Analyst Forecast Bias: The Interaction of Earnings Skewness and Information Environment

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ABSTRACT: We explore the implications of earnings skewness for analysts' forecasts. We propose a representation of analyst forecasts where, assuming analysts are rational, forward-looking earnings skewness interacts with the analyst's external constraints, including changes in the information environment and busyness, leading to forecast bias. We predict that analysts will be more optimistic (pessimistic) when the information environment deteriorates for firms with underlying right-skewed (left-skewed) earnings distributions. Similarly, we predict that busier analysts will be more optimistic (pessimistic) for firms with underlying right-skewed (left-skewed) earnings distributions. Our directional predictions for forecast bias are confirmed using multiple proxies for analyst's constraints and for earnings skewness. Further, we document that the phenomenon is not restricted to a single time period or setting. Finally, we simulate analysts' forecasts and confirm that our characterization of the analyst forecasting process is descriptive of observed patterns documented in prior literature. One implication of our findings is that improvements to analysts' information environment can not only improve analyst forecast accuracy, but can also mitigate their forecast bias.

Key Words: Information environment; Skewness insensitivity; analyst; earnings forecasts; optimism; bias.

1. INTRODUCTION

Analysts' cognitive failures, such as anchoring and adjustment or motivated reasoning (e.g. Abarbanell and Bernard 1992; Cen, Hilary, and Wei 2013; Bradshaw, Lee, and Peterson 2016; Kong, Lin, Wang, Xiang 2021), and their incentives to establish or maintain relationships with managers (e.g. Bradshaw, Lee, and Peterson 2016; Ham, Kaplan, Lemayian 2022; Lehmer, Lourie, Shanthikumar 2022) frequently increase their forecast optimism. However, these sources of forecast bias are challenging for regulators to reduce. For example, concerns about the effect of analyst incentives on forecast bias underlie multiple regulatory changes, including Regulation Fair Disclosure (Reg FD), the Global Research Analyst Settlement, and FINRA 2241. Despite these regulatory changes, analyst forecasts remain, on average, optimistic (Zhou 2021; Lehmer et al. 2022). In this paper, we explore how an analyst's constraints, including their information environment and processing time, combine with the skewness of a firm's earnings distribution to influence the optimism or pessimism of their forecasts. A key feature of our explanation of forecast bias is that it is unlikely to be mitigated by regulatory efforts to reduce conflicts of interest. Rather, the bias can be reduced or exacerbated by changes in a firm's information environment or an analyst's information processing time, including through regulatory interventions.

When researchers argue that forecast bias reflects the incentives faced by analysts, they implicitly assume that an analyst who forecasts from unbiased expectations will, on average, be correct (e.g. Crichfield, Dyckman, and Lakonishok 1978). Allowing analysts to deviate from this – relaxing the constraint that bias must reflect opportunism – is held by researchers to be evidence of analysts' cognitive failures. Instead, we argue that the properties of the firm and its information environment can lead to bias even among rational analysts. We propose a forecasting model where an analyst forecasts from a skewed earnings distribution which, with constraints in the analyst's forecasting environment, leads to a predictably biased forecast.[1]

All analysts have limited time (time constraints) and information processing ability (information constraints) when issuing a forecast. Analysts who are pressed for time are only able to consider a limited, truncated set of a firm's possible earnings (Payne, Bettman and Luce 1996). In addition, because analysts possess limited information about a firm, they face uncertainty about the true distribution of a firm's potential earnings. This uncertainty causes analysts to implicitly rely on a more uniform distribution of earnings (i.e. with a higher variance) relative to a firm's true earnings distribution (Keynes 1921; Fox and Clemen 2005; Wolfe, Fitzgerald and Newton 2017).[2] Neither analysts' consideration of a truncated earnings distribution nor their implicit shift in its variance alone or together result in biased forecasts. However, when a firm's earnings distribution is skewed, these behaviors do result in predictable forecast bias, where direction of bias is determined by the direction of a firm's earnings skewness. Further, the effect of skewness on an analyst's bias should be largest when their uncertainty or time constraints are greatest.[3]

We test three hypotheses: 1.) declines in the firm information environment increases the optimism or pessimism of analysts' forecasts in a direction determined by the left or right skewness of the firm's EPS distribution; 2.) increases in analyst busyness increases the optimism or pessimism of an analyst's forecasts in a direction determined by the left or right skewness of the

[1]Prior research documents that firms frequently have skewed earnings distributions (Givoly and Hayn 2000), and this skewness can influence market participants expectations of firm outcomes (Chang, Monahan, Ouzad, and Vasvari 2021) as well as analysts' forecasts (Gu and Wu 2003).
[2]See Keynes (1921) principle of insufficient reason, which states if an individual has no reason to believe that one outcome is more probable than the next, then he should assign equal probabilities to all outcomes. Over a finite set of outcomes, the distribution reflecting the principle of insufficient reason is the uniform distribution.
[3]This expectation aligns with bounded rationality (Simon 1955; Simon 1990), which illustrates how internal and external constraints affect decision making. We focus on the effect of external constraints on analysts, as these constraints can be altered by regulatory or brokerage interventions. Importantly, while our model aligns with bounded rationality, it does not reflect all ways in which bounded rationality may present in real world settings.

firm's EPS distribution; and 3.) the rate of change of analyst forecast bias is greatest when the firm information environment is weakest, where the rate of change is influenced by the right or left skewness of the firm's EPS distribution. All of our directional predictions for forecast bias are confirmed.

To test our hypotheses, we use four firm-specific proxies for a firm's earnings skewness, two of which are based on the ex-post measures outlined in Gu and Wu (2003) and two of which are ex-ante measures based on the growth option literature. We partition firms based on the direction of skewness of their EPS distributions to test our hypotheses. We find frequencies of left and right skewed earnings distributions that are consistent with prior literature.

We test our first hypothesis, which connects a firm's earnings skewness and constraints in analysts' information environment to their forecast bias, by exploiting the unequal change in firm information environments that occurred around the implementation of Regulation Fair Disclosure (Reg FD). We predict that analyst forecast optimism (pessimism) increases more for firms whose information environment deteriorated following Reg FD that have right (left) skewed earnings distributions. Using a difference-in-differences design, we document increased forecast bias after Reg FD for the subset of firms that do not issue public guidance in the post period, in a direction consistent with the firm's earnings skewness. Because one objective of Reg FD was to eliminate the preferential interaction between managers and analysts, catering theory predicts that analyst optimism should decrease following Reg FD. Instead, we find that the median signed analyst forecast error increases for the affected subset of right-skewed firms by ~36 percent more (0.0044/0.0121) than unaffected right-skewed control firms.

We test our second hypothesis using analyst busyness as an alternative setting where time constraints are likely to interact with earnings skewness to impact forecast bias. We predict that analyst forecast optimism (pessimism) is greater among busy analysts that follow firms that have right (left) skewed earnings distributions. For a sample of analyst forecasts from 2000 to 2018, we find that analysts that follow more than the median number of firms in a given year issue forecasts whose bias is directionally influenced by the skewness of a firm's earnings distribution. The sample period also allows us to confirm that skewness continues to interact with analyst constraints to impact bias in more recent time periods.

Finally, we examine the differential effect of changes in the information environment at long and short horizons, given the skewness of a firm's earnings distribution. We assume that the information environment declines exponentially with the forecast horizon. We compare the change in scaled forecast errors in the three months immediately preceding an earnings announcement (short horizons, where the information environment is stronger) to the change in scaled forecast errors in the three months immediately following the previous earnings announcement (long horizons, where the information environment is weaker). We expect and find that the rate of decline in analyst forecast errors is greatest at long horizons, when the information environment is weakest. Above all, we demonstrate that the magnitude of this effect is determined by the right or left skewness of a firm's earnings distribution. We also confirm that a simulation of a time and information constrained analyst's forecasts can predict the frequency of positive and negative forecasts at long horizons and can produce a distribution of forecast errors consistent with prior literature.

Our paper is related to Gu and Wu (2003), who document that the on-average left skewness of firm's earnings distributions leads to an optimistic forecast bias when an analyst forecasts to minimize the median, rather than mean, of their forecast error. We consider the implications of the combination of analysts' *external constraints* and the direction of skewness on forecast bias.

Importantly, the effect of these constraints on analyst forecast bias holds whether an analyst forecasts the mean or median of an earnings distribution. Our paper complements Gu and Wu (2003) by providing additional evidence on the conditions in which the skewness of a firms' earnings distribution affects forecast bias. In contrast to Gu and Wu (2003), our model of the forecasting process indicates that analysts following firms with right-skewed earnings distributions will issue more optimistic, rather than pessimistic, forecasts. Although our predictions are directionally opposite, the findings of Gu and Wu (2003) and our own are not mutually exclusive.[4]

Our findings contribute to ongoing efforts to identify determinants of analyst forecast bias other than incentives (Bradshaw et al. 2016).[5] Most firms have skewed earnings distributions. We demonstrate that the skewness of a firm's earnings distribution contributes to analyst forecast bias, but this bias can be reduced through improvements to a firm's information environment or by increasing the time or processing capacity of an analyst. One implication of previous incentive-based analyst research is that reducing analysts' incentive to bias forecasts will lead to less biased (and potentially less accurate) forecasts. This argument is consistent with the aim of regulatory interventions, including the Global Analyst Research Settlement, Regulation Fair Disclosure, and FINRA 2241 enacted to reduce the perverse incentives analysts face to bias their forecasts. We demonstrate that the regulatory interventions aimed at reducing incentive-induced bias, which also led to a deterioration in firms' information environments, instead *increased* bias for a subset firms.

Our setting also provides additional insight on analysts' information processing costs

[4] Both effects, constraints and minimizing the mean absolute forecast error, can occur simultaneously. We demonstrate such simultaneity in Section 3.7.

[5] Importantly, we do not argue forecast accuracy or reduction in bias are first order concerns for the analyst. Numerous papers show that analysts provide a range of services to investors, including through their information discovery role (e.g. Jackson 2005; Huang, Lehavy, Zang and Zheng 2018; Harford, Jiang, Wang and Xie 2019), and that forecast accuracy, and by extension bias, are of lesser importance to analysts. Rather, we argue that forecast bias continues to influence the perceptions of market participants and consequently are of ongoing interest to investors and regulators.

(Blakespoor et al. 2020). We find that these costs, as measured by busyness and the firms' information environment, interact with earnings skewness to result in predictable forecast bias.

2. MOTIVATION AND REPRESENTATION OF ANALYST FORECASTING

Research repeatedly documents analysts' incentives to bias their forecasts in order to gain access to, or develop a relationship with, firm management (Francis, Hanna, and Philbrick 1997; Lim 2001; Richardson et al. 2004; Ham, Kaplan, Lemayian 2022; Lehmer, Lourie, Shanthikumar 2022), to increase trading with their brokerage house (Lin and McNichols 1998; Michaely and Womack 1999; Cowen, Groysberg, and Healy 2006), and to improve their own career outcomes (Hong and Kubik 2003).[6] Despite decades of documentation, analyst forecast bias is a persistent phenomenon that investors still fail to fully unravel (Bradshaw, Richardson and Sloan 2001; Hughes, Liu, and Su 2008; So 2013; Veenman and Verwijmeran 2018).[7]

Given the propensity for analyst forecast bias to mislead market participants, regulators have issued, updated, and enforced multiple regulations whose implicit or explicit intent is to reduce forecast bias, generally by seeking to reduce analyst's incentives to bias. FINRA 2241 prohibits analysts from being supervised by individuals engaged in investment banking activities, Reg FD limits selective disclosure to analysts, the Global Research Analyst Settlement mandates the physical and supervisory separation of investment banking and analysis departments, and Regulation Analyst Certification requires the disclosure of potential conflicts (Bradshaw 2009). Although these regulations were largely enacted in the early 2000's, the regulations themselves

[6] In contrast to the proposition that analysts intentionally alter their forecasts to cater to management, Louis, Sun, and Urcan (2013) find that analysts will sometimes sacrifice forecast accuracy to provide more informative forecasts to investors by backing out the component of earnings that may be managed. However, our study explicitly uses I/B/E/S to calculate forecast error, which reduces the influence of abnormal accruals and one-time items on the calculation of actual earnings per share, compared to Louis et al.'s explicit examination of street earnings.

[7] See Kothari, So and Verdi 2016 for a recent review of related studies.

have been repeatedly updated. The largest enforcement settlement of Regulation Fair Disclosure ever occurred in 2022 (Kirby and Bucio 2023). Analyst forecast bias continues to impact investor decisions and be of interest to investors, researchers, and regulatory bodies. [8]

2.1 External Constraints

Analysts face meaningful constraints on their time when issuing EPS forecasts. The average analyst in our sample period follows 15 to 20 firms and issues three to four forecasts during the year for each firm she follows (Myring and Wrege 2009; Kim, Lobo, and Song 2011). While this would suggest the average analyst has approximately one week to issue a forecast, analysts typically update their earnings forecast for a firm within one to three trading days of an earnings announcement, and earnings announcements tend to cluster in time (Chakrabarty, Moulton, and Wang 2015).[9] Consequently, large numbers of forecasts are issued over relatively short windows.

Analysts also possess limited, incomplete information when forecasting EPS. Analysts may curry favor with management to reduce this limitation (Ke and Yu 2006), but nevertheless analysts frequently rely on estimates of factors including firm revenue, growth, and expenses that feed into models to arrive at an EPS estimate (Berger and Kaplan 2014). The complexity of an analyst's portfolio, including the number of firms and industries an analyst follows, is linked to cross-sectional differences in analyst forecast accuracy (e,g, Clement 1999; Clement and Tse 2005). Consequently, consistent with the effects of constraints on decision making, analysts are

[8] Prior research also documents an association between cognitive biases and analysts' forecast errors. (e.g. Cen et al. 2013; Kong, Lin, Wang, Xiang 2021). We focus on time constraints and imperfect information because, while most cognitive biases reflect unchanging or innate human characteristics, the limitations documented in this paper are at least partially under the control of analysts, brokerage houses, and regulatory bodies.

[9] The length of time between forecast revisions in our sample is considerably shorter than in Kim et al. (2011). This may reflect differences in the cutoffs required for analysts to be considered 'active.'

likely to focus on the most relevant information available when forecasting earnings (e.g. Blankespoor, deHaan, and Marinovic 2020), rather than a theoretical 'complete' information set.

In the next section, we explain why and when analysts who issue forecasts under these constraints are likely to issue a predictably biased forecast.

2.2 Uncertainty and Skewness

In order to explore the ramifications of constraints on analyst forecasting, we first consider a representation of the forecasting process of a theoretical, perfectly rational analyst who is subject to no external constraints. When tasked with forecasting the EPS of a firm, this analyst has a complete information set, allowing the analyst to be aware of all possible EPS outcomes, as well as the probability assigned to each possible outcome. This analyst forecasts the mean of the firm's perfectly-known forward-looking EPS probability distribution if she wishes to minimize the mean squared forecast error or the median of the distribution if she wishes to minimize the mean absolute forecast error. The rational, unconstrained analyst is unaffected by changes in the information environment of a firm or the limitations of time because, by definition, she always possesses complete information with which to make her decisions; she is logically omniscient.

Real analysts, however, are affected by external constraints. Analysts' constraints, by themselves, do not necessarily lead to biased forecasts; hence why we claim the effect of these constraints does not reflect irrational behavior. When the forward-looking earnings distribution of a firm is symmetric, these analysts will still form unbiased estimates of earnings even when constrained by time and limited information. However, if the EPS distribution of a given firm is skewed, then forecasts issued by constrained analysts will be biased. The combination of analysts' limited time, incomplete information, and a skewed forward-looking earnings distribution results in biased earnings forecasts irrespective of whether analysts seek to forecast the mean or median of a firm's earnings distribution. A detailed explanation of our representation can be found in Appendix 3.

We illustrate the effect of information constraints on analyst forecasting visually in Figure 1, Panel A. We present a firm's symmetric forward-looking earnings distribution in the upper figure, followed by the same distribution with increased variance below, where the lower figure represents the distribution our analyst forecasts their earnings expectations from. We represent the effect of incomplete information available to our analyst when forecasting (i.e. a need to rely to some degree on an ignorance prior) through the increased variance of the earnings distribution in the lower figure.[10] However, this increased variance affects neither the mean nor the median of the distribution our analyst forecasts from relative to the firm's true forward-looking earnings distribution.

Our analyst also has limited time with which to issue her forecast, so can only consider a subset of all possible EPS outcomes. Our representation does not rely on the elimination of the extreme ends of the EPS distribution, but rather that the analyst considers any finite subset of all possible EPS outcomes. The tail truncation represented by the vertical lines in Figure 1, Panel A provides the simplest visualization of the effect of an analyst constrained by limited time. As with increased variance, the truncation affects neither the mean nor the median of the distribution the analyst forecasts from, provided the EPS distribution is symmetric.

In Figure 1, Panel B, we illustrate the joint effect of a constrained analyst and a skewed

[10] In practice, and verified by multiple experimental studies, when individuals are uncertain about the probabilities of a set of outcomes, the individual tends towards assigning more (rather than less) similar probabilities; the variance of their subjective probability distribution is greater than the variance of the 'true' probability distribution (e.g. Keynes 1921; Gonzalez and Wu 1999; Fox and Rottenstreich 2003; Fox and Levav 2004; Fox and Clemen 2005; Urminski 2015). This behavior of increased expected variance across probabilities is consistent with the addition of a 'noise' term to a distribution. Our analyst is not omniscient; she has incomplete information when issuing her forecast, represented by the increased variance of the distribution.

earnings distribution on analyst forecasts. We present a right-skewed forward-looking EPS distribution. As before, the truncation of extreme outcomes on its own does not, in conjunction with skewness, introduce bias into the analyst's forecast. However, when imperfect information is introduced (bottom figure), the increase in variance over the truncated distribution results in a shift of the mean and median to the right (i.e. optimistic) relative to the untruncated distribution. A shift to the left (i.e. pessimistic) would be observed for a left-skewed distribution. That is, a forecast issued by an analyst with limited time and information will be predictably biased when the firm has a skewed earnings distribution.

The extent to which a firm's earnings skewness will influence analyst forecasts depends on the severity of the constraints the analyst faces – in our setting, the information environment and the time available to an analyst when issuing her forecast. Thus, we hypothesize that a decline in a firm's information environment will lead to an increase in forecast bias that is determined by the direction of skewness of a firm's earnings distribution.[11] We predict that analysts will issue more optimistic (or less pessimistic) forecasts for firms whose forward-looking earnings distribution is right-skewed when the information environment declines.

H1: Analyst forecast bias changes with declines in a firms' information environment in the direction consistent with the skewness of the firm's earnings distribution.

Our primary contribution is documenting a compelling explanation for forecast bias that regulators and firms can attend to.[12] Thus, we also consider the association of constraints on

[11] Prior research documents an association between the information available to an analyst and her forecast accuracy (e.g. Beyhaghi, Khashabi, Mohammadi 2023 for a recent example). We examine the association between the information available to an analyst and her forecast bias, conditional on the skewness of the firm's earnings.
[12] We do not argue that this is the only source of analyst forecast bias, merely one that is largely correctable and which does not reflect cognitive failures on the part of analysts (e.g. Amir and Ganzach 1998; Zhang 2006; Marsden, Veeraghavan, and Ye 2008).

analysts' time (analyst busyness) with forecast bias. An analyst has limited time with which to prepare forecasts, time that is further constrained depending on the nature, size, and complexity of the analyst's portfolio.[13] Prior literature has documented an association between the size and complexity of an analyst's portfolio and their accuracy (e.g. Clement 1999; Kini, Mian, Rebello, and Venkateswaran 2009; Pisciotta 2023; Bourveau, Garel, Joos, and Petit-Romec 2024), though the literature has rarely examined whether portfolio size is, or should be, linked to forecast bias (Drake and Myers 2011).[14] Under the relatively benign assumption that the increased variance (limited information) in Figure 1 affects all analysts to some degree, our next hypothesis focuses on the effect of the truncation of the distribution in Figure 1B, which represents the ability of an analyst to focus on only a subset of all possible EPS outcomes for firms in their portfolio. When an analyst follows more firms, their portfolio increases in size, and the time the analyst has to devote to any one firm declines. As a consequence, the truncation observed in Figure 1B would be more extreme for analysts following more firms, increasing the bias of the analyst's forecasts when the firm's earnings distribution is skewed. We formally state our second hypothesis as follows:

H2: Analyst forecast bias changes with the busyness of the analyst, in the direction consistent with the skewness of the firm's earnings distribution.

Finally, we consider the effect of earnings skewness on changes in forecast bias as the information environment changes over the fiscal year. We assume that the information available about a firm's EPS is weakest (most uncertain) at long horizons, and that changes in the

[13] Although outside of the purview of this study, prior literature documents that the number of firms an analyst follows that issue bundled earnings announcements has an influence on analyst output, lending support to the belief that analyst busyness or distractedness influences their reports and forecasts (Hsu and Wang 2021).

[14] In a similar vein, Drake, Joos, Pacelli, and Twedt (2020) document that bundled forecasts, where forecasts for multiple firms are issued on the same day, are less accurate. They attribute this finding to analysts providing specialized services elsewhere. However, the finding also provides evidence that analysts are likely to intentionally make trade offs to make the best use of their limited time.

information available to an analyst have a greater impact at long horizons than short horizons. For example, prior to a firm's first quarter EPS announcement, an analyst has significant uncertainty about each quarter's possible EPS. Following the firm's third quarter EPS announcement, the same analyst knows with certainty three fourths of the firm's annual EPS, so only faces uncertainty about the final quarter's EPS. Thus, on average, information changes earlier in the year have a greater impact on analyst forecasts than later information changes. In Figure 1, this would equate to a reduction in variance that is greater at longer horizons than shorter horizons. As with our other hypotheses, the effect this change should have on forecast bias is determined by the direction of skewness of the firm's earnings distribution.

We expect a firm with a left-skewed earnings distribution will have a lower magnitude of earnings skewness than a firm with a right skewed earnings distribution. This results from an unbounded right tail for right-skewed firms (there is no limit to a possible upside), while there is a bounded left tail for left skewed distributions (the liquidation value of the firm). Taken together, we anticipate greater declines in forecast bias at long horizons for both left and right skewed firms. We also expect that the decline for left skewed firms should, on average, be smaller than for right skewed firms. Thus, we hypothesize:

H3: The month-to-month decrease in analyst forecast error is greater at long horizons than at short horizons in a manner consistent with the skewness of the earnings distribution.

3. METHODOLOGY AND SAMPLE

3.1 Measures of Skewness

We use four measures of earnings skewness to test our hypotheses: two ex-ante and two ex-post measures. We use ex-post measures of earnings skewness from prior literature to measure skewness on a rolling two-year basis using the previous eight quarters of EPS observations, consistent with Gu and Wu (2003). As outlined in Gu and Wu (2003), the skewness of a distribution can be measured as the difference between the distribution's median and mean. In the context of an earnings distribution, this is captured by:

$$MNMD_{jt} = \frac{Mean(EPS_{jt}) - Median(EPS_{jt})}{Price_{jt-1}} X\ 100$$

where the subscript *j* indicates a firm and *t* indicates the first quarter of an 8-quarter window.

Alternatively, the skewness of a firm's earnings distribution can be captured by the skewness coefficient. Again, as defined in Gu and Wu (2003):

$$SKEW = \frac{n}{(n-1)(n-2)} \sum_{t} \left(\frac{EPS - \overline{EPS}}{S} \right)^3$$

where *n* is the number of EPS observations within the relevant 8-quarter rolling window. We define a firm as having a right (left) skewed distribution if their measure of *SKEW* or *MNMD* is above (below) the median of all firms.[15]

Ex-post measures of skewness benefit from being readily observable and easily calculable by both analysts and researchers. However, they are also subject to concerns that the underlying earnings distribution is non-stationary, resulting in unreliable estimates of earnings distribution skewness. To address this concern, we also incorporate two additional theory-based ex-ante skewness measures.

A common attribute of proxies for ex-ante skewness is a reliance on measures of growth options (Del Viva, Kasanen, and Trigeorgis 2013). Unlike posterior distributions, ex-ante distributions are not directly observable. Thus, our first ex-ante measure of the skewness of a firm's

[15] Our results are robust to a cutoff for left and right skewed firms with a given skewness measure above or below 0.

earnings distribution is the growth option measure (*GO*) outlined in Del Viva et al. (2013):

$$GO_t = \frac{MV_t - \frac{FCF_{t-fy}(ng)}{w.a.c.c._{t-fy}}}{MV_t}$$

where MV_t is the market value of equity, FCF is the free cash flow under an assumption of no growth, and w.a.c.c. is the weighted average cost of capital. *GO* represents the portion of the market value of a firm that is not captured by a perpetual discounted stream of the firm's current cash flows assuming null growth.[16] We define a firm as right (left) skewed if its measure of *GO* falls in the top (bottom) decile of all firms for which *GO* can be calculated.

We also we use the Altman Z-Score (*Z-Score*) measure of bankruptcy risk as an ex-ante measure of earnings skewness (Altman 1968). Where the *Z-Score* is measured as:

$$Altman\ Z\ Score = 1.2\frac{working\ capital}{total\ assets} + 1.4\frac{retained\ earnings}{total\ assets} + 3.3\frac{EBIT}{total\ assets} + 0.6\frac{market\ value\ of\ equity}{total\ liabilities} + \frac{sales}{total\ assets}$$

While the Altman Z-Score has been criticized as a measure of the likelihood of bankruptcy, we do not intend to predict bankruptcy but simply to measure the ex-ante skewness of a firms' earnings distribution.[17] The left-or-right-skewness of a distribution is determined by the probability of the most and least likely outcomes. If the least likely outcomes are to the right of the mass of the distribution, it is likely the distribution will be determined to be right skewed, and vice versa. Skewness is unrelated to the mean of the distribution. A firm's overall prospects might

[16] Del Viva et al. (2013) confirm that the earnings distributions of firms they measure as having high growth options (*GO*) are right skewed. Del Viva et al.'s (2013) *GO* measure was not designed to capture left-skewed earnings distributions, and the absence of growth options may not be informative of the probability of poor outcomes so much as the absence of extreme right tail events. Although we are not certain low *GO* firms will have left-skewed distributions, we expect they have less right skewed ex-ante earnings distributions.

[17] The Altman Z-Score generalizes across firms and time better than competing bankruptcy measures, making it a more reliable measure of skewness for our sample of firms than other bankruptcy measures (Altman, Iwanicz-Drozdowska, Laitinen, and Suvas 2017).

be positive (or negative) but its distribution left skewed if the odds of extremely poor outcomes are small, or right skewed for the same firm if the probability of unusually high outcomes is small. In determining expectations of left or right skewness, we focus on whether the effect of the extremely low or extremely high outcomes dominates.

Because firms in financial distress (low *Z-Score*) are more likely to experience negative than positive outcomes, we expect low *Z-Score* firms to have right-skewed earnings distributions, reflecting the relatively low likelihood of extreme positive earnings outcomes and an inherent lower bound on extreme negative outcomes.[18] Firms not in financial distress (high *Z-Score*) have less right skewed distributions and may even have left skewed ex-ante earnings distributions. We define a firm as right (left) skewed if its measure of *Z-Score* falls in the top (bottom) quintile of all firms for which *Z-Score* can be calculated.

3.2 Research Settings and Sample Construction

Table 1 describes the sample selection process for Hypotheses 1, 2, and 3. We use three settings to test our hypotheses. First, we use the implementation of Reg FD in October 2000. Reg FD provides an exogenous shock to firms' information environments that we use to test Hypothesis 1. Reg FD explicitly requires that when managers provide material information about the firm to securities market professionals, managers must also reveal the information publicly.[19] The limits

[18] Although discussed in the context of returns, rather than earnings, consider the argument in Zhang (2013): "[S]ince the negative stock return is capped at -1, whereas the upside is potentially unlimited, such an asymmetry can add a certain degree of positive skewness in the return distribution." This would also be consistent with prior literature that finds an on-average right-skewness of earnings (e.g. Berger, Ofek, and Swary 1996; Ackert and Athanassakos 1997; Khanna 2014).

[19] Despite the explicit requirements of Reg FD, a loophole did and does exist in which managers can reveal information that, while not material on its own, may be material as a piece in the 'mosaic of information' an analyst considers when making a forecast. We anticipate that this loophole was less employed in the early years of Reg FD (See Heflin, Subramanyam, and Zhang 2003), when it was unknown to what extent the regulation would be enforced. For this reason, we limit our analysis to years close to the implementation of Reg FD.

on private, back-door communications leave two alternatives for management – they can either disclose information through public channels, as the regulation requires, or not disclose the information at all.[20] Some firms that had been providing information to analysts privately chose not to switch to public disclosures following Reg FD, causing a decline in those firms' information environments (Wang 2007). Because analysts following this type of firm had less information on average than immediately prior to Reg FD, the variance of these analysts' forecast distributions should increase. This should lead to an increase in analysts' forecast bias in a direction determined by the skewness of firms' earnings distributions. These firms are our treatment group for Hypothesis 1.[21]

Our sample starting point to test Hypothesis 1 is the intersection of Compustat fundamental annual and historical segments files, Thomson Reuters Institutional Holdings, First Call Company Issued Guidance, and the I/B/E/S summary and detail files. In all our samples we exclude forecast observations that are issued after the earnings announcement date or whose error is greater than 100% of firm price. We also exclude duplicate forecast observations. Following Wang (2007), we require firms to have data on management guidance. We define a firm as not providing public guidance during a period if the First Call Company Issued Guidance database has one or fewer observations for the firm in the pre (1997-2000) or post (2001-2003) Reg FD periods (Wang

[20] Recent survey and empirical research suggest that in the intervening years following Reg FD analysts have developed avenues to gain private information from management (e.g. Green, Jame, Markov, and Subasi 2014; Brown, Call, Clement, and Sharp 2015; Gleason, Ling, and Zhao 2020). Our analysis focuses on the period immediately surrounding Reg FD for which Wang (2007) documents a decline in the information environment for firms that replace private earnings guidance with non-disclosure, consistent with analysts failing to fully replace the private information with other sources immediately following the regulation's implementation.
[21] If too few managers provided private guidance to analysts prior to Reg FD, we will not find significant results because the information available to analysts of NND firms will not sufficiently decline.

2007).[22] Management guidance includes any of the forecasted items in First Call, including EPS, sales, gross profit margin, and cash flow per share. Our final sample is comprised of 16,783 firm-year-month observations, for which 12,235 contain data necessary to calculate *SKEW* and *MNMD*, 15,006 contain data necessary to calculate *Z-Score*, and 10,081 contain data necessary to calculate *GO*.[23] Our regressions for Hypothesis 1 are then limited to firms that did not provide public guidance prior to Reg FD.

To test Hypothesis 2, we use the number of firms in an analyst's portfolio as a proxy for analyst busyness. In contrast to the Reg FD setting, the constraint on analysts arises from analysts' limited time with which to forecast a firm's earnings, increasing the truncation of analysts' forecast distribution. We examine the interaction of limited time with skewness and their joint impact on analyst forecast bias.

Our starting point to test Hypothesis 2 is the intersection of the IBES summary and detail files and Compustat from the years 2000 to 2018. We require that all observations have the data necessary to calculate *SKEW* and *MNMD*. We include only the first forecast for an analyst for the fiscal year (FPI = 1), exclude firms with an ending price less than $5, and remove outliers (MSFE > 1) and observations missing control variables. This results in a final sample size of 470,308 individual forecast observations.

To test Hypothesis 3, we use forecast horizon as a proxy for the effect of changes in the information environment on analyst forecast bias. We expect that the rate of change in forecast errors at long horizons prior to the earnings announcement to be greater than the rate of change in

[22] The number of First Call Guidance observations to distinguish *NND* and *NPD* is similar to the number used in Wang (2007) to distinguish *NND* and *NPD*.
[23] Samples for GO and Z-Score in our regressions include only those observations that are coded as either High GO (Z-Score) or low GO (Z-Score) as defined in our measures of skewness.

forecast errors at shorter horizons, where the sign of the forecast error is determined by the skewness of the firm's earnings distribution. In addition, we expect that the magnitude of the rate of change differs between left and right-skewed distributions, given the latter's unbounded right tail. Our sample for the test of Hypothesis 3 parallels our Reg FD sample. We begin with the intersection of the IBES summary and detail files and Compustat for the years 1997-2003. We require that all observations have the data necessary to calculate *SKEW*, *MNMD*, *GO* and *Z-Score*. We exclude firms followed by fewer than two analysts and remove duplicates, outliers, and observations missing control variables. This results in a final sample size of 14,265 individual forecast observations.

3.3 Regression Specification for Hypothesis 1

To test Hypothesis 1, we conduct a difference in differences (DID) test to control for time trends and events concurrent with Reg FD, including the dot-com bubble burst, the Global Settlement, and accounting scandals like Enron and WorldCom, which affected all firms. We test our hypothesis by estimating the following DID regression on firms that did not provide public guidance prior to Reg FD:

$$MSFE = \beta_0 + \beta_1 NND + \beta_2 postfd + \beta_3 NND \; x \; postfd + controls + e_i \qquad (1)$$

MSFE is the median scaled forecast error, measured as the I/B/E/S actual EPS less the median analyst forecast divided by firm price at the beginning of the fiscal year (e.g. Bartov, Faurel, and Mohanram 2018).[24] Thus, negative errors are interpreted as optimistic. *NND* (new non-discloser) is equal to one for firms that do not issue public disclosure both prior to and following

[24] We use the median analyst forecast to calculate forecast error to reduce the likelihood that our results are driven by outlier or stale forecasts (e.g. McNichols and O'Brien 1997; Richardson et al. 2004). IBES ACTUAL EPS has been adjusted for non-recurring items and is typically not the same number one could derive from Compustat data.

Reg FD and zero otherwise, following Wang (2007). We infer that these firms had been providing information to analysts privately. Thus, the decision to not provide public disclosures following Reg FD causes a decline in the firms' information environment. In contrast *NPD* (new public discloser) firms begin providing public disclosures following Reg FD, mitigating the loss of information that was previously provided only privately. Figure 2 provides a visual diagram of the definition of *NND*. In regression (1), β_3 represents the difference in differences coefficient, which our first hypothesis predicts will be negative (more optimistic) for firms with right skewed earnings distributions and positive for firms with left skewed earnings distributions. A negative coefficient on β_3 would indicate that analysts who follow firms that stop providing guidance (*NNDs*) issue more optimistically biased forecasts than analysts following firms that continue providing guidance, but after Reg FD do so publicly (*NPDs*). We include a number of controls for firm attributes associated with the firm information environment, including the number of analysts following the firm, number of firm segments, market to book (*MTB*), and percent institutional ownership (Hutton 2005). Variable definitions are included in Appendix 1. We also include year fixed effects in our regression.[25]

We assume high *SKEW*, *MNMD*, and *GO* firms and low *Z-Score* firms have right skewed distributions, and low *SKEW*, *MNMD*, and *GO* and high *Z-Score* firms have less right skewed and possibly left-skewed distributions.

3.4 Descriptive Statistics – Regulation Fair Disclosure

Table 2 provides univariate statistics for our sample of firms that did not provide guidance

[25] In robustness analyses, we confirm that our results in all our regressions are qualitatively the same with the addition of industry fixed effects. Year fixed effects do not result in over-identification because our pre and post FD periods each lasts multiple years. However, to address this concern, we re-ran all of our main Reg-FD tests absent year fixed effects. All results were directionally consistent and were statistically stronger than the results presented in this paper.

prior to Reg FD. We partition our sample into *NND* and *NPD* firms. Panel A shows the skewness measures for the pre-Reg FD period at the 25th, 50th, and 75th, percentiles. During the pre-Reg FD period, we find that both the mean and median of *SKEW* and *MNMD* are negative (left-skewed) consistent with Gu and Wu (2003) and Abarbanell and Lehavy (2003), but more than a quarter of the sample have positive (right-skewed) earnings distributions. On average, *NPD* firms are more likely to have left-skewed distributions in the pre-Reg FD period. *NPD* and *NND* firms also differ with respect to several other firm attributes, which we control for in our analysis. Post Reg FD, (Panel B) the mean and median measures of *SKEW* and *MNMD* are now positive (right-skewed). We also observe changes in *GO* and *Z-Score* that are consistent with a shift to more right-skewness. The change in median skewness also suggests that the skewness of a firm's earnings distribution is not static across time. While this does not imply that ex-post measures of earnings skewness are invalid, it does suggest that it is important to include ex-ante measures of skewness in our analysis.

3.5 Test of Hypothesis 1: Skewness and the Information Environment

The validity of difference in differences tests rests on the assumption that the treatment and control groups (here, *NND* and *NPD* firms) exhibit parallel trends in forecast bias prior to external intervention. In Figure 3 we illustrate that the forecast errors for analysts following *NND* and *NPD* firms in our sample exhibited parallel trends prior to the introduction of Reg FD. We split forecast-error trends for *NND* and *NPD* firms into left and right skewed subsamples to match our empirical tests. We observe that prior to Reg FD, *NPD* and *NND* firms had parallel trends, and following Reg FD the trendlines of the two types of firms diverged, though this divergence is more clearly observed among right skewed firms.[26] We conclude that the assumption of parallel trends is

[26] When interpreting the divergence in trendlines in a difference in differences test, it is not possible to determine

reasonable for left and right skewed *NND* and *NPD* firms.

Table 3 presents the results of our difference in differences test of Hypothesis 1. We expect that the changes in the information environment will be associated with changes in forecast bias that are consistent with the direction of skewness of the firms' earnings distribution. Panel A provides results for firms based on ex-post skewness metrics (*SKEW* and *MNMD*) while Panel B provides results based on ex-ante skewness metrics (*GO* and *Z-Score*). Columns (1) and (2) in both panels report results for right-skewed firms and columns (3) and (4) report results for left-skewed firms.

On average, *NND* firms have more pessimistic (or less optimistic) forecast errors than *NPD* firms, as evidenced by the positive and significant co-efficient on *NND* in all four columns of Panel A, and three of four columns in Panel B. Following Reg FD, and before considering the effect of changes in the information environment (*postfd*), forecasts become more optimistic on average in Panel A. This is consistent with the shift to more right skewed earnings distributions in the post period, which we observe in Table 2.

As predicted, the sign of our coefficient of interest (*NND x postfd*) is negative and significant for firms with right-skewed earnings distributions using *MNMD, GO*, and *Z-Score* to measure skewness, and positive and significant for firms with left-skewed distributions across all four measures. When we measure skewness using *SKEW,* the coefficient is not different from zero for right-skewed firms. Consistent with Hypothesis 1, when the distribution of expected earnings is skewed, a decline in a firm's information environment results in a change in forecast bias in a

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whether one group was the driver of the effect over the other; rather, an appropriate interpretation is that the event affected the behavior of the test group differently from the behavior of the control group. For instance, in our setting it is not possible to distinguish between NPDs improving their information environment and NNDs remaining stagnant from NPDs not improving their information environment and NNDs deteriorating.

direction consistent with the skewness of the firm's earnings distribution. Optimism increases more for analysts following a right-skewed firm whose information environment deteriorated after the implementation of Reg FD and pessimism (or a reduction in optimism), likewise, increases more for analysts following a left-skewed firm.

Overall, our results are consistent with earnings skewness predicting the optimism or pessimism of analyst forecast bias. Our evidence is also consistent with the assumption that analyst forecasts reflect the influence of analysts' external constraints. More importantly, our results support our hypothesis that declines in the firm information environment interact with the skewness of the earnings distribution leading to increases in the magnitude of analyst forecast bias.

Our characterization of the forecasting process offers an explanation for evidence that forecast optimism increased after the implementation of Regulation Fair Disclosure, the opposite of what theory predicts had analysts been catering to firm managers with excessively optimistic forecasts (Richardson, Teoh, and Wysocki 2004). First, information asymmetry among market participants decreased following Reg FD (Chiyachantana, Jiang, Taechapiroontong, and Wood 2004; Lee, Rosenthal, and Gleason 2004; Eleswarapu, Thompson, and Venkataraman 2004), while the level of earnings management remained unchanged (Kwag and Small 2007).[27] If, prior to Reg FD, analysts walked their optimistic forecasts down in an effort to cater to management, then the findings of Chiyachantana et al. (2004), Eleswarapu et al. (2004) and Kwag and Small (2007) imply we should observe a decline in forecast bias and an increase in accuracy in the post-FD period. Instead, bias increased and accuracy decreased (Agrawal, Chadha, and Chen 2006; Kwag and Small 2007; Bagnoli, Watts, and Zhang 2008). Our findings show that the change in analyst

[27] See Koch, Lefanowicz, and Robinson (2013) for a review of the literature around Regulation Fair Disclosure.

forecast bias and accuracy following Reg FD can be tied to the change in the firm-specific information environment. Our results suggest regulators concerned with reducing analyst forecast bias could consider regulations that improve the firm information environment.

3.6 Capturing Analyst Busyness and Regression Specification for Hypothesis 2

We test Hypothesis 2 with the following regression:

$$MSFE = \beta_0 + \beta_1 Right\ Skew + \beta_2 Busy\ Analyst + \beta_3 Right\ Skewed\ x\ Busy + controls + e_i \quad (3)$$

MSFE is calculated at the analyst-firm-year level rather than firm-year level, given the analyst specific nature of busyness. We use *SKEW* and *MNMD* to measure skewness. *Right Skewed* is an indicator variable equal to one if a firm year has a *SKEW* (*MNMD*) above the median across the sample. The evidence in Gu and Wu (2003) implies a positive coefficient on the main effect of *Right Skewed* (β_1) if analysts forecast the median of the distribution. *Busy Analyst* is an indicator variable equal to one if the analyst associated with a forecast follows more than the median number of firms followed among all analysts in a given year in the sample (Clement 1999).[28] *Busy Analyst* captures the effect of analyst busyness on the sign of their forecast error for left skewed firms. We expect the coefficient on β_2 to be positive: analysts who follow the most firms have less time to issue each forecast and consequently their forecasts drift in the direction of skewness (left) of the firm's earnings distribution. This results in more pessimism or less optimism. We expect the coefficient on the interaction (β_3) to be negative (optimistic) for right skewed firms. Controls are identical to Eqn (1). Errors are two-way clustered by analyst id (ANALYS) and firm (CUSIP).

[28] Clement (1999) uses the total number of firms an analyst forecasts for during a year as a measure of that analyst's portfolio complexity. Because we are interested in analysts that are the most (least) busy, we split the sample at the median in for each year rather than using a cardinal variable. Similar measures of busyness and portfolio complexity continue to be used in the accounting literature (e.g. Driskill, Kirk and Tucker 2020; Hsu and Wang 2021; Bratten and Larocque 2024).

This ensures that the forecasts of analysts who forecast for more firms, and firms with greater analyst following, will not be treated as independent observations, which if not corrected for would inflate significance estimates.

Table 4 Panel A reports sample statistics for our busyness sample. The number of observations (N) reflects the number of forecasts issued by analysts who are classified as more (high) or less (low) busy. Consequently, the number of observations between the two subsamples are unequal. The median busy analyst covers approximately 15 more firms or 4.5 times more firms than the median less-busy analyst. The difference in means for all variables between the sample subpopulations is statistically significant, which is expected given the relatively large sample sizes. Despite this, the difference in the magnitudes of *SKEW* and *MNMD* of forecasts for firms followed by busier and less busy analysts is small, suggesting busier and less busy analysts follow similar types of firms. Forecasts are also issued at roughly equal points in the forecast horizon regardless of analyst busyness, providing some comfort that our results are unlikely to reflect a horizon effect.

3.7 Test of Hypothesis 2: Skewness and Analyst Busyness, Skewness

Table 4 Panel B reports the regression results for eqn (3). The intercept, which reflects firms with left-skewed distributions, is negative and significant, while the coefficient on *RightSkewed* is positive and significant, consistent with Gu and Wu (2003), who predict and find that analysts forecast the median, rather than the mean, of an earnings distribution. The results of this test provide evidence that the effects documented in Gu and Wu (2003) and the effects of external constraints can occur simultaneously. Consistent with prior research and the analysis in Table 3, both the intercept and the net coefficient for firms with right skewed distributions (-0.0043 + 0.0022 = -0.0021) are negative indicating that on average, analysts are optimistic at long horizons.

The coefficient on *Busy Analyst* is positive, consistent with our predictions; when earnings are left skewed and analysts are busiest, forecasts become more pessimistic or less optimistic. Similarly, the coefficient on the interaction *RightSkewed*×*Busy is* negative. When analysts are relatively busy, analyst forecasts for firms with the right-most earnings' skewness become more optimistic.

3.8 Hypothesis 3: Skewness and Forecast Horizon

We test our third hypothesis with the following regression:

$$\Delta MSFE = \beta_0 + \beta_1 LongHorizon + controls + e_i \qquad (2)$$

Δ*MSFE* is the absolute value of the change in forecast error. Thus, a negative coefficient in regressions can be interpreted as a decrease in the rate of change in forecast errors; improvements in forecast accuracy would be decelerating. *LongHorizon* is an indicator variable equal to one if the horizon is 11, 10, or 9 months until the earnings announcement date or equal to 0 if the horizon is 2, 1, or 0 months until the earnings announcement date.[29] A negative coefficient on *LongHorizon* indicates that forecasts improve their accuracy faster when forecasts are issued further from the earnings announcement date than when they are issued closer to the earnings announcement date.

According to Hypothesis 3, the rate of change in forecast errors should be influenced by the left-or-right skewness of a firm's earnings distribution. Absent other incentives and biases, we would expect analysts following left-skewed firms to issue forecasts that are the most pessimistic at long horizons and the least pessimistic at short horizons, with forecast errors following a roughly logarithmic curve. We would expect analysts following right-skewed firms to follow a similar

[29] We omit forecasts made in the 3-8 months prior to the earnings announcement, though our results are qualitatively similar when LongHorizon is equal to 0 for months 0-8.

pattern with forecast optimism. We would expect, in this scenario, that the coefficient on *LongHorizon* would be equal for left and right skewed firms, with oppositely signed intercepts.

However, left-skewed firms tend to have a smaller magnitude of skewness than right-skewed firms, and analysts face incentives and exhibit biases when issuing their forecasts. As a result, we expect that analysts following left-skewed firms will issue forecasts whose bias is less pessimistic than would otherwise be expected. As a result, we predict that the co-efficient on *LongHorizon* will be smaller for left than for right skewed firms.

As in our test of Hypothesis 1 and 2, we include controls for market to book (MTB), number of analysts, number of segments, institutional ownership percentage, and year fixed effects. We also separate our sample into high and low *SKEW*, *MNMD*, *GO* and *Z-Score* subsamples, following the same logic and cutoff criteria used to test Hypothesis 1. As before, we assume high *SKEW*, *MNMD*, and *GO* firms and low *Z-score* firms have right skewed distributions, and low *SKEW*, *MNMD*, and *GO* and high *Z-Score* firms have less right skewed and possibly left-skewed distributions.

3.9 Test of Hypothesis 3: Skewness and Forecast Horizon

We present the results of our tests of Hypothesis 3 in Table 5 and Figure 4.[30] Table 5 provides results for firms based on ex-post skewness metrics (*SKEW* and *MNMD*). Columns (2) and (3) report results for right-skewed firms and columns (4) and (5) for left-skewed firms. The negative and significant co-efficient on *LongHorizon* in column (1) indicates the reduction in forecast error from month to month is greatest at long horizons, consistent with Richardson et al. (2004).

[30] For parsimony, walkdown figures are provided in Figure 4 for *Z-Score* (Panel A) and *GO* (Panel B). Walkdowns are qualitatively similar for *SKEW* and *MNMD*.

When we partition firms based on ex-ante skewness (untabulated), the magnitude of the coefficient on *LongHorizon* is 26% to more than 400% greater for right-skewed firms than left-skewed firms.[31] This is depicted visually in Figure 4. In total, our results are consistent with our representation of the analyst forecasting process: the change in forecast error is greater when the information environment is weaker, and the magnitude of this effect is determined by the direction of skewness of the firms EPS distribution.

3.10 Simulation: Frequency of Optimistic and Pessimistic Forecast Errors

Finally, we compare the results of a simulation of our representation of the analyst forecast process using archival data and confirm that our representation is consistent with forecast related patterns actually observed in prior literature. Details of the simulation process can be found in Appendix 2.

We first test whether the simulation correctly predicts the overall observed frequency of optimistic and pessimistic forecasts, using the realized EPS distribution as an approximation of an average firm's objective earnings distribution g(e). We compare the frequency of optimistic and pessimistic errors generated by our simulation to the frequency of actual optimistic and pessimistic forecasts over the forecast horizon from 1997-2003, where the years map to our Reg FD sample.[32] Our results are summarized in Table 6.

Of our 5,800 simulated observations, 3,404 are optimistic and 2,396 are pessimistic, which gives us a predicted frequency of optimistic errors of 58 percent and pessimistic errors of 41 percent respectively, broadly in line with the observed frequency of optimistic and pessimistic

[31] The coefficient on LongHorizon for our left-skewed ex-ante measures is insignificant, but remains significantly smaller than the coefficient on LongHorizon for our right-skewed firms (F statistic = 9.11, $p<0.01$ for Z-Score and F statistic = 37.55 $p<0.0001$ for GO).

[32] We remove zero error forecasts so that the frequencies of optimistic and pessimistic forecasts sum to one.

forecast errors at long horizons.[33] We caution that although the results of the simulation are suggestive, they are not conclusive, in part because our results rely upon the reasonableness of our simulation parameters.

Our simulation also allows us to predict the shape of the analyst forecast error distribution. Abarbanell and Lehavy use the distribution of forecast errors as a central discussion piece in their 2003 paper, which motivates us to address whether our characterization of the analyst's forecasting process can produce a distribution of forecast errors similar to the distribution they document.

We replicate Figure 1 of Abarbanell and Lehavy (2003) using 93,734 observations drawn from the combined I/B/E/S summary and CRSP monthly files over the period 1994 to 2014, the same time period used for the EPS distribution from which we simulated forecast errors for our test of the effect of the skewness of on the optimism or pessimism of analyst forecasts. Following Abarbanell and Lehavy (2003), scaled analyst forecast errors are defined as the difference between actual EPS and the end of quarter consensus analyst forecast divided by beginning of quarter stock price and multiplied by 100. Forecast errors are winsorized at the 1st and 99th percentiles.

We first confirm that the distribution of scaled forecast errors is not sensitive to scaling by price because our simulation generates unscaled forecast errors, and the distribution of price may influence the distribution of scaled forecast errors. Figure 5 Panel A depicts the 1st through 100th percentiles of the distributions of forecast errors over the period from 1994 to 2014, both scaled and unscaled by price. Moving from left to right, forecast errors range from the most negative to

[33] Recall that pessimistic errors are more common and smaller in magnitude across the full earnings horizon. However, frequency of pessimistic forecast errors varies depending on the forecast horizon, with fewer pessimistic forecast errors at long horizons and more at shorter horizons. Our simulation best predicts optimistic and pessimistic forecast error frequency at long horizons, when the information environment is weakest and the effect of constraints is likely to play a larger role in influencing analyst forecasts.

the most positive.

Visual inspection of Figure 5 Panel A confirms that the shape, relative magnitudes, and ratio of positive to negative forecasts are comparable to Figure 1 Panel A of Abarbanell and Lehavy (2003). The distribution of unscaled forecast errors does not noticeably differ from the distribution of scaled errors in the shape of the distribution or the ratio of positive to negative forecasts. The principal difference between the scaled and unscaled forecast error distributions is the scale of the y-axis, supporting the validity of comparing actual unscaled forecast errors to simulated unscaled forecast errors.

We employ the same simulation used to test whether the skewness of a firm's earnings distribution explains the optimism or pessimism of analyst forecasts to generate our forecast error distribution.[34] Figure 5 Panel B depicts an overlay of our simulated forecast errors for a 0.50 EPS range (5 types of analysts) on the unscaled forecast errors from Figure 5 Panel A. The similarity between the simulated distribution of forecast errors and the replication of Abarbanell and Lehavy (2003) is striking; the shape of the simulated errors closely coincides over the entirety of the distribution, the tendency for optimistic errors to be larger in magnitude than pessimistic errors is reflected in our simulation, and the relative magnitude of the left and right tails are approximately the same between the replication and the simulation. We conclude that our representation of the

[34] One of the contributions of Abarbanell and Lehavy (2003) is the documentation of the existence and drivers of asymmetry in the center of the analyst forecast distribution, tying this middle asymmetry to management's propensity to manage earnings. To address the possibility that middle asymmetry, and differences in earnings management between our groups of interest, drives our results, we compare the frequency of positive and negative forecast errors around zero using the same thresholds as defined in Abarbanell and Lehavy (2003). We do not observe any middle asymmetry in our Reg FD sample, nor in a larger sample from 2000-2020. We attribute the lack of a middle asymmetry to differences in the datasets used, I/B/E/S vs Zacks, and the nature of non-recurring items removed by I/B/E/S. However, this may also reflect changes in analysts' ability to easily disentangle managements' incentives. As a result, we do not believe our findings are attributable to the middle asymmetry in the forecast distribution (and hence earnings management) documented in Abarbanell and Lehavy (2003).

analysts' forecasting process generates a forecast error distribution whose shape aligns with prior literature.

4. DISCUSSION AND CONCLUSION

We demonstrate how changes in analysts' constraints, including their information environment or their busyness, in conjunction with earnings skewness, can result in predictable changes in forecast optimism or pessimism. This bias in forecasts arises independent of any conflicts of interest or incentives analysts may have. Our characterization of the analyst forecasting process offers a compelling explanation for prior results in the literature and expands our understanding of the circumstances in which analysts issue biased forecasts. Our analyses suggest that attempts to reduce analyst forecast bias that negatively affect firms' information environments are unlikely to mitigate forecast optimism or pessimism. We provide a simple explanation for analyst forecast bias that demonstrates that, while some degree of bias may be inevitable, forecast bias may be reduced by improving the analyst's information environment or by increasing the time available to an analyst to issue a forecast.

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Appendix 1: Variable Definitions

Variable	Description
Altman Z-Score (Z-Score)	We follow Altman (1968) in calculating the Altman Z-score: $1.2\,\frac{working\ capital}{total\ assets} + 1.4\,\frac{retained\ earnings}{total\ assets} + 3.3\,\frac{EBIT}{total\ assets} + 0.6\,\frac{market\ value\ of\ eq}{total\ liabilities} + \frac{sales}{total\ assets}$ All variables are derived from the CRSP and Compustat fundamental annual file files.
Busy Analyst	An indicator variable equal to one if the analyst issuing the forecast follows more than the median number of firms within a given year.
CostDebt	The cost of debt, defined as the interest payments in a period over the outstanding book value of debt. $Cost\ of\ Debt = \frac{INTPN}{DLTT}$
CostEquity	The cost of equity as a function of dividends, repurchases, and net income, divided by market value of equity. $Cost\ of\ Equity = \frac{(DV + PRSTKCC + NI)}{(prcc\_f * csho)}$
EPS	Actual EPS for a period (ACTUAL) from the IBES Summary file. This value differs from unadjusted EPS.
Forecast Horizon	The number of months remaining (negative) until an annual earnings announcement date, specific to the firm, taken as the difference between the STATPERS (IBES summary file) and Earnings announcement date.
GO	Growth options, measured following Del Viva et al. (2013): $GO_t = \frac{MV_t - \frac{FCF_{t-fy}(ng)}{WACC_{t-fy}}}{MV_t}$ Where MV is the firm market value, FCF is free cash flow, and WACC is the weighted average cost of capital.
Institutional Percentage	The percent institutional ownership, as measured by the Thomson Reuters Institutional Holdings file.

LEV	Leverage; the proportion of assets attributable to long term debt. $$Lev = \frac{dltt+lct}{at}$$
LongHorizon	Indicator variable equal to one if the forecast horizon is 9, 10, or 11 months until the next earnings announcement date and equal to 0 if the forecast horizon is 0, 1 or 2 months.
Market to Book (MTB)	Following standard measurement of market to book: $$MTB = prcc\_f \; x \frac{csho}{ceq}$$ Where prcc_f is the share price at the close of the fiscal year, chso is common shares outstanding, and ceq is common equity. Data was collected from the Compustat fundamental annual file.
MNMD	The difference between a firm's EPS distribution's mean and median, scaled by share price. $$MNMD_{jt} = \frac{Mean(EPS_{jt}) - Median(EPS_{jt})}{Price_{jt-1}} \; X \; 100$$ Where the subscript *j* indicates a firm and *t* indicates the first quarter within an 8-quarter rolling window. A positive (negative) value for MNMD indicates a right (left) skewed distribution.
MSFE	The scaled median forecast error is calculated by taking the difference between a firms actual annual EPS and the median analyst forecast (MEDEST and ACTUAL, both from the IBES Summary file), divided by beginning of period share price (Compustat). $$MSFE = \frac{actual - medest}{prcc\_f}$$ MEDEST to determine forecast error is taken at each STATPERS in the IBES summary file. A negative (positive) MSFE is interpreted as an optimistic (pessimistic) forecast error.
$\Delta MSFE$	The absolute value of the difference in scaled median forecast error from $month_i$ to $month_{i+1}$. $$\Delta MSFE = \lvert MSFEmonth_i - MSFEmonth_{i+1} \rvert$$

NND	'New Non-Disclosers': A dummy variable equal to 1 for firms that provided public guidance 1 or fewer times (FirstCall) in the period from 2001-2003. These firms switched from private disclosure prior to Regulation Fair Disclosure to non-disclosure following Regulation Fair Disclosure. If NND = 0, the firm is classified as a New Public Discloser (NPD). NPD indicates a firm switched from private disclosure prior to Regulation Fair Disclosure to providing public disclosure following Regulation Fair Disclosure.
NND x postfd	Interaction term for firms who do not issue guidance in the post FD period and the forecast observation occurs in the post Reg FD period. This is the variable of interest in our DID tests.
# Analysts	Calculated by counting the number of unique analyst identification numbers issuing forecasts for a firm (IBES Detail file) in a given firm-year.
# Segments	Calculated by counting the number of unique firm segments found in a specific firm year, according to the Compustat Historical segments file.
% Optimistic	% Optimistic is the percent of optimistic forecasts in a given month prior to the earnings announcement date, defined as the total number of optimistic forecast errors in a given month divided by the total number of individual analyst forecasts in that same month for the period 1997-2003.
% Pessimistic	% Pessimistic is the percent of pessimistic forecasts in a given month prior to the earnings announcement date, defined as the total number of pessimistic forecast errors in a given month divided by the total number of individual analyst forecasts in that same month for the period 1997-2003.
postfd	An indicator variable equal to one for observations in the Post-FD period (2001-2003) and zero otherwise (1997-1999).
Right Skewed	An indicator variable equal to one if the value of *SKEW* (*MNMD*) is greater than the median *SKEW* (*MNMD*) for all firm-years.

SKEW The skewness coefficient of a firms EPS distribution.

$$SKEW = \frac{n}{(n-1)(n-2)} \sum_{t} \left(\frac{EPS - \overline{EPS}}{S} \right)^{3}$$

Where *n* is the number of EPS observations within the relevant rolling window. Measured on a rolling two-year basis, consistent with Gu and Wu (2003). A positive (negative) value for *SKEW* indicates a right (left) skewed distribution.

WACC The weighted average cost of capital defined in Del Viva et al. (2013) as

$$WACC = CostEquity\ (1\text{-}LEV) + CostDebt(Lev)$$

Appendix 2: Additional Selection and Testing Procedures Detail

Reg FD Difference in Differences test:

Our difference in differences test uses data from the Compustat Historical Segments file, Fundamental Annual file, Thomson Reuters Institutional Holdings, First Call Company Issued Guidance, and the I/B/E/S summary and detail files for the years 1997-2003. Analyst estimates (and hence analyst forecast errors) are drawn for annual EPS (FPI = 1). Company issued guidance includes all forms of guidance captured by First Call. To combine data from all sources, we merge on CUSIP and Date (where date varied depending on the data sets merged).

All continuous variables are winsorized at the 1st and 99th percentiles prior to regression estimation. We restrict our sample to only those firms represented in all years pre- and post-FD who were not missing any other regression variables and who are 'silent' in the pre-FD period (i.e. had 1 or fewer disclosures in the First Call dataset from 1997-1999). Of 242,314 observations in the joined set of IBES Summary, Compustat, and Thomson Reuter Institutional Ownership, 16,783 had no missing variables during the period from 1997-2003, a MTB greater than 0, a price greater than \$5, was silent prior to Reg FD, and was not determined to be an outlier or duplicate. Thus, the final sample for our full-sample Reg FD test includes 16,783 observations.

Our full Reg FD sample is further reduced when running regressions for our left and right skewed distribution tests, which require non-missing values for *SKEW*, *MNMD*, *Z-Score*, or *GO* variables. To calculate *SKEW* and *MNMD*, we require a firm to have earnings per share data available for the preceding 8 quarters. This results in 12,235 observations for both *SKEW* and *MNMD*. High (low) *SKEW* and *MNMD* are defined as observations above (below) the median *SKEW* or *MNMD*. Our results are not sensitive to defining high (low) *SKEW* and *MNMD* as greater than (less than) 0. To calculate *GO*, we required that an observation have non-missing data for dividends, repurchases, and interest payments which resulted in truncation of our initial Reg FD dataset to 10,081 observations. High (low) *GO* are defined as the highest (lowest) deciles of *GO*. 15,006 observations had the data necessary to calculate the Altman Z-Score.

The Altman Z-Score defines a firm as far from bankruptcy when its score is larger than three, and at greater risk of bankruptcy when its score is less than 1.8. Defining high and low *Z-Score* based on these criteria results in vastly unequal sample sizes. As such, to maintain the spirit of the *Z-Score* bankruptcy criteria while improving comparability of sample sizes, high and low *Z-Score* are defined as the top and bottom quintile of *Z-Scores*. In untabulated tests, we confirm that our results are qualitatively unchanged using the traditional definition of high and low *Z-Score* (3 and 1.8).

Year fixed effects are implemented by adding indicator variables for each year in our sample – 1997, 1998, 1999, 2000, 2001, 2002, and 2003. Untabulated means show that, on average, firms that offer public guidance in the Pre-FD period have slightly larger market-to-book ratios, institutional ownership percentages, number of segments, and a greater number of analysts following the firm than those silent in the Pre-FD period. Within those firms that do not offer public guidance in the pre-FD period, post-FD variable differences are as found in Table 2.

Simulation of Analyst Forecast Errors:

Our characterization of the forecast process relies on the unobservable firm-specific earnings distribution, labeled $g(e)$ (see Appendix 3). As a proxy for $g(e)$ across firms, we use the frequency distribution of actual EPS for all IBES firms.

To find the frequency distribution of actual EPS, we collect EPS observations drawn from I/B/E/S for the years 1994 to 2014 and calculate the number of EPS observations in each pennywidth bin between –\$2.97 and\$9.13.[35] We use the frequency distribution to calculate and estimate the mean of the distribution between any two endpoints (e_l , e_h), defined as the range. In our simulation we attempt to use reasonable ranges; too small of a range suggests an analyst who ignores significant parts of the forecast distribution, while a large range limits the number of error predictions we are able to make. We run simulations over three ranges of \$0.50, \$1.00 and \$1.50.[36]

We next vary the analyst's information environment, α. The difference between the mean of the frequency distribution over a range and the mean of the uniform ($I(e)$) over the same range is the greatest forecast error an analyst can make that is attributable to our theory and simulation specifications. Mathematically, an analyst forecasting with a weight on $I(e)$of α = 0.5 has a forecast error half as large as an analyst forecasting from the $I(e)$ alone, where $\alpha = 1$. An α = 0.0 equates to an analyst who possesses and incorporates perfect firm-specific information.

After defining the range and α for a simulation, we determine the starting point for calculating simulated forecast errors by adding half of the simulation range to the lowest EPS for which we calculated frequency (-2.97). We calculate the mean of the interval between -2.97 and -2.97 plus the range, and define this number as the unbiased forecast. The midpoint of the interval between -2.97 and -2.97 plus the range is defined as the forecast where $\alpha = 0$. The difference between the two forecasts is our first predicted forecast error. We repeat this process, moving the range to the right in one cent increments, until our last observation over the EPS of 9.13 minus the range to 9.13.

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[35]This is a truncated winsorization of the whole EPS distribution, at the 1st and 99th percentiles. EPS below or above this range were too scarce within each penny group to provide meaningful predicted forecast errors.
[36]We also attempted to simulate forecast errors using variable ranges that were a percentage of the mean EPS. These ranges proved to be problematic at small EPS because the ranges must be in cent increments, and did not truncate properly at large EPS.

To maintain the largest number of observations possible, given that granularity in the error distribution occurs for smaller samples, and to use assumptions that were as realistic as possible, our empirical comparisons use the results from our simulation with a range of 50 cents. We include predicted forecast errors for 5 levels of α, to reflect a range of applied weights across analysts. This creates 5800 predicted forecast errors ranging from a low of -24 cents to a high of 11 cents.

Percentage of Optimistic/Pessimistic Observations:

Calculating the percentage of actual optimistic and pessimistic errors uses data from the I/B/E/S summary and detail files for the years 1997-2003, for forecasts of annual EPS. We calculate the months remaining until the earnings announcement date by taking the difference between the statistical period (STATPERS) of the analyst forecast and the announcement date of actual EPS (ANNDATS_ACT). After calculating the number of months prior to the earnings announcement date, we find the scaled median forecast error and use an indicator variable to capture whether the error is negative (optimistic) or positive (pessimistic). The frequency of actual optimistic and pessimistic forecasts are calculated for each month-horizon and converted into the percentages in Table 6.

Abarbanell and Lehavy Replication:

Our replication of Abarbanell and Lehavy (2003) uses the I/B/E/S summary and detail files from the years 1994-2014. The mean scaled forecast error is defined as the actual EPS (from IBES) less the mean analyst forecast (IBES Summary), divided by beginning of period price (PRCC_F) and multiplied by 100. Unscaled errors omit division by beginning of period price and multiplication by 100 (see Appendix 1). We require a non-zero share price and EPS observations between -2.18 and 9.13 to correspond to our simulation EPS range. The scaled, unscaled, and price variables are all winsorized at the 1^{st} and 99^{th} percentiles.

Appendix 3: Representation of the Forecasting Process Under Constraints

We make two assumptions in our representation of the constrained analyst forecasting process – first, that the analyst considers only a finite number of possible earnings per share outcomes when forecasting for a firm, and secondly that an analyst's expectation in the extreme limit of no information on the relative likelihood of the EPS outcomes considered by an analyst is best represented by the uniform distribution (a.k.a the ignorance prior).[37]

Our first assumption, stemming from the limited time an analyst has to issue a forecast, is that an analyst considers only a subset of all possible earnings per share outcomes. The finiteness of EPS outcomes explicitly considered by an analyst holds true regardless of whether the firm has a discrete (i.e. finite) EPS distribution or a continuous (i.e. infinite) EPS distribution. Thus, the analyst's limited time is a constraint that exists and affects forecasting irrespective of the nature of the firm's earnings distribution.

Given the above assumption, we next represent the forecasting process in the analyst setting by letting $e \in [\underline{e}, \overline{e}]$ designate the realized earnings per share (EPS), $g(e)$ the *objective* distribution of e, $I(e)$ the uniform distribution (ignorance prior) and $P(e, \alpha)$ the analysts' *subjective* distribution (from which they forecast) of e, where:

$$P(e, \alpha) = (1 - \alpha)g(e) + \alpha I(e)$$

and α indicates a weight with $0 \leq \alpha \leq 1$, where α indicates the degree of reliance on the uniform distribution.

We propose that an analysts' reliance on the uniform distribution ($I(e)$) changes with

[37] Partial or complete reliance on a uniform distribution in the absence of information (or the presence of uncertainty) has been experimentally documented (e.g. Fox and Rottenstreich 2003; Fox and Levav 2004; Urminsky 2015).

information releases by the firm. *By definition*, greater information available to an analyst will reduce her reliance on the non-informative prior. We also interpret a decreasing α as representative of an analyst who becomes more knowledgeable or has incorporated more information into her model at the time of the forecast. Explicitly, we contend that there is *by definition* an inverse relation between an analysts' reliance on a non-informative prior and the degree to which she is informed, as reliance on the non-informative prior reflects *external constraints* and not cognitive failures.

Figure 1B depicts an $P(e, \alpha)$ for a right-skewed *pdf*, illustrating the effect of reliance on the uniform distribution (increased variance). The subjective forecast distribution $P(e, \alpha)$ is flatter in appearance than $g(e)$. By definition, $P(e, 0) = g(e)$, where $g(e)$ is represented in Figure 1B by the blue line. The subjective mean of EPS increases with α for a right skewed distribution and decreases with α for a left skewed distribution.

TABLE 1 Sample Selection

Panel A: Reg FD Sample	
Criteria	
	Forecasts
Full sample: Intersection of IBES Summary, Compustat, Institutional Ownership Data	242,314
Less: No Match for Number of Analysts, Segments	(53,958)
Less: Missing Guidance Data	(40,969)
Less: MTB < 0 and Price < $5	(24,683)
Less: Extreme Outliers, Duplicates, Data Errors	(432)
Less: Not Silent pre-Reg-FD	(100,308)
Less: Fiscal year within 1997-2003	(2,435)
Less: Missing Control Variables	(2,746)
Reg FD Sample Size:	**16,783**
Obervations with GO	10,081
Observations with Z-Score	15,006
Observations with Skew	12,235
Observations with MNMD	12,235

Panel B: Busyness Sample	
Criteria	
Full sample: Intersection of IBES Summary, Detail, Compustat (2000-2020)	7,545,754
Less: FPI < > 1	(3,381,266)
Less: Missing Data to calculate busyness or MSFE, MSFE > 1, PRCC_F < 5	(3,522,807)
Less: Missing Data to calculate MNMD or SKEW	(146,497)
Less: Missing control variables	(24,876)
Full Busyness Sample Size:	**470,308**

Panel C: Walkdown Sample	
Criteria	
Full sample: IBES Summary & Detail	469,389
Less: Missing Compustat Data	(171,793)
Less: Missing Data to Calculate Go, Altman, MNMD or SKEW	(249,058)
Less: Number of analysts < 2	(4,419)
Less: Duplicates, outliers	(253)

Less: Missing control variables	(29,601)
Full Walkdown Sample Size:	**14,265**

This table reports the sample selection process for our Regulation Fair Disclosure (Reg FD) and Walkdown tests. For our Reg FD tests, we begin with the intersection of Compustat, IBES Summary file, and Thomson Reuter Institutional Holdings file. We require firms to have at least one guidance observation in First Call Company Issued Guidance, a positive Market to Book ratio (MTB >0), and a share price greater than $5 as of the beginning of the period. We further exclude firms who issue public guidance more than once prior to Reg FD (1997-1999). This results in 16,783 forecasts in our full Reg FD sample, within which we calculate our skewness measures of GO, Z-Score, SKEW, and MNMD. Our Walkdown sample begins with the intersection of IBES Summary and Detail files and Compustat. We omit firms that do not have the data necessary to calculate all skewness measures, and require that firms have a following of at least two analysts. This results in a final walkdown sample size of 14,265 observations.

TABLE 2 Sample Statistics Regulation Fair Disclosure

Panel A: Reg FD Sample – Pre-Regulation Fair Disclosure (1997-1999)

	N	Mean	S.D.	p25	p50	p75	Diff.
GO	4026	2446.15	7482.03	96.06	426.16	1576.36	
NPD	1935	1864.72	6609.22	61.78	347.36	1258.29	1119.47
NND	2091	2984.19	8172.26	130.34	630.62	2255.58	(4.79)
Z-Score	9259	6.89	9.20	2.34	3.79	6.97	
NPD	4804	6.03	7.86	2.40	3.64	5.91	1.78
NND	4455	7.81	10.38	2.17	3.99	8.49	(9.25)
SKEW	7995	-0.20	0.92	-0.76	-0.14	0.41	
NPD	4284	-0.25	0.93	-0.88	-0.17	0.41	0.10
NND	3711	-0.14	0.90	-0.68	-0.11	0.46	(5.37)
MNMD	7995	-0.08	0.53	-0.14	-0.01	0.06	
NPD	4284	-0.07	0.51	-0.18	-0.02	0.09	-0.02
NND	3711	-0.09	0.56	-0.10	-0.01	0.05	(-1.66)
MSFE	9259	-0.02	0.05	-0.02	0.00	0.00	
NPD	4804	-0.02	0.05	-0.02	0.00	0.00	0.01
NND	4455	-0.01	0.04	-0.01	0.00	0.00	(10.66)
MTB	9233	3.57	4.29	1.34	2.09	3.70	
NPD	4804	3.20	3.79	1.31	1.98	3.30	0.76
NND	4429	3.97	4.74	1.38	2.26	4.13	(8.58)
# Analysts	9259	5.97	4.70	3.00	4.00	7.00	
NPD	4804	6.11	4.74	3.00	5.00	8.00	-0.28
NND	4455	5.83	4.66	3.00	4.00	7.00	(-2.87)
Institutional Percentage	9242	0.43	0.23	0.25	0.43	0.60	
NPD	4799	0.45	0.22	0.27	0.45	0.61	-0.03
NND	4443	0.42	0.23	0.23	0.42	0.60	(-6.40)
# Segments	9259	5.06	3.21	3.00	4.00	7.00	
NPD	4804	5.28	3.34	3.00	4.00	7.00	-0.45
NND	4455	4.83	3.04	3.00	4.00	6.00	(-6.79)
EPS	9259	0.60	1.07	0.17	0.55	1.04	
NPD	4804	0.66	0.94	0.23	0.68	1.13	-0.12
NND	4455	0.53	1.20	0.13	0.41	0.85	(-5.77)

TABLE 2 Cont'd

Panel B: Reg FD Sample – Post-Regulation Fair Disclosure (2001-2003)

	N	Mean	S.D.	p25	p50	p75	Diff.
GO	1678	3786.92	9296.82	478.30	1612.08	3207.61	
NPD	531	1126.90	3104.87	547.98	1165.86	2445.66	3891.47
NND	1147	5018.37	10827.00	439.05	1910.63	5041.22	(11.22)
Z-Score	6082	6.20	7.97	2.04	3.47	6.66	
NPD	2362	4.98	6.28	2.07	3.36	5.13	1.99
NND	3720	6.97	8.79	2.02	3.73	8.06	(10.28)
SKEW	3420	0.07	0.88	-0.38	0.07	0.57	
NPD	1316	-0.07	0.84	-0.46	0.01	0.43	0.24
NND	2104	0.17	0.89	-0.30	0.14	0.65	(7.94)
MNMD	3420	0.04	0.36	-0.04	0.01	0.09	
NPD	1316	0.04	0.35	-0.05	0.01	0.09	0.00
NND	2104	0.03	0.36	-0.03	0.01	0.09	(0.80)
MSFE	6082	-0.01	0.04	-0.01	0.00	0.00	
NPD	2362	-0.01	0.06	-0.01	0.00	0.00	0.01
NND	3720	-0.01	0.03	-0.01	0.00	0.00	(5.76)
MTB	6054	3.43	3.63	1.48	2.17	4.10	
NPD	2362	3.26	4.05	1.36	2.00	3.07	0.27
NND	3692	3.53	3.33	1.57	2.35	4.30	(2.71)
# Analysts	6082	6.60	5.46	3.00	5.00	9.00	
NPD	2362	6.72	5.48	2.00	4.00	10.00	-0.19
NND	3720	6.53	5.45	3.00	5.00	8.00	(-1.32)
Institutional Percentage	6082	0.56	0.24	0.39	0.60	0.75	
NPD	2362	0.59	0.21	0.43	0.62	0.77	-0.04
NND	3720	0.54	0.25	0.37	0.58	0.73	(-8.40)
# Segments	6082	5.92	3.45	3.00	6.00	8.00	
NPD	2362	6.16	3.48	3.00	6.00	8.00	-0.38
NND	3720	5.78	3.41	3.00	5.00	8.00	(-4.18)
EPS	6082	0.57	1.02	0.15	0.58	1.11	
NPD	2362	0.51	1.09	0.09	0.49	1.07	0.10
NND	3720	0.61	0.97	0.17	0.62	1.14	(3.64)

This table provides sample descriptive statistics by period, prior to (A: 1997-1999) and post (B:2001-2003) Regulation Fair Disclosure. Variables are as defined in Appendix 1.

TABLE 3 Forecast Bias Changes Around Regulation Fair Disclosure

Panel A: SKEW and MNMD (Ex-Post Measures of Skewness)

Difference in differences test of analysts' median scaled forecast error around Reg FD, based on firm guidance behavior for firms with right skewed distributions (High MNMD, High SKEW) and left skewed distributions (Low MNMD, Low SKEW).

	(1)	(2)	(3)	(4)
	Right Skewed		Left Skewed	
Dep Variable = MSFE	High MNMD	High SKEW	Low MNMD	Low SKEW
Intercept	-0.0185 ***	-0.0166 ***	-0.0205 ***	-0.0212 ***
	(-11.03)	(-13.16)	(-12.29)	(-11.48)
NND	0.0097 ***	0.0050 **	0.0025 *	0.0055 ***
	(6.99)	(4.18)	(1.80)	(3.75)
postfd	-0.0077 ***	-0.0069 ***	-0.0114 ***	-0.0130 ***
	(-4.53)	(-2.75)	(-3.32)	(-3.72)
NND x postfd	-0.0044 **	0.0000	0.0115 ***	0.0083 ***
	(-2.14)	(-0.01)	(3.75)	(3.00)
Market to Book	0.0014 ***	0.0013 ***	0.0006 ***	0.0007 ***
	(16.65)	(15.83)	(3.09)	(3.13)
# Analysts	0.0002 ***	0.0003 ***	0.0004 ***	0.0003 ***
	(3.37)	(3.33)	(4.21)	(3.60)
Institutional Percentage	0.0136 ***	0.0118 ***	0.0316 ***	0.0321 ***
	(4.86)	(5.54)	(10.04)	(9.49)
# Segments	-0.0010 ***	-0.0008 ***	-0.0011 ***	-0.0012 ***
	(-5.77)	(-4.03)	(-4.59)	(-5.17)
Fixed Year Effects	Y	Y	Y	Y
R2	0.073	0.053	0.057	0.064
Number of Observations	5821	5819	6414	6416

Scaled forecast errors are defined as the difference between the actual annual EPS (ACTUAL) and the median consensus analyst forecast (MEDEST), divided by beginning of period price (prcc_f). Negative forecast errors are interpreted as optimistic. Scaled forecast errors are winsorized at the 1st and 99th percentiles. Data is derived from the I/B/E/S summary file, First Call Company Issued Guidance, Compustat Historical Segment and Fundamental Annual files, and Thomson Reuter Institutional Holdings. Column (1) provides results for the High *MNMD* sample, (2) for the High *SKEW* sample, (3) for the Low *MNMD* sample, and (4) for the Low *SKEW* sample. High (Low) for *MNMD* and *SKEW* represent observations whose *MNMD* or *SKEW* value are above (below) the median for the respective measure. *, **, *** indicate 0.10, 0.05, and 0.01 significance, respectively. Variable definitions are found in Appendix 1.

TABLE 3 Cont'd

Panel B: GO and Altman Z-Score (Ex-Ante Measures of Skewness)

Difference in differences test of analysts' median scaled forecast error around Reg FD, based on firm guidance behavior for firms with right skewed distributions (High GO, Low Z-Score) and left skewed distributions (Low GO, High Z-Score).

	(1)		(2)		(3)		(4)	
	Right Skewed				Left Skewed			
Dep Variable = MSFE	High GO		Low Z-Score		Low GO		High Z-Score	
Intercept	-0.0587	***	-0.0354	***	-0.0122	**	-0.0048	***
	(-7.88)		(-9.30)		(-2.18)		(-6.99)	
NND	0.0211	***	0.0166	***	-0.0015		-0.0033	***
	(4.67)		(4.88)		(-0.59)		(-4.67)	
postfd	0.0205	***	0.0147	***	-0.0138	***	-0.0028	**
	(4.07)		(3.87)		(-4.18)		(-2.50)	
NND x postfd	-0.0209	***	-0.0082	*	0.0091	**	0.0004	***
	(-4.09)		(-1.86)		(2.50)		(3.45)	
Market to Book	0.0009	***	-0.0001		0.0003		0.0004	***
	(5.97)		(-0.27)		(1.36)		(7.45)	
# Analysts	0.0014	***	0.0016	***	0.0002	*	0.0001	*
	(7.54)		(9.47)		(1.74)		(2.97)	
Institutional Percentage	0.0291	***	0.0136	***	0.0174	***	0.0041	***
	(3.92)		(2.58)		(2.62)		(3.34)	
# Segments	-0.0002		-0.0016	***	0.0002		0.0003	*
	(-0.50)		(-5.28)		(0.80)		(2.87)	
Fixed Year Effects	Y		Y		Y		Y	
R2	0.242		0.087		0.072		0.049	
Number of Observations	1017		3103		962		2998	

Scaled forecast errors are defined as the difference between the actual annual EPS (ACTUAL) and the median consensus analyst forecast (MEDEST), divided by beginning of period price (prcc_f). Negative forecast errors are interpreted as optimistic. Scaled forecast errors are winsorized at the 1st and 99th percentiles. Data is derived from the I/B/E/S summary file, First Call Company Issued Guidance, Compustat Historical Segment and Fundamental Annual files, and Thomson Reuter Institutional Holdings. Column (1) provides results for the High GO sample, (2) for the Low Z-Score, (3) for the Low GO sample, and (4) for the High Z-Score sample. High (Low) for GO represent observations whose GO value are above (below) the 90th percentile (10th percentile). High (Low) for Z-Score represent observations whose Z-Score is above (below) the 80th percentile (20th percentile). *, **, *** indicate 0.10, 0.05, and 0.01 significance, respectively. Variable definitions are found in Appendix 1.

TABLE 4 Analyst Busyness and Forecast Bias 2000-2018

Panel A: Analyst Busyness Sample Statistics

Analyst Busyness Sample – High and Low Analyst Busyness							
	N	Mean	S.D.	p25	p50	p75	Diff.
Skew	494338	0.11	0.89	-0.45	0.18	0.73	
High Busy	446686	0.11	0.89	-0.45	0.18	0.73	-0.01
Low Busy	47652	0.10	0.89	-0.47	0.16	0.73	(-3.09)
MNMD	495184	-0.02	0.53	-0.05	0.00	0.06	
High Busy	447185	-0.02	0.52	-0.05	0.00	0.06	-0.01
Low Busy	47999	-0.02	0.61	-0.06	0.00	0.06	(-3.06)
Experience	495184	7.14	5.47	2.52	5.90	10.91	
High Busy	447185	7.56	5.46	2.95	6.41	11.42	-4.34
Low Busy	47999	3.21	3.71	0.45	1.76	4.85	(-170.38)
MSFE	495184	0.00	0.02	0.00	0.00	0.00	
High Busy	447185	0.00	0.02	0.00	0.00	0.00	0.00
Low Busy	47999	0.00	0.02	0.00	0.00	0.00	(12.08)
MTB	479667	4.10	5.23	1.57	2.53	4.36	
High Busy	432902	4.13	5.29	1.57	2.53	4.38	-0.32
Low Busy	46765	3.81	4.68	1.55	2.50	4.18	(-5.76)
# Analysts	495184	17.27	10.31	9.00	16.00	24.00	
High Busy	447185	17.35	10.29	9.00	16.00	24.00	-0.82
Low Busy	47999	16.53	10.39	8.00	14.00	23.00	(-12.56)
Institutional Ownership	492901	0.72	0.25	0.58	0.77	0.90	
High Busy	445266	0.73	0.24	0.59	0.78	0.90	-0.12
Low Busy	47635	0.61	0.30	0.41	0.67	0.85	(-101.01)
# Segments	487901	16.21	10.08	9.00	15.00	21.00	
High Busy	445266	16.05	9.99	9.00	15.00	21.00	1.72
Low Busy	47487	17.76	10.77	9.00	15.00	24.00	(35.18)
Months Prior to EA	495184	-5.54	3.73	-9.00	-4.00	-3.00	
High Busy	447185	-5.50	3.70	-9.00	-4.00	-3.00	-0.43
Low Busy	47999	-5.92	3.94	-9.00	-5.00	-3.00	(-23.79)
# Firms Followed	495184	17.36	8.66	12.00	17.00	22.00	
High Busy	447185	18.80	7.82	13.00	18.00	23.00	-0.43
Low Busy	47999	3.94	2.14	2.00	4.00	6.00	(-414.66)

This table provides sample descriptive statistics for the analyst busyness test for the years 2000-2018. Variables are as defined in Appendix 1.

TABLE 4 Cont'd Analyst Busyness and Forecast Bias 2000-2018

Panel B: SKEW and MNMD (Ex-Post Measures of Skewness)

Relation between analysts' busyness and the bias of analysts' first forecast for a firm-year.

	(1)	(2)
Dep Variable = MSFE	MNMD	SKEW
Intercept	-0.0043 ***	-0.0048 ***
	(-15.63)	(-17.29)
Right Skewed	0.0022 ***	0.0036 ***
	(10.29)	(16.67)
Busy Analyst	0.0009 ***	0.0009 ***
	(4.74)	(4.59)
Right Skewed x Busy	-0.0005 **	-0.0006 **
	(-2.28)	(-2.51)
Market to Book	0.0001 ***	0.0001 ***
	(19.30)	(17.10)
Number of Analysts	0.0001 ***	0.0001 ***
	(27.28)	(24.93)
Institutional Percentage	0.0014 ***	0.0014 ***
	(9.43)	(9.21)
Number of Segments	0.0000 ***	0.0000 ***
	(3.51)	(3.34)
Fixed Year Effects	Y	Y
R2	0.020	0.025
Number of Observations	470308	470308

Scaled forecast errors are defined as the difference between the actual annual EPS (ACTUAL) and the first EPS forecast issued by an analyst for that firm-year, scaled by beginning of period price (prcc_f). Negative forecast errors are interpreted as optimistic. All continuous variables are winsorized at the 1st and 99th percentiles. Data is derived from the I/B/E/S detail file, Compustat Historical Segment and Fundamental Annual files, and Thomson Reuter Institutional Holdings. Column (1) provides results for the High (right skewed) *MNMD* sample, and (2) for the High (right skewed) *SKEW* sample. Low *MNMD* and Low *SKEW* are mathematically identical to columns (1) and (2), except *Right Skewed* and its interaction term have opposite signs. High *MNMD* (*SKEW*) represent observations whose *MNMD* (*SKEW*) value are above the median *MNMD* (*SKEW*) value across the full sample. Errors are dual clustered at the analyst-firm level. *, **, *** indicate 0.10, 0.05, and 0.01 significance, respectively. Variable definitions are in Appendix 1.

TABLE 5 Walkdown Magnitude of Analyst Forecasts by Horizon

Panel A: SKEW and MNMD (Ex-Post Measures of Skewness)

Walkdown of analysts' median scaled forecast error for firms with right skewed distributions (High MNMD, High SKEW) and left skewed distributions (Low MNMD, Low SKEW).

	(1)	(2)	(3)	(4)	(5)
	Full Sample	Right Skewed		Left Skewed	
Dep Variable = Change in MSFE		High MNMD	High SKEW	Low MNMD	Low SKEW
Intercept	0.0000	-0.0050 *	-0.0027	0.0053 **	0.0025
	(-0.01)	(-1.88)	(-0.93)	(1.98)	(1.13)
LongHorizon	-0.0147 ***	-0.0164 ***	-0.0189 ***	-0.0130 ***	-0.0107 ***
	(-14.58)	(-10.90)	(-11.26)	(-9.75)	(-9.29)
Market to Book	0.0001	0.0004	0.0001	0.0000	0.0000
	(1.43)	(1.23)	(1.03)	(1.31)	(1.24)
# Analysts	0.0001 ***	0.0001 *	0.0001 ***	0.0001 ***	0.0001
	(3.54)	(2.02)	(2.96)	(2.59)	(1.43)
Institutional Percentage	0.0077 ***	0.0129 ***	0.0113 ***	0.0019	0.0038
	(4.02)	(4.85)	(3.73)	(0.70)	(1.58)
# Segments	-0.0001	-0.0001	-0.0003	-0.0002	0.0000
	(-1.29)	(-0.71)	(-1.36)	(-1.14)	(0.11)
Fixed Year Effects	Y	Y	Y	Y	Y
R2	0.029	0.039	0.035	0.024	0.024
Number of Observations	14451	7217	7174	7234	7277

Change in scaled forecast error is defined as the absolute value of the difference between the MSFE of $month_i$ and $month_{i+1}$. Negative values are interpreted as a decline in the magnitude of the forecast error from $month_i$ to $month_{i+1}$. LongHorizon is one for monthly forecast error changes over the 11^{th}, 10^{th}, and 9^{th} months prior to an earnings announcement and zero for forecast error changes over the 2^{nd} ,1^{st}, and 0^{th} months prior to an earnings announcement. Changes in scaled forecast errors are winsorized at the 1^{st} and 99^{th} percentiles. Data is derived from the I/B/E/S summary and detail files, Compustat Historical Segment and Fundamental Annual files, and Thomson Reuter Institutional Holdings. Column (1) provides the results for the full sample of observations for which *SKEW, MNMD, GO*, and *Z-Score* could be calculated, (2) for the High *MNMD* sample, (3) for the High *SKEW* sample, (4) for the Low *MNMD* sample, and (5) for the Low *SKEW* sample. High (Low) for *MNMD* and *SKEW* represent observations whose *MNMD* or *SKEW* value is above (below) the median for the respective measure. *, **, *** indicate 0.10, 0.05, and 0.01 significance, respectively. Variable definitions are found in Appendix 1.

TABLE 6 Predicted Frequency of Optimistic and Pessimistic Forecasts

Frequency of actual and simulated optimistic and pessimistic forecast errors by months prior to the earnings announcement.

Forecast Horizon	% Optimistic	% Pessimistic	N
0	43.67	56.33	73762
-1	45.73	54.27	81041
-2	47.04	52.96	76566
-3	49.62	50.38	83952
-4	51.77	48.23	84803
-5	53.20	46.80	80502
-6	54.46	45.54	88781
-7	55.38	44.62	83894
-8	56.17	43.83	82055
-9	56.93	43.07	90094
-10	57.45	42.55	81214
-11	57.89	42.11	79641
Simulated %	58.69	41.31	

Data is derived from the I/B/E/S summary and detail files for the period 1997-2003. The simulated percentage of positive and negative observations are derived from our simulation with a boundary of 50 cents, with 5 types of analysts. This frequency is robust to other tested simulation specifications to within +/- 3%. Simulation parameters can be found in Appendix 2. Variable definitions can be found in Appendix 1.

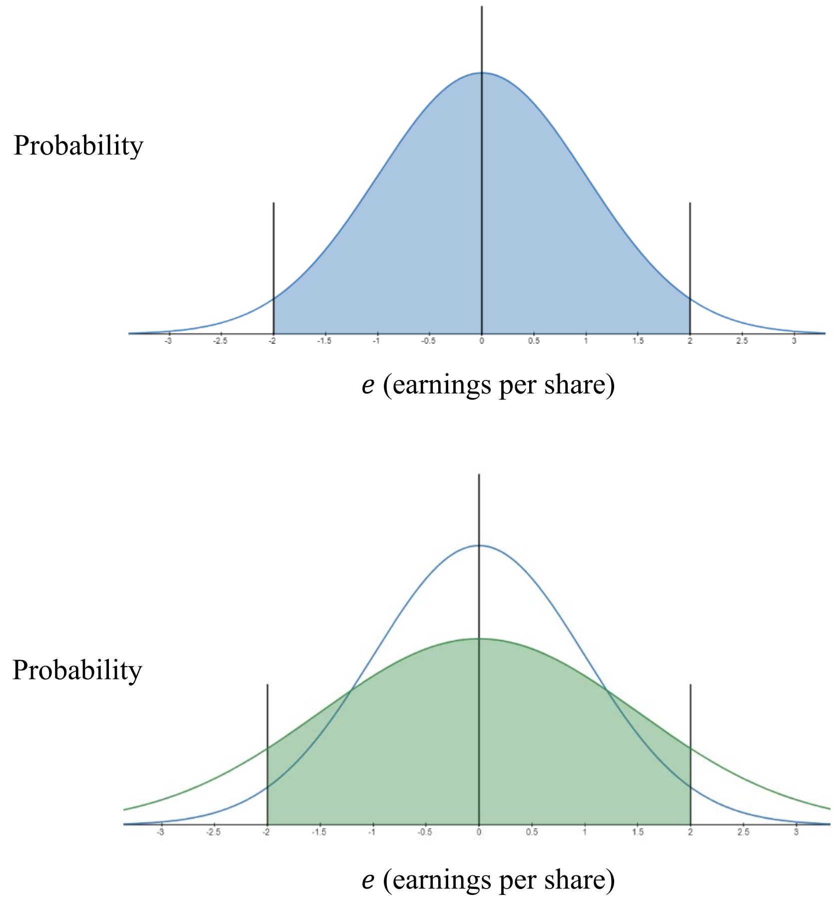
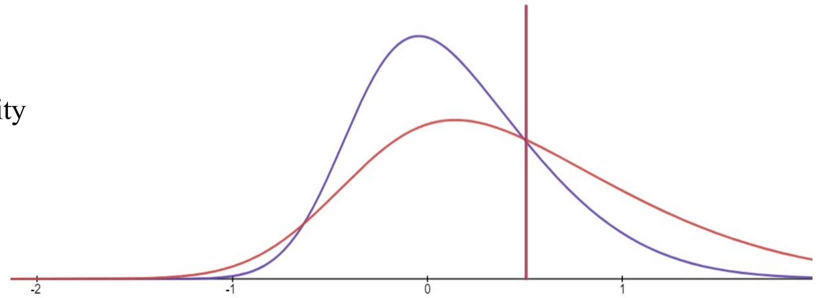


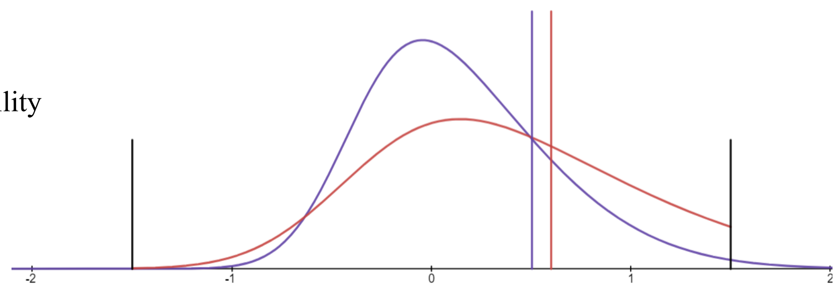
FIGURE 1 (A): The upper figure captures a normal (symmetric) distribution with mean of zero and standard deviation of one. Truncating this distribution (darker blue) does not shift the mean or median of this distribution. Similarly, changing the variance in the lower figure does not change the mean or median of the distribution, nor does simultaneously increasing the variance and truncating the distribution (dark green).

Probability



e (earnings per share)

Probability



e (earnings per share)

FIGURE 1 (B): The upper figure captures a right skewed distribution (dark blue). Changing the variance of a skewed distribution does not, in itself, change the mean or median of the distribution (red), but simultaneously increasing the variance and truncating the distribution shifts the mean and median in the direction of skewness. For right (left) skewed distributions, this results in means and medians greater than (less than) would be suggested by the unaltered distribution.

Wang's Nomenclature

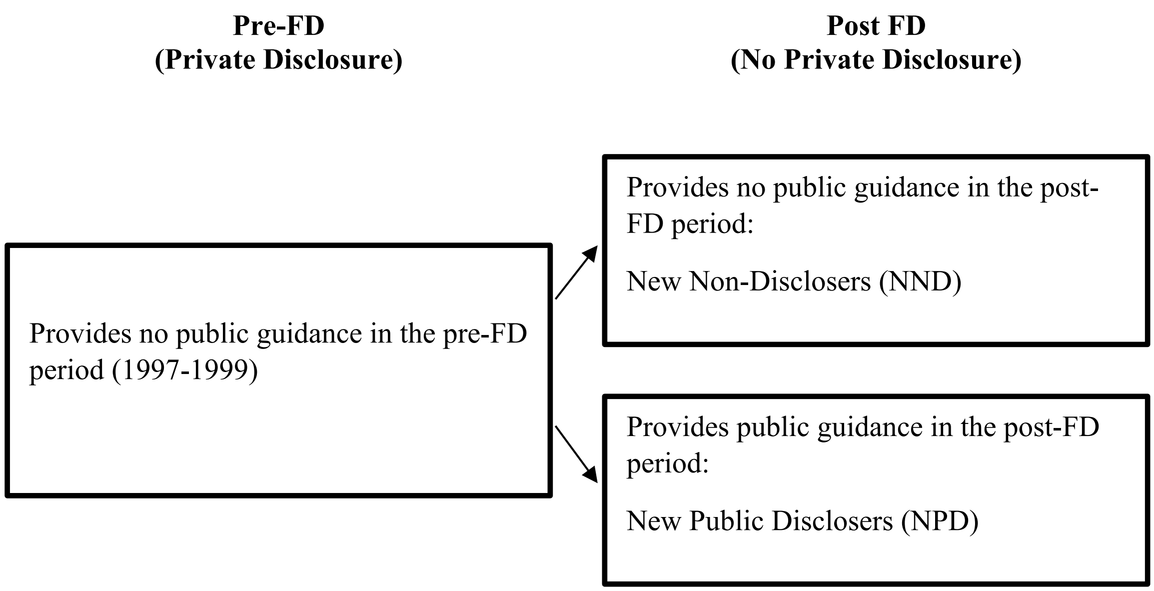
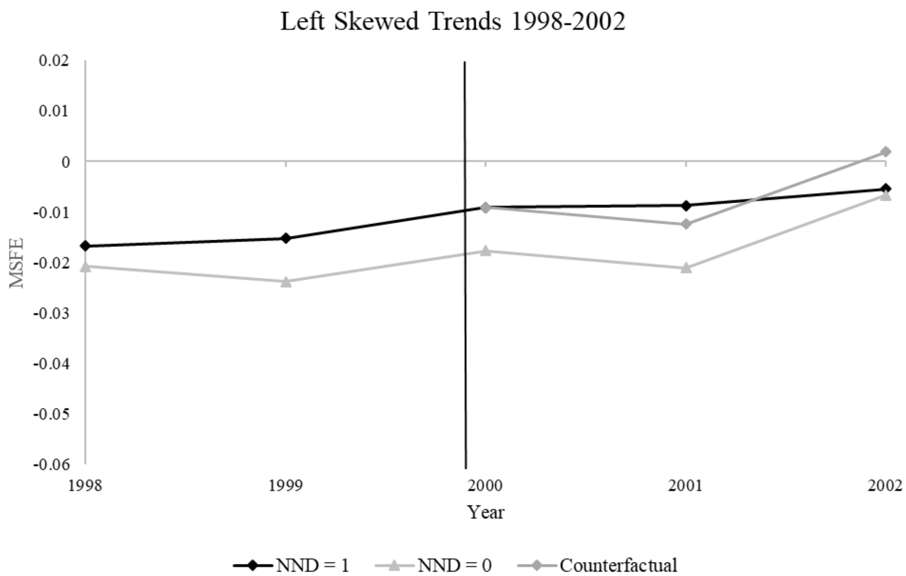


FIGURE 2: Reconciliation of Wang's (2007) nomenclature to our setting. Our firms of interest are those that do not provide public guidance in the pre-Reg FD period and do not provide public guidance in the post-Reg FD period (NND = 1).



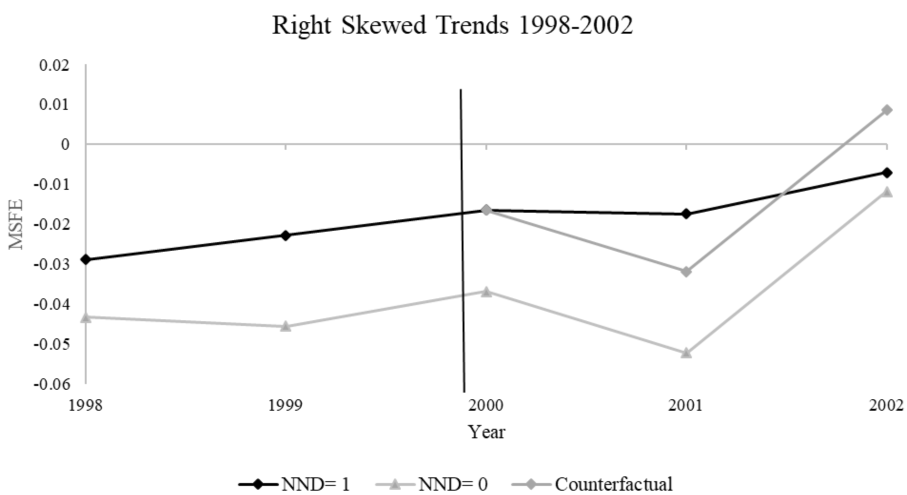


FIGURE 3: Forecast error trend lines for NND (new non-disclosure) and NPD (new public disclosure) firms with left-skewed (top) and right-skewed (bottom) earnings distributions prior to and following Regulation Fair Disclosure. The medium-gray line illustrates the counterfactual for both left-and-right skewed firms had the forecast error trends for firms that did not issue guidance following Reg FD (NND) continued to mirror that of firms who issue public guidance following Reg FD (NPD).

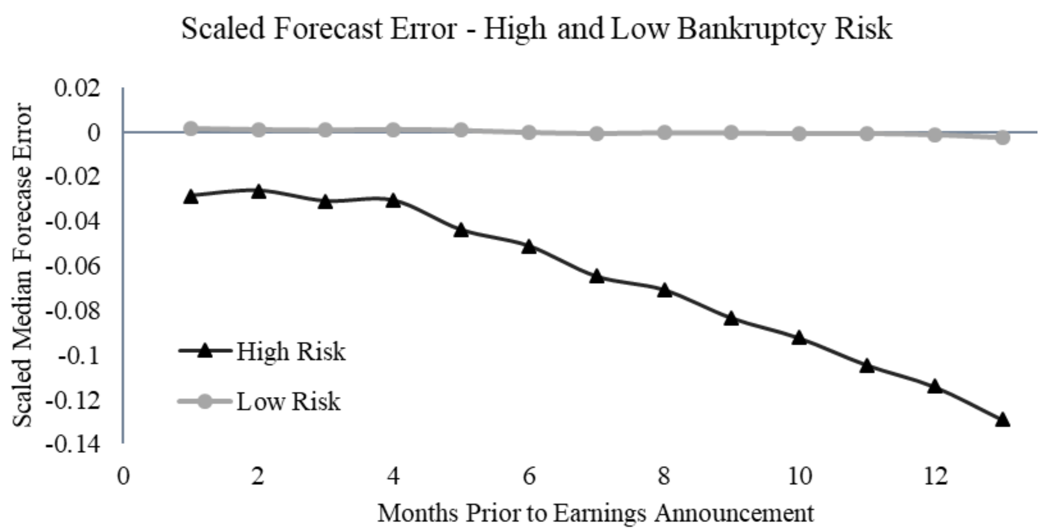


FIGURE 4 (A): Scaled median analyst forecast errors over the annual forecast horizon for high and low bankruptcy risk firms as determined by Z-Score. Scaled median forecast errors are defined as the difference between actual EPS and the median forecast, divided by beginning of period price and multiplied by 100.

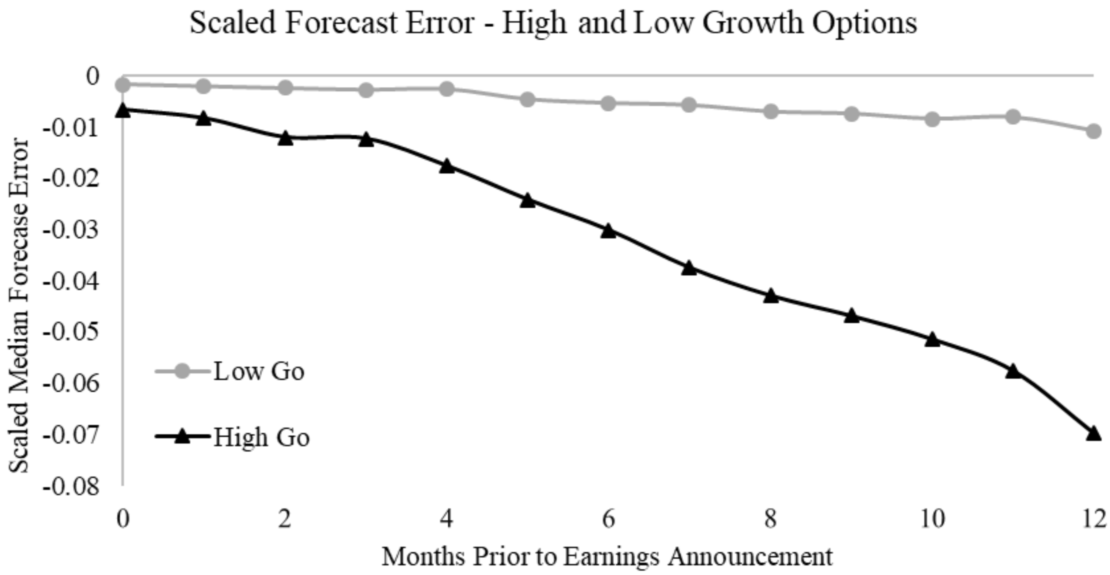


FIGURE 4 (B): Scaled median analyst forecast errors over the annual forecast horizon for high and low growth option firms. Scaled median forecast errors are defined as the difference between actual EPS and the median forecast, divided by beginning of period price and multiplied by 100.

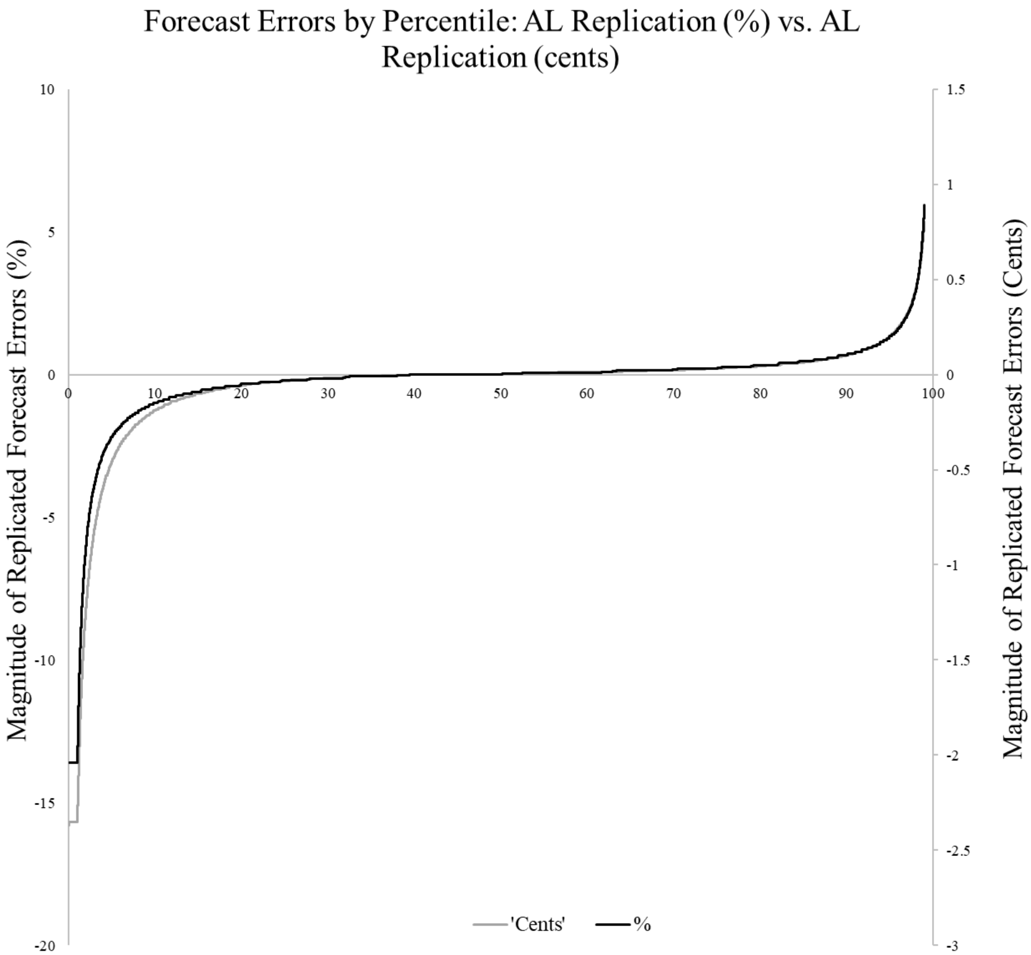


FIGURE 5 (A): 1st through 100th percentiles of annual EPS forecast errors from 1994 to 2014, both scaled and unscaled by beginning of period price. Moving from left to right, forecast errors range from the most negative (optimistic) to the most positive (pessimistic). Forecast error is defined as the difference between the actual EPS and the mean analyst forecast. Scaled errors are divided by beginning of period price and multiplied by 100. This figure illustrates that the shape and qualitative aspects of the distribution shown in Abarbanell and Lehavy (2003) are not sensitive to scaling by price.

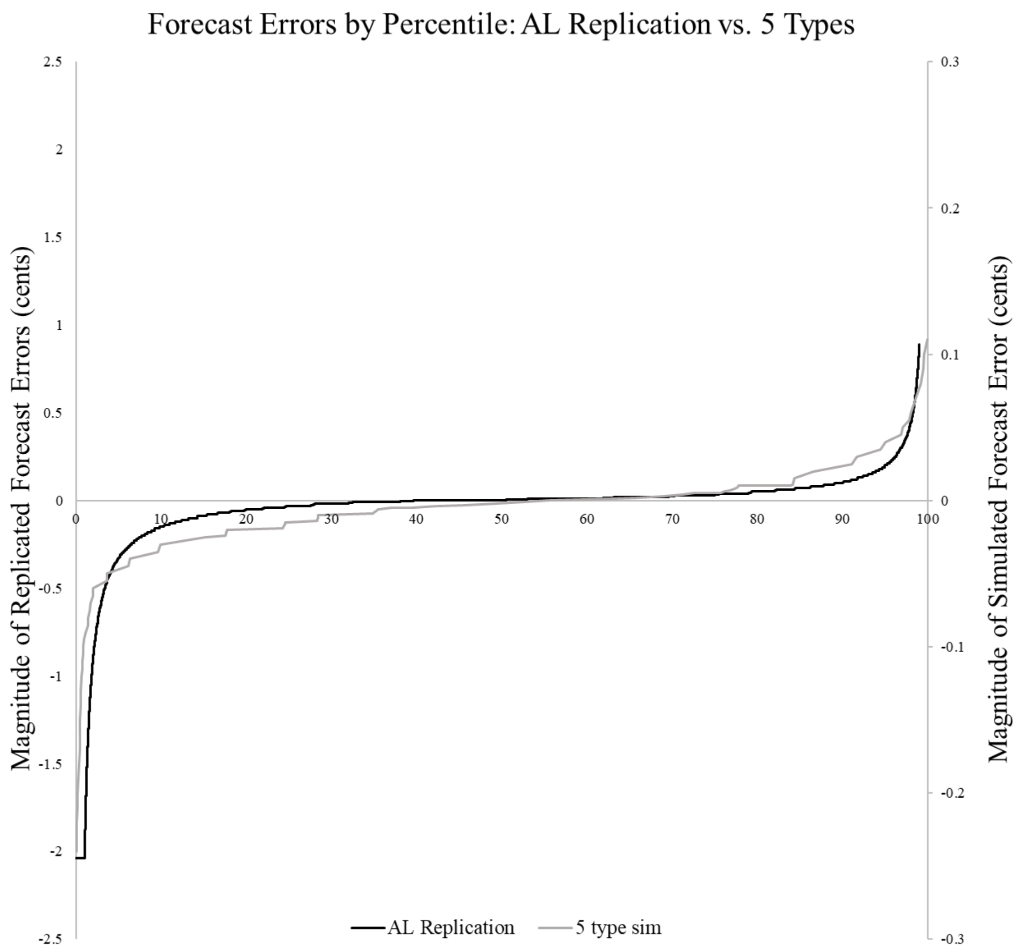


FIGURE 5 (B): 1st through 100th percentiles of annual EPS forecast errors from 1994 to 2014, both simulated and unscaled by price. Moving from left to right, forecast errors range from the most negative (optimistic) to the most positive (pessimistic). Empirical forecast error is defined as the difference between the actual EPS and the mean analyst forecast. Specifications used to derive simulated forecast errors are: Range = \$0.50, Number of Weights = 5, from to -\$2.18 to \$9.13.