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 implications 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. We provide detailed empirical evidence that suggests that this effect is not entirely due to the recession. The effect is particularly pronounced in small firms, less followed firms, firms with losses, and firms in technology and consumer services sectors. Second, individual analysts following a company become more dispersed in their earnings forecasts post-FD. This effect is stronger in small firms and firms in technology and consumer durables sectors. Third, analyst performance rankings become somewhat more stable following the adoption of these rules. These results are generally robust to alternative methodologies and empirical procedures, and are consistent with a reduction in selective guidance following the adoption of fair disclosure rules.

Keywords: FD; Reg FD; Regulation fair disclosure; Fair disclosure rules; Security analysts; Analyst forecasts

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, customers, 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 two aspects of analyst performance, namely the accuracy of their earnings forecasts and the stability of rankings of their performance as forecasters, and an aspect of their forecast behavior, namely the dispersion of their forecasts. 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, analyst following, industry, and for firms with profits vs. losses.

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 (i.e., median of all analysts). We provide detailed empirical evidence that suggests that this effect can not be entirely attributed to the recession. The effect is more pronounced in small firms, firms followed by fewer analysts, firms with losses, and firms in technology and consumer services sectors. Second, forecasts become more dispersed following Reg FD. This effect is bigger for small firms and firms in the technology and consumer durables sectors. Third, analyst rankings become somewhat more stable following Reg FD. These results are generally robust to alternative methodologies and 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. We discuss forecast accuracy in section 2.1, forecast dispersion in section 2.2, and changes in analyst rankings in section 2.3.

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 theirs 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

[1]Prior studies find that the 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)).

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 absence of effective enforcement, the rules may have scant effect. So whether, and to what extent, the accuracy of analyst forecasts reduces post-FD 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 whether forecast dispersion increases post-FD 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] To the extent that this was true, the stability of analyst rankings from year to year can change immediately following the adoption of Reg FD. This is an important issue because rankings can affect analysts' influence on stock prices as well as analysts' careers (see, e.g., Mikhail, Walther and Willis (1999), and Hong and Kubik (2003)). Preferential treatment by companies can conceivably take one of two forms. A company can either favor the same analyst(s)

[2]For instance, Arthur Levitt, the former SEC Chairman, is quoted as saying, "Some in corporate management treat material information as a commodity – a way to gain and maintain favor with particular analysts" (see Ryan (2000)). Similarly, a prominent technology analyst is quoted as saying, "The analysts that are held in high esteem these days are those that are spoon-fed by management" (see Nocera (2000)).

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 of consistent preference pre-FD. Here, analyst rankings should become more variable when Reg FD begins if companies favored inferior analyst(s) pre-FD; the variability of rankings should remain unchanged if companies favored superior analyst(s) pre-FD. This should be true regardless of whether analysts differ in their research abilities.

Now consider the case of random preference pre-FD. Here, if all analysts are equally good at research, the new rules would leave the variability of rankings unchanged. But if some analysts are better than others, the banning of preferential treatment under Reg FD would actually reduce the variability of rankings by taking away the noise created by random preference. Of course, if the rules are not effectively enforced, no change should be observed. So whether analyst rankings become more or less variable when Reg FD begins is ultimately an empirical issue.

3. Prior studies

Since Reg FD is so recent, we are not aware of any published study that investigates its effects on the behavior and performance of stock analysts.[3] On the other hand, the behavior and performance of stock analysts in general 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 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. Again, the answer seems to be "yes" (see, e.g., Stickel (1992) and Sinha, Brown and Das (1997)). A third question is: "what determines differences in forecast accuracy across analysts?". The answer here seems to be: characteristics of analysts (such as experience and the number

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[3]In concurrent work, Heflin, et al. (2001) examine one quarter of post-FD data and find that stock prices adjust more quickly and stock returns are less volatile around earnings announcements, and firms increase the frequency of voluntary disclosures. They also look briefly at analyst forecast accuracy and dispersion. To the small extent that the two papers overlap, our results are similar.

of companies they follow) and of the brokerage houses that employ 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 firms with 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)).

4. Sample and data

In this section, we discuss our data in section 4.1, the origins of Reg FD in section 4.2, our choice of forecast periods in section 4.3, and sample sizes in section 4.4

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.

4.2 Origins of the rules

The rules were formally proposed by the SEC on December 15, 1999. They were open for public comment until March 29, 2000. Before its formal proposal, the first public hint of the SEC's concern with selective guidance came in a speech by Arthur Levitt, then Chairman of the SEC, at the "SEC Speaks" conference in Washington, DC on February 27, 1998 (SEC 1998a). Levitt subsequently spoke more forcefully against the practice at a speech at New York University on September 28, 1998 (SEC 1998b).

Could the rules have had an effect prior to their formal adoption? That is, companies may have seen the writing on the wall and stopped providing selective guidance to analysts once they became aware of the SEC's concern. This is certainly a possibility, although two pieces of evidence point against it. First, there was intense lobbying by analysts, brokerage firms and companies against the proposed rules up until their adoption. The only group in favor of the rules was individual investors who felt left out of the communication loop between companies, analysts and institutional investors. This may have led to uncertainty about the adoption of the rules. Second, in a January 2000 survey, 84% of corporate investor relations officers indicated that they would not reduce the amount of meetings they hold with investment professionals such as analysts in anticipation of the rules.[4] This suggests that guidance to analysts may not have reduced before the rules' adoption. Nonetheless, we repeated all our subsequent tests using the pre-1998 period as our pre-FD benchmark. These results are generally quite similar to those presented in the paper.

4.3 Forecast periods

For the quarter ended December 31, 2000, we analyze forecasts made over two time intervals of approximately similar lengths 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 adoption 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

[4] Investor Relations Business, Gray Areas in New Disclosure Regulation Worries IROs, January 24, 2000, page 1.

forecast period, we use the latest forecast made by each analyst following a company. This is an attempt at putting all analysts on an equal footing regarding the age of their forecasts. As discussed in section 5.4.2 below, the results are similar if we explicitly control for forecast age in our fixed effects regressions.

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.[5] Our results are robust to the choice of these forecast periods. As discussed in section 5.4.3, the results are similar when we use a different procedure that does not require us to make this choice.

4.4 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). Column 1 of 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

[5] In 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.

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 number in the last column for row 1 of Table 2. Column 2 of Table 1 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:

$$NFE_{ijt} = | e_{jt} - \hat{e}_{ijt} | / p_{jt} \qquad (1)$$

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 5.4.4, 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.

We start by presenting the results of univariate tests in section 5.1. Section 5.2 presents the results of fixed effects regressions. Section 5.3 examines whether the results differ based on four firm characteristics. Section 5.4 discusses the results of a variety of robustness checks.

5.1. Univariate tests

We present the results for individual analysts in section 5.1.1 and for consensus forecasts in section 5.1.2.

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.[6]

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 both forecast periods in the second and third quarters post-FD; 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 :

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

where $\hat{e}_{jt}$ = the latest median of all analyst forecasts of e_{jt} made within a given forecast window, and p_{jt} = 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

[6]We 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.

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 .05 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 the following cross-sectional time series regression of normalized forecast errors:

$$NFE_{ijt} = b_1\, LOSS_{ijt} + b_2\, REGFD_{ijt} + u_{ijt} \qquad (3)$$

where the indicator variable $LOSS_{ijt} = 1$ if $e_{jt}<0$; it equals zero otherwise. 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. The sample period is 1997-2000 for the December ending quarter and 1998-2001 for the two subsequent quarters. 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 each of the two forecast periods for each of the three quarters. We also estimate a combined regression where we pool the data from the three quarters.

Since we are only interested in examining the effect of Reg FD on forecast errors, rather than in assessing the usual determinants of forecast errors, we use a model with analyst-company fixed effects.[7] This involves adding a dummy variable for each analyst-company pair to the right hand side of equation (3). Alternatively, one can subtract from each variable in equation (3) its mean value for each analyst i following company j over

[7] See Wooldridge (2002) for a detailed exposition of the fixed effects model.

the sample period.[8] By treating analyst-company effects as fixed, we do not try to explain what determines the accuracy of analyst forecasts in general.[9] Instead, 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 observed in the forecast accuracy of analysts for profits versus losses (see, e.g., Brown (2001)). So we control for that effect by adding LOSS as an explanatory variable in equation (3). This allows us to focus on the effect of Reg FD. A positive coefficient on REGFD 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.[10] The estimated coefficient ($\hat{b}_2$) of the REGFD 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 non-trivial. For example, for period 1 of the combined sample, $\hat{b}_2 = .006$. For a \$50 stock, this implies an average increase in absolute earnings forecast error of 30 cents per share post-FD. Interestingly, 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. These results largely mirror those of Panel A. The coefficient of REGFD 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.

Consistent with earlier studies (e.g., Brown (2001)), forecast errors are substantially larger for loss firms than for profit firms. The coefficient of the LOSS variable is large, positive and statistically significant in all 16 regressions in the table. In

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[8]Prior studies (e.g., Clement (1999)) have also used the fixed effects model to analyze analyst forecasts. Wooldridge (2002) shows that the two methods of controlling for fixed effects are mathematically equivalent. All fixed effects regressions in the paper are estimated using STATA.

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

[10]In all fixed effects regressions reported in the paper, the null hypothesis that all unobserved effects are jointly zero has a p-value < .0001 (not shown in the tables).

section 5.3.4, we describe results of tests where we separately analyze post-FD changes in forecast errors for profit vs. loss firms.

5.3 Differential effects across firms

We next examine whether post-FD changes in forecast accuracy differ based on four firm characteristics: size, analyst following, industry, and for firms with profits vs. losses. In each case, we estimate variants of equation (3) for the combined sample of the three quarters and treat analyst-company effects as fixed.

5.3.1 Firm size effect

If small 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 these firms post-FD. In order to test this premise, we estimate the following panel regression:

$$\begin{aligned} NFE_{ijt} = {} & b_{1S}\, LOSS_{ijt} * SMALL_{ijt} + b_{2S}\, REGFD_{ijt} * SMALL_{ijt} \\ & + b_{1L}\, LOSS_{ijt} * LARGE_{ijt} + b_{2L}\, REGFD_{ijt} * LARGE_{ijt} + u_{ijt} \end{aligned} \tag{4}$$

where 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. The indicator variable $LARGE_{ijt}$ = 1 - $SMALL_{ijt}$. The other variables are as defined earlier in this section. Estimating equation (4) is analogous to estimating equation (3) separately for small and large firms and allows us to test for the equality of the coefficients for the two groups of firms.

Part I of Panel A in Table 5 shows that at the individual analyst level, forecast errors increase following Reg FD for both small and large firms in both forecast periods. The coefficient of the REGFD variable is highly statistically significant in all four cases. However, the effect is much bigger for small firms than for large firms, both statistically and economically. The null hypothesis that $b_{2S} = b_{2L}$ has a p-value < .0001.

The results for consensus forecasts shown in Part II of Panel A in Table 5 are quite similar to those in Part I of Panel A. Both individual analyst and consensus forecasts became less accurate following the adoption of fair disclosure rules. This effect is significantly bigger for smaller firms.

5.3.2 Analyst following

If companies followed by fewer analysts made more use of selective disclosure as a tool to attract and retain analyst coverage pre-FD, we would expect analyst forecasts to become particularly less accurate in these firms post-FD. To examine this issue, we estimate the following panel regression:

$$\begin{aligned} NFE_{ijt} = {} & b_{1L}\, LOSS_{ijt} * LESS_{ijt} + b_{2L}\, REGFD_{ijt} * LESS_{ijt} \\ & + b_{1M}\, LOSS_{ijt} * MORE_{ijt} + b_{2M}\, REGFD_{ijt} * MORE_{ijt} + u_{ijt} \end{aligned} \tag{5}$$

where the indicator variable $LESS_{ijt}$ equals one if company j is followed by four or fewer analysts in year t, and zero otherwise. The indicator variable $MORE_{ijt} = 1 - LESS_{ijt}$. The other variables are as defined earlier. Estimating equation (5) is similar to estimating equation (3) separately for less and more followed firms and allows us to test for the equality of the coefficients for the two groups of firms.

Panel B of Table 5 shows that normalized forecast errors increase post-FD for both less and more widely followed firms, at the level of the individual analyst as well as the consensus. The estimated increase in forecast errors is bigger for firms followed by fewer analysts in both forecast periods and is statistically significant in the later period.

5.3.3 Industry effect

Next, it is interesting to examine whether post-FD changes in forecast accuracy differ by the industry sector. We estimate the following panel regression:

$$NFE_{ijt} = \sum_{k=1}^{11} (b_{1k}\, LOSS_{ijt} * IND_{kijt} + b_{2k}\, REGFD_{ijt} * IND_{kijt}) + u_{ijt} \tag{6}$$

where the industry indicator variable $IND_{1ijt} = 1$, if the first two digits of company j's I/B/E/S Sector/Industry/Group (S/I/G) code equal 01; it equals zero otherwise. Similarly, $IND_{2ijt} = 1$ if company j belongs to S/I/G code 02, and zero otherwise; etc. The other variables are as defined earlier. Estimating equation (6) is similar to estimating equation (3) separately for each industry and allows us to test for the joint equality of the coefficients for the 11 industry sectors.

Panel C of Table 5 shows that post-FD changes in forecast accuracy differ widely across the various industry sectors. The last column of the table shows that the null hypothesis of equality of the coefficients of REGFD across all sectors can be rejected at the .0001 level. Forecast accuracy increases significantly post-FD for the consumer services and technology sectors in both forecast periods at both the individual analyst and consensus levels; it does not change for the healthcare, energy, transportation and capital goods sectors.

5.3.4 Profit vs. loss firms

We finally examine whether post-FD changes in forecast errors differ for profit vs. loss firms. We estimate the following panel regression:

$$NFE_{ijt} = b_1\, LOSS_{ijt} + b_{2L}\, REGFD_{ijt} * LOSS_{ijt} + b_{2N}\, REGFD_{ijt} * NOLOSS_{ijt} + u_{ij} \quad (7)$$

where $NOLOSS_{ijt} = 1 - LOSS_{ijt}$ and other variables are as defined earlier.

We find that forecast errors increase post-FD for both groups of firms, but the increase is substantially larger for loss firms than for profit firms. The null hypothesis that the coefficient of REGFD is equal for the two groups of firms can be rejected at the .0001 level. To save space, these results are not shown in a table.

5.4 Robustness checks

We next check the robustness of our results to the confounding effect of the recession, an explicit control for forecast age, and our choices of forecast periods and of the variable used to normalize forecast errors.

5.4.1 Effect of the recession

Reg FD became effective in October 2000. According to the National Bureau of Economic Research, the economy went into a recession in March 2001. Could our finding of greater forecast errors post-FD be an artifact of the possibility that earnings may be harder to predict during economic downturns or during turning points of the business cycles?

That is certainly a possibility. However, four pieces of evidence point against the recession being the sole explanation for the greater forecast errors that we observe post-FD. First, Table 4 shows a large increase in forecast errors for the quarter ended December 2000, a period that precedes the onset of recession. Second, the timing and magnitude of any business cycle effects can differ across companies. To the extent that the downturn causes a company to have losses, the LOSS variable in equation (3) controls for this effect at the firm level. Table 4 shows that losses are indeed harder to forecast than profits. But even after controlling for this effect, forecast errors are greater post-FD. Third, a recession may cause a large decline in a company's earnings, though earnings may still be positive. Our LOSS variable does not control for this possibility. To control for this effect, we add a dummy variable called LDECLINE to the right hand side of equation (3). LDECLINE = 1, if the eps in the current quarter declines by 50% or more relative to the same quarter of the previous year, and 0 otherwise. We then re-estimate each of the 16 fixed effects regressions reported in Table 4. In all 16 cases, the coefficient of the LDECLINE variable is positive and statistically significant at the 5% level or better. But the coefficient of the REGFD variable remains positive and highly statistically significant in all cases, with only a small drop in the magnitude of the coefficient estimate. To save space, these results are not reported in a table.

Fourth, the timing and magnitude of an economic downturn can also vary across industries. We use such variation to separate the effects of the recession and FD on the accuracy of analyst forecasts. Using data from I/B/E/S, we compute the aggregate net profits for each of the three post-FD quarters for each of the 11 I/B/E/S industry sectors mentioned in section 5.3.3 above. We define an industry as experiencing a downturn in a given quarter if profits decline by 10% or more relative to the same quarter the prior year.[11] We then estimate equation (6) separately for each of the three post-FD quarters (rather than for the combined sample of the three quarters, as in section 5.3.3 above).

Table 6 shows for each industry, and for each of the three post-FD quarters, the incidence of a downturn and the magnitude of all changes in forecast accuracy, as measured by the coefficients of $\hat{b}_2$ in equation (6). For each post-FD quarter, the first column indicates (with a 'Y') industries that suffered a downturn. The next two columns report the coefficient $\hat{b}_2$ (only where statistically significant, to avoid cluttering the table) in equation (6) for individual analyst forecasts made during each of the two forecast periods; the following two columns report the corresponding coefficients for the consensus forecasts.

In the second post-FD quarter (ending March 2001), the incidence of an industry downturn largely coincides with an increase in forecast errors. But the first and third post-FD quarters allow us to separate the effects of FD from possible effects of a downturn. In the first post-FD quarter (ending December 2000), the only industry that suffered a downturn is consumer services (SIG = 04). Analysts following this industry become certainly less accurate. But they also become less accurate in finance (SIG = 01), consumer non-durables (03), technology (08), and basic industries (09). In the third post-FD quarter (ending June 2001), industries with SIG codes 01, 05, 07, 08, 09 and 11 suffer a downturn. Of these, there is some evidence of an increase in forecast errors for industries 01, 05, 08, and 11; there is no increase for industries 07 and 08. Furthermore, there is an increase in forecast errors for three industries (SIG codes 03, 04 and 10) that have no downturn. So Reg FD appears to have an effect even in industries that do not suffer an economic downturn.

5.4.2 Control for forecast age

In tests involving individual analyst forecasts in section 5.2, we have examined the *latest* forecast made by an analyst following a given company during a given forecast period of roughly two months preceding a given quarter. As discussed in section 4.3, we pick the latest forecast made by an analyst during a forecast period to put all analysts following a company on roughly equal footing regarding the age of their forecasts. But this procedure does not control for differences in forecast age across analysts in the latest forecasts made by them for a given company for a given quarter. In order to examine whether this omission affects our results, we add a variable called AGE to the right hand side of equation (3). AGE equals the number of days between the forecast date and the date of the actual earnings announcement. We then re-estimate each of the eight regressions in Panel A of Table 4. The AGE variable is positive and statistically

[11]The results are qualitatively similar when we define a downturn as *any* decline in industry profits.

significant at the 5% level or better in seven out of the eight regressions. However, the sign, magnitude and statistical significance of the REGFD dummy remain essentially unchanged. To save space, we do not present these results in a table.

5.4.3. Choice of forecast periods

In tests involving individual analyst forecasts in section 5.2, we have examined the latest forecast made by an analyst following a given company during each of two forecast periods (of approximately two months each) preceding a given quarter. As discussed in section 4.3, this procedure increases the likelihood that an analyst will issue at least one forecast during a given forecast period and to put all analysts on a roughly equal footing regarding the age of their forecasts. But this procedure does not make use of all observations on forecasts issued by an analyst following a given company. To see if this procedure affects our results, we pool all forecasts made by an analyst following a company and re-estimate equation (3) after adding a forecast AGE variable on the right hand side. AGE equals the number of days between the forecast date and the date of the actual earnings announcement. For each of the three quarters as well as for the combined sample, the coefficient of the REGFD variable is positive, slightly bigger than in Panel A of Table 4, and highly statistically significant. To save space, these results are not shown in a table.

5.4.4 Choice of the normalizing variable

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.[12] 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.

We present the results of univariate tests in section 6.1 and fixed effects regressions in section 6.2. Section 6.3 examines whether the results differ based on four firm characteristics.

6.1 Univariate tests

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

$$COV_{jt} = (\sigma_{jt} / | \overline{X}_{jt} |), \qquad (8)$$

where σ_{jt} and $\overline{X}_{jt}$ 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 7 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 7 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

[12] We 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. Obtaining sales data from Compustat also results in loss of firms from the sample.

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:

$$COV_{jt} = b_1 \, LOSSF_{jt} + b_2 \, REGFD_{jt} + u_{jt}, \qquad (9)$$

where 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. 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. The sample period is 1995-2000 for the December ending quarter and 1996-2001 for the two subsequent quarters. 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. The combined sample pools observations from the three quarters.

In estimating equation (9), we treat company effects as fixed. 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 company fixed effects estimate of equation (8) allows us to do this. Once again, we control for potential differences for profit versus loss firms. Given the striking differences in forecast accuracy of individual analysts across profit and loss firms observed in section 5.2 above, it is natural to explore differences in forecast dispersion between the two groups of firms.

We estimate equation (9) separately for both forecast periods preceding each quarter as well as for the combined sample of the three quarters. Table 8 shows that the mean COV increases following Reg FD. The coefficient of the REGFD 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. Beginning in the second post-FD quarter, analysts start to become more dispersed in their forecast behavior. For the first post-FD quarter, analysts may still have been relying on guidance they received from companies pre-FD. As the availability of guidance dries up post-FD, its effect starts to be felt.

As with forecast errors, the dispersion of forecasts is also substantially larger for loss firms than for profit firms. The coefficient of the LOSS variable is large, positive and statistically significant in all eight regressions in the table. In section 6.3.4, we separately analyze post-FD changes in forecast dispersion for profit vs. loss firms.

6.3 Differential effects across firms

We next examine if this effect differs based on four firm characteristics: size, analyst following, industry, and for firms with profits vs. losses. In each case, we estimate variants of equation (9) for the combined sample of the three quarters and use the company fixed effects model.

6.3.1 Firm size effect

If small firms engaged more in selective disclosure pre-FD, the effect of Reg FD should be more pronounced in such firms. To examine this issue, we estimate the following panel regression:

$$\begin{aligned} COV_{jt} = {} & b_{1S}\, LOSSF_{jt} * SMALL_{jt} + b_{2S}\, REGFD_{jt} * SMALL_{jt} \\ & + b_{1L}\, LOSSF_{jt} * LARGE_{jt} + b_{2L}\, REGFD_{jt} * LARGE_{jt} + u_{jt} \qquad (10) \end{aligned}$$

where 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. The indicator variable $LARGE_{jt} = 1 - SMALL_{jt}$. The other variables are as defined earlier in this section. The sample period for this test is 1996-2001 because I/B/E/S data on stock prices begins in 1996.

Panel A of Table 9 shows estimates of equation (10) for both forecast periods for the combined sample of the three quarters. COV increases following Reg FD for both small and large firms, but the magnitude of the increase is much bigger for small firms in both forecast periods. The null hypothesis of equality of the coefficients of REGFD for small and large firms can be rejected at the .01 level in both periods.

6.3.2 Analyst following

We next examine whether post-FD changes in the dispersion of analyst forecasts differ for firms with less vs. more analyst following. We estimate the following panel regression:

$$COV_{jt} = b_{1L}\, LOSSF_{jt} * LESS_{jt} + b_{2L}\, REGFD_{jt} * LESS_{jt} + b_{1M}\, LOSSF_{jt} * MORE_{jt} + b_{2M}\, REGFD_{jt} * MORE_{jt} + u_{jt} \qquad (11)$$

The indicator variable $LESS_{jt}$ = 1, if company j is followed by four or fewer analysts in year t; it equals zero otherwise. The indicator variable $MORE_{jt} = 1 - LESS_{jt}$. The other variables are as defined earlier in this section. The sample period is 1996-2001.

Panel B of Table 9 shows that forecast dispersion increases following Reg FD for firms with less analyst following as well as for more widely followed firms. This effect does not differ significantly across the two groups of firms.

6.3.3 Industry effect

We next examine whether the effect differs across the various industry sectors. We estimate the following panel regression:

$$COV_{jt} = \sum_{k=1}^{11} (b_{1k}\, LOSSF_{jt} * IND_{kjt} + b_{2k}\, REGFD_{jt} * IND_{kjt}) + u_{jt} \qquad (12)$$

where the industry indicator variable IND_{1jt} = 1, if the first two digits of company j's I/B/E/S Sector/Industry/Group (S/I/G) code equal 01; it equals zero otherwise. Similarly, IND_{2jt} = 1 if company j belongs to S/I/G code 02, and zero otherwise; etc. The other variables are as defined earlier in this section. The sample period is 1995-2001.

Panel C of Table 9 shows that post-FD changes in the dispersion of analyst forecasts differ widely across the 11 industry sectors. In both forecast periods, there is a significant increase in dispersion for consumer durables, transportation, technology, basic industries and capital goods; a significant decrease in dispersion for the energy sector; and no significant change for healthcare, consumer non-durables, and public utilities. The magnitude of the increase in dispersion is particularly striking for the consumer durables and technology sectors. The null hypothesis that the coefficients of REGFD are equal across all the industries can be rejected at the .0001 level in both periods.

6.3.4 Profit vs. loss firms

We next examine whether post-FD changes in the dispersion of analyst forecasts differ for profit vs. loss firms. We estimate the following panel regression:

$$COV_{jt} = b_1\, LOSS_{jt} + b_{2L}\, REGFD_{jt} * LOSS_{jt} + b_{2N}\, REGFD_{jt} * NOLOSS_{jt} + u_{jt} \quad (13)$$

where $NOLOSS_{jt} = 1 - LOSS_{jt}$ and other variables are as defined earlier.

We find that forecast dispersion increases post-FD for both groups of firms. While the magnitude of the increase is somewhat larger for loss firms than for profit firms, the difference is not statistically significant at the .05 level. These results are not shown in a table.

7. Stability of analyst rankings

Finally, we examine changes in the stability of analyst rankings from year to year immediately following the adoption of fair disclosure rules. As discussed in section 2.3, rankings should become less variable if analysts differ in their research abilities and companies favored different analysts over time pre-FD. Alternatively, rankings should become more variable if pre-FD, companies followed a policy of consistent preference and favored inferior analyst(s). No change should be observed if companies followed a policy of consistent preference and favored superior analyst(s) pre-FD, or if all analysts are equally good at research and companies favored different analysts over time pre-FD, or if the rules are not effectively enforced.

We present the results of univariate tests in section 7.1 and fixed effects regressions in section 7.2. We analyze extreme changes in analyst rankings in consecutive years in section 7.3.

7.1 Univariate tests

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

$$\Delta SCORE_{it} = |SCORE_{it} - SCORE_{i,t-1}| \qquad (14)$$

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

$$s_{ijt} = 100 - \{(r_{ijt} - 1) / (n_{jt} - 1)\} * 100 \qquad (15)$$

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.[13] 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.[14] The sample excludes all companies that are followed by only one analyst and all analysts that follow only one company.

The performance score simply converts an analyst's raw rank to a percentile ranking that takes into account the number of analysts following a company. As an example, for a company followed by 11 analysts, the top analyst gets a score of 100 using equation (15), the analyst ranked 6 gets a score of 50 and the bottom analyst gets a score of 0. The average performance score across all companies followed by an analyst is more meaningful than the average of her raw ranks. Consider, for example, an analyst who follows just two companies and is ranked 4 on each based on her forecast accuracy. Five analysts follow company 1, while 26 follow company 2. Using equation (15), her performance score, s, works out to 25 for company 1 and 88 for company 2, for an average score of 56.5. That denotes just slightly above-average performance. On the other hand, her average rank is 4, which is not very informative of her performance.

Table 10 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

[13]We analyze changes in *average* performance scores of analysts rather than changes in performance scores for individual companies followed by them to reduce data requirements and to avoid the associated selection issues.

[14]Cooper, Day and Lewis (2001) find that performance rankings of analysts based on the timeliness of their forecasts are more informative than rankings based on forecast accuracy. Reg FD has important implications about changes in analyst rankings based on forecast accuracy, but has no obvious implications about changes in rankings based on forecast timeliness. So we analyze ranking changes based on the former measure rather than the latter.

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 10 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, 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 regressions

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

$$\Delta SCORE_{it} = b_1\ REGFD_{it} + u_{it} \qquad (16)$$

where 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. The sample consists of ΔSCORE observations over the years 1995-96, 1997-98 and 1999-2000 for the December ending quarter, and 1996-97, 1998-99 and 2000-2001 for the March and June ending quarters. It includes all analysts in the I/B/E/S database that have a ΔSCORE observation post-FD and at least one ΔSCORE observation pre-FD. The combined sample pools observations from the three quarters.

We estimate equation (16) 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 cannot control for potential differences across profit and loss companies.

Columns 1 and 2 of Table 11 show a reduction in ΔSCORE following Reg FD for each of the three quarters examined; the effect is statistically significant at the 5% level or better for the quarters ending March 31 and June 30. For the combined sample of the three quarters, the reduction amounts to about 2.6 and 5 percentage points for the first and second forecast periods, respectively; both are statistically significant at the 1% level. Analyst rankings, on which the performance scores are based, become somewhat more stable following the adoption of fair disclosure rules. As discussed in section 2.3, this finding is consistent with the joint propositions that analysts differ in their research abilities and companies favored different analysts over time pre-FD. The former proposition is consistent with the findings of prior research (e.g., Sinha, Brown and Das (1997)). The latter behavior is consistent with a company's desire to avoid alienating a large group of its analysts, as would happen if it persistently favored just one or a select few analysts. A company relies on its analysts to generate and sustain institutional interest in the stock and therefore has an incentive to maintain good relations with them.

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. A large incidence of such dramatic changes in performance scores over consecutive periods would indicate that analyst rankings are not very meaningful. 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 12 shows the percentage of analysts that flip from being a top ranked (quartile 4) analyst one year to being a bottom ranked (quartile 1) 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 12 shows that pre-FD, about one-eighth of all analysts flip ranks from being in the top quartile one year to being in the bottom quartile the next year. There is no significant change in the proportion of flippers following Reg FD, except for an increase of 2.1 percentage points (from 10.73% to 12.83%) 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 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, analyst following, industry, and for firms with profits vs. losses. The analysis is based on a large sample of public companies and the analysts following them.

We have three main findings. First, earnings forecasts become 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. We provide detailed empirical evidence that suggests that this effect can not be entirely attributed to the economic downturn during our post-FD period. Second, individual analysts following a company are more dispersed in their earnings forecasts post-FD. 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.

We find that analyst forecasts are less accurate in each of the three post-FD quarters relative to their pre-FD benchmarks. But the increase in forecast dispersion and in the stability of analyst rankings is observed beginning only in the second quarter post-FD; these effects are absent in the first post-FD quarter. A possible explanation for this pattern is that in the first post-FD quarter, private information provided by managers to analysts may still have been out there. With the passage of time, private information starts to dry out and the rules start to have an effect.

We find that the decrease in forecast accuracy post-FD is more pronounced for small firms, less followed firms, firms with losses, and firms in technology and consumer services sectors. Similarly, the increase in forecast dispersion is bigger for small firms and firms in technology and consumer durables sectors. These findings are consistent with the notion that the practice of selective disclosure was more prevalent in these sectors.

To summarize, we find that post-FD, analysts become less accurate and more dispersed in their forecasts, and their performance rankings become somewhat more stable. These findings are consistent with a reduction in selective guidance following the adoption of fair disclosure rules.

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.

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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 December 31, 2000	10,104	3,984
3. Item 2 with actual eps available	9,544	3,440
4. Item 3 with stock price available	8,516	2,585
5. Item 4 with stock price of $1 or more	8,461	2,581

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

[1]The "Post" Reg FD period consists of the year 2000 for the quarter ended December 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.

[2]P-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 *Latest forecast made during*	Mean Pre[1]	Mean Post[1]	Mean p-value[2]	Median Pre[1]	Median Post[1]	Median Wilcoxon p-value[2]	Sample size (# Companies) Pre[1]	Sample size (# Companies) Post[1]
Quarter ended Dec. 31								
Aug. 10 – Oct. 22	.0183	.0202	.424	.0040	.0031	<.0001	3,719	2,581
Oct. 23 – Jan. 10	.0134	.0209	.031	.0023	.0020	.0008	3,893	2,531
Quarter ended March 31								
Oct. 23-Dec. 22	.0119	.0276	<.0001	.0033	.0045	<.0001	3,455	2,185
Dec. 23-Feb. 22	.0099	.0196	<.0001	.0024	.0029	.0196	3,735	2,307
Quarter ended June 30								
Feb. 1-March 31	.0135	.0216	.007	.0035	.0049	<.0001	3,713	2,182
April 1-May 31	.0149	.0135	.59	.0025	.0023	.0004	3,880	2,496

[1]The "Post" Reg FD period consists of the year 2000 for the quarter ended December 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.

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

Table 4

Fixed effects regressions of forecast errors normalized by stock price

Panel A shows the estimated coefficients, t-statistics and adjusted R^2 values from the following cross-sectional time series regression:

$$NFE_{ijt} = b_1\ LOSS_{ijt} + b_2\ REGFD_{ijt} + u_{ijt}$$

where $NFE_{ijt} = | e_{jt} - \hat{e}_{ijt} | / p_{jt}$; 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. The indicator variable $LOSS_{ijt}$ =1 if e_{jt}<0; it equals zero otherwise. 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. The regression treats analyst-company effects as fixed. The reported R^2 values are based on overall variation within and across analyst-company pairs. The sample period is 1997-2000 for the December ending quarter and 1998-2001 for the two subsequent 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 where company effects are treated as fixed. The combined sample pools observations from the three quarters.

Table 4 (cont.)

Forecast for period *Latest forecast made during*	$\hat{b}_1$	$t(\hat{b}_1)$	$\hat{b}_2$	$t(\hat{b}_2)$	$\bar{R}^2$	Sample Size	p-value of F-test
A. Individual analyst forecasts							
Quarter ended Dec. 31							
Aug.10 – Oct. 22	.052	12.57[a]	.009	6.00[a]	.041	7,978	<.0001
Oct. 23 – Jan. 10	.027	7.18[a]	.007	4.64[a]	.011	10,555	<.0001
Quarter ended March 31							
Oct. 23 – Dec. 22	.018	9.73[a]	.005	6.39[a]	.079	3,303	<.0001
Dec. 23 – Feb. 22	.012	26.25[a]	.002	8.76[a]	.115	10,898	<.0001
Quarter ended June 30							
Feb. 1 – March 31	.017	22.08[a]	.003	9.89[a]	.159	6,140	<.0001
April 1 – May 31	.011	14.56[a]	.002	4.50[a]	.026	15,961	<.0001
Combined Sample							
Forecast period 1	.030	17.33[a]	.006	8.98[a]	.037	17,421	<.0001
Forecast period 2	.015	14.27[a]	.003	6.99[a]	.012	37,414	<.0001
B. consensus forecasts							
Quarter ended Dec. 31							
Aug. 10 – Oct. 22	.051	13.09[a]	.009	5.10[a]	.045	6,516	<.0001
Oct. 23 – Jan. 10	.049	8.57[a]	.014	5.34[a]	.022	6,928	<.0001
Quarter ended March 31							
Oct. 23 – Dec. 22	.024	8.44[a]	.012	8.45[a]	.048	5,748	<.0001
Dec. 23 – Feb. 22	.017	6.79[a]	.009	6.97[a]	.031	6,444	<.0001
Quarter ended June 30							
Feb. 1 – March 31	.025	10.1[a]	.009	7.21[a]	.045	6,177	<.0001
April 1 – May 31	.019	7.17[a]	.006	4.57[a]	.021	7,165	<.0001
Combined Sample							
Forecast period 1	.029	18.43[a]	.010	11.8[a]	.045	18,441	<.0001
Forecast period 2	.025	12.17[a]	.010	9.08[a]	.022	20,537	<.0001

[a]Denotes statistical significance at the 1% level in two-tailed tests.

Table 5

Fixed effects regressions of forecast errors for the combined sample of the three quarters, partitioned by firm size, analyst following and industry sector

The table shows the estimated coefficients, t-statistics and adjusted R^2 values from cross-sectional time series regressions. Part I of Panels A, B, and C show, respectively, the results from models (1), (2) and (3) below for individual analyst forecasts.

$$(1) \qquad NFE_{ijt} = b_{1S}\, LOSS_{ijt} * SMALL_{ijt} + b_{2S}\, REGFD_{ijt} * SMALL_{ijt} + b_{1L}\, LOSS_{ijt} * LARGE_{ijt} + b_{2L}\, REGFD_{ijt} * LARGE_{ijt} + u_{ijt}$$

$$(2) \qquad NFE_{ijt} = b_{1L}\, LOSS_{ijt} * LESS_{ijt} + b_{2L}\, REGFD_{ijt} * LESS_{ijt} + b_{1M}\, LOSS_{ijt} * MORE_{ijt} + b_{2M}\, REGFD_{ijt} * MORE_{ijt} + u_{ijt}$$

$$(3) \qquad NFE_{ijt} = \sum_{k=1}^{11} (b_{1k}\, LOSS_{ijt} * IND_{kijt} + b_{2k}\, REGFD_{ijt} * IND_{kijt}) + u_{ijt}$$

where $NFE_{ijt} = | e_{jt} - \hat{e}_{ijt} | / p_{jt}$; 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. The indicator variable $LOSS_{ijt} = 1$ if $e_{jt}<0$; it equals zero otherwise. 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. The indicator variable $SMALL_{ijt} = 1$ if company j's market value of equity is $200 million or lower in year t; it equals zero otherwise. The indicator variable $LARGE_{ijt} = 1 - SMALL_{ijt}$. The indicator variable $LESS_{ijt} = 1$, if company j is followed by four or fewer analysts in year t; it equals zero otherwise. The indicator variable $MORE_{ijt} = 1 - LESS_{ijt}$. The industry indicator variable $IND_{1ijt} = 1$, if the first two digits of company j's I/B/E/S Sector/Industry/Group (S/I/G) code equals 01; it equals zero otherwise. Similarly, $IND_{2ijt} = 1$ if company j belongs to S/I/G code 02, etc. The sample period is 1997-2001. The dataset combines observations from the December, March, and June ending quarters. The regression treats analyst-company effects as fixed. The reported R^2 values are based on overall variation within and across analyst-company pairs. 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. Part II of each panel shows corresponding regressions for the consensus forecasts.

Table 5 (cont.)
Panel A: Results partitioned by firm size

Latest forecast made during *Sub-sample*	$\hat{b}_1$	$t(\hat{b}_1)$	$\hat{b}_2$	$t(\hat{b}_2)$	$\bar{R}^2$	Sample Size	p(F-test)[1]	p(F-test)[2]
I. Individual analyst forecasts								
Forecast period 1								
Small firms	.053	16.47[a]	.026	10.20[a]				
Large firms	.022	12.64[a]	.004	5.29[a]	.061	17,421	<.0001	<.0001
Forecast period 2								
Small firms	.038	18.32[a]	.018	10.02[a]				
Large firms	.008	8.13[a]	.001	2.77[a]	.035	37,414	<.0001	<.0001
II. Consensus forecasts								
Forecast period 1								
Small firms	.047	21.24[a]	.025	13.19[a]				
Large firms	.016	8.62[a]	.005	4.91[a]	.072	18,441	<.0001	<.0001
Forecast period 2								
Small firms	.041	14.96[a]	.029	12.42[a]				
Large firms	.009	4.12[a]	.003	2.19[a]	.042	20,537	<.0001	<.0001

[1]For the null hypothesis that all estimated coefficients equal zero.

[2]For the null hypothesis that the coefficient b_2 is the same for each sub-group.

[a]Denotes statistical significance at the 1% level in two-tailed tests.

Table 5 (cont.)
Panel B: Results partitioned by analyst following

Latest forecast made during *Sub-sample*	$\hat{b}_1$	$t(\hat{b}_1)$	$\hat{b}_2$	$t(\hat{b}_2)$	$\bar{R}^2$	Sample Size	p-value of F-test[1]	p-value of F-test[2]
I. Individual analyst forecasts								
Forecast period 1								
Less followed firms	.023	9.21[a]	.009	6.89[a]				
Widely followed firms	-.003	-2.40[b]	.007	7.84[a]	.022	17,421	<.0001	.144
Forecast period 2								
Less followed firms	.010	6.34[a]	.007	6.75[a]				
Widely followed firms	-.003	-3.83[a]	.003	5.86[a]	.010	37,414	<.0001	.001
II. Consensus forecasts								
Forecast period 1								
Less followed firms	.031	17.95[a]	.011	11.08[a]				
Widely followed firms	.025	9.43[a]	.008	4.99[a]	.046	18,441	<.0001	.142
Forecast period 2								
Less followed firms	.028	12.42[a]	.014	9.71[a]				
Widely followed firms	.017	6.14[a]	.005	3.17[a]	.024	20,537	<.0001	.0001

[1]For the null hypothesis that all estimated coefficients equal zero.

[2]For the null hypothesis that the coefficient b_2 is the same for each sub-group.

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

Table 5 (cont.)
Panel C: Results by industry sector

Latest forecast made during *Industry (S/I/G2)*	$\hat{b}_1$	$t(\hat{b}_1)$	$\hat{b}_2$	$t(\hat{b}_2)$	$\bar{R}^2$	Sample Size	p-value of F-test[1]	p-value of F-test[2]
I. Individual analyst forecasts								
Forecast period 1								
Finance (01)	.255	26.48[a]	.010	4.44[a]				
Healthcare (02)	.016	2.64[a]	.0004	0.22				
Consumer non-durables (03)	.051	6.49[a]	.007	2.15[b]				
Consumer services (04)	.021	3.68[a]	.009	4.59[a]				
Consumer durables (05)	.070	8.14[a]	.010	2.80[a]				
Energy (06)	.015	3.00[a]	-.0002	-0.12				
Transportation (07)	.043	5.44[a]	.003	0.78				
Technology (08)	.015	5.91[a]	.006	4.22[a]				
Basic industries (09)	.027	5.05[a]	.020	7.75[a]				
Capital goods (10)	.025	2.28[b]	.003	1.25				
Public utilities (11)	.002	0.15	.000	0.01	.079	17,204	<.0001	<.0001
Forecast period 2								
Finance (01)	.089	15.31[a]	.001	0.82				
Healthcare (02)	.014	3.92[a]	-.001	-0.97				
Consumer non-durables (03)	.029	4.98[a]	.003	1.41				
Consumer services (04)	.009	2.51[b]	.007	5.55[a]				
Consumer durables (05)	.043	6.91[a]	.002	0.86				
Energy (06)	.007	2.30[b]	-.001	-0.41				
Transportation (07)	.027	6.13[a]	.003	1.07				
Technology (08)	.007	4.92[a]	.006	5.99[a]				
Basic industries (09)	.009	2.87[a]	.003	1.63				
Capital goods (10)	.023	3.89[a]	.001	0.42				
Public utilities (11)	.004	0.52	.006	2.84[a]	.023	37,052	<.0001	<.0001

Table 5 (cont.)
Panel C: Results by industry sector (cont.)

Latest forecast made during *Industry (S/I/G2)*	$\hat{b}_1$	$t(\hat{b}_1)$	$\hat{b}_2$	$t(\hat{b}_2)$	$\bar{R}^2$	Sample Size	p-value of F-test[1]	p-value of F-test[2]
II. Consensus forecasts								
Forecast period 1								
Finance (01)	.169	19.28[a]	.015	5.61[a]				
Healthcare (02)	.016	3.27[a]	.002	0.71				
Consumer non-durables (03)	.030	3.51[a]	.005	1.13				
Consumer services (04)	.014	3.06[a]	.019	9.10[a]				
Consumer durables (05)	.034	3.30[a]	.014	2.82[a]				
Energy (06)	.019	3.29[a]	-.0003	-.09				
Transportation (07)	.044	3.82[a]	.006	0.94				
Technology (08)	.024	9.62[a]	.012	7.01[a]				
Basic industries (09)	.046	6.57[a]	.018	4.59[a]				
Capital goods (10)	.054	7.16[a]	-.001	-.18				
Public utilities (11)	.007	0.63	.005	1.17	.059	18,201	<.0001	<.0001
Forecast period 2								
Finance (01)	.228	19.64[a]	.016	4.82[a]				
Healthcare (02)	.014	2.35[b]	.002	0.56				
Consumer non-durables (03)	.023	1.98[b]	.004	0.68				
Consumer services (04)	.010	1.74[c]	.020	7.49[a]				
Consumer durables (05)	.027	1.98[b]	.008	1.25				
Energy (06)	.020	2.74[a]	-.000	-.00				
Transportation (07)	.039	3.15[a]	.003	0.41				
Technology (08)	.018	5.89[a]	.013	5.92[a]				
Basic industries (09)	.020	2.40[b]	.007	1.56				
Capital goods (10)	.027	2.81[b]	.003	0.77				
Public utilities (11)	.005	0.40	.007	1.31	.031	20,232	<.0001	<.0001

Table 6

Post-FD economic downturn and changes in forecast accuracy by industry and quarter

The table shows the incidence of an economic downturn and changes in forecast accuracy for each post-FD quarter and for each I/B/E/S 2-digit S/I/G industry sector. For each post-FD quarter, the first column indicates (with a 'Y') industries that suffered a downturn, defined as a decline of 10% or more in the aggregate net profits for the industry relative to the same quarter the prior year. The next two columns report the coefficient $\hat{b}_2$ (only where statistically significant) from the following cross-sectional time series regression for individual analyst forecasts made during each of the two forecast periods; the following two columns report the corresponding coefficients for the consensus forecasts.

$$NFE_{ijt} = \sum_{k=1}^{11} (b_{1k}\, LOSS_{ijt} * IND_{kijt} + b_{2k}\, REGFD_{ijt} * IND_{kijt}) + u_{ijt}$$

where $NFE_{ijt} = | e_{jt} - \hat{e}_{ijt} | / p_{jt}$; 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. The indicator variable $LOSS_{ijt}$ = 1 if $e_{jt}<0$; it equals zero otherwise. 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. The industry indicator variable IND_{1ijt} = 1, if the first two digits of company j's I/B/E/S Sector/Industry/Group (S/I/G) code equals 01; it equals zero otherwise. Similarly, IND_{2ijt} = 1 if company j belongs to S/I/G code 02, etc. 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. The regression treats analyst-company effects as fixed.

Table 6 (cont.)

Industry (S/I/G2)	Post-FD Quarter														
	December 2000					March 2001					June 2001				
	Downturn?	$\hat{b}_2$				Downturn?	$\hat{b}_2$				Downturn?	$\hat{b}_2$			
		Individual Analysts		Consensus			Individual Analysts		Consensus			Individual Analysts		Consensus	
		Forecast period					Forecast period					Forecast period			
		1	2	1	2		1	2	1	2		1	2	1	2
Finance (01)		$.016^{a}$		$.018^{a}$	$.030^{a}$						Y		$-.002^{b}$	$.01^{a}$	
Healthcare (02)															
Consumer non-durables (03)		$.013^{c}$	$.013^{a}$									$.003^{c}$			
Consumer Services (04)	Y	$.012^{b}$		$.012^{a}$	$.021^{a}$	Y	$.008^{a}$	$.003^{a}$	$.024^{a}$	$.021^{a}$		$.004^{a}$	$.004^{a}$	$.02^{a}$	$.017^{a}$
Consumer durables (05)						Y	$.011^{b}$		$.017^{c}$		Y	$.003^{b}$			
Energy (06)												$-.002^{c}$			
Transporation (07)						Y		$.001^{c}$			Y				
Technology (08)			$.013^{a}$	$.008^{b}$	$.014^{a}$	Y	$.008^{a}$	$.004^{a}$	$.017^{a}$	$.015^{a}$	Y	$.006^{a}$	$.002^{a}$	$.011^{a}$	$.009^{a}$
Basic Industries (09)		$.032^{a}$		$.022^{a}$		Y	$.008^{b}$	$.002^{b}$	$.025^{a}$		Y				
Capital Goods (10)												$.004^{a}$			
Public Utilities (11)						Y					Y		$.012^{a}$		$.012^{b}$

[a,b,c] Denotes statistical significance at the 1%, 5% and 10% levels, respectively, in two-tailed tests.

Table 7
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 *Latest forecast made during*	Mean Pre[1]	Mean Post[1]	Mean p-value[2]	Median Pre[1]	Median Post[1]	Median Wilcoxon p-value[2]	Sample size (# Companies) Pre[1]	Sample size (# Companies) Post[1]
Quarter ended Dec. 31								
Aug. 10 – Oct. 22	.1177	.1050	.038	.0628	.0510	< .0001	3,318	1,517
Oct. 23 – Jan. 10	.1221	.1069	.016	.0614	.0511	< .0001	4,048	1,870
Quarter ended March 31								
Oct. 23-Dec. 22	.1081	.1040	.45	.0584	.0615	.84	2,544	1,098
Dec. 23-Feb. 22	.1000	.0979	.66	.0541	.0480	.002	3,272	1,524
Quarter ended June 30								
Feb. 1-March 31	.1024	.1104	.088	.0524	.0590	.088	3,263	1,312
April 1-May 31	.0988	.1019	.53	.0523	.0507	.66	3,837	1,883

[1]The "post" Reg FD period consists of the year 2000 for the quarter ended December 31, and the year 2001 for the two subsequent quarters. The "pre" Reg FD period consists of the prior five years.

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

Table 8

Fixed effects regressions of dispersion of analyst forecasts

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

$$COV_{jt} = b_1\ LOSSF_{jt} + b_2\ REGFD_{jt} + u_{jt}$$

where COV_{jt} is the absolute value of the coefficient of variation (σ / | $\bar{X}$ |); 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. For each window, the latest forecast made by each analyst is used to compute σ and $\bar{X}$. 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. 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. The regression treats company effects as fixed. The reported R^2 values are based on overall variation within and across companies. The sample period is 1995-2000 for the December ending quarter and 1996-2001 for the two subsequent quarters. 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. The combined sample pools observations from the three quarters.

Forecast for period *Latest forecast made during*	$\hat{b}_1$	t($\hat{b}_1$)	$\hat{b}_2$	t($\hat{b}_2$)	$\bar{R}^2$	Sample Size	p-value of F-test
Quarter ended Dec. 31							
Aug.10 – Oct. 22	.213	10.85[a]	.003	.572	.033	4,559	<.0001
Oct. 23 – Jan. 10	.311	22.60[a]	.003	.714	.103	5,944	<.0001
Quarter ended March 31							
Oct. 23 – Dec. 22	.104	3.85[a]	.012	2.58[a]	.012	2,521	<.0001
Dec. 23 – Feb. 22	.209	15.11[a]	.003	.643	.059	4,929	<.0001
Quarter ended June 30							
Feb. 1 – March 31	.202	11.19[a]	.015	3.79[a]	.047	3,947	<.0001
April 1 – May 31	.171	10.95[a]	.013	3.16[a]	.029	6,037	<.0001
Combined Sample							
Forecast period 1	.191	17.53[a]	.009	3.88[a]	.032	11,027	<.0001
Forecast period 2	.238	27.70[a]	.006	2.92[a]	.061	16,910	<.0001

[a]Denotes statistical significance at the 1% level in two-tailed tests.

Table 9

Fixed effects regressions of dispersion of analyst forecasts for the combined sample of the three quarters, partitioned by firm size, analyst following and industry sector

The table shows the estimated coefficients, t-statistics and adjusted R^2 values from cross-sectional time series regressions. Panels A, B, and C show, respectively, the results from models (1), (2) and (3) below.

$$\text{(1)} \quad COV_{jt} = b_{1S}\, LOSSF_{jt} * SMALL_{jt} + b_{2S}\, REGFD_{jt} * SMALL_{jt} + b_{1L}\, LOSSF_{jt} * LARGE_{jt} + b_{2L}\, REGFD_{jt} * LARGE_{jt} + u_{jt}$$

$$\text{(2)} \quad COV_{jt} = b_{1L}\, LOSSF_{jt} * LESS_{jt} + b_{2L}\, REGFD_{jt} * LESS_{jt} + b_{1M}\, LOSSF_{jt} * MORE_{jt} + b_{2M}\, REGFD_{jt} * MORE_{jt} + u_{jt}$$

$$\text{(3)} \quad COV_{jt} = \sum_{k=1}^{11} (b_{1k}\, LOSSF_{jt} * IND_{kjt} + b_{2k}\, REGFD_{jt} * IND_{kjt}) + u_{jt}$$

where COV_{jt} is the absolute value of the coefficient of variation (σ / | $\bar{X}$ |); 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. For each window, the latest forecast made by each analyst is used to compute σ and $\bar{X}$. 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. 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. The indicator variable $SMALL_{jt}$ = 1 if company j's market value of equity is $200 million or lower in year t; it equals zero otherwise. The indicator variable $LARGE_{jt}$ = 1 - $SMALL_{jt}$. The indicator variable $LESS_{jt}$ = 1, if company j is followed by four or fewer analysts in year t; it equals zero otherwise. The indicator variable $MORE_{jt}$ = 1 - $LESS_{jt}$. The industry indicator variable IND_{1jt} = 1, if the first two digits of company j's I/B/E/S Sector/Industry/Group (S/I/G) code equals 01; it equals zero otherwise. Similarly, IND_{2jt} = 1 if company j belongs to S/I/G code 02, etc. The sample period is 1996-2001 in Panels A and B and 1995-2001 in Panel C. The dataset combines observations from the December, March, and June ending quarters. The regression treats company effects as fixed. The reported R^2 values are based on overall variation within and across companies. The sample includes all company-analyst pairs 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.

Table 9 (cont.)

Panel A: Results partitioned by firm size

Latest forecast made during *Sub-sample*	$\hat{b}_1$	$t(\hat{b}_1)$	$\hat{b}_2$	$t(\hat{b}_2)$	$\bar{R}^2$	Sample Size	p-value of F-test[1]	p-value of F-test[2]
Forecast period 1								
Small firms	.151	8.32[a]	.042	3.70[a]				
Large firms	.147	10.71[a]	.011	3.69[a]	.072	6,858	<.0001	.008
Forecast period 2								
Small firms	.145	9.49[a]	.060	5.62[a]				
Large firms	.218	20.06[a]	.005	1.68[c]	.049	10,084	<.0001	<.0001

Panel B: Results partitioned by analyst following

Latest forecast made during *Sub-sample*	$\hat{b}_1$	$t(\hat{b}_1)$	$\hat{b}_2$	$t(\hat{b}_2)$	$\bar{R}^2$	Sample Size	p-value of F-test[1]	p-value of F-test[2]
Forecast period 1								
Less followed firms	-.007	-0.65	.015	3.95[a]				
Widely followed firms	-.023	-6.12[a]	.013	2.98[a]	.024	6,858	<.0001	.629
Forecast period 2								
Less followed firms	.012	1.35	.007	1.65[c]				
Widely followed firms	-.013	-3.24[a]	.014	3.67[a]	.022	10,084	<.0001	.302

[1]For the null hypothesis that all estimated coefficients equal zero.

[2]For the null hypothesis that the coefficient b_2 is the same for each sub-group.

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

Table 9 (cont.)
Panel C: Results by industry sector

Latest forecast made during *Industry (S/I/G2)*	$\hat{b}_1$	$t(\hat{b}_1)$	$\hat{b}_2$	$t(\hat{b}_2)$	$\bar{R}^2$	Sample Size	p-value of F-test[1]	p-value of F-test[2]
Forecast period 1								
Finance (01)			.012	1.73[c]				
Healthcare (02)	.137	2.96[a]	.000	0.02				
Consumer non-durables (03)	.171	3.89[a]	-.009	-0.83				
Consumer services (04)	-.00	-.01	.013	1.84[c]				
Consumer durables (05	.214	3.24[a]	.059	4.79[c]				
Energy (06)	.191	7.60[a]	-.073	-8.64[a]				
Transportation (07)	.577	12.98[a]	.025	1.85[c]				
Technology (08)	.109	5.33[a]	.044	7.09[a]				
Basic industries (09)	.191	6.63[a]	.023	2.53[b]				
Capital goods (10)	.368	6.27[a]	.022	2.40[b]				
Public utilities (11)	.008	0.15	-.014	-1.23	.060	10,752	<.0001	<.0001
Forecast period 2								
Finance (01)	.282	2.98[a]	.004	0.74				
Healthcare (02)	.281	9.12[a]	-.000	-0.05				
Consumer non-durables (03)	.349	8.56[a]	.010	0.94				
Consumer services (04)	.088	2.61[a]	.005	0.84				
Consumer durables (05)	.541	14.03[a]	.057	4.76[a]				
Energy (06)	.197	9.15[a]	-.065	-7.65[a]				
Transportation (07)	.154	6.05[a]	.030	2.36[b]				
Technology (08)	.159	10.61[a]	.020	3.29[a]				
Basic industries (09)	.165	9.29[a]	.018	2.22[b]				
Capital goods (10)	.386	10.44[a]	.029	3.45[a]				
Public utilities (11)	.146	3.59[a]	-.015	-1.61	.072	16,492	<.0001	<.0001

Table 10
Changes in analyst performance scores around Reg FD

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

$$\Delta SCORE_{it} = |SCORE_{it} - SCORE_{i,t-1}|,$$

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 $s_{ijt} = 100 - \{(r_{ijt} - 1) / (n_{jt} - 1)\} * 100$, 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. 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 *Latest Forecast made during*	Mean Pre[1]	Mean Post[1]	Mean p-value[2]	Median Pre[1]	Median Post[1]	Median Wilcoxon p-value[2]	Sample size (# Analysts) Pre[1]	Sample size (# Analysts) Post[1]
Quarter ended Dec. 31								
Aug. 10 – Oct. 22	25.11	23.96	.0910	20.83	18.83	.0031	1,777	1,637
Oct. 23 – Jan. 10	21.21	21.18	.9633	16.67	16.67	.5210	2,146	1,795
Quarter ended March 31								
Oct. 23-Dec. 22	30.01	27.40	.0048	26.04	23.61	.0029	1,199	993
Dec. 23-Feb. 22	23.07	21.39	.0093	18.16	15.84	.0003	1,869	1,583
Quarter ended June 30								
Feb. 1-March 31	26.16	24.25	.0078	22.20	19.82	.0038	1,670	1,375
April 1-May 31	21.39	19.53	.0008	17.08	15.00	<.0001	2,061	1,777

[1]The "post" Reg FD period consists of change in average scores of analysts between the years 1999 and 2000 for the quarter ended December 31; it consists of the years 2000 and 2001 for the two subsequent quarters. The column for the "pre" Reg FD period shows the change in average scores of analysts in 1995-96 and 1997-98 for the December 31 quarter and the years 1996-97 and 1998-99 for the two subsequent quarters.

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

Table 11

Fixed effects regressions of changes in analyst performance scores

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

$$\Delta SCORE_{it} = b_1 \, REGFD_{it} + u_{it}$$

where $\Delta SCORE_{it} = | SCORE_{it} - SCORE_{i,t-1} |$; and $SCORE_{it}$ = analyst i's performance score in year t. 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. The regression treats analyst effects as fixed. The reported R^2 values are based on overall variation within and across analysts. The sample consists of ΔSCORE observations over the years 1995-96, 1997-98 and 1999-2000 for the December ending quarter, and 1996-97, 1998-99 and 2000-2001 for the March and June ending quarters. 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. The combined sample pools observations from the three quarters.

Forecast for period *Latest forecast made during*	$\hat{b}_1$	$t(\hat{b}_1)$	$\bar{R}^2$	Sample Size
Quarter ended Dec. 31				
Aug.10 – Oct. 22	-.366	-.61	-.0001	4,336
Oct. 23 – Jan. 10	-.464	-.96	.000	5,078
Quarter ended March 31				
Oct. 23 – Dec. 22	-2.13	-2.23[b]	.0028	2,197
Dec. 23 – Feb. 22	-1.68	-2.98[a]	.0027	4,211
Quarter ended June 30				
Feb. 1 – March 31	-1.83	-2.72[a]	.0028	3,418
April 1 – May 31	-2.88	-4.75[a]	.0060	4,966
Combined Sample				
Forecast period 1	-1.27	-2.64[a]	.0013	9,951
Forecast period 2	-1.46	-4.96[a]	.0024	14,255

[a,b]Denote statistical significance at the 1% and 5%, levels, respectively, in two-tailed tests.

Table 12

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

[1]The post-FD period consists of flipping between the years 1999 and 2000 for the quarter ended December 31; it consists of the years 2000 and 2001 for the two subsequent quarters. The pre-FD period consists of 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.

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