

Who is Afraid of Reg FD? The Behavior and Performance of Sell-Side Analysts Following the SEC's Fair Disclosure Rules

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Abstract

Effective October 23, 2000, the Securities and Exchange Commission adopted a set of fair disclosure rules ("Reg FD") that prohibit companies from disclosing earnings or other material business information to some analysts or large investors before announcing it publicly. This paper empirically analyzes the impact of these new rules on several aspects of the behavior and performance of sell-side equity analysts. We analyze forecasts made for a large sample of public companies for three post-FD quarters and for several pre-FD years. We use panel regressions and the fixed effects model. We have three main findings. First, earnings forecasts become less accurate post-FD at the levels of both the individual analyst and the consensus. This effect is particularly pronounced in small firms. Second, individual analysts following a company become more dispersed in their earnings forecasts post-FD. Third, analyst performance rankings become somewhat more stable following the adoption of these rules. These results are generally robust to different methodologies and empirical procedures.

JEL classification: G14, K22, L51, M4

Who is Afraid of Reg FD? The Behavior and Performance of Sell-Side Analysts Following the SEC's Fair Disclosure Rules

1. Introduction

On August 10, 2000, the Securities and Exchange Commission (SEC) approved a set of “fair disclosure” rules, generally referred to as “Reg FD”. These rules require a company to reveal any “material” information to all investors and to Wall Street analysts simultaneously in case of intentional disclosures, or within 24 hours in case of unintentional disclosures. The rules became effective October 23, 2000. These rules are intended to put an end to the practice of “selective disclosure,” whereby companies give Wall Street analysts and large shareholders crucial earnings and business information prior to making it public. The rules prohibit companies from tipping off some favored analysts, investors, and media outlets before others.

Analysts have been an important link between companies and investors. Pre-FD, companies used analysts as a tool to manage the market's expectations (see, e.g., Ryan (2000) and Opdyke (2000)). Instead of announcing detailed, forward-looking operational and performance information publicly, managers liked to communicate it via analysts. Managers could be more candid and precise in their one-on-one communications with analysts because they did not have to worry about liability issues. They also did not have to worry about sensitive information falling in the hands of competitors, suppliers or trade unions, which might use it for their own purposes. So analysts served as a useful filter to communicate information to the market. Maintaining good relations with analysts also increased the likelihood of getting a favorable recommendation for the stock.

Analysts obviously liked precise guidance from companies because it allowed their forecasts to be more accurate.

Reg FD throws a fly in this ointment. Companies now have to either disclose a piece of information publicly or refrain from discussing it with analysts. In a recent survey by the Association for Investment Management and Research (2001), about 90% of sell-side analysts reported regularly holding individual interviews with top managements of the companies they followed pre-FD. About 70% of the respondents reported a drop in such contact post-FD, while the remaining reported no change. More specifically, 80% of the analysts reported that they used to regularly request and receive earnings guidance from the companies they covered pre-FD. Post-FD, 80% of the analysts reported a drop in the availability of guidance, 7% reported an increase and the remaining reported no change. By a 65% to 12% margin, respondents also reported a drop in the overall quality of written and oral information they receive from the companies they cover.

This paper empirically assesses the impact of Reg FD on three aspects of analyst behavior and performance. These are: the accuracy of their earnings forecasts, the dispersion of their forecasts, and the stability of rankings of their performance as forecasters. We analyze forecasts for three quarters following the adoption of fair disclosure rules and for several years before their adoption for a large sample of public companies. We employ univariate tests and panel regressions with the fixed effects model. We also examine whether the effects vary according to firm characteristics such as size and analyst following.

We have three main findings. First, analyst forecasts become less accurate following the adoption of fair disclosure rules. This effect is found both at the individual analyst level and at the level of the consensus. The effect is more pronounced in small companies, which might have had bigger incentives to provide selective guidance in order to attract and retain analyst coverage. Second, forecasts become more dispersed following Reg FD. Third, analyst rankings become somewhat more stable following Reg FD. These results are generally robust to alternative empirical procedures.

The paper proceeds as follows. Section 2 discusses the issues in more detail. Section 3 briefly reviews some themes in the prior literature on analyst forecasts. Section 4 describes the sample and data. Section 5 presents our tests and results on forecast accuracy. Section 6 deals with forecast dispersion, and section 7 tackles the issue of stability of analyst rankings. Section 8 concludes the paper.

2. Issues

This section discusses the potential effects of Reg FD on three aspects of the behavior and performance of stock analysts: forecast accuracy, forecast dispersion, and changes in analyst rankings.

2.1 Forecast accuracy

Numerous articles in the business press claim that before Reg FD took effect, “earnings guidance” was an important facet of communication between a company and the analysts following it. A company attempted to “guide” analysts to a quarterly

earnings number that it could meet or beat, as a way of managing investor expectations.¹ As a result of these direct contacts with companies, analysts had a better idea of the earnings numbers for the coming quarter and the year before they were announced to the public. So their forecasts tended to be close to the subsequently announced actual earnings number, thereby making forecast errors small. For example, McGough and Bryan-Low (2000) say, “For a long time, Wall street analysts have resembled a highly unlikely group of golfers. In making their quarterly earnings estimates, they essentially all lined up at the tee, took their shots – and all the balls landed at just about the same spot on the golf course.” However with the adoption of Reg FD, the job of predicting earnings may become harder for analysts because the rules prohibit pre-announcement disclosures to analysts by companies. This implies that Reg FD should have a positive effect on the absolute values of forecast errors (actual minus forecast earnings per share).

Three factors can act to attenuate this positive effect. First, in the absence of direct guidance from companies, analysts may increase the time and effort they spend on forecasting earnings (i.e., on “being analysts”) and decrease the time spent on client relations (i.e., on “being salesmen”). They may increase their efforts at monitoring the company’s business and performance, perhaps gathering information from alternate sources such as customers, suppliers, trade and industry groups, and employees. Second, companies may change their behavior too in response to the new rules. In the face of restrictions on one-on-one communication with analysts, companies may disclose more forward-looking information publicly. This may offset any effect of Reg FD. Third, the effectiveness of the new rules depends upon their enforcement by the SEC. In the

¹Prior studies find that stock market rewards firms for meeting or beating analyst forecasts consistently (see, e.g., Degeorge, Patel and Zeckhauser (1999), and Bartov, Givoly and Hayn(2000)).

absence of effective enforcement, the rules may have scant effect. So whether Reg FD reduces the accuracy of analyst forecasts is ultimately an empirical question.

2.2 Forecast dispersion

To the extent that companies' pre-FD earnings guidance was informative, the distribution of analysts' forecasts should have been more concentrated near the average of all analyst forecasts. If the rules are effective, there should now be more dispersion of analyst forecasts, as companies can no longer "guide" analysts to a precise earnings number. Without guidance, analysts will now have to rely more on their individual analyses. This should have a positive effect on the dispersion of earnings forecasts. Once again, this effect will be reduced if companies substitute more public disclosure instead of guidance to analysts, or if the new rules are not effectively enforced. So the net effect of Reg FD on forecast dispersion remains an empirical issue.

2.3 Stability of analyst rankings

Numerous stories in the financial press suggest that before Reg FD, companies sometimes favored certain analysts in providing earnings guidance.² Such preferential treatment can conceivably take one of two forms. A company can either favor the same analyst consistently (consistent preference) or it can favor different analysts over time (random preference). As for analysts, they are either equally good at research or they differ in their research abilities. Consider first the case where all analysts are equally good at research. Here, with consistent preference pre-FD, analyst rankings would

²For instance, Nocera (2000) quotes a prominent technology analyst as saying, "The analysts that are held in high esteem these days are those that are spoon-fed by management." Ryan (2000) quotes Arthur Levitt,

become more variable when Reg FD begins. But with random preference pre-FD, the new rules would leave the variability of rankings unchanged.

Now suppose that some analysts are better than others. Here, under consistent preference pre-FD, analyst rankings would again become more variable when Reg FD begins. But with random preference pre-FD, the banning of preferential treatment under Reg FD would actually reduce the variability of rankings. Of course, if the rules are not effectively enforced, no change should be observed. So whether analyst rankings become more or less stable post-FD is ultimately an empirical issue.

2.4 Differential effects across firms

Finally, Reg FD can have differential impacts across firms. These rules potentially affect smaller companies more. Since these firms typically have fewer analysts covering them, they may have relied more on one-on-one communication with analysts to obtain and maintain coverage for their stocks. Because selective guidance is no longer possible, there is less information available to analysts about these companies post-FD. This should lead to bigger effects on small firms. For the same reason, the rules may also have a bigger effect on companies followed by fewer analysts. So any effects on the accuracy or dispersion of analyst forecasts or in the stability of analyst rankings should be stronger for smaller and less-followed firms.

3. Prior studies

The behavior of stock analysts is a widely researched topic. We do not attempt to review this vast literature here. Instead, we briefly provide a flavor for some themes in

the former SEC Chairman, as saying, “Some in corporate management treat material information as a

this literature. A large strand of this literature focuses on the accuracy of analyst forecasts. One question is whether analysts add value over time-series models of earnings. The answer seems to be “yes” (see, e.g., Brown, et al. (1987)). Another question is whether forecasting ability differs across analysts. Early answer was “no” (e.g., O’Brien (1990)). But after controlling for forecast age, the answer seems to be “yes” (see, e.g., Stickel (1992) and Sinha, Brown and Das (1997)). A third issue is about the determinants of differences in forecast accuracy across analysts. The answer here seems to be: characteristics of analysts (such as experience and how busy they are) and of the brokerage house that employs them (such as size, industry specialization, and analyst turnover). See, e.g., Mikhail, Walther and Willis (1997), Clement (1999), and Jacob, Lys and Neale (1999). A fourth issue is whether analyst forecasts are unbiased. Brown (2001) reports that analyst bias has changed over the last two decades. Forecasts were somewhat optimistic during the mid to late 1980s, unbiased during the early 1990s, and somewhat pessimistic in the latter part of the 1990s. But this pattern differs for profits versus losses.

Another theme is the tendency of analysts to herd, i.e., issue forecasts similar to those previously released by other analysts (see, e.g., Trueman (1994), Welch (2000), and Graham (1999)). A different strand focuses on potential conflicts of interest faced by analysts in their dual role as forecasters and salesmen (e.g., Michaely and Womack (1999)). Career concerns of analysts is yet another theme (e.g., Hong, Kubik and Solomon (2000)).

Since Reg FD is so recent, we are not aware of any published study that investigates its effects on the behavior and performance of sell-side equity analysts. In concurrent work, Heflin, Subramanyam and Zhang (2001) examine a range of issues

commodity – a way to gain and maintain favor with particular analysts.”

about the post-FD financial information environment. The two papers largely complement each other. Heflin, et al. has a broad scope. They find that when firms announce earnings post-FD, stock prices adjust more quickly to the news and stock returns are less volatile. They also find that firms disclose more forward-looking information voluntarily. In addition, they look at analyst forecast accuracy and dispersion. Our paper focuses on changes in the accuracy and dispersion of analyst forecasts and analyst rankings.

Our paper also differs from Heflin, et al. in several other respects. First, they look at only one post-FD quarter, while we look at three quarters of post-FD data. Second, Heflin et al. use a matched-pairs methodology, where the pre-FD control period is the prior quarter or the same quarter a year ago. We use panel regressions and a fixed effects model. For each post-FD quarter, we use the prior three to five years of data for the corresponding quarter. Third, Heflin et al. only look at the accuracy of consensus forecasts, while we also look at the accuracy of individual analysts. Fourth, Heflin et al. only examine the average effects of Reg FD across all firms, while we also investigate differential effects across firms.

Our results on forecast accuracy and dispersion differ from Heflin et al. They find “no reliable evidence of a change” in either consensus forecast accuracy or forecast dispersion. We find statistically significant evidence of a decrease in forecast accuracy, both at the individual analyst level and at the consensus level, and an increase in the dispersion of analyst forecasts. The decrease in forecast accuracy is more pronounced for small firms. We also document that analyst rankings become somewhat more stable post-FD.

4. Sample and data

4.1 Data

The data for this study come from the I/B/E/S detail and summary history databases. Fair disclosure rules were approved by the SEC on August 10, 2000 and became effective on October 23, 2000. So the quarter ending December 31, 2000 was the first quarter affected by these rules. We analyze forecasts for that quarter and the two subsequent quarters as the post-FD period. For each post-FD quarter, the pre-FD period consists of the average of the corresponding quarter over the prior three to five years, depending upon the availability of data.

For the quarter ended December 31, 2000, we analyze forecasts made over two time intervals of approximately similar length preceding the earnings announcement date. These are: August 10, 2000 to October 22, 2000, and October 23, 2000 to January 10, 2001. The first period starts with the announcement of these rules and ends the day before the rules became effective. The second period starts the day the rules became effective and ends before the first day that any firm announces its results for the quarter. For the quarter ended March 31, 2001, we pick two successive intervals of two months each starting on October 23, 2000. Finally, for the quarter ended June 30, 2001, we pick two successive intervals of two months each starting on February 1, 2001. During each forecast period, we use the latest forecast made by each analyst following a company.

Companies usually start announcing the results for a quarter beginning about two weeks after the quarter ends. An analyst following a company typically issues multiple forecasts about the earnings for a given quarter over roughly a six-month period preceding the earnings announcement. Obviously, with the passage of time, forecasts

become more accurate as more information becomes available. Various analysts following a company issue and revise their forecasts at different times over this six-month interval. We choose forecast periods of about two months each to increase the likelihood that an analyst issues a forecast during the interval and to put those analysts on roughly equal footing as to the quantity and quality of information available to them.³

4.2 Sample sizes

We conduct multiple tests of each of the three hypotheses discussed in section 2. For each test, we analyze forecasts made during two periods for each of the three quarters. Each test is based on the maximum data available for the test. Consequently, sample sizes vary across the tables depending upon the availability of data.

Table 1 gives a flavor for how sample sizes were arrived at for the tests presented below in sections 5.1.1 and 5.1.2 for the first forecast period for the quarter ended December 31, 2000 (i.e., for the last column for the first row in Tables 2 and 3). Table 1 shows that for this quarter, individual analysts made a total of 73,851 forecasts. Out of these, we focused on the latest forecast made by each analyst during our first forecast period: August 10, 2000 to October 22, 2000. There were a total of 10,104 of these, out of which actual eps data was available for 9,544. Of the latter, stock price data was available for 8,516 cases, and the stock price was \$1 or more in 8,461 cases. This is the

³In other words, if we expand the forecast period to, say, six months, then the analyst who issues the latest forecast in the interval has the best chance of winning and the one who issues the earliest forecast has the worst chance. On the other extreme, if we reduce the forecast period to, say, one day, there may not be a single analyst that issued a forecast during the interval. Since several of our tests are about the accuracy and ranking of individual analysts following a company, the choice of a two-month forecast period is a compromise between these two extremes. As discussed earlier, we use the latest forecast made by each analyst within this two-month window.

number in the last column for row 1 of Table 2. Column 2 of Table 1 similarly shows the corresponding sample sizes for consensus forecasts (Table 3).

5. Forecast accuracy

The first issue we investigate is the behavior of forecast errors (actual minus forecast eps) following Reg FD. We examine this issue both at the level of the individual analyst as well as at the level of the consensus forecast. We define the normalized forecast error for analyst i following company j for forecast period t as:

$$\text{NFE}_{ijt} = |e_{jt} - \hat{e}_{ijt}| / p_{jt} \quad (1)$$

where e_{jt} = earnings per share (eps) for company j for quarter t , \hat{e}_{ijt} = estimate of e_{jt} by analyst i , and p_{jt} = the latest stock price in the I/B/E/S database for company j within a given time window.

We choose the stock price rather than eps to normalize forecast errors to avoid the inference problems caused by division by zero or negative earnings. In section 5.3, we discuss results for robustness checks where we normalize forecast errors by the median analyst estimate of sales per share instead of stock price. In general, the results are qualitatively similar to those presented here. In order to avoid the problem of inflated forecast errors caused by division by very small numbers, we omit from the sample companies that have a stock price of \$1 or less.

5.1. Univariate tests

5.1.1. Individual analysts

Table 2 presents the mean and median values of normalized forecast errors pre and post-FD for both forecast periods preceding each of the three quarters. For each forecast period, the column labeled “post” shows the mean (median) value of NFE across all analyst-company pairs during the post-FD quarter. The column labeled “pre” shows the corresponding pre-FD period values based on the prior three years.⁴

The first two columns of Table 2 show that the mean value of the normalized forecast error increases following Reg FD in both forecast periods for each of the three quarters. Column 3 shows that the p-value for this difference is <.0001 in five of the six cases. The magnitude of the increase in these five cases ranges from 44% to 119%, and has a mean of 68%.

Columns 4 and 5 show that the median NFE is higher following Reg FD in four of the six forecast periods; all four differences are statistically significant at the 5% level or better using the Wilcoxon test. The magnitude of the increase here is somewhat lower; it ranges from 8% to 74%, and has a mean of 47%.

5.1.2. Consensus Forecast

We next define the normalized consensus forecast error for company j for forecast period t as :

$$NFE_{jt} = |e_{jt} - \hat{e}_{jt}| / p_{jt} \quad (2)$$

⁴We compute this as follows. For each analyst-company pair, we first compute the average NFE over all the years out of the prior three years that the pair exists in I/B/E/S. We then compute the average of these averages across all analyst-company pairs. This approach gives equal weight to each analyst-company pair.

where \hat{e}_{jt} = the latest median of all analyst forecasts of e_{jt} made within a given forecast window, and p_t = the latest stock price for company j in the I/B/E/S database within the window. Once again, companies with stock price under \$1 are excluded.

Table 3 presents the mean and median values of normalized consensus forecast errors pre and post-FD in a format similar to Table 2. Columns 1 and 2 show that the mean forecast error increases following Reg FD in five out of the six forecast periods; the p-value is less than .05 in four of these cases. The magnitude of the increase ranges from 36% to 137% in the four significant cases, with a mean of 85%. Columns 3 and 4 show that the median forecast error also increases in three out of the six forecast periods; the p-value for the Wilcoxon test is less than .01 in all three cases. The magnitude of the increase in these three cases ranges from 28% to 42%, with a mean of 36%. However, in the remaining three periods, the median forecast error decreases significantly. The magnitude of the decrease in these three cases ranges from 7% to 21%, with a mean of 12%.

5.2 Fixed effects regressions

We next estimate cross-sectional time series regressions of normalized forecast errors. Since we are only interested in the effect of Reg FD on NFE, we use a model with analyst-company fixed effects. Instead of using a large number of dummy variables (one for each analyst-company pair), we use the computationally simpler procedure of subtracting from each variable in the regression its mean value for each analyst i

following company j over the sample period.⁵ Accordingly, we estimate the following regression:

$$DNFE_{ijt} = b_1 DLOSS_{ijt} + b_2 DREGFD_{ijt} + u_{ijt} \quad (3)$$

where $DNFE_{ijt} = NFE_{ijt} - \overline{NFE}_{ij}$; and \overline{NFE}_{ij} is the mean NFE for analyst i following company j over the sample period. $DLOSS_{ijt} = LOSS_{ijt} - \overline{LOSS}_{ij}$. The indicator variable $LOSS_{ijt} = 1$ if $e_{jt} < 0$; it equals zero otherwise. \overline{LOSS}_{ij} is the mean value of $LOSS$ for analyst i following company j over the sample period. $DREGFD_{ijt} = REGFD_{ijt} - \overline{REGFD}_{ij}$. The indicator variable $REGFD_{ijt}$ equals one for the post-Reg FD period (year 2000 for the December ending quarter and year 2001 for March and June ending quarters), and zero otherwise. \overline{REGFD}_{ij} is the mean value of $REGFD$ for analyst i following company j over the sample period. The sample period is 1997-2001. The sample includes all analyst-company pairs in the I/B/E/S database that have a NFE observation post-FD and at least one NFE observation pre-FD. As with the univariate tests reported above, we estimate equation (3) for forecasts made during both forecast periods for each of the three quarters. We also estimate a combined regression where we pool the data from the three quarters.

Equation (3) does not try to explain what determines the accuracy of analyst forecasts in general.⁶ By controlling for analyst-company effects, our panel data and the fixed effects model allow us to largely abstract from that question. Controlling for analyst-company fixed effects, however, does not control for the striking differences

⁵This procedure is similar to the one used by, e.g., Clement (1999). Greene (1993) shows that the two methods of controlling for fixed effects are mathematically equivalent. Note that the intercept term drops out in this specification due to differencing.

observed in the forecast accuracy of analysts for profits versus losses (see, e.g., Brown (2001)). So we control for that effect by adding DLOSS as an explanatory variable in equation (3). This allows us to focus on the effect of Reg FD. A positive coefficient on DREGFD would imply that forecast errors increase following the adoption of Reg FD from their normal levels for a given analyst following a certain company.

Panel A of Table 4 shows the estimates of equation (3) at the level of individual analyst forecasts. The estimated coefficient (\hat{b}_2) of the DREGFD dummy is positive and highly statistically significant in all eight regressions. Forecasts of individual analysts become less accurate following the adoption of fair disclosure rules. The magnitude of this effect is bigger for forecasts made earlier in the quarter than for those made later.

Panel B shows the corresponding regressions for consensus forecasts. Here there is only one NFE observation per company for each time period. So we use a model with company fixed effects. Once again, the coefficient of DREGFD is positive and highly statistically significant in all eight estimations. The results indicate that the consensus of analyst forecasts also becomes less accurate following Reg FD.

5.2.1 Differential effects across firms

We next examine whether forecast accuracy changes differentially based on two firm characteristics: size and analyst following. If small and less followed companies engaged more in selective disclosure pre-FD in order to attract and retain analyst coverage, we would expect analyst forecasts to become particularly less accurate in those

⁶See Mikhail, Walther and Willis (1997), Clement (1999), and Jacob, Lys and Neale (2000) for some excellent work on that topic.

firms. In order to test this premise, we estimate the following regression for the combined sample of the three quarters:

$$\begin{aligned} \text{DNFE}_{ijt} = & b_1 \text{DLOSS}_{ijt} + b_2 \text{DSMALL}_{ijt} + b_3 \text{DLOWFOLL}_{ijt} + b_4 \text{DREGFD}_{ijt} \\ & + b_5 \text{DSMALL}_{ijt} * \text{DREGFD}_{ijt} + b_6 \text{DLOWFOLL}_{ijt} * \text{DREGFD}_{ijt} + u_{ijt} \end{aligned} \quad (4)$$

where $\text{DSMALL}_{ijt} = \text{SMALL}_{ijt} - \overline{\text{SMALL}}_{ij}$. The indicator variable SMALL_{ijt} equals one if company j 's market value of equity is \$200 million or lower in year t , and zero otherwise. $\overline{\text{SMALL}}_{ij}$ is the mean value of SMALL for analyst i following company j over the sample period. $\text{DLOWFOLL}_{ijt} = \text{LOWFOLL}_{ijt} - \overline{\text{LOWFOLL}}_{ij}$. The indicator variable LOWFOLL_{ijt} equals one if company j is followed by four or fewer analysts in year t , and zero otherwise. $\overline{\text{LOWFOLL}}_{ij}$ is the mean value of LOWFOLL for analyst i following company j over the sample period. The other variables are as defined earlier in this subsection. Once again, this regression uses a model with analyst-company fixed effects.

Panel A of Table 5 shows that at the individual analyst level, forecast errors increase following Reg FD in all three variants of equation (4) in both forecast periods. The coefficient of the DREGFD variable is highly statistically significant in all six cases. The effect is particularly pronounced for small firms. The coefficient of the interaction term $\text{DSMALL} * \text{DREGFD}$ is positive and highly statistically significant in all cases. But the effect is no more pronounced in firms followed by fewer analysts. The coefficient of the $\text{DLOWFOLL} * \text{DREGFD}$ variable is generally positive, but is statistically insignificant.

The results for consensus forecasts shown in Panel B generally mirror those in Panel A. Both individual analyst and consensus forecasts became less accurate following

the adoption of fair disclosure rules that bar selective disclosure. This effect is particularly pronounced in small firms.

5.3 Robustness checks

In the tests presented so far, we use the stock price to normalize forecast errors. This avoids the problem of interpretation caused by the use of eps as the normalizing variable, because eps is sometimes non-positive. A number of prior studies (such as Butler and Lang (1991), Francis, Hanna and Philbrick (1997), Mikhail, Walther and Willis (1997), and Easterwood and Nutt (1999)) have also used stock price to scale earnings forecast errors.

However, Jacob, Lys and Neale (1999) point out that stock price has problems of its own as a normalizing variable due to changes in stock valuation over time. So we use the consensus analyst estimate of sales per share as an alternative variable to scale forecast errors.⁷ These results are generally quite similar to those reported above.

6. Forecast dispersion

We next examine changes in the dispersion of analyst forecasts post-FD. Since a company can no longer guide analysts to a precise earnings number, analysts now have to rely on their individual analyses. This is likely to result in more disperse forecasts, unless the rules are not effectively enforced or companies substitute more public disclosure for private guidance to analysts.

6.1 Univariate tests

We compute the coefficient of variation of analysts' forecasts of eps for company j for forecast period t as

$$\text{COV}_{jt} = (\sigma_{jt} / \bar{X}_{jt}), \quad (5)$$

where σ_{jt} and \bar{X}_{jt} equal, respectively, the standard deviation and the mean of the forecasts of all analysts following the company. Companies followed by two or fewer analysts and companies with mean eps forecasts of \$ 0.10 or lower are excluded.

Table 6 shows the mean and median COV values pre and post-FD for both forecast periods for each of the three quarters. The post-FD period consists of the year 2000 for the quarter ended December 31, and the year 2001 for the two subsequent quarters. The pre-FD period consists of the prior five years.

Table 6 paints a mixed picture. Columns 1 and 2 show that following Reg FD, the mean COV values decrease significantly in two periods, increase significantly in one period, and do not change significantly in the remaining three periods. Columns 4 and 5 show a somewhat similar pattern. The median COV values decrease significantly in three periods, increase significantly in one period, and do not change significantly in the remaining two periods.

6.2 Fixed effects regressions

We next estimate the following cross-sectional time-series regression of the dispersion of analyst forecasts:

$$\text{DCOV}_{jt} = b_1 \text{DLOSSF}_{jt} + b_2 \text{DREGFD}_{jt} + u_{jt}, \quad (6)$$

⁷We normalize by the forecast, rather than actual, sales per share in order to maximize data availability. Data on actual sales available in the I/B/E/S database are spotty in the early part of our sample period.

where $DCOV_{jt} = COV_{jt} - \overline{COV}_j$; and \overline{COV}_j is the mean COV for firm j over the sample period. $DLOSSF_{jt} = LOSSF_{jt} - \overline{LOSSF}_j$. The indicator variable $LOSSF_{jt} = 1$ if the median of all analyst forecasts of eps for company j in year t is negative; it equals zero otherwise. \overline{LOSSF}_j is the mean value of $LOSSF$ for company j over the sample period. $DREGFD_{jt} = REGFD_{jt} - \overline{REGFD}_j$. The indicator variable $REGFD_{jt}$ equals one for the post-Reg FD period (year 2000 for the December ending quarter and year 2001 for March and June ending quarters), and zero otherwise. \overline{REGFD}_j is the mean value of $REGFD$ for company j over the sample period. The sample period is 1995-2001. The sample includes all companies in the IB/E/S database that have a COV observation post-FD and at least one COV observation pre-FD.

As in section 5.2, we are not interested in explaining differences across firms in the normal level of COV. Instead, we focus on whether COV changes in response to Reg FD, after controlling for the normal level of COV for each company over the sample period. The estimate of equation (6) allows us to do this. As with equation (3) in section 5.2 above, this mean-adjusted form of the equation is a computationally efficient way of controlling for firm fixed effects. Once again, we control for potential differences for profit versus loss firms.

We estimate equation (6) separately for both forecast periods preceding each quarter as well as for the combined sample of the three quarters. Table 7 shows that the mean COV increases following Reg FD. The coefficient of the $DREGFD$ variable is positive in all eight estimations; it is statistically significant in five cases corresponding to the March and June ending quarters and for the combined sample of the three quarters.

Obtaining sales data from Compustat also results in loss of firms from the sample.

6.2.1 Differential effects across firms

We next examine if this effect differs based on two firm characteristics: size and analyst following. We estimate the following panel regression:

$$\begin{aligned} \text{DCOV}_{jt} = & b_1 \text{DLOSSF}_{jt} + b_2 \text{DSMALL}_{jt} + b_3 \text{DLOWFOLL}_{jt} + b_4 \text{DREGFD}_{jt} + \\ & b_5 \text{DSMALL}_{jt} * \text{DREGFD}_{jt} + b_6 \text{DLOWFOLL}_{jt} * \text{DREGFD}_{jt} + u_{jt} \end{aligned} \quad (7)$$

where $\text{DSMALL}_{jt} = \text{SMALL}_{jt} - \overline{\text{SMALL}}_j$. The indicator variable SMALL_{jt} equals one if company j 's market value of equity is \$200 million or lower in year t , and zero otherwise.

$\overline{\text{SMALL}}_j$ is the mean value of SMALL for company j over the sample period.⁸

$\text{DLOWFOLL}_{jt} = \text{LOWFOLL}_{jt} - \overline{\text{LOWFOLL}}_j$. The indicator variable LOWFOLL_{jt} equals one if company j is followed by four or fewer analysts in year t , and zero otherwise.

$\overline{\text{LOWFOLL}}_j$ is the mean value of LOWFOLL for company j over the sample period. The other variables are as defined earlier.

Table 8 shows estimates of three variants of equation (7) for both time periods for the combined sample of the three quarters. COV increases following Reg FD. The coefficient of the DREGFD variable is always positive and statistically significant. Apparently, as earnings guidance from a company reduces, analysts are no longer able to herd at the precise eps number. Instead they become more disperse in their forecasts. There is no differential effect of Reg FD for either small firms or less followed firms.

7. Analyst rankings

Finally, we examine changes in the stability of analyst rankings from year to year following the adoption of fair disclosure rules. As discussed in section 2.3, rankings

⁸The sample period for this test is 1996-2001 because I/B/E/S data on stock prices begins in 1996.

should become more stable if analysts differ in their research abilities and companies favored different analysts over time pre-FD. Alternatively, rankings should become less stable if companies consistently favored the same analyst(s) pre-FD. No change should be observed if all analysts are equally good at research and companies favored different analysts over time, or if the rules are not effectively enforced.

7.1 Univariate tests

We compute a change in the performance ranking of analyst i for forecast period t as:

$$\Delta \text{SCORE}_{it} = |\text{SCORE}_{it} - \text{SCORE}_{i,t-1}| \quad (8)$$

where SCORE_{it} = analyst i 's average performance score in year t . The performance score of analyst i following company j for forecast period t is calculated as

$$s_{ijt} = 100 - \{(r_{ijt} - 1) / (n_{jt} - 1)\} * 100 \quad (9)$$

where r_{ijt} is the rank of analyst i following company j in year t and n_{jt} is the number of analysts following company j in year t . The most accurate analyst following company j receives the rank of one. The average performance score of an analyst in a given year is the average score across all companies followed by her. This algorithm for computing SCORE follows Hong, Kubik and Solomon (2000), and takes into account differences across analysts in the number of companies covered and in the analyst coverage of those companies. The sample excludes all companies that are followed by only one analyst and all analysts that follow only one company.

Table 9 shows the mean and median values of changes in analysts' average performance scores pre and post-FD. The post-FD period consists of changes from 1999

to 2000 for the quarter ending December 31, and from 2000 to 2001 for the two subsequent quarters. The pre-FD period consists of changes over 1995 to 1996 and 1997 to 1998 for the December 31 quarter, and over 1996 to 1997 and 1998 to 1999 for the two subsequent quarters.

Table 9 shows that performance scores of analysts are fairly unstable over time. Column 1 shows that for the first forecast period for the December 31 quarter pre-FD, an analyst's mean performance score changed by an average of 25.11 percentage points from one year to the next. Post-FD, the performance is still fairly unstable from year to year, though the instability abates a bit. Changes in mean performances scores reduce post-FD in all six forecast periods examined; the decrease is statistically significant at the 5% level or better in the four forecast periods corresponding to the quarters ending March 31 and June 30. A similar picture emerges from an examination of median changes shown in columns 4 and 5. Here, there is a statistically significant decrease in year-to-year performance score changes post-FD in five of the six forecast periods examined.

7.2 Fixed effects regression

We next examine this issue after controlling for analyst fixed effects. We estimate the following cross-sectional time series regression:

$$DSCORE_{it} = b_1 DREGFD_{it} + u_{it} \quad (10)$$

where $DSCORE_{it} = \Delta SCORE_{it} - \overline{\Delta SCORE}_i$; and $DREGFD_{it} = REGFD_{it} - \overline{REGFD}_i$. The indicator variable $REGFD_{it}$ equals one for the post-FD period (year 2000 for the December ending quarter and year 2001 for March and June ending quarters), and zero otherwise. \overline{REGFD}_i is the mean value of $REGFD$ for analyst i over the sample period.

The sample consists of DSCORE observations over all successive pairs of years over the period 1995-2001. It includes all analysts in the I/B/E/S database that have a DSCORE observation post-FD and at least one DSCORE observation pre-FD.

We estimate equation (10) for both forecast periods for each of the three quarters and for the combined sample of the three quarters. The model ignores normal variations in score changes across analysts. Instead, it focuses on variation in score changes following Reg FD, after controlling for the normal level of score change for each analyst over the sample period. Unlike the regressions in sections 5.2 and 6.2 above, the analysis here is at the level of an analyst rather than an analyst-company or a company. So we can not control for potential differences across profit and loss companies.

Columns 1 and 2 of Table 10 show a reduction in DSCORE following Reg FD for each of the three quarters examined; the effect is statistically significant at the 1% level for the quarters ending March 31 and June 30. The reduction is also statistically significant at the 1% level for the combined sample of the three quarters. Analyst rankings, on which the performance scores are based, became somewhat more stable following the adoption of fair disclosure rules. This is consistent with the joint propositions that analysts differ in their research abilities and companies favored different analysts over time pre-FD.

7.3 Analysis of “flipping”

Finally we examine the incidence of extreme changes in the performance score of an analyst from one year to the next. This happens when an analyst “flips” from being in the top quartile of all analysts in one year (based on her average performance score for a

given forecast period) to the bottom quartile the following year, or vice versa. We compute the average performance score of each analyst covering any set of two or more companies in two consecutive years (not necessarily the same set of companies each year) for a given forecast period. This average is computed across all the companies followed by an analyst. As in sections 7.1 and 7.2 above, companies followed by only one analyst are omitted.

Table 11 shows the percentage of analysts that flip from being a top ranked (quartile 1) analyst one year to being a bottom ranked (quartile 4) analyst the following year, or vice versa. The post Reg FD period consists of flipping from 1999 to 2000 for the quarter ended December 31, and flipping from 2000 to 2001 for the two subsequent quarters. The pre Reg FD period consists of flipping from 1995 to 1996 and from 1997 to 1998 for the December 31 quarter, and from 1996 to 1997 and from 1998 to 1999 for the two subsequent quarters.

Column 1 of Table 11 shows that pre-FD, about one-eighth of all analysts that have portfolios of two or more companies in two successive years flip ranks from being a top-ranked analyst one year to being bottom-ranked the next year. There is no significant change in the proportion of flippers following Reg FD, except for an increase for the second forecast period for the quarter ending June 30.

8. Summary and concluding remarks

This paper analyzes changes in the behavior and performance of sell-side equity analysts following the October 2000 adoption of fair disclosure rules by the SEC. These rules put severe restrictions on one-on-one communication between a company and the

analysts following it, and between the company and its investors. Generally referred to as Reg FD, these rules ban the practice of “selective earnings guidance”, where a company provides future earnings and other crucial business information to analysts and large investors without simultaneously releasing it to all investors. Pushed by the then SEC chairman Arthur Levitt, these rules are intended to level the playing field for all investors.

We analyze forecasts of earnings for three quarters following the adoption of these rules. We do a “before” vs. “after” comparison, where the period before Reg FD consists of the average of the corresponding quarter over the previous three to five years. We conduct univariate tests and perform panel regressions using the fixed effects model. We also investigate whether the effects differ based on firm characteristics such as size and analyst following. The analysis is based on a large sample of public companies and the analysts following them.

We have three main findings. First, earnings forecasts became less accurate following Reg FD, both at the level of the individual analyst and at the consensus level. This effect is found both in univariate tests and in panel regressions controlling for analyst-company fixed effects. The effect is particularly pronounced in small firms. Second, individual analysts following a company are more dispersed in their earnings forecasts. This effect, while not evident in univariate tests, shows up strongly in panel regressions that control for company fixed effects. Third, analyst performance rankings become somewhat more stable following the adoption of fair disclosure rules. This effect is found both in univariate tests and in panel regressions that control for analyst fixed effects. However, we find no evidence of any more “flipping”, where an analyst goes

from being in the top quartile of all analysts one year to the bottom quartile the next year or vice versa, following Reg FD than before.

While this research has examined changes in the behavior and performance of sell-side analysts, it will also be interesting to look at changes in the behavior of companies, as well as the response of investors and stock prices to the new regulatory environment. For example, do companies substitute public disclosure of forward-looking earnings-relevant information for private disclosure via analysts? How does informed trading before earnings announcements change? An analysis of longer-run effects of Reg FD will also be interesting. Detailed knowledge of the long history of interactions between analysts and companies will be useful in putting the effects of the new rules in perspective. For instance, how old is the practice of selective earnings guidance? How was information transmitted from companies to analysts to investors before that? And how does the post-FD equilibrium differ from the pre-selective guidance days? All of these are interesting questions for future research.

References

- Association for Investment Management and Research, 2001, Regulation FD e-survey summary, http://www.aimr.com/pressroom/01releases/regfd_surveysum.htm.
- Bartov, Eli, Dan Givoly and Carla Hayn, 2000, The rewards to meeting or beating earnings expectations, Working paper, NYU.
- Brown, Lawrence D., 2001, A temporal analysis of earnings surprises: Profits versus losses, *Journal of Accounting Research* 39, 221-241.
- Brown, Lawrence D., Robert L. Hagerman, Paul A. Griffin, and Mark E. Zmijewski, 1987, Security analyst superiority relative to univariate time-series models in forecasting quarterly earnings, *Journal of Accounting and Economics* 9, 61-87.
- Butler, Kirt C. and Larry H. P. Lang, 1991, The forecast accuracy of individual analysts: Evidence of systematic optimism and pessimism, *Journal of Accounting Research* 29 Supplement, 150-156.
- Clement, Michael B., 1993, Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter?, *Journal of Accounting and Economics* 27, 285-303.
- DeGeorge, Francois, Jayendu Patel and Richard Zeckhauser, 1999, Earnings management to exceed thresholds, *Journal of Business* 72, 1-33.
- Easterwood, John C. and Nutt, Stacey R., 1999, Inefficiency in analysts' earnings forecasts: Systematic misreaction or systematic optimism?, *Journal of Finance* 54, 1777-1797.
- Francis, Jennifer, J. Douglas Hanna, and Donna R. Philbrick, 1997, Management communications with security analysts, *Journal of Accounting and Economics* 24, 363-394.
- Graham, John, 1999, Herding Among Investment Newsletters: Theory and Evidence, *Journal of Finance* 54, 237-268.
- Greene, William, 1993, *Econometric Analysis*, MacMillan Publishing Company, New York, NY.
- Heflin, Frank, K. R. Subramanyam, and Yuan Zhang, 2001, Regulation FD and the Financial Information Environment, Working paper, Purdue University.
- Hong, Harrison, Jeffrey D. Kubik, and Amit Soloman, 2000, Security Analysts' Career Concerns and Herding of Earnings Forecasts, *RAND Journal of Economics* 31, 121-144.

Jacob, John, Thomas Z. Lys, and Margaret A. Neale, 1999, Expertise in forecasting performance of security analysts, *Journal of Accounting and Economics* 28, 51-82.

McGough, R. and C. Bryan-Low, 2000, SEC disclosure Rule May Be Source of Diverging Estimates, *Wall Street Journal*, November 2.

Michaely, Roni, and Kent Womack, 1999, Conflict of Interest and the Credibility of Underwriter Analyst Recommendations, *Review of Financial Studies* 12, 653-686.

Mikhail, Michael B., Beverly R. Walther, and Richard H. Willis, 1997, Do security analysts improve their performance with experience?, *Journal of Accounting Research* 35 Supplement, 131-157.

Nocera, Joseph, 2000, No whispering Allowed, *Money*, December, 71-74.

O'Brien, Patricia C., 1990, Forecast accuracy of individual analysts in nine industries, *Journal of Accounting Research* 28, 286-304.

Opdyke, Jeff D., 2000, The Big Chill: Street Feels Effect of 'Fair Disclosure' Rule, *Wall Street Journal*, October 23, C1.

Ryan, Vincent, 2000, Interpreting the fair disclosure rule, *Telephony* 239, August 28, 34-35.

Sinha, Praveen, Lawrence D. Brown and Somnath Das, 1997, A re-examination of financial analysts' differential earnings forecast accuracy, *Contemporary Accounting Research* 14, 1-42.

Stickel, Scott E., 1992, Reputation and performance among security analysts, *Journal of Finance* 47, 1811-1836.

Trueman, Brett, 1994, Analyst Forecasts and Herding Behavior, *Review of Financial Studies* 7, 97-124.

Welch, Ivo, 2000, Herding Among Security Analysts, *Journal of Financial Economics* 58, 369-396.

Womack, Kent, 1996, Do Brokerage Analysts' Recommendations Have Investment Value?, *Journal of Finance* 51, 137-167.

Table 1

Sample sizes

The table shows the number of individual and consensus forecasts on the I/B/E/S database for the quarter ended December 31, 2000 that satisfy various data requirements. Column 1 for row 2 is for the latest forecast made by individual analysts during August 10-October 22, 2000 for the quarter ending December 31, 2000; column 2 for row 2 is for the latest consensus forecasts.

	Number of forecasts	
	Individual Analyst	Consensus
1. All forecasts for the quarter ending December 31, 2000	73,851	45,407
2. Latest forecasts made during August 10-October 22, 2000 for the quarter ending Dec. 31, 2000	10,104	3,356
3. Item 2 with actual eps available	9,544	2,891
4. Item 3 with stock price available	8,516	2,336
5. Item 4 with stock price of \$1 or more	8,461	2,321

Table 2
Individual analyst forecast errors normalized by stock price around Reg FD

The table shows normalized forecast errors for analyst *i* following company *j* for forecast period *t*, calculated as:

$$NFE_{ijt} = |e_{jt} - \hat{e}_{ijt}| / p_{jt}$$

where e_{jt} = earnings per share (eps) for company *j* for quarter *t*; \hat{e}_{ijt} = estimate of e_{jt} by analyst *i*; and p_{jt} = the latest stock price in the I/B/E/S database for company *j* within a given time window. For each window, the latest eps estimate made by an analyst is used. Companies with stock price under \$1 are excluded.

Forecast for Period <i>Latest Forecast made during</i>	Mean			Median Wilcoxon			Sample size (# Analyst-companies)	
	Pre ¹	Post ¹	p-value ²	Pre ¹	Post ¹	p-value ²	Pre ¹	Post ¹
Quarter ended Dec. 31								
<i>Aug. 10 – Oct. 22</i>	.0088	.0133	<.0001	.0018	.0018	.25	18,603	8,461
<i>Oct. 23 – Jan. 10</i>	.0068	.0119	<.0001	.0011	.0010	.04	21,560	10,837
Quarter ended March 31								
<i>Oct. 23-Dec. 22</i>	.0082	.0188	<.0001	.0019	.0033	<.0001	10,980	5,373
<i>Dec. 23-Feb. 22</i>	.0048	.0069	<.0001	.0012	.0016	<.0001	20,144	9,598
Quarter ended June 30								
<i>Feb. 1-March 31</i>	.0071	.0106	<.0001	.0018	.0031	<.0001	16,318	6,893
<i>April 1-May 31</i>	.0067	.0077	.22	.0012	.0013	.019	23,237	12,732

¹The “Post” Reg FD period consists of the year 2000 for the quarter ended Dec. 31 and 2001 for the other two quarters. The “Pre” Reg FD period consists of the average across all unique analyst-company pairs over the three prior years.

²P-values are based on 2-tailed tests.

Table 3
Consensus forecast errors around Reg FD, normalized by stock price

The table shows normalized consensus forecast errors for company j for forecast period t , calculated as:

$$NFE_{jt} = |e_{jt} - \hat{e}_{jt}| / p_{jt}$$

where e_{jt} = earnings per share (eps) for company j for quarter t ; \hat{e}_{jt} = median of all analyst estimates of e_{jt} ; and p_{jt} = the latest stock price in the I/B/E/S database for company j within a given time window. In each window, the latest median estimate of eps is used. Companies with stock price under \$1 are excluded.

Forecast for Period <i>Latest forecast made during</i>	Mean			Median Wilcoxon			Sample size (# Companies)	
	Pre ¹	Post ¹	p-value ²	Pre ¹	Post ¹	p-value ²	Pre ¹	Post ¹
Quarter ended Dec. 31								
<i>Aug. 10 – Oct. 22</i>	.0182	.0187	.79	.0043	.0034	<.0001	3,319	2,321
<i>Oct. 23 – Jan. 10</i>	.0133	.0181	.037	.0025	.0023	.013	3,477	2,272
Quarter ended March 31								
<i>Oct. 23-Dec. 22</i>	.0126	.0298	<.0001	.0036	.0051	<.0001	3,073	1,962
<i>Dec. 23-Feb. 22</i>	.0103	.0212	<.0001	.0025	.0032	.004	3,329	2,089
Quarter ended June 30								
<i>Feb. 1-March 31</i>	.0138	.0224	.008	.0038	.0052	<.0001	3,318	1,976
<i>April 1-May 31</i>	.0156	.0144	.68	.0028	.0026	.001	3,492	2,249

¹The “Post” Reg FD period consists of the year 2000 for the quarter ended Dec. 31 and 2001 for the other two quarters. The “Pre” Reg FD period consists of the average across all consensus forecast errors for each company over the three prior years.

²P-values are based on 2-tailed tests.

Table 4

Coefficient estimates from cross-sectional time series regressions of forecast errors normalized by stock price

Panel A shows the estimated coefficients, t-statistics and adjusted R² values from the following panel regression:

$$DNFE_{ijt} = b_1 DLOSS_{ijt} + b_2 DREGFD_{ijt} + u_{ijt}$$

where $DNFE_{ijt} = NFE_{ijt} - \overline{NFE}_{ij}$; $NFE_{ijt} = |e_{jt} - \hat{e}_{ijt}| / p_{jt}$; e_{jt} = earnings per share (eps) for company j for quarter t ; \hat{e}_{ijt} = estimate of e_{jt} by analyst i ; and p_{jt} = the latest stock price in the I/B/E/S database for company j within a given time window. \overline{NFE}_{ij} is the mean NFE for analyst i following company j over the sample period. $DLOSS_{ijt} = LOSS_{ijt} - \overline{LOSS}_{ij}$. The indicator variable $LOSS_{ijt} = 1$ if $e_{jt} < 0$; it equals zero otherwise. \overline{LOSS}_{ij} is the mean value of $LOSS$ for analyst i following company j over the sample period. $DREGFD_{ijt} = REGFD_{ijt} - \overline{REGFD}_{ij}$. The indicator variable $REGFD_{ijt}$ equals one for the post-Reg FD period (year 2000 for the December ending quarter and year 2001 for March and June ending quarters), and zero otherwise. \overline{REGFD}_{ij} is the mean value of $REGFD$ for analyst i following company j over the sample period. The sample period is 1997-2001. The sample includes all company-analyst pairs in the I/B/E/S database that have a NFE observation post-FD and at least one NFE observation pre-FD. For each window, the latest eps estimate made by an analyst is used. Companies with stock price under \$1 are excluded. Panel B shows corresponding regressions for the consensus forecasts.

Table 4 (cont.)

Forecast for period <i>Latest forecast made during</i>	\hat{b}_1	$t(\hat{b}_1)$	\hat{b}_2	$t(\hat{b}_2)$	\bar{R}^2	Sample Size
<u>A. Individual analyst forecasts</u>						
Quarter ended Dec. 31						
<i>Aug. 10 – Oct. 22</i>	.052	16.26 ^a	.009	7.77 ^a	.041	7,978
<i>Oct. 23 – Jan. 10</i>	.027	9.25 ^a	.007	5.98 ^a	.011	10,555
Quarter ended March 31						
<i>Oct. 23 – Dec. 22</i>	.018	12.83 ^a	.005	8.43 ^a	.079	3,303
<i>Dec. 23 – Feb. 22</i>	.012	33.43 ^a	.002	11.16 ^a	.115	10,898
Quarter ended June 30						
<i>Feb. 1 – March 31</i>	.017	28.74 ^a	.003	12.89 ^a	.159	6,140
<i>April 1 – May 31</i>	.011	18.57 ^a	.002	5.74 ^a	.026	15,961
Combined Sample						
<i>Period 1</i>	.030	21.74 ^a	.006	10.82 ^a	.037	17,421
<i>Period 2</i>	.015	18.05 ^a	.003	8.42 ^a	.012	37,414
<u>B. consensus forecasts</u>						
Quarter ended Dec. 31						
<i>Aug. 10 – Oct. 22</i>	.037	17.83 ^a	.007	7.07 ^a	.062	5,879
<i>Oct. 23 – Jan. 10</i>	.027	9.84 ^a	.010	7.83 ^a	.026	6,250
Quarter ended March 31						
<i>Oct. 23 – Dec. 22</i>	.024	9.29 ^a	.013	9.70 ^a	.038	5,159
<i>Dec. 23 – Feb. 22</i>	.017	7.51 ^a	.010	8.16 ^a	.023	5,862
Quarter ended June 30						
<i>Feb. 1 – March 31</i>	.023	11.31 ^a	.009	8.39 ^a	.040	5,600
<i>April 1 – May 31</i>	.018	7.51 ^a	.007	5.87 ^a	.016	6,483
Combined Sample						
<i>Period 1</i>	.028	21.79 ^a	.010	14.43 ^a	.044	16,638
<i>Period 2</i>	.020	14.26 ^a	.009	12.43 ^a	.021	18,595

^aDenotes statistical significance at the 1% level in two-tailed tests.

Table 5
Coefficient estimates from cross-sectional time-series regressions for the combined sample of forecast errors
normalized by stock price

Panel A shows the estimated coefficients, t-statistics and adjusted R² values from variations of the following panel regression:

$$DNFE_{ijt} = b_1 DLOSS_{ijt} + b_2 DSMALL_{ijt} + b_3 DLOWFOLL_{ijt} + b_4 DREGFD_{ijt} + b_5 DSMALL_{ijt} * DREGFD_{ijt} + b_6 DLOWFOLL_{ijt} * DREGFD_{ijt} + u_{ijt}$$

where $DNFE_{ijt} = NFE_{ijt} - \overline{NFE}_{ij}$; $NFE_{ijt} = |e_{jt} - \hat{e}_{ijt}| / p_{jt}$; e_{jt} = earnings per share (eps) for company j for quarter t; \hat{e}_{ijt} = estimate of e_{jt} by analyst i; and p_{jt} = the latest stock price in the I/B/E/S database for company j within a given time window. \overline{NFE}_{ij} is the mean NFE for analyst i forecasting company j over the sample period. $DLOSS_{ijt} = LOSS_{ijt} - \overline{LOSS}_{ij}$. The indicator variable $LOSS_{ijt} = 1$ if $e_{jt} < 0$; it equals zero otherwise. \overline{LOSS}_{ij} is the mean value of $LOSS$ for analyst i following company j over the sample period. $DSMALL_{ijt} = SMALL_{ijt} - \overline{SMALL}_{ij}$. The indicator variable $SMALL_{ijt}$ equals one if company j's market value of equity is \$200 million or lower in year t, and zero otherwise. \overline{SMALL}_{ij} is the mean value of $SMALL$ for analyst i following company j over the sample period. $DLOWFOLL_{ijt} = LOWFOLL_{ijt} - \overline{LOWFOLL}_{ij}$. The indicator variable $LOWFOLL_{ijt}$ equals one if company j is followed by four or fewer analysts in year t, and zero otherwise. $\overline{LOWFOLL}_{ij}$ is the mean value of $LOWFOLL$ for analyst i following company j over the sample period. $DREGFD_{ijt} = REGFD_{ijt} - \overline{REGFD}_{ij}$. The indicator variable $REGFD_{ijt}$ equals one for the post-Reg FD period (year 2000 for the December ending quarter and year 2001 for March and June ending quarters), and zero otherwise. \overline{REGFD}_{ij} is the mean value of $REGFD$ for analyst i following company j over the sample period. The sample period is 1997-2001. The dataset combines observations from the December, March, and June ending quarters. The sample includes all company-analyst pairs in the I/B/E/S database that have a NFE observation post-FD and at least one NFE observation pre-FD. For each window, the latest eps estimate made by an analyst is used. Companies with stock price under \$1 are excluded. Panel B shows corresponding regressions for the consensus forecasts.

Table 5 (cont.)

Independent Variable	Panel A: Individual Analyst						Panel B: Consensus					
	Period 1			Period 2			Period 1			Period 2		
	1	2	3	4	5	6	7	8	9	10	11	12
DLOSS	.028 (19.84) ^a	.030 (21.79) ^a	.028 (19.87) ^a	.013 (14.94) ^a	.015 (18.04) ^a	.013 (14.94) ^a	.025 (19.35) ^a	.028 (21.78) ^a	.025 (19.31) ^a	.017 (11.74) ^a	.020 (14.23) ^c	.017 (11.73) ^a
DSMALL	.031 (16.34) ^a		.030 (16.37) ^a	.027 (22.32) ^a		.027 (22.30) ^a	.020 (16.24) ^a		.020 (16.27) ^a	.021 (15.01) ^a		.021 (14.90) ^a
DLOWFOLL		.002 (2.31) ^b	.002 (1.72) ^c		.001 (.82)	-.0001 (-.19)		-.0004 (-.43)	-.001 (-1.06)		.002 (2.12) ^b	.001 (1.30)
DREGFD	.006 (10.40) ^a	.006 (10.94) ^a	.006 (10.50) ^a	.003 (7.42) ^a	.003 (8.48) ^a	.003 (7.40) ^a	.009 (14.45) ^a	.010 (14.39) ^a	.009 (14.37) ^a	.009 (12.12) ^a	.009 (12.66) ^a	.009 (12.24) ^a
DSMALL*DREGFD	.015 (3.95) ^a		.015 (3.92) ^a	.006 (2.57) ^a		.006 (2.54) ^b	.008 (2.92) ^a		.008 (2.95) ^a	.008 (2.51) ^b		.007 (2.41) ^b
DLOWFOLL*DREGFD		.003 (1.27)	.003 (1.23)		.001 (.81)	0.0008 (.54)		.0002 (.10)	-.0006 (-.30)		.004 (1.60)	.003 (1.16)
Adjusted R ²	.052	.037	.052	.025	.012	.025	.06	.044	.06	.033	.022	.034
p-value for F-test	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
Sample Size	17,421	17,421	17,421	37,414	37,414	37,414	16,638	16,638	16,638	18,595	18,595	18,595

^{a,b,c}Denote statistical significance at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

Table 6
Dispersion of analyst forecasts around Reg FD

The table shows the coefficient of variation (COV) of analyst forecasts. For company j for forecast period t , $COV_{j,t} = (\sigma_{jt} / |\bar{X}_{jt}|)$, where σ_{jt} and \bar{X}_{jt} equal, respectively, the standard deviation and the mean of the forecasts of all analysts following the company. For each window, the latest forecast made by each analyst is used to compute σ and \bar{X} . Companies followed by two or fewer analysts and companies with mean eps forecasts of \$.10 or lower are excluded.

Forecast for Period <i>Latest forecast made during</i>	Mean			Median Wilcoxon			Sample size (# Companies)	
	Pre ¹	Post ¹	p-value ²	Pre ¹	Post ¹	p-value ²	Pre ¹	Post ¹
Quarter ended Dec. 31								
<i>Aug. 10 – Oct. 22</i>	.1177	.1050	.038	.0628	.0510	< .0001	3,318	1,517
<i>Oct. 23 – Jan. 10</i>	.1221	.1069	.016	.0614	.0511	< .0001	4,048	1,870
Quarter ended March 31								
<i>Oct. 23-Dec. 22</i>	.1081	.1040	.45	.0584	.0615	.84	2,544	1,098
<i>Dec. 23-Feb. 22</i>	.1000	.0979	.66	.0541	.0480	.002	3,272	1,524
Quarter ended June 30								
<i>Feb. 1-March 31</i>	.1024	.1104	.088	.0524	.0590	.088	3,263	1,312
<i>April 1-May 31</i>	.0988	.1019	.53	.0523	.0507	.66	3,837	1,883

¹The “post” Reg FD period consists of the year 2000 for the quarter ended Dec. 31, and the year 2001 for the two subsequent quarters. The “pre” Reg FD period consists of the prior five years.

²P-values are based on two-tailed tests.

Table 7

Coefficient estimates from cross-sectional time series regressions of dispersion of analyst forecasts

The table shows the estimated coefficients, t-statistics and adjusted R² values from the following panel regression:

$$DCOV_{jt} = b_1 DLOSSF_{jt} + b_2 DREGFD_{jt} + u_{jt}$$

where $DCOV_{jt} = COV_{jt} - \overline{COV}_j$; COV_{jt} is the absolute value of the coefficient of variation ($\sigma / | \bar{X} |$); σ and \bar{X} equal the standard deviation and the mean of the forecasts of eps by all analysts following company j in year t ; and \overline{COV}_j is the mean coefficient of variation for firm j over the sample period. For each window, the latest forecast made by each analyst is used to compute σ and \bar{X} . $DLOSSF_{jt} = LOSSF_{jt} - \overline{LOSSF}_j$. The indicator variable $LOSSF_{jt} = 1$ if the median of all analyst forecasts of eps for company j in year t is negative; it equals zero otherwise. \overline{LOSSF}_j is the mean value of $LOSSF$ for company j over the sample period. $DREGFD_{jt} = REGFD_{jt} - \overline{REGFD}_j$. The indicator variable $REGFD_{jt}$ equals one for the post-Reg FD period (year 2000 for the December ending quarter and year 2001 for March and June ending quarters), and zero otherwise. \overline{REGFD}_j is the mean value of $REGFD$ for company j over the sample period. The sample period is 1995-2001. The sample includes all companies in the I/B/E/S database that have a COV observation post-FD and at least one COV observation pre-FD. Companies followed by two or fewer analysts or with mean eps forecasts of \$0.10 or lower are excluded.

Forecast for period <i>Latest forecast made during</i>	\hat{b}_1	$t(\hat{b}_1)$	\hat{b}_2	$t(\hat{b}_2)$	\bar{R}^2	Sample Size
Quarter ended Dec. 31						
<i>Aug.10 – Oct. 22</i>	.213	12.53 ^a	.003	.66	.033	4,559
<i>Oct. 23 – Jan. 10</i>	.311	25.94 ^a	.003	.82	.103	5,944
Quarter ended March 31						
<i>Oct. 23 – Dec. 22</i>	.104	4.58 ^a	.012	3.07 ^a	.012	2,521
<i>Dec. 23 – Feb. 22</i>	.209	17.40 ^a	.003	.74	.059	4,929
Quarter ended June 30						
<i>Feb. 1 – March 31</i>	.202	13.00 ^a	.015	4.41 ^a	.047	3,946
<i>April 1 – May 31</i>	.171	12.62 ^a	.013	3.64 ^a	.029	6,037
Combined Sample						
<i>Period 1</i>	.191	18.36 ^a	.009	4.18 ^a	.032	11,026
<i>Period 2</i>	.238	32.73 ^a	.006	3.06 ^a	.061	16,910

^{a,b,c}Denote statistical significance at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

Table 8
Coefficient estimates from cross-sectional time-series regressions for
the combined sample of dispersion of analyst forecasts

The table shows the estimated coefficients, t-statistics and adjusted R^2 values from the following panel regression:

$$\text{DCOV}_{jt} = b_1 \text{DLOSSF}_{jt} + b_2 \text{DSMALL}_{jt} + b_3 \text{DLOWFOLL}_{jt} + b_4 \text{DREGFD}_{jt} + b_5 \text{DSMALL}_{jt} * \text{DREGFD}_{jt} + b_6 \text{DLOWFOLL}_{jt} * \text{DREGFD}_{jt} + u_{jt}$$

where $\text{DCOV}_{jt} = \text{COV}_{jt} - \overline{\text{COV}}_j$; COV_{jt} is the absolute value of the coefficient of variation ($\sigma / |\bar{X}|$); σ and \bar{X} equal the standard deviation and the mean of the forecasts of all analysts following firm j in year t ; and $\overline{\text{COV}}_j$ is the mean coefficient of variation for firm j over the sample period. For each window, the latest forecast made by each analyst is used to compute σ and \bar{X} . $\text{DLOSSF}_{jt} = \text{LOSSF}_{jt} - \overline{\text{LOSSF}}_j$. The indicator variable $\text{LOSSF}_{jt} = 1$ if the median of all analyst forecasts of eps for company j in year t is negative; it equals zero otherwise. $\overline{\text{LOSSF}}_j$ is the mean value of LOSSF for company j over the sample period. $\text{DSMALL}_{jt} = \text{SMALL}_{jt} - \overline{\text{SMALL}}_j$. The indicator variable SMALL_{jt} equals one if company j 's market value of equity is \$200 million or lower in year t , and zero otherwise. $\overline{\text{SMALL}}_j$ is the mean value of SMALL for company j over the sample period. $\text{DLOWFOLL}_{jt} = \text{LOWFOLL}_{jt} - \overline{\text{LOWFOLL}}_j$. The indicator variable LOWFOLL_{jt} equals one if company j is followed by four or fewer analysts in year t , and zero otherwise. $\overline{\text{LOWFOLL}}_j$ is the mean value of LOWFOLL for company j over the sample period. $\text{DREGFD}_{jt} = \text{REGFD}_{jt} - \overline{\text{REGFD}}_j$. The indicator variable REGFD_{jt} equals one for the post-Reg FD period (year 2000 for the December ending quarter and year 2001 for March and June ending quarters), and zero otherwise. $\overline{\text{REGFD}}_{ij}$ is the mean value of REGFD for company j over the sample period. The sample period is 1996-2001. The sample includes all companies in the I/B/E/S database that have a COV observation post-FD and at least one COV observation pre-FD. Companies followed by two or fewer analysts and companies with mean eps forecasts of \$0.10 or lower are excluded.

Table 8 (cont.)

Independent Variable	Period 1			Period 2		
	1	2	3	4	5	6
DLOSSF	.141 (11.90) ^a	.152 (12.90) ^a	.142 (12.07) ^a	.237 (25.61) ^a	.239 (26.03) ^a	.237 (25.63) ^a
DSMALL	.047 (6.30) ^a		.05 (6.73) ^a	.010 (1.41)		.011 (1.61)
DLOWFOLL		-.029 (-9.58) ^a	-.03 (-9.87) ^a		-.015 (-4.76) ^a	-.015 (-4.82) ^a
DREGFD	.012 (5.03) ^a	.012 (5.12) ^a	.011 (4.70) ^a	.006 (2.71) ^a	.005 (2.27) ^b	.005 (2.15) ^b
DSMALL*DREGFD	-.011 (-.74)		-.011 (-.72)	.009 (.61)		.009 (.63)
DLOWFOLL*DREGFD		-.004 (-.66)	-.004 (-.65)		-.009 (-1.20)	-.009 (-1.23)
Adjusted R ²	.033	.040	.046	.065	.067	.067
p-value for F-test	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001
Sample Size	6,858	6,858	6,858	10,084	10,084	10,084

^{a,b,c}Denote statistical significance at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

Table 9
Changes in analyst performance scores around Reg FD

The table shows changes in performance rankings of analyst *i* for forecast period *t*, calculated as

$$\Delta \text{SCORE}_{it} = |\text{SCORE}_{it} - \text{SCORE}_{i,t-1}|,$$

where SCORE_{it} = analyst *i*'s average performance score in year *t*. The performance score of analyst *i* following company *j* for forecast period *t* is calculated as $s_{jt} = 100 - \{(r_{ijt} - 1) / (n_{jt} - 1)\} * 100$, where r_{ijt} is the rank of analyst *i* following company *j* in year *t*, and n_{jt} is the number of analysts following company *j* in year *t*. The most accurate analyst following company *j* receives the rank of one. The average performance score of an analyst in a given year is the average score across all companies followed by her. For each window, the forecast included for each analyst is the latest forecast made by her during the window. The sample excludes all companies that are followed by only one analyst and all analysts that follow only one company.

Forecast for Period <i>Latest Forecast made during</i>	Mean			Median Wilcoxon			Sample size (# Analysts)	
	Pre ¹	Post ¹	p-value ²	Pre ¹	Post ¹	p-value ²	Pre ¹	Post ¹
Quarter ended Dec. 31								
<i>Aug. 10 – Oct. 22</i>	25.11	23.96	.0910	20.83	18.83	.0031	1,777	1,637
<i>Oct. 23 – Jan. 10</i>	21.21	21.18	.9633	16.67	16.67	.5210	2,146	1,795
Quarter ended March 31								
<i>Oct. 23-Dec. 22</i>	30.01	27.40	.0048	26.04	23.61	.0029	1,199	993
<i>Dec. 23-Feb. 22</i>	23.07	21.39	.0093	18.16	15.84	.0003	1,869	1,583
Quarter ended June 30								
<i>Feb. 1-March 31</i>	26.16	24.25	.0078	22.20	19.82	.0038	1,670	1,375
<i>April 1-May 31</i>	21.39	19.53	.0008	17.08	15.00	<.0001	2,061	1,777

¹The column for the post-FD period shows changes in the average scores of analysts between the years 1999 and 2000 for the quarter ended December 31, and between the years 2000 and 2001 for the two subsequent quarters. The column for the “pre” Reg FD period shows changes in the average scores of analysts during 1995-96 and 1997-98 for the December 31 quarter, and during 1996-97 and 1998-99 for the two subsequent quarters.

²P-values are based on two-tailed tests.

Table 10**Coefficient estimates from cross-sectional time series regressions of changes in analyst performance scores**

The table shows the estimated coefficients, t-statistics and adjusted R^2 values from the following panel regression:

$$DSCORE_{it} = b_1 DREGFD_{it} + u_{it}$$

where $DSCORE_{it} = \Delta SCORE_{it} - \overline{\Delta SCORE}_i$; $\Delta SCORE_{it} = |SCORE_{it} - SCORE_{i,t-1}|$; $SCORE_{it}$ = analyst i 's performance score in year t ; and $\overline{\Delta SCORE}_i$ is the mean of the change in score of analyst i over the sample period. $DREGFD_{it} = REGFD_{it} - \overline{REGFD}_i$. The indicator variable $REGFD_{it}$ equals one for the post-Reg FD period (year 2000 for the December ending quarter and year 2001 for March and June ending quarters), and zero otherwise. \overline{REGFD}_i is the mean value of $REGFD$ for analyst i over the sample period. The sample consists of $DSCORE$ observations over all successive pairs of years over the period 1995-2001. The sample includes all analysts in the I/B/E/S database that have a $DSCORE$ observation post-FD and at least one $DSCORE$ observation pre-FD. The sample excludes all companies that are followed by only one analyst and all analysts that follow only one company.

Forecast for period <i>Latest forecast made during</i>	\hat{b}_1	$t(\hat{b}_1)$	\overline{R}^2	Sample Size
Quarter ended Dec. 31				
<i>Aug. 10 – Oct. 22</i>	-.366	-.72	-.0001	4,336
<i>Oct. 23 – Jan. 10</i>	-.464	-1.13	.000	5,078
Quarter ended March 31				
<i>Oct. 23 – Dec. 22</i>	-2.13 ^b	-2.67 ^a	.0028	2,197
<i>Dec. 23 – Feb. 22</i>	-1.68 ^c	-3.54 ^a	.0027	4,211
Quarter ended June 30				
<i>Feb. 1 – March 31</i>	-1.83 ^c	-3.23 ^a	.0028	3,418
<i>April 1 – May 31</i>	-2.88 ^a	-5.56 ^a	.0060	4,966
Combined Sample				
<i>Period 1</i>	-1.27	-3.69 ^a	.0013	9,951
<i>Period 2</i>	-1.46	-5.89 ^a	.0024	14,255

^{a,b,c}Denote statistical significance at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

Table 11**Changes in analyst performance scores between top and bottom quartiles around Reg FD**

The table shows the proportion of all analysts covering two or more companies in two consecutive years whose average performance scores for a given forecast period “flipped” from the top quartile of all analysts to the bottom quartile or vice versa over the two years. The performance score of analyst i following company j for forecast period t is calculated as

$$s_{ijt} = 100 - \{(r_{ijt} - 1) / (n_{jt} - 1)\} * 100,$$

where r_{ijt} is the rank of analyst i following company j in year t , and n_{jt} is the number of analysts following company j in year t . The most accurate analyst following company j receives the rank of one. Average performance score of an analyst in a given year is the average score across all companies followed by her. For each window, the forecast included for each analyst is the latest forecast made by her during the window. The sample excludes all companies that are followed by only one analyst and all analysts that follow only one company.

Forecast for Period <i>Latest forecast made during</i>	% of flippers			Sample size (# Analysts)	
	Pre ¹	Post ¹	p-value ²	Pre ¹	Post ¹
Quarter ended Dec. 31					
<i>Aug. 10 – Oct. 22</i>	13.48	13.01	.66	2,462	1,637
<i>Oct. 23 – Jan. 10</i>	12.15	11.53	.52	3,077	1,795
Quarter ended March 31					
<i>Oct. 23-Dec. 22</i>	11.46	11.18	.83	1,544	993
<i>Dec. 23-Feb. 22</i>	12.86	14.02	.29	2,559	1,583
Quarter ended June 30					
<i>Feb. 1-March 31</i>	13.02	12.29	.52	2,220	1,375
<i>April 1-May 31</i>	10.73	12.83	.03	2,897	1,777

¹The column for the post-FD period shows flipping between the years 1999 and 2000 for the quarter ended December 31, and between the years 2000 and 2001 for the two subsequent quarters. The pre-FD period column shows flipping between the years 1995 and 1996, and 1997 and 1998 for the December 31 quarter; and between the years 1996 and 1997, and 1998 and 1999 for the two subsequent quarters.

²P-values are based on two-tailed tests.