests of this hypothesis provide direct evidence concerning the speed with which investors react to the information contained in analyst's forecast revisions.

The regression specification that we use to examine the relation between forecast surprises and the excess returns during the post-release period includes a dummy variable to capture any post-release drift attributable to the differential impact of the bad news implicit in negative forecast surprises. This regression model, which is similar to the specification used in the previous sub-section, is given by

$$XR_t = b_0 + b_1 BN_t + b_2 FSL_t + b_3 FSF_t + \varepsilon_{it}, \tag{18}$$

where BN_t represents a dummy variable that is equal to one if the forecast revision at date t is bad news (and zero otherwise) and, as in the previous sub-section, the coefficients b_2 and b_3 can be interpreted as respective post-release forecast response coefficients for lead and follower analysts.

The estimated regression coefficients reported in Table 7 show that there is a positive relation between forecast revisions by high-tech analysts and post-release excess returns. In particular, we find that the relation between

Table 6
Pre-release period forecast response coefficients for lead and follower analysts

This table reports pre-release period estimates of the respective forecast response coefficients for lead and follower analysts during the period January 1, 1994 through March 31, 1995 based on the following regression model:

$$XR_t = b_0 + b_1 FSL_t + b_2 FSF_t + \varepsilon_t,$$

where XR_t is the cumulative excess return over the 20-day pre-release period, FSL_t is the forecast surprise if an analyst is a leader (and zero otherwise), and FSF_t is the forecast surprise if an analyst is a follower (and zero otherwise). Cumulative excess returns are computed as the difference in the buy-and-hold returns for the relevant common stock and the I/B/E/S industry index over the 20-day pre-release period. Each forecast surprise represents the difference between an analyst's current forecast and a consensus earnings forecast this measured as the average of the most recent forecasts by each analyst during the past 60 days. The forecast surprises for lead and follower analysts respectively represent the average forecast surprises for all lead or follower analysts releasing earnings forecasts on a given day. T-statistics are reported in parentheses. We also report an F-statistic for our test of the null hypothesis that the forecast response coefficients for leader and follower analysts are equal.

Independent variables	Timeliness leaders	Volume leaders	Accuracy leaders
Panel A. High-tech firms – semiconductors and printed circuit boards			
Intercept	0.0271***	0.0282***	0.0280***
	(5.540)	(5.390)	(5.719)
Leader forecast surprise	0.0048***	0.0018***	.001185**
	(3.819)	(5.273)	(1.970)
Follower forecast surprise	0.0020***	0.0170***	0.0021***
	(7.300)	(4.540)	(7.501)
F test – leader/follower	4.6043**	0.0203	1.7499
Adjusted R^2	0.0716	0.0538	0.0630
Panel B. Low-tech firms – restaurants			
Intercept	−0.0242***	−0.0235***	−0.0231***
	(−6.321)	(−6.184)	(−6.016)
Leader forecast surprise	0.0014	0.0024	0.0008
	(0.389)	(1.318)	(0.317)
Follower focrcast surprise	0.0004**	0.0005***	0.0003**
	(2.468)	(2.755)	(2.199)
F test – leader/follower	0.0829	1.0907	0.0379
Adjusted R^2	0.0052	0.0094	0.0036

***, **, * Denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7
Post-release period forecast response coefficients for lead and follower analysts

This table reports post-release period estimates of the respective forecast response coefficients for lead and follower analysts based on the following regression model:

$$XR_t = b_0 + b_1 BN_t + b_2 FSL_t + b_3 FSF_t + \varepsilon_t,$$

where XR_t is the cumulative excess return over the 21-day post-release period, BN_t is a bad news dummy variable that equals one if $FSL_t < 0$ (and zero otherwise), FSL_t is the forecast surprise if an analyst is a leader (and zero otherwise), and FSF_t is the forecast surprise if an analyst is a follower (and zero otherwise). Cumulative excess returns are computed as the difference in the buy-and-hold returns for the relevant common stock and the I/B/E/S industry index over the 21-day post-release period. Each forecast surprise represents the difference between an analyst's current forecast and a consensus earnings forecast this measured as the average of the most recent forecasts by each analyst during the past 60 days. The forecast surprises for lead and follower analysts respectively represent the average forecast surprises for all lead or follower analysts releasing earnings forecasts on a given day. T-statistics are reported in parentheses. We also report an F-statistic for our test of the null hypothesis that the forecast response coefficients for leader and follower analysts are equal.

Independent variables	Timeliness leaders	Volume leaders	Accuracy leaders
Panel A. High-tech firms – semiconductors and printed circuit boards			
Intercept	0.0253	0.0446***	0.0256*
	(1.075)	(4.491)	(1.923)
Bad news dummy	0.0033	−0.0199*	0.0041
	(0.137)	(−1.717)	(0.286)
Leader forecast surprise	0.0037***	0.0001	0.0001
	(2.817)	(0.349)	(0.141)
Follower forecast surprise	0.0003	0.0004	0.0049**
	(1.161)	(1.279)	(2.022)
F test – leader/follower	6.5212***	0.4240	0.3983
Adjusted R^2	0.0106	0.0043	0.0013
Panel B. Low-tech firms – restaurants			
Intercept	0.0103	−0.0088	−0.0053
	(0.559)	(−0.830)	(−0.386)
Bad news dummy	−0.0234	−0.0028	−0.0071
	(−1.222)	(−0.230)	(−0.482)
Leader forecast surprise	0.0090**	0.0008	0.0029
	(−2.266)	(0.379)	(−0.998)
Follower forecast surprise	0.0001	0.0002	0.0001
	(1.015)	(1.208)	(0.838)
F test – leader/follower	5.2602**	0.9043	1.0652
Adjusted R^2	0.0034	−0.0022	−0.0016

***, **, * Denote significance at the 1%, 5%, and 10% levels, respectively.

post-release excess returns and forecast surprises by timeliness leaders is statistically significant, with an estimated regression coefficient of 0.0037. The magnitude of this coefficient implies that an investor who initiates a trade at the beginning of the post-release period can expect to earn an excess return of 37 basis points for each unit of standard deviation by which the lead analyst's revised earnings forecast exceeds the consensus. By contrast, the post-release FRC for followers is not statistically significant, with a coefficient estimate of only 0.0003. Finally, it should be noted that the dummy variable for bad news is not statistically significant, indicating that the is no asymmetry to the relation between forecast surprises and post-release excess returns for analysts classified according to the timeliness of their forecasts.

The estimated post-release FRCs for forecast surprises by trading volume and accuracy leaders are not statistically significant, with coefficient estimates that are close to zero. However, we find that the post-release FRC for follower analysts ranked according to forecast accuracy is statistically significant, with a coefficient estimate of 0.0049. The significant post-release impact of forecast surprises by follower analysts ranked according to forecast accuracy can be attributed to the fact that none of the timeliness leaders identified by the LFR statistic were ranked among the most accurate analysts in our sample.

The significant relation between the post-release excess returns for high-tech firms and forecast surprises by timeliness leaders suggests that investors underreact to the information contained in lead analysts' forecast revisions. One explanation for this result is that analysts who are followers react to forecast surprises by adjusting their own earnings forecasts, confirming the accuracy of the lead analysts' forecast revisions.

The estimated regression coefficients reported in Table 7 for low-tech firms show a tendency for investors to overreact to forecast revisions by timeliness leaders. The estimated regression coefficient implies that an investor who initiates a trade at the beginning of the post-release period can expect to earn a negative excess return of 90 basis points for each unit of standard deviation by which the lead analyst's revised earnings forecast exceeds the consensus. By contrast, the post-release FRC for followers is not statistically significant, with a coefficient estimate of only 0.0001. Further, the dummy variable for bad news is not statistically significant, indicating that there is no asymmetry to the relation between forecast surprises and post-release excess returns for analysts classified according to the timeliness of their forecasts.

Our results for low-tech trading volume and accuracy leaders show that there is no significant relation between forecast surprises and the post-release excess returns for low-tech firms. This suggests that investors react quickly and efficiently to forecast revisions by these leaders.

6. Highly informative forecast revisions

This section takes a closer look at the relation between forecast revisions by timeliness leaders and release period excess returns. In particular, we examine the importance of classifying forecast revisions by these lead analysts as either more informative or less informative based on the relation between the revised earnings forecast and the consensus forecast. By controlling for the level of information conveyed by certain revisions, we increase the power of our tests to detect the differential information that lead analysts supply to investors.

We use two alternative procedures to classify forecasts by lead analysts as informative. Under the first approach, a lead analyst's forecast revision is classified as being informative whenever the revised forecast breaks with the consensus forecast. In particular, we refer to forecast revisions where an analyst reduces (increases) an earnings forecast that was previously above (below) the consensus to a level below (above) the current consensus as aggressive trend breaks. This definition of informative identifies cases where an analyst's forecast provides information at variance with that supplied by other analysts. Two contrasting aggressive trend breaks are illustrated in Fig. 5. Panel A depicts the forecast revision by a lead analyst who was formerly optimistic but has recently reduced the forecast to a more pessimistic level. By contrast, Panel B depicts an aggressive trend break by an analyst who has gone from pessimistic to optimistic.

Alternatively, informative forecasts can be defined according to whether the revised forecast unambiguously reflects either good news or bad news. For

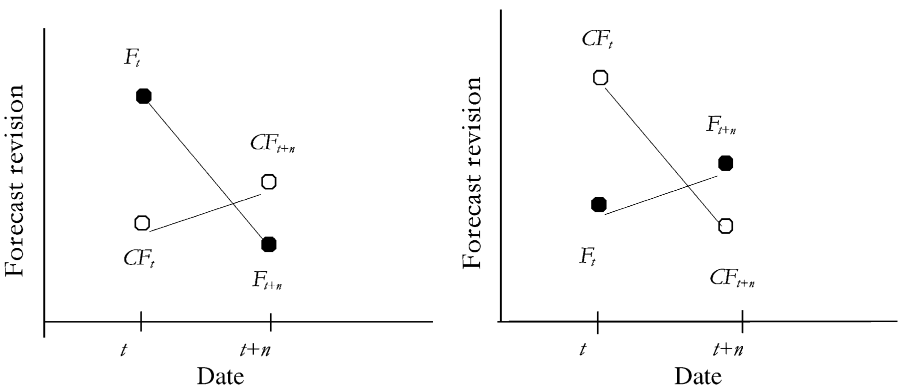

Fig. 5. Aggressive trend breaks. Panel A. "Bad news" aggressive trend break. A bad news aggressive trend break occurs when the lead analyst is optimistic at time t ($F_t > CF_t$) and revises his forecast downward ($F_t > F_{t+n}$) to the point that the forecast is pessimistic ($F_{t+n} < CF_{t+n}$). Panel B. "Good news" aggressive trend break. A good news aggressive trend break occurs when the lead analyst is pessimistic at time t ($F_t < CF_t$) and revises his forecast downward ($F_t < F_{t+n}$) to the point that the forecast is pessimistic ($F_{t+n} > CF_{t+n}$).

example, consider an upward revision of an optimistic forecast (one that exceeds the consensus) that also reflects a decrease in the analyst's forecast relative to the consensus. While the revised forecast would be considered good news if the forecast surprise were measured relative to the current consensus, the convergence of the analyst's forecast toward the consensus implies that the revised forecast provides little new information. By contrast, forecast revisions that reflect both an increase in an optimistic earnings estimate and an increase relative to the consensus forecast are likely to be highly informative. Fig. 6 illustrates both unambiguous good news and bad news forecasts. For example, Panel B depicts a downward revision in a pessimistic forecast. The increase in the gap between the lead analyst's forecast and the consensus implies that this forecast unambiguously reflects bad news.

The differential impact of informative forecasts by lead analysts can be examined using a regression specification that includes an interaction term

$$XR_t = b_0 + b_1 FSL_t \times I_t + b_2 FSL_t \times (1 - I_t) + b_3 FSF_t + \varepsilon_t, \tag{19}$$

where I_t represents a dummy variable that is equal to one if a lead analyst's forecast is either an aggressive trend break or an unambiguous revision and zero otherwise.

The results reported in Table 8 show that when timeliness leaders' forecast revisions are classified as either aggressive trend breaks or as unambiguous forecast revisions, the FRC is greater than the FRCs for both forecast revisions by follower analysts and the uninformative forecast revisions by lead analysts.

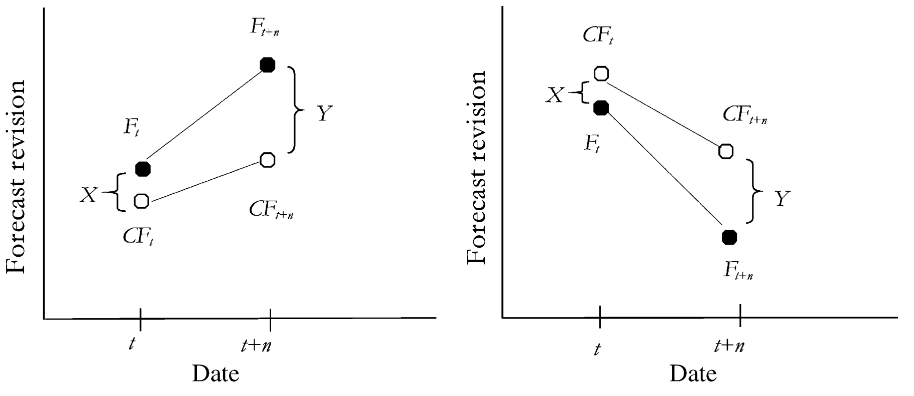

Fig. 6. Unambiguous revisions. Panel A. Unambiguous "good news" revision. An unambiguous good news revision occurs when the lead analyst is optimistic at time t ($F_t > CF_t$), the consensus forecast increases ($CF_t < CF_{t+n}$), and the leader revises his forecast upward ($F_t < F_{t+n}$) so that the revised forecast is even more optimistic ($X < Y$). Panel B. Unambiguous "bad news" revision. An unambiguous bad news revision occurs when the lead analyst is pessimistic at time t ($F_t < CF_t$), the consensus forecast decreases ($CF_t > CF_{t+n}$), and the leader revises his forecast downward ($F_t > F_{t+n}$) so that the revised forecast is even more pessimistic ($X < Y$).

Table 8
The release period impact of highly informative forecasts by lead analysts

This table reports release period estimates of the respective forecast response coefficients for lead and follower analysts during the period January 1, 1994 through March 31, 1995 based on the following regression model:

$$XR_t = b_0 + b_1 FSL_t \times I_t + b_2 FSL_t \times (1 - I_t) + b_3 FSF_t + \varepsilon_t,$$

where XR_t is the cumulative excess return over the two-day forecast release period, FSL_t is the forecast surprise if an analyst is a leader (and zero otherwise), and FSF_t is the forecast surprise if an analyst is a follower (and zero otherwise). Cumulative excess returns are computed as the difference in the buy-and-hold returns for the relevant common stock and the I/B/E/S Industry Index over the two -day forecast release period. Each forecast surprise represents the difference between an analyst's current forecast and a consensus earnings forecast this measured as the average of the most recent forecasts by each analyst during the past 60 days. The forecast surprises for lead and follower analysts respectively represent the average forecast surprises for all lead or follower analysts releasing earnings forecasts on a given day. Forecast revisions by lead analysts are classified as informative if either the revised forecast reverses the relation between the analyst's previous forecast and the consensus (aggressive trend breaks) or the revised forecast increases the differential between the revised forecast and the consensus forecast (unambiguous revisions). Informative forecasts are identified using an interaction dummy, I_t. The interaction dummy variable in the aggressive trend break model takes the value one if there is an aggressive trend break (and zero otherwise). The interaction dummy variable in the unambiguous revision model takes the value one if there is an unambiguous forecast revision (and zero otherwise). T-statistics are reported in parentheses. We also report two F-statistics. *F-test (informative/follower)* tests the null hypothesis that the forecast response coefficients for *informative* revisions and follower revisions are equal. *F-test (uninformative/follower)* tests the null hypothesis that the forecast response coefficients for *uninformative* revisions and follower revisions are equal.

	High-tech firms – semiconductors		Low-tech firms – restaurants	
Independent variables	Aggressive trend break ($\times$ 100)	Unambiguous revision ($\times$ 100)	Aggressive trend break ($\times$ 100)	Unambiguous revision ($\times$ 100)
Intercept	0.0838	0.1687***	−0.1586	−0.1449
	(0.679)	(1.313)	(−1.548)	(−1.383)
Informative forecast surprise by timeliness leader	0.1468***	0.1239***	0.9902***	0.3730***
	(3.312)	(2.914)	(3.819)	(2.633)
Uninformative forecast surprise by timeliness leader	0.0231	0.0170	0.0107	−0.0713
	(0.544)	(0.323)	(0.013)	(−0.469)
Follower forecast surprise	0.0124*	0.0162**	0.0090**	0.0085**
	(1.791)	(2.266)	(2.304)	(2.169)
F-test – informative/follower	8.8531***	6.1312**	14.3072***	6.5904***
F-test – uninformative/follower	0.0615	0.0002	0.0003	0.2760
Adjusted R^2	0.0106	0.0137	0.0205	0.0114

***, **, *Indicate significance at the 1%, 5%, and 10% levels, respectively.

For example, in the high-tech industry the FRC for forecast revisions classified as aggressive trend breaks is 11.8 times the FRC for follower analysts, with an F-statistic of 8.8531. Thus, we can reject the null hypothesis that the FRCs for lead and follower analysts are equal with a p-value of 0.0001. By contrast, the F-statistic for the null hypothesis that the FRCs for uninformative forecasts by lead analysts and forecast revisions by follower analysts are equal is 0.0615, indicating that the null hypothesis cannot be rejected. These results hold for both high-tech and low-tech analysts. Further, our results appear to be robust to the procedure used to classify forecasts as informative.

Our findings suggest that investors condition their response to lead analysts' forecast revisions on both the analysts' prior forecasts and the current analyst consensus. Further, informative forecasts appear to explain a significant amount of the relation between forecast revisions and release period excess returns.

7. Conclusion

This paper presents evidence suggesting that lead analysts can be identified based on the timeliness of their earnings forecasts. We introduce a new statistic for ranking analysts based on the timeliness of their earnings forecasts. The performance rankings based on this statistic are then compared with alternative rankings based on forecast accuracy and the abnormal trading volume associated with analysts' forecasts. Our results suggest that analyst rankings based on forecast timeliness are more informative than rankings based on abnormal trading volume and forecast accuracy. Although we find that analyst rankings based on forecast timeliness and abnormal trading volume tend to identify the same core group of analysts, the differential stock price response to forecast surprises by timeliness leaders suggests that abnormal trading volume is a noisy measure of analyst performance. Similarly, analyst rankings based on forecast accuracy appear to result in a high percentage of misclassification errors, consistent with the hypothesis that weak analysts are able to improve the accuracy of their forecasts by mimicking the forecasts of superior analysts.

We also present evidence that forecast revisions by lead analysts ranked according to the timeliness of their earnings forecasts are more informative than forecast revisions by other analysts. In particular, we find evidence that the market response to selected forecast revisions by timeliness leaders is greater than that for forecast revisions by follower analysts. This suggests that forecast revisions by timeliness leaders provide greater value to investors than forecasts by other analysts. In addition, we find that forecast revisions by lead analysts are positively correlated with recent changes in stock prices. This suggests that a portion of the release period excess returns associated with forecast revisions by lead analysts may be attributable to the fact that they provide confirmatory evidence that recent changes in the stock prices are justified by underlying changes in firm fundamentals. Finally, we show that forecast revisions by timeliness leaders can be classified as informative and uninformative by conditioning on the lead analyst's previous forecast and the current consensus forecast. Our results show that there is a significant difference in the market response to lead analysts' forecasts depending on whether the forecast revision is classified as informative or uninformative.

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