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Analyst information precision and small earnings surprises

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Abstract This study proposes and tests an alternative to the extant earnings management explanation for zero and small positive earnings surprises (i.e., analyst forecast errors). We argue that analysts' ability to strategically induce slight pessimism in earnings forecasts varies with the precision of their information. Accordingly, we predict that the probability that a firm reports a small positive instead of a small negative earnings surprise is negatively related to earnings forecast uncertainty, and we present evidence consistent with this prediction. Our findings have important implications for the earnings management interpretation of the asymmetry around zero in the frequency distribution of earnings surprises. We demonstrate how empirically controlling for earnings forecast uncertainty can materially change inferences in studies that employ the incidence of zero and small positive earnings surprises to categorize firms as suspected of managing earnings.

Keywords Earnings surprise · Analyst forecast error · Forecast uncertainty · Analyst incentives · Earnings management · Discontinuity · Benchmark beating

JEL classification D80 · M41 · G24 · G29

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1 Introduction

The literature provides robust evidence of an asymmetry around zero in the frequency distribution of U.S. firms' earnings surprises (i.e., analyst forecast errors), suggesting a systematic tendency of firms to meet or just beat rather than just miss analyst expectations (Degeorge et al. 1999; Brown 2001; Abarbanell and Lehavy 2003; Dechow et al. 2003). The common explanation for this is that firms systematically manage earnings to meet expectations (e.g., Degeorge et al. 1999), and subsequent research frequently categorizes firms as suspected of managing earnings when their earnings meet or just beat analyst expectations (e.g., Cheng and Warfield 2005; Lim and Tan 2008; Fang et al. 2015).

However, empirical evidence on the earnings management explanation is mixed. We show that strategic analyst forecast pessimism provides an important alternative explanation. Strategic forecast pessimism refers to sell-side analysts understating their public forecasts relative to their private expectations about a firm's earnings. Incentives to issue pessimistic forecasts are rooted in analysts' relations with firms' management (e.g., Francis and Philbrick 1993; Lim 2001). One way in which analysts can maintain good relations with managers is by slightly understating their forecasts and thus helping firms meet or just beat expectations. Empirical studies show that analysts obtain informational benefits from such behavior, by documenting relations between forecast pessimism and analysts' subsequent forecast accuracy and career outcomes (Ke and Yu 2006; Hilary and Hsu 2013). Recent research also suggests that, even after SEC Regulation Fair Disclosure (Reg FD), private communication with management remains widespread and continues to figure in analyst research (Brown et al. 2015). In the strategic research and supplied the supplied to the supplied to

Our premise is that ex ante forecast pessimism (i.e., the forecast is lower than the analyst's expectation) can differ from ex post forecast pessimism (i.e., a positive earnings surprise) because analysts generally face uncertainty about the earnings outcome. This uncertainty can be defined as the imprecision of the information signals analysts use when generating a point estimate earnings expectation. This precision is determined by both the precision of public information (i.e., the predictability of earnings given publicly available information) and the precision of analysts' unique private information.

When analysts' information about earnings is relatively precise, the range of earnings outcomes around their point estimate is relatively small. A smaller range leads to a greater likelihood that a slightly understated forecast will actually induce

¹ Evidence in studies such as those of Soltes (2014), Green et al. (2014), and Brown et al. (2015) suggests that private communication between managers and analysts occurs frequently post-Reg FD. Even if managers do not selectively disclose material private information, analysts can still benefit from nonverbal cues and nonmaterial information disclosures that are valuable in combination with their private information. For instance, Mayew (2008) shows in a post-Reg FD setting that managers reward supportive analysts by allowing them to ask questions during conference calls. Asking questions allows these analysts to convert the public information revealed from management's responses into material private information. We conclude that analysts' incentives to please management and obtain access to information remain important post-Reg FD.



a positive surprise when earnings are announced.² Thus, given the incentives to please managers, the ability of analysts to be strategically pessimistic relates positively to the precision of their information. Accordingly, we hypothesize that the likelihood that a firm's earnings just beat analyst expectations (i.e., the firm reports a small positive earnings surprise) is negatively associated with earnings forecast uncertainty.

We test our hypothesis using a large sample of U.S. firms' quarterly earnings surprises over the period 1993–2013. Earnings forecast uncertainty is measured using analyst forecast dispersion, which is the standard deviation of individual analysts' latest forecasts before earnings announcements (e.g., Barron and Stuerke 1998; Clement et al. 2003). In initial descriptive analyses, we document a strong link between the sign of small earnings surprises and levels of earnings forecast uncertainty. Specifically, we find that earnings that ultimately just beat analyst expectations are associated with substantially lower forecast dispersion before earnings announcements than earnings that just miss expectations. The average dispersion in firm-quarters with an earnings surprise of –1 cents or –2 cents per share is about 50 % higher than the average dispersion in firm-quarters with a small positive surprise of similar magnitude.

We formally test our hypothesis using a multiple logistic regression framework that explains the likelihood that firms report a small positive (1 or 2 cents) versus a small negative (-1 or -2 cents) earnings surprise, and control for an array of other determinants of earnings surprises. Regression results reveal a strong negative relation between earnings forecast uncertainty and the likelihood that firms just beat instead of just miss analyst expectations. This relation is statistically and economically highly significant and—given the link between uncertainty and analysts' ability to issue slightly pessimistic forecasts—supports the notion that strategic forecast pessimism helps shape the distribution of earnings surprises around zero.

We also examine other subsets of the earnings surprise distribution that are commonly used to capture earnings management. We predict that earnings forecast uncertainty becomes even more salient when considering the likelihood that a firm reports a 0 or 1 cent earnings surprise because, statistically, firms are more likely to report a small earnings surprise when analysts face little uncertainty. When we introduce variables that capture whether firms report a 0 or 1 cent surprise relative to (1) all other surprises and (2) all negative surprises, respectively, the empirical results confirm that the relation with earnings forecast uncertainty strengthens. For instance, we find that an inter-quartile reduction in forecast dispersion increases the conditional probability that a firm reports a 0 or 1 cent surprise from 14 to 35 %.

To illustrate this argument, consider the case where an analyst's point-estimate is 20 cents, with an expected range of possible earnings outcomes of 18–22 cents per share (i.e., relatively low uncertainty). Assume the analyst is willing to induce strategic pessimism of 2 cents per share. In this case, the likelihood that a forecast understated by 2 cents per share will result in a positive earnings surprise is high. (The firm is expected to meet or beat the 18 cents estimate.) In contrast, at the same level of strategic pessimism of 2 cents per share, this likelihood is much lower in the case where the expected range of possible earnings outcomes would be 0–40 cents per share (i.e., relatively high uncertainty).



We illustrate the implications of our findings by examining potential research settings that make use of the above subsets of the earnings surprise distribution. Specifically, we examine the consequences of controlling for earnings forecast uncertainty for the relation between small positive earnings-surprise incidence and variables that capture constraints on firms' ability to manage earnings. We show that each of these variables is both negatively related to small positive surprise incidence and positively related to forecast dispersion. After controlling for dispersion, most of the significant relations with small positive earnings-surprise incidence disappear. In other words, controlling for analysts' ability to strategically issue pessimistic forecasts can overturn conclusions about earnings management.

We do several additional tests that rule out alternative explanations. First, we introduce an alternative measure of earnings forecast uncertainty that exploits information on the relative precision of individual analysts' prior forecasts issued for *other* firms and again find a strong negative association with the likelihood of small positive earnings surprises. Second, we show that our results are not driven by firms' use of (and ability to use) earnings management, expectations management, or the relation between dispersion and future firm performance. Third, we show that our findings are not simply an artifact of previously documented relations between uncertainty and analyst forecast *optimism*.

This study contributes to the earnings discontinuity literature.³ The common explanation for the asymmetry in the earnings surprise distribution is earnings management, although empirical evidence for this explanation is limited and mixed.⁴ Durtschi and Easton (2005) provide an alternative perspective and interpret the earnings surprise distribution in terms of the magnitude of optimistic versus pessimistic analyst forecast errors. They show that pessimistic forecast errors are smaller than optimistic ones, and conclude that forecast error patterns provide an alternative explanation for the asymmetry around zero earnings surprise: positive surprises cluster around zero, while negative surprises spread away from zero. By showing how forecast uncertainty maps into both the *magnitude* and *sign* of forecast errors, we provide an explanation for why forecast pessimism is concentrated in smaller earnings surprises.

Our findings have important implications for research designs that employ the incidence of zero and small positive earnings surprises to capture constructs related

⁴ See Dechow et al. (2010, 364–366) for an overview of the mixed and mostly indirect evidence on the earnings management explanation. Badertscher et al. (2012) examine restatement firms that have likely managed earnings and find no evidence of elevated discretionary accruals for the 0 and +1 cent earnings surprise bins. Moreover, they conclude: "Roughly 55 % of the observations where earnings are deemed to be opportunistically managed do not fall into the zero or just beat (0.01) earnings surprise bins that are typically used to infer earnings management. Thus, these cases would be missed in studies that use the zero bin and the bin just to the right of zero to infer earnings management" (pp. 346–347). The survey evidence of Brown et al. (2015) further suggests that sell-side analysts do not support the common conjecture that firms' consistent meeting or beating of expectations is a red flag for financial misreporting.



³ By focusing on earnings surprises, our research differs fundamentally from prior work debating the validity of economic versus artifactual explanations for "discontinuities" around zero earnings and zero earnings change (Durtschi and Easton 2005, 2009; Jorgensen et al. 2014; Burgstahler and Chuk 2015).

to earnings management.⁵ We show that these designs are more likely to sort samples based on earnings forecast uncertainty than on earnings management, and that controlling for dispersion can materially change inferences in settings where a variable of interest relates to uncertainty. We expect these implications to apply to a wider range of settings, given that variables of interest are commonly related to a firm's information environment. Moreover, the relation between forecast uncertainty and the sign of earnings surprises is likely to be important for studies that rely on signed earnings surprises in other contexts, such as when modeling predictable variation in analysts' forecast errors (e.g., Hughes et al. 2008; Mohanram and Gode 2013; So 2013).

2 Background and hypothesis development

Degeorge et al. (1999) document a strong asymmetry around zero in the frequency distribution of U.S. firms' quarterly earnings surprises and show that firms are substantially more likely to just beat rather than just miss analyst forecasts. Brown (2001) finds this asymmetry has strengthened over time, and Dechow et al. (2003) find a similar pattern for annual earnings surprises. The financial media also commonly acknowledge the tendency of firms to beat rather than miss analyst earnings forecasts, even in economic downturns when firms' earnings are weak (Zweig 2011; Jakab 2013).

In this study, we examine the role of predictable variation in sell-side analyst forecast errors in explaining this phenomenon. Forecast errors arise because the information analysts use to generate their forecasts is not perfect. Analysts have incentives to minimize their forecast errors by generating and acquiring better information, as prior research suggests that forecast accuracy matters to them because of career and reputational concerns. This suggests that rational analysts can be expected to issue forecasts that reflect their best estimate of a firm's future earnings.

At the same time, analysts face incentives to issue forecasts that deviate from their best estimate (e.g., Lim 2001; Hong and Kubik 2003). Such strategically biased forecasts may arise from analysts' attempts to win trading commissions for the brokerages they work for (e.g., Cowen et al. 2006), from efforts to acquire

⁶ Although analysts are generally not directly compensated for their forecast accuracy, prior research finds that larger errors (relative to analysts' peers) are associated with greater analyst turnover (Mikhail et al. 1999; Groysberg et al. 2011), while smaller errors are associated with promotions (Hong and Kubik 2003) and *Institutional Investor* All-Star rankings (Stickel 1992; Leone and Wu 2007). In addition, analysts face incentives to protect their reputations with clients by issuing accurate forecasts (Jackson 2005; Cowen et al. 2006; Ljungqvist et al. 2007; Fang and Yasuda 2009).



Variables based on the incidence of zero and small positive earnings surprises are commonly used to empirically proxy for constructs such as earnings management (e.g., Cheng and Warfield 2005; Brochet et al. 2015; Fang et al. 2015) and audit quality (e.g., Lim and Tan 2008; Reichelt and Wang 2010). Zero and small positive earnings surprises are also used to select samples of "suspect" firms (Balsam et al. 2002; Cohen et al. 2008). Other studies rely on the likelihood of firms reporting a nonnegative earnings surprise regardless of magnitude (e.g., Matsumoto 2002) or the likelihood of meeting/just beating versus just missing expectations (e.g., McVay et al. 2006).

investment banking deals (e.g., Lin and McNichols 1998), and from attempts to ingratiate themselves with firm managers to obtain privileged access to information (e.g., Francis and Philbrick 1993). For instance, Lim (2001) models analysts' trade-off between issuing their best-estimate forecasts and issuing biased forecasts that increase access to management. Access to management increases the precision of analysts' estimates and thereby reduces expected forecast errors.

Whether strategic forecast bias is optimistic (i.e., the forecast is above the analyst's best estimate) or pessimistic (i.e., the forecast is below the best estimate) depends on analysts' specific incentives and the forecast horizon. Brokerage trading commissions and investment banking typically induce incentives for forecast optimism. Incentives to please managers lead to both optimism in long-horizon forecasts to support high market valuations (Dechow et al. 2000; Bradshaw et al. 2006) and pessimism in short-horizon forecasts to help firms meet or beat expectations. Ke and Yu (2006) and Hilary and Hsu (2013) present empirical evidence suggesting that analysts obtain benefits from short-horizon pessimism in terms of greater access to management and more consistent and influential forecasts.

Meeting analysts' earnings expectations matters to firms because of the negative consequences of missing expectations (e.g., Skinner and Sloan 2002; Frankel et al. 2010). In addition, managers prefer *small* positive earnings surprises and therefore *slightly* understated analyst earnings forecasts. Survey evidence by Graham et al. (2005) suggests that managers believe that large earnings surprises negatively influence investor perceptions of the predictability of firm performance and increase the cost of capital. Based on their interviews with CFOs, Graham et al. (2005, 43) note, "When asked about whether they would prefer to meet or to beat the earnings target, several CFOs say they would rather meet (or slightly beat) the earnings target rather than positively surprising the market in a big way every quarter."

The costs that firms incur from more volatile earnings surprises are unlikely to be overcome by the benefits of reporting large positive surprises, for two reasons. First, Freeman and Tse (1992) document that the marginal stock price benefits of beating expectations decrease sharply with the magnitude of earnings surprises. In other words, the marginal benefits to managers of beating expectations by a large versus a small amount are much smaller than the marginal benefits of meeting versus missing expectations. Second, stock prices respond to analyst forecast revisions (e.g., Lys and Sohn 1990; Stickel 1991), which implies that when analysts are overly pessimistic before earnings announcements, the negative pricing effects of understated forecasts are likely to outweigh the positive consequences of beating expectations by a greater margin.

⁸ In this regard, theoretical work such as that of Beyer (2008) assumes that managers' utility with respect to meeting versus missing expectations is asymmetric. In her study, managers are assumed to be indifferent between meeting and beating analysts' expectations, while the costs of missing expectations increase with the amount of the miss.



⁷ While both forecast optimism and pessimism can induce trading commissions when triggering investor belief revision, the effect is stronger for forecast optimism. Cowen et al. (2006) argue this is due to constraints on, and costs of, short-selling. Beyer and Guttman (2011) show that as a result of investor risk aversion, analysts are more likely to bias their forecasts upward in response to trading incentives.

Given managers' preference for small positive earnings surprises, the extent to which analysts can please managers depends on their ability to induce such surprises. This ability, in turn, depends on the precision of analysts' information. Consider the contrast between the required strategic bias for a firm with relatively low uncertainty—for example, with an expected range of possible earnings outcomes of 18–22 cents per share—and the required strategic bias for a firm with relatively high uncertainty—for example, with an expected range of possible earnings outcomes of 0–40 cents per share. Assume the analyst privately has an ex ante 20 cents point estimate expectation for both firms (i.e., the mid-point of both ranges). To obtain a similar probability of a small positive earnings surprise for both firms ex post, the analyst would have to pessimistically bias the forecast for the high uncertainty firm by a much larger amount than for the low uncertainty firm. Such larger bias is costly to the analyst because of the expected increase in forecast error. As a result, the analyst's forecast is much less likely to display ex post pessimism for the high uncertainty firm than for the low uncertainty firm.

To summarize, given the *existence* of incentives for analysts to induce strategic pessimism in their forecasts, we posit that analysts' *ability* to slightly understate their forecasts and please managers is greater when their information signals about a firm's future earnings are more precise. We therefore predict that when earnings forecast uncertainty is relatively low, firms are more likely to report earnings that just beat rather than just miss consensus analyst expectations. Our main hypothesis is stated below (in alternative form):

H1 The likelihood that a firm reports earnings that just beat instead of just miss consensus analyst expectations is negatively related to earnings forecast uncertainty.

3 Research design

3.1 Sample selection

Table 1 presents the sample selection procedure. Our initial sample consists of all quarterly earnings per share (EPS) forecasts in the I/B/E/S unadjusted detail file for U.S. firms with fiscal quarters ending in 1993–2013. We require actual EPS data from I/B/E/S and retain each analyst's latest forecast before the quarterly earnings announcement. The sample is restricted to firm-quarters with at least three individual forecasts, as in, for example, Ke and Yu (2006). We drop late earnings announcements that occur more than 180 calendar days after fiscal quarter-end, and, following standard I/B/E/S methodology, we remove stale forecasts made more than 180 days before the quarterly earnings announcement. We merge the I/B/E/S

¹⁰ We impose the 180-day restriction for earnings announcement timing because some earnings announcements in the I/B/E/S data are extremely delayed relative to the fiscal quarter-end, reflecting either extreme cases of firms in trouble or data errors. Our results are not sensitive to excluding this restriction or using alternative numbers of days.



⁹ The sample period starts in 1993 because, until the early 1990s, I/B/E/S data suffer from a mismatch between the definitions of forecasted and actual earnings (Cohen et al. 2007).

Table 1 Sample selection

Description	No. obs.
Panel A: Initial selection of earnings surprise sample	
One-quarter-ahead forecasts of EPS on I/B/E/S 1993–2013 ("FPI" = 6)	2,486,904
Less: Analyst code missing or equal to 0 or 1, or CUSIP code missing	-24,694
Less: No CUSIP-PERMNO match with CRSP "stocknames" file	-39,207
Less: Missing actual EPS value or announcement date on I/B/E/S	-15,511
Less: Earnings announcement date more than 180 days after fiscal quarter end	-4906
Less: Individual forecast more than 180 days before earnings announcement date	-22,995
Less: Retain only last forecast by each individual analyst	-640,562
Cleaned sample of individual forecasts	1,739,029
Unique firm-quarters with earnings surprise data	301,027
Panel B: Final sample of firm-quarters	
Firm-quarters in CRSP/COMPUSTAT with positive total assets 1993-2013	463,527
Less: Missing SIC code or exchange code on CRSP	-417
Less: Firm not listed on NYSE, AMEX, or NASDAQ	-3473
Less: Utilities and financial firms (SIC codes 4400-4999 and 6000-6499)	-94,722
Less: Missing data for control variables in COMPUSTAT	-51,919
Less: No quarterly earnings surprise data available on I/B/E/S	-120,041
CRSP/COMPUSTAT firm-quarters with I/B/E/S earnings surprise data	192,955
Less: Missing prior return (CRSP) and firm-specific ERC data	-28,320
Less: Fewer than three individual analyst forecasts available for firm-quarter	-45,905
Final sample of firm-quarter observations	118,730

EPS forecast and actual data are obtained from the I/B/E/S unadjusted detail files. We include all fiscal quarters ending in the first calendar quarter of 1993 through the fourth calendar quarter of 2013

sample with CRSP and Compustat and restrict the sample to firms that have nonnegative total assets and are listed on NYSE, AMEX, or NASDAQ. We delete utilities and financial services firms (SIC codes 4400–4999 and 6000–6499) and obtain a final sample of 118,730 firm-quarter observations after eliminating observations with missing data to compute our main regression variables. ¹¹

The quarterly earnings surprise (*SURPRISE*) is defined as actual EPS less our consensus forecast, which is calculated as the mean of individual analysts' latest EPS forecasts. ¹² Before taking the difference between actual earnings and the consensus forecast, both figures are rounded to cents per share to ensure consistency

¹² We focus on unscaled earnings surprises per share, because managers and the investment community are mainly concerned with earnings per share rather than scaled earnings numbers. Also, Degeorge et al. (1999) and Cheong and Thomas (2011) show that earnings surprise magnitude does not vary with scale



¹¹ To adjust for stock splits between the analyst forecast and earnings announcement dates, cumulative stock split factors are obtained from CRSP and merged separately with the forecast and announcement dates. If the cumulative split factor at the forecast date differs from the cumulative split factor at the earnings announcement date, the forecast of earnings per share is multiplied by the ratio of the cumulative price adjustment factor at the announcement date to the cumulative price adjustment factor at the forecast date. This ensures that differences in split levels do not erroneously drive firms towards (or away from) zero earnings surprise.

with the presentation of these numbers in press releases and financial media. Based on *SURPRISE*, we create three dependent variables.

The first variable captures the incidence of small positive versus negative surprises. *Just beat versus just miss* is an indicator variable that equals 1 for positive 1 and 2 cent earnings surprises and 0 for small negative surprises of 1 or 2 cents per share. Although we are unaware of prior literature using this specific classification, it is best suited in our setting to test H1. The design of Singer and You (2011) comes closest to our classification, except theirs focuses on price-scaled earnings surprises. McVay et al. (2006), Brown and Pinello (2007), and Shon and Veliotis (2013) do focus on unscaled surprises, but they include 0 cent surprises as small "beats." Our choice to focus on 1 and 2 cent surprises, though arbitrary, is driven by our motivation to obtain a reasonable small interval around zero while also maintaining enough observations for the analyses. Results are not affected by choosing alternative intervals around zero and extend to examining positive versus negative surprises of any magnitude.

Given managers' (Graham et al. 2005), investors' (Keung et al. 2010), and academics' emphasis on zero and small earnings surprises, we also create a variable *Meet/just beat versus all other*, which is an indicator variable that equals 1 for 0 and 1 cent earnings surprises and 0 for all other surprises (e.g., Cheng and Warfield 2005; Lim and Tan 2008; Brochet et al. 2015). We create a similar variable, *Meet/just beat versus miss*, that equals 0 only for negative earnings surprise observations. This classification comports with studies such as that of McVay et al. (2006), except that it includes misses of *any* magnitude in the 0 category. This variable can provide important additional insights, since a common assumption is that firms would have missed expectations in the absence of earnings management.

3.2 Measuring earnings forecast uncertainty

Earnings forecast uncertainty is measured as the dispersion in the individual analysts' forecasts used to construct the consensus forecast (*DISP*). The intuition for this measurement is that when analysts' information precision increases, forecast dispersion decreases. Dispersion has been widely used in the literature as an empirical proxy for forecast uncertainty (e.g., Barron and Stuerke 1998; Kinney et al. 2002; Clement et al. 2003; Ke and Yu 2006). Consistent with our focus on unscaled earnings surprises, we use the unscaled standard deviation measured in cents per share (Cheong and Thomas 2011). ¹³

The use of dispersion as a measure of earnings forecast uncertainty has benefits and drawbacks. A clear advantage of dispersion is that it is an ex ante measure and available in real-time (Sheng and Thevenot 2012). Other proxies, such as realized earnings volatility, rely on time-series data and result in stale measures of

¹³ Our results are qualitatively similar if we scale the standard deviation of forecasts by the absolute value of the consensus, i.e., use the coefficient of variation (Diether et al. 2002).



Footnote 12 continued

⁽i.e., share price). This lack of variation in scale results in an asymmetry around zero in both the unscaled and scaled distributions.

uncertainty. A drawback of dispersion is that it is not a perfect measure of earnings forecast uncertainty (Barry and Jennings 1992; Abarbanell et al. 1995; Sheng and Thevenot 2012). In addition, while our study focuses on the uncertainty faced by individual analysts, the use of dispersion hinges on the assumption that *inter*-analyst variation in forecasts captures average *intra*-analyst uncertainty.

Barron et al. (1998) show how dispersion is conceptually related to earnings forecast uncertainty, and Barron and Stuerke (1998) provide empirical evidence that validates the use of dispersion as a proxy for earnings forecast uncertainty. Levidence suggesting that lower quality disclosures are associated with greater dispersion (Lang and Lundholm 1996; Lehavy et al. 2011; Rajgopal and Venkatachalam 2011) further supports the link between dispersion and the precision of the information available to the average analyst. Lahiri and Sheng (2010) and Sheng and Thevenot (2012) provide evidence suggesting that dispersion approximates earnings forecast uncertainty for short-horizon forecasts, the forecasts we consider in this study.

3.3 Control variables

Prior studies show that firm size relates to forecast accuracy (Lang and Lundholm 1996) and analyst optimism (Das et al. 1998). We therefore control for the natural logarithm of market value of equity (MV) at the beginning of the fiscal quarter to control for firm size. Also, the evidence of Skinner and Sloan (2002) suggests that growth firms are associated with asymmetrically negative stock market reactions to negative earnings surprises, which implies that growth is associated with managers' incentives to avoid missing expectations. We control for growth using the book-to-market ratio (BTM) at the end of the previous fiscal quarter and a variable that captures the fraction of the most recent eight quarterly earnings numbers that exceed earnings of the same quarter in the previous year (GROWTH).

We further control for market-based incentives to meet expectations by including fixed effects for each of the 84 calendar quarters in our sample, because the incidence and market reward for zero or small positive earnings surprises vary over the sample period (Keung et al. 2010). Next, we calculate a firm-specific measure

¹⁵ We include calendar-quarter fixed effects as opposed to fiscal-quarter fixed effects because one firm's first fiscal quarter can occur at a different point in time than another firm's first fiscal quarter. Controlling for calendar-quarter fixed effects allows us to better capture general time trends. Nevertheless, results are virtually the same when using fiscal-quarter fixed effects.



¹⁴ Barron et al. (1998) show that the expected squared error in consensus (average) forecasts can be viewed as the sum of common uncertainty and 1/N times idiosyncratic uncertainty (where N is the number of analysts). If uncertainty is not purely idiosyncratic, the earnings forecast uncertainty faced by individual analysts is expected to increase consensus forecast error magnitude. At the same time, even if uncertainty is purely idiosyncratic, which maps into forecast dispersion, our sample's median firm-quarter has seven analysts issuing a forecast. This suggests that idiosyncratic uncertainty is unlikely to be fully diversified in the consensus for the average firm-quarter. Also, prior empirical research confirms that forecast dispersion is positively associated with the magnitude of earnings surprises (e.g., Kinney et al. 2002).

of stock price sensitivity to earnings news based on the earnings response coefficient (*ERC*) obtained from firm-specific time-series regressions of earnings announcement returns on earnings surprises. Kinney et al. (2002) show that ERCs are larger for firms with lower forecast dispersion, which implies stronger stock price declines when firms miss expectations and dispersion is relatively low. Higher ERCs imply greater price sensitivity to earnings news and potentially greater incentives to meet expectations.

Managers have incentives to meet expectations and maintain high stock prices around mergers and acquisitions (M&As). For instance, the evidence of Erickson and Wang (1999) suggests firms manage earnings around M&As to inflate stock prices in stock-for-stock mergers. At the same time, Erickson et al. (2012) show that M&A announcements lead to increases in forecast dispersion. We control for M&As by creating an indicator variable capturing whether or not M&A announcements take place in the 90 days before the quarterly earnings announcement (MNA). We further control for managers' trading incentives to meet expectations (Richardson et al. 2004; McVay et al. 2006) by controlling for seasoned equity offering (SEO) and insider selling (INSELL) activity. We control for institutional ownership (INST), because Matsumoto (2002) suggests that managerial incentives to avoid missing expectations increase with institutional ownership.

Prior research suggests that, on average, analysts' forecasts do not fully incorporate public news (e.g., Lys and Sohn 1990; Abarbanell 1991). We control for prior news by including variables that capture firms' recent stock price performance (LAGRET) and the prior quarter's seasonally differenced earnings change (LAGDQEPS). If analysts underreact to news, these variables will be positively correlated with the earnings surprise, because analyst underreaction to good (bad) news should lead to a forecast that is too low (high), which induces a positive (negative) earnings surprise.

We also control for the number of shares outstanding (SHRS), because earnings surprises more easily round to zero when a greater number of shares is used to compute EPS. Although forecast errors and dispersion tend not to vary with price per share (Cheong and Thomas 2011), we also include the natural logarithm of lagged price to control for any unobserved scale-related effects (PRICE). Since a rounded zero earnings surprise can also be driven by stock splits over the prior period, we control for splits over the year before the earnings announcement (SPLIT). We further control for the natural logarithm of analyst following by including NUMEST, the number of analysts contributing to our consensus. Lastly, HORIZON controls for the average age of the forecasts in the consensus. This control is included because late-quarter revisions in forecasts are more likely influenced by guidance (e.g., Richardson et al. 2004), and because later forecasts are likely to be based on more precise information than forecasts made earlier in the quarter.



4 Results

4.1 Descriptive statistics

Panel A of Table 2 presents descriptive statistics on earnings surprises and our dependent variables. ¹⁶ The median firm-quarter has a positive earnings surprise of 1 cent per share. The first and third quartile values of *SURPRISE* are -1 and +4 cents, respectively. These figures corroborate the asymmetry in the earnings-surprise distribution and comport with other studies (Cheong and Thomas 2014). *Just beat versus just miss* equals 1 for 67.5 % of observations, while 26.3 % of sample firm-quarters have a 0 or 1 cent earnings surprise (*Meet/just beat vs. all other*). *Meet/just beat versus miss* equals 1 in 47.5 % of cases, which suggests zero and small positive earnings surprises occur almost as frequently as negative surprises of any amount.

Panel B presents means of forecast dispersion by cents of earnings surprise. We find a strong V-shaped pattern for *DISP* across the earnings surprise distribution, which supports the use of forecast dispersion as a proxy for the average precision of information in analysts' forecasts. Greater dispersion is associated with larger (ex post) earnings surprises. More importantly, there is a strong asymmetry in the V-shape based on the average dispersion for positive versus negative earnings surprises. Small negative surprises are associated with greater forecast uncertainty than small positive earnings surprises. The average dispersion in the -1 and -2 cents bins (2.754) is about 50 % higher than the average dispersion in the +1 and +2 cents bins (1.868). This difference is statistically highly significant. As a result of the asymmetry, we find that the 0 and +1 cent earnings surprise bins are associated with the lowest dispersion.

Figure 1 presents graphical evidence on the link between dispersion and small earnings surprises. Panel A visualizes the strongly asymmetric nature of the V-shaped relation between earnings surprises and forecast dispersion around zero earnings surprise. Panel B illustrates the relation between dispersion and the likelihood that firms just beat versus just miss expectations. When uncertainty is lowest (i.e., dispersion decile 1), firms are more likely to just beat instead of just miss expectations. As uncertainty increases, the likelihood of just beating versus just missing decreases monotonically. In fact, firms in the highest two deciles are more likely to just miss instead of just beat expectations. Focusing on 0 and +1 cent surprises relative to all other surprises and negative surprises, the strength of the relation with dispersion increases.

Panel B of Table 2 further shows that the 0 and +1 cent earnings surprise bins are also associated with the lowest average *BTM*, highest *GROWTH*, highest *ERC*, and most frequent *MNA*.¹⁷ Consistent with analyst underreaction to news, *LAGRET*

¹⁷ The firm-specific earnings response coefficients (*ERC*) based on time series data are relatively high compared to those based on pooled samples in prior research but more consistent with values predicted by theory. This finding is consistent with the evidence of, for example, Kinney et al. (2002) and Cheong and Thomas (2014), who suggest that the pooling of observations across firms results in significant downward biases in *ERCs*.



¹⁶ All continuous variables are winsorized to the 1st and 99th percentiles of their distributions. Our results are qualitatively similar when we exclude extreme observations rather than winsorize them.

Table 2 Descriptive statistics

			u		Mean	St.	St. dev.	p25	Median	p75
Panel A: Descriptive statistics f	otive statistics	s for quarterly	earnings surp	or quarterly earnings surprise variables						
SURPRISE			118,730	730	1.137	10.	10.317	-1.000	1.000	4.000
Just beat (1) versus just miss (0)	ersus just mis	(0)	39,	39,227	0.675	0.	0.468	0.000	1.000	1.000
Meetfjust beat (1) versus all other (0)	(I) versus all	other (0)	118,	118,730	0.263	0.	0.440	0.000	0.000	1.000
Meet/just beat (1) versus miss (0)	(I) versus mi.	(0) ss:	65,	62,809	0.475	0.	0.499	0.000	0.000	1.000
	SURPRISE:	::						Mean	Mean	Diff.
	<>-3	-2	1-	0	1	2	>3	$+1\phi$ or $+2\phi$ surprise	-1ϕ or -2ϕ surprise	
Panel B: Mean earnings forecast uncertainty and firm characteristics by quarterly earnings surprise bin	arnings forec	cast uncertaint	y and firm cha	aracteristics by	v quarterly ea	rnings surpris	se bin			
DISP	696.9	3.185	2.487	1.667	1.725	2.060	4.447	2.754	1.868	0.885***
MV	2974	3387	4068	5618	5418	5373	5221	3808	5399	-1591***
BTM	0.576	0.503	0.462	0.424	0.425	0.436	0.484	0.478	0.430	0.048***
GROWTH	0.546	0.592	0.621	0.660	0.655	0.642	909.0	0.610	0.649	-0.039***
ERC	7.523	10.745	13.216	16.177	16.258	15.842	11.467	12.274	16.080	-3.806***
MNA	0.126	0.144	0.168	0.189	0.188	0.179	0.160	0.159	0.184	-0.025***
SEO	0.065	0.059	0.052	0.048	0.048	0.049	0.050	0.054	0.049	***900.0
INSELL	0.378	0.398	0.418	0.461	0.478	0.492	0.482	0.411	0.484	-0.073***
INST	0.532	0.529	0.539	0.546	0.571	0.589	0.614	0.535	0.579	-0.044***
LAGRET	-0.037	-0.033	-0.023	-0.007	0.015	0.026	0.038	-0.027	0.020	-0.046***
LAGDQEPS	-0.070	-0.009	-0.009	0.023	0.033	0.030	0.039	-0.009	0.032	-0.041***
SHRS	92	111	131	164	157	151	135	123	154	-31***
PRICE	25.619	23.764	24.777	26.836	27.774	28.802	32.384	24.391	28.214	-3.823***
SPLIT	0.048	0.068	0.087	0.114	0.115	0.113	0.075	0.080	0.114	-0.034***



Table 2 continued

	SURPRISE:	· ·						Mean	Mean	Diff.
	<u><-3</u>	-2	-1	0	1	2	>3	$+1\varphi$ or $+2\varphi$ surprise	-1ϕ or -2ϕ surprise	
NUMEST	7.787	7.921	8.231	8.376	8.579	8.803	9.216	8.113	8.675	-0.562***
HORIZON	60.848	59.850	60.630	62.366	64.268	64.634	64.151	60.333	64.424	-4.092

See Table 1 for sample selection details and the "Appendix" for variable descriptions. All continuous variables are winsorized to the 1st and 99th percentiles of their distributions. Test statistics in Panel B are calculated using standard errors adjusted for two-way clustering by firm and quarter. ***, **, and * reflect statistical significance at the level of 0.01, 0.05, and 0.10, respectively



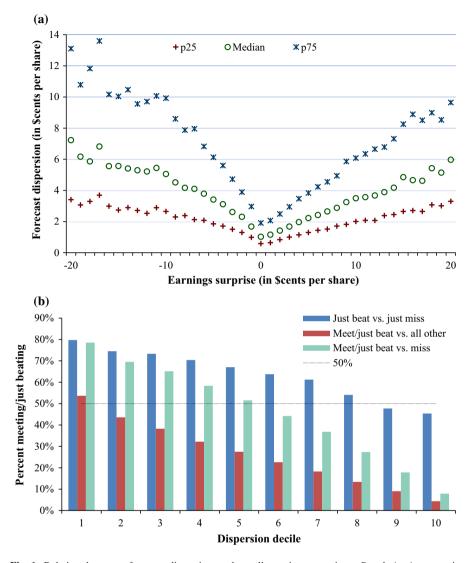


Fig. 1 Relation between forecast dispersion and small earnings surprises. *Panel A*: Asymmetric distribution of forecast dispersion across earnings surprise bins. *Panel B*: Frequency of zero and small positive earnings surprises by deciles of forecast dispersion. *Panel A* is based on the 111,181 firm-quarters with an absolute earnings surprise smaller than or equal to 20ϕ per share. *Panel B* is based on the full sample of 118,730 firm-quarters. See Table 1 for sample selection details. See the "Appendix" for information on the construction of the forecast dispersion measure and the earnings surprise category variables. Deciles based on forecast dispersion are constructed each calendar quarter

and *LAGDQEPS* are positively correlated with small positive earnings surprises. Zero and small positive surprises are also associated with the highest *SHRS* and *SPLIT*, confirming that surprises round more easily to the target level with more outstanding shares. *HORIZON* is greater for small positive versus small negative surprises, which is not consistent with an interpretation that small positive surprises



are induced by late downward revisions in forecasts that result from expectations management. ¹⁸ All differences in average characteristics between small positive and small negative surprise firm-quarters are statistically significant, as indicated by the two rightmost columns of Panel B.

Due to the mechanical relations among *MV*, *SHRS*, and *PRICE*, untabulated variance inflation factors indicate potential multicollinearity. Therefore, in our analyses to follow, we exclude *SHRS* as a control variable. Results are qualitatively similar regardless of whether *SHRS* is included. Variance inflation factors for the other variables indicate no cause for concern. After excluding *SHRS*, the highest variance inflation factor is only 1.65 (for *PRICE*). Due to the right-skewness in variables *DISP*, *MV*, *PRICE*, and *NUMEST*, we use the natural logarithm of these variables in our regression analyses. ¹⁹ Because *DISP* can take on the value of zero, ln(*DISP*) is defined as the natural logarithm of 0.001 plus the standard deviation in forecasts. ²⁰

4.2 Main results

Table 3 presents results of testing our hypothesis. All models are estimated using logit regression, and standard errors are clustered by firm and time (year-quarter). Estimation results indicate that forecast uncertainty (ln(DISP)) is significantly negatively related to the likelihood of a small positive versus a small negative earnings surprise. This finding supports H1 and suggests that, after controlling for other determinants of earnings surprises, less forecast uncertainty is associated with a greater likelihood that a firm reports earnings that just beat analyst expectations. Focusing on the other two columns of Table 3, we find that the relation with forecast uncertainty is also highly significant when we compare zero and small positive earnings surprises to all other firm-quarters or to negative surprises.

Focusing on the coefficients on the control variables in the *Just beat versus just miss* estimation, we find no evidence to suggest that the incidence of small positive versus small negative earnings surprises is significantly associated with our variables for management incentives to meet expectations. Of the incentive variables, only *INST* is significantly positively associated with the likelihood of a small positive versus a small negative surprise at p < 0.05. The significant positive coefficients on *LAGRET* and *LAGDQEPS* are consistent with earnings surprises being partly determined by the staleness of information in the consensus forecast.

In Panel B, we quantify the effect of changing the variable of interest $(\ln(DISP))$ on the conditional probability of a small positive earnings surprise. This test measures the marginal effect of a change in earnings forecast uncertainty on the

 $^{^{20}}$ Our findings are not sensitive to this specific design choice. We obtain qualitatively highly similar results when we i) split $\ln(DISP)$ into a variable that captures the log of dispersion when dispersion is nonzero and an indicator variable for zero dispersion or ii) use the quarterly decile rank of dispersion as the test variable.



 $^{^{18}}$ The average HORIZON of >60 calendar days is consistent with most analysts issuing forecasts after the previous quarterly earnings announcement.

¹⁹ Even though *ERC* is relatively right-skewed, we do not use its logarithm because the estimated earnings response coefficient is negative for some firm-quarter observations. Nevertheless, our results are qualitatively similar if we set negative values equal to zero and take the natural logarithm of *ERC*.

Table 3 Earnings forecast uncertainty and small positive earnings surprises

Logit regression							
Dependent variable	Just beat miss (0)	(1) vers	us just	Meet/just b all other (0	eat (1) versus	Meet/just miss (0)	beat (1) versus
	Coeff.	z-stat		Coeff.	z-stat	Coeff.	z-stat
Panel A: Regression	results						
ln(DISP)	-0.524	-22.7	9***	-0.854	-55.63***	-1.079	-53.78***
ln(MV)	0.015	0.8	37	0.122	8.37***	0.097	6.65***
BTM	0.053	1.1	0	-0.213	-5.74***	-0.191	-4.63***
GROWTH	0.085	1.4	.9	0.389	9.03***	0.385	7.91***
ERC	0.000	0.3	4	0.004	6.54***	0.003	4.29***
MNA	0.003	0.1	0	0.093	4.21***	0.087	3.49***
SEO	-0.172	-1.1	2	-0.169	-1.92*	-0.423	-3.57***
INSELL	0.102	1.9	3*	0.036	1.02	0.131	3.09***
INST	0.207	4.3	3***	0.110	3.27***	0.245	6.29***
LAGRET	1.241	15.7	6***	-0.332	-6.74***	0.861	13.86***
LAGDQEPS	0.072	3.4	1***	0.001	0.08	0.069	4.46***
ln(PRICE)	0.291	7.6	4***	-0.308	-13.84***	0.011	0.32
SPLIT	0.121	2.4	3**	-0.007	-0.26	0.105	2.67***
ln(NUMEST)	0.178	4.5	6***	0.143	4.86***	0.310	9.01***
HORIZON	0.006	7.8	66***	-0.003	-5.19***	0.001	0.91
Quarter fixed effects		Inc	luded		Included		Included
n		39,	227		118,730		65,809
Pseudo R ²		0.0	67		0.138		0.212
Dependent variable			Just be versus	eat (1) just miss (0)	Meet/just bed versus all ot		leet/just beat (1) ersus miss (0)
Panel B: Marginal e	ffects analy	sis					
Probability with low	DISP (p25	value)	0.730		0.346		0.638
Probability with high	DISP (p75	value)	0.567		0.140		0.284
Difference p25-p75			0.163		0.206		0.354
Percentage difference	e		28.7 %		147.0 %	12	24.3 %
Probability with low	DISP (p10	value)	0.777		0.445		0.748
Probability with high	<i>DISP</i> (p90	value)	0.478		0.083		0.160
Difference p10-p90			0.299		0.361		0.589
Percentage difference	•		62.5 %)	433.0 %	30	68.0 %

See Table 1 for sample selection details and the "Appendix" for variable descriptions. Test statistics are calculated using standard errors adjusted for two-way clustering by firm and quarter. ***, ***, and * reflect statistical significance at the level of 0.01, 0.05, and 0.10, respectively. Marginal effects are calculated as the effect of an inter-quartile range (or 10th to 90th percentile) shift in $\ln(DISP)$ on the likelihood that the dependent variable equals 1, while holding all other variables constant at their means. The number of shares outstanding variable (SHRS) is excluded from the regressions to avoid multicollinearity problems



likelihood of observing a small positive earnings surprise, while controlling for the influence of other factors. Results suggest that an interquartile move from high to low dispersion is associated with a 28.7 % increase in the conditional probability that firms report a small positive instead of a small negative earnings surprise. When we increase the magnitude of the shift in forecast dispersion from the 90th to the 10th percentile, this figure even increases to 62.5 %. Thus the relation we document is not only statistically significant but also economically highly significant.

The *Meet/just beat versus all other* indicator variable is affected by both the sign and magnitude of analysts' forecast errors, since greater forecast uncertainty is associated with larger absolute forecast errors. Our results suggest that a move from high to low earnings forecast uncertainty is associated with a large increase in the conditional probability of identifying a zero or small positive earnings surprise from 14.0 to 34.6 %. That is, the odds that a firm is identified as meeting or just beating expectations more than double. Similarly, a move from high to low forecast uncertainty more than doubles the likelihood that a firm is identified as meeting or just beating instead of missing expectations.

Overall, these findings provide strong support for our hypothesis and suggest that variation in strategic analyst-forecast pessimism may explain the systematic tendency of firms to report zero and small positive earnings surprises. This conclusion follows from our conceptual reasoning in Sect. 2, which suggests that variation in earnings forecast uncertainty allows us to empirically identify variation in the analysts' role in shaping small earnings surprises. Our findings are particularly important for studies that use zero and small positive earnings surprises as a screen for earnings management, since variables of interest are often correlated with a firm's information environment. Because earnings forecast uncertainty also relates to the information environment, omitted correlated variable problems are likely to arise if uncertainty is not controlled for. We illustrate this issue in the following section.

4.3 Implications for research

We illustrate the implications of controlling for forecast uncertainty for relations between earnings surprises and three variables identified as constraints on managers' ability to manage earnings: balance sheet "bloat" (Barton and Simko 2002), the fourth fiscal quarter (Brown and Pinello 2007), and analyst cash flow forecasts (McInnis and Collins 2011).²² If these variables capture constraints on

²² We *extend*, rather than replicate, these studies to illustrate the potential implications of our findings. While Barton and Simko (2002) and Brown and Pinello (2007) focus on the association between earnings management constraints and nonnegative earnings surprises, we focus on zero and *small* positive surprises. In untabulated tests, we find the results of Barton and Simko (2002) and Brown and Pinello (2007) to be robust when using an indicator for nonnegative earnings surprise as dependent variable and controlling for forecast dispersion. Barton and Simko (2002) control for dispersion, while Brown and Pinello (2007) control for the absolute forecast error. McInnis and Collins (2011) examine differences in



 $^{^{21}}$ To further gauge the strength of our findings, we also ran (untabulated) quarterly logit regressions. Out of the 84 quarterly estimations, the coefficient on dispersion in the model explaining *Just beat versus just miss* incidence is negative in 83 cases and significantly negative (p value <0.05) in 74 cases.

earnings management *and* our dependent variables for zero and small positive earnings surprise incidence measure variation in earnings management, we should observe negative associations between the constraint variables and our dependent variables. However, these variables are also conceptually related to earnings forecast uncertainty.

Barton and Simko (2002) suggest that prior-period earnings management translates from the income statement to the balance sheet as an overstatement of net operating assets. A firms' ability to manage earnings upward is therefore constrained by the level of overstated net operating assets (balance sheet "bloat"). At the same time, balance sheet bloat is expected to be positively related to forecast uncertainty because past earnings management deteriorates the quality of earnings. Prior studies such as Rajgopal and Venkatachalam (2011) provide evidence suggesting that earnings quality negatively relates to forecast dispersion.

Because the fourth fiscal quarter is subject to the annual audit, prior research suggests that firms are more constrained in their ability to manage earnings in the fourth quarter (Brown and Pinello 2007). At the same time, fourth quarter earnings are likely to be more difficult to forecast, given relatively more unpredictable year-end accounting adjustments. Consistent with this notion, Mikhail et al. (1997) document significantly less accurate analyst forecasts in the fourth fiscal quarter. Lastly, McInnis and Collins (2011) suggest that analysts' initiation of cash flow forecasts constrains managers' ability to manage earnings to meet or beat expectations. However, DeFond and Hung (2003) show that analysts are more likely to forecast cash flows when earnings are volatile and difficult to predict.

Table 4, Panel A, presents descriptive statistics confirming that each of the three earnings management constraint variables (continuous variable BLOAT, the indicator variable Q4, and an indicator variable for cash flow forecasts, CFF) is positively correlated with forecast dispersion. Mean dispersion is substantially higher for firms in the highest quartile of balance sheet bloat (4.76) compared to firms in the other three quartiles (3.45). The fourth fiscal quarter (Q4) is associated with higher mean dispersion (4.06) than the other three quarters (3.68). Lastly, average DISP for quarters with cash flow forecasts (4.43) is substantially higher compared to firm-quarters without such forecasts (3.25).

Panel B presents results of testing the relations of *BLOAT*, *Q4*, and *CFF* with our dependent variables without controlling for dispersion but including our main set of control variables. Consistent with the conjecture that balance sheet bloat constrains firms' ability to meet or just beat expectations, the coefficients on *BLOAT* are significantly negative in the first and third specifications. Similarly, coefficients on *Q4* are significantly negative, suggesting it is more difficult to meet or just beat

²³ All differences in dispersion are statistically significant. The significant positive associations between *DISP* and *BLOAT*, *Q4*, and *CFF* are robust to controlling for our firm characteristic control variables in a multiple OLS regression.



Footnote 22 continued

the frequency of nonnegative earnings surprises around analysts' cash flow forecast initiations. We examine differences in the frequency of zero and small positive earnings surprises between firms with and without cash flow forecasts. McInnis and Collins (2011) control for forecast uncertainty by matching their treatment and control firms using earnings volatility as one of the covariates.

BLOAT quartile	Mean DISP	Fiscal quarter	Mean DISP	Cash florecas		Mean DISP
Panel A: Relation	between fore	cast dispersion ar	ıd variables	for constraints	on earnings	s management
1	3.60	1	3.71	0		3.25
2	3.32	2	3.60			
3	3.43	3	3.74	1		4.43
4	4.76	4	4.06			
Logit regression						
Dependent variable	Just be versus	at (1) just miss (0)	Meet/just versus ali	beat (1) l other (0)	Meet/just versus mi	٠,
	Coeff.	z-stat	Coeff.	z-stat	Coeff.	z-stat
Panel B: Relation controls	between earn	ings management	constraints	and meeting/ju	st beating be	efore dispersio
	between earn		constraints 0.000	and meeting/ju: 0.17	st beating be -0.012	efore dispersion -4.30***
controls		-5.90***				•
controls BLOAT	-0.016	-5.90*** -3.08***	0.000	0.17	-0.012	-4.30***
controls BLOAT Q4	-0.016 -0.110	-5.90*** -3.08***	0.000 -0.091	0.17 -3.53***	-0.012 -0.188	-4.30*** -6.84***
controls BLOAT Q4 CFF	-0.016 -0.110 -0.017	-5.90*** -3.08*** -0.39	0.000 -0.091	0.17 -3.53*** -2.78***	-0.012 -0.188	-4.30*** -6.84*** -2.52**
controls BLOAT Q4 CFF Control variables	-0.016 -0.110 -0.017	-5.90*** -3.08*** -0.39 Included	0.000 -0.091	0.17 -3.53*** -2.78*** Included	-0.012 -0.188	-4.30*** -6.84*** -2.52** Included
controls BLOAT Q4 CFF Control variables Quarter fixed effe	-0.016 -0.110 -0.017	-5.90*** -3.08*** -0.39 Included Included	0.000 -0.091	0.17 -3.53*** -2.78*** Included Included	-0.012 -0.188	-4.30*** -6.84*** -2.52** Included Included
controls BLOAT Q4 CFF Control variables Quarter fixed effe	-0.016 -0.110 -0.017	-5.90*** -3.08*** -0.39 Included Included 38,610 0.042	0.000 -0.091 -0.092	0.17 -3.53*** -2.78*** Included Included 116,839 0.058	-0.012 -0.188 -0.099	-4.30*** -6.84*** -2.52** Included Included 64,708 0.094
controls BLOAT Q4 CFF Control variables Quarter fixed effe n Pseudo R ² Panel C: Relatior controls	-0.016 -0.110 -0.017	-5.90*** -3.08*** -0.39 Included Included 38,610 0.042 ings managemen.	0.000 -0.091 -0.092	0.17 -3.53*** -2.78*** Included Included 116,839 0.058	-0.012 -0.188 -0.099	-4.30*** -6.84*** -2.52** Included Included 64,708 0.094
controls BLOAT Q4 CFF Control variables Quarter fixed effe n Pseudo R ² Panel C: Relatior controls	-0.016 -0.110 -0.017 ects	-5.90*** -3.08*** -0.39 Included Included 38,610 0.042 ings managemen5.08***	0.000 -0.091 -0.092	0.17 -3.53*** -2.78*** Included Included 116,839 0.058 and meeting/ju	-0.012 -0.188 -0.099	-4.30*** -6.84*** -2.52** Included Included 64,708 0.094 after dispersio
controls BLOAT Q4 CFF Control variables Quarter fixed effe n Pseudo R ² Panel C: Relation controls BLOAT	-0.016 -0.110 -0.017 ects	-5.90*** -3.08*** -0.39 Included Included 38,610 0.042 ings management -5.08*** -1.44	0.000 -0.091 -0.092 t constraints	0.17 -3.53*** -2.78*** Included Included 116,839 0.058 and meeting/ju	-0.012 -0.188 -0.099	-4.30*** -6.84*** -2.52** Included Included 64,708 0.094 after dispersio -3.80***
controls BLOAT Q4 CFF Control variables Quarter fixed effen Pseudo R ² Panel C: Relation controls BLOAT Q4	-0.016 -0.110 -0.017 ects -0.015 -0.053	-5.90*** -3.08*** -0.39 Included Included 38,610 0.042 ings managemen5.08*** -1.44 0.62	0.000 -0.091 -0.092 t constraints 0.006 0.022	0.17 -3.53*** -2.78*** Included Included 116,839 0.058 and meeting/ju 3.35***	-0.012 -0.188 -0.099 ust beating a -0.008 -0.024	-4.30*** -6.84*** -2.52** Included Included 64,708 0.094 utter dispersio -3.80*** -0.93

Analyses are based on a reduced sample of 116,839 firm-quarters with available data to compute *BLOAT*. See Table 1 for sample selection details and the "Appendix" for variable descriptions. Test statistics are calculated using standard errors adjusted for two-way clustering by firm and quarter. ***, **, and * reflect statistical significance at the level of 0.01, 0.05, and 0.10, respectively

Included

116,839

0.138

Included

64,708

0.213

Included

38,610

0.068

expectations in the fourth fiscal quarter. The coefficient on *CFF* is significantly negative in the second and third specifications, suggesting the ability to meet or just beat expectations is constrained by analysts' cash flow forecasts.

In Panel C, we control for dispersion and no longer find negative significant coefficients for five out of seven cases that were significantly negative in Panel B. For *BLOAT*, the coefficient in the meet/just beat specification even switches from statistically insignificant to significantly positive. For *Q4* and *CFF*, all coefficient estimates turn insignificant after we control for dispersion. These findings highlight



Quarter fixed effects

Pseudo R2

that, given our previous findings on the importance of forecast uncertainty in explaining the incidence of zero and small positive earnings surprises, researchers should consider controlling for forecast uncertainty when examining variables that capture the incidence of small positive (and zero) earnings surprises.

5 Additional analyses

5.1 Alternative uncertainty measure

To assess the robustness of our main findings, we introduce a different measure of earnings forecast uncertainty. Specifically, we measure the uncertainty component of each analyst's private information by computing the average individual (relative) forecast ability of analysts in the consensus. For each firm-quarter, we first identify the individual analysts that contribute to a consensus forecast. For each of these analysts, we calculate the fraction of all their absolute forecast errors over the preceding 5 years (excluding forecasts for firm *i*) that exceeded the median absolute consensus forecast error. We then define a new variable, *INACCR*, as the firm-quarter average of these figures across the individual analysts that contribute to the consensus forecast for the current firm-quarter.

Panel A of Table 5 replicates the descriptive analysis of Table 2, Panel B, for our alternative measure of earnings forecast uncertainty. We compute the quarterly decile rank of this variable to enhance the interpretation of the variation in this variable. Consistent with results for dispersion, the 0 and +1 cent surprise bins are associated with the lowest level of earnings forecast uncertainty based on our alternative measure. In addition, average *INACCR* is significantly lower for small positive earnings surprises, which confirms the prediction that firms are more likely to report earnings that just beat expectations when analysts' information is more precise.

Panel B presents results of replicating our main tests using the alternative measure. The coefficient on *INACCR* is significantly negative in each of the estimations. For instance, results for the *Just beat versus just miss* specification suggest that firms characterized by low uncertainty due to analysts' (lack of) private information (*INACCR*) are significantly more likely to report earnings that just beat rather than just miss expectations. Overall, we conclude that these findings are consistent with our results using forecast dispersion, and that they further support our interpretation that variation in the precision of analysts' information has important implications for the likelihood of identifying firms reporting a (zero or) small positive earnings surprise.

5.2 Earnings management as alternative explanation

The findings in Kinney et al. (2002) suggest that ERCs are substantially greater when forecast dispersion is relatively low. This could imply that managers have greater incentives to manage earnings to meet expectations when dispersion is



Table 5 Earnings forecast uncertainty measured by analysts' relative information imprecision

SURPRISE						Mean	Mean	Diff.
≦-3 -2	-1	0	1	2	≧3	+1¢ or +2¢ surprise	−1¢ or −2¢ surprise	

Panel A: Average rank of relative analyst information imprecision across earnings surprise bins

INACCR 6.143 5.589 5.292 4.868 4.905 5.051 5.773 4.967 5.405 -0.438***

Logit regression						
Dependent variable	Just beat versus jus	(1) st miss (0)	Meet/just versus ali	beat (1) tother (0)	Meet/just versus mi	. ,
	Coeff.	z-stat	Coeff.	z-stat	Coeff.	z-stat
Panel B: Logit regress	sion results v	vith alternative	measure			
INACCR	-0.047	-9.99***	-0.081	-20.40***	-0.096	-19.79***
Control variables		Included		Included		Included
Quarter fixed effects		Included		Included		Included
N		39,227		118,730		65,809
Pseudo R ²		0.044		0.066		0.104

See Table 1 for sample selection details and the "Appendix" for variable descriptions. *INACCR* is the decile rank of a firm-quarter measure based on the past relative (to other analysts in the consensus) absolute forecast inaccuracy of individual analysts. A higher rank implies that the consensus is composed by analysts with relatively lower (ex ante) information precision. Test statistics are calculated using standard errors adjusted for two-way clustering by firm and quarter. ***, **, and * reflect statistical significance at the level of 0.01, 0.05, and 0.10, respectively

low.²⁴ If earnings management would explain our main findings, we should observe (1) a significantly positive association between our dependent variables and variables for earnings management, and (2) a significantly stronger (i.e., more negative) relation between dispersion and our dependent variables in cases where earnings management is observed. We test this alternative story in Panel A of Table 6.

We measure earnings management using an indicator variable (AAER) that captures whether a firm-quarter is identified as materially overstated in an SEC Accounting and Auditing Enforcement Release (AAER) based on the extended dataset of Dechow et al. (2011). Panel A of Table 6 shows that this AAER indicator is significantly positively associated with the meet/just beat classification (Meet/just beat vs. all other) but not with the incidence of a small positive versus a small negative earnings surprise. Focusing on the interactions of dispersion with AAER, we find that none of the coefficients is significantly negative. These results are not

²⁴ Payne and Robb (2000) argue that managers have more incentives to manage earnings to meet analyst expectations when dispersion is low. They find a significant negative association between dispersion and discretionary accruals and conclude that firms use more income-increasing earnings management tactics when dispersion is low. However, the results of their tests do not support their additional conjecture that firms use more income-increasing discretionary accruals to meet or beat expectations when dispersion is low.



Table 6 Earnings management and expectations management as alternative explanations

Logit regression						
Dependent variable	Just beat versus jus	(1) st miss (0)	Meet/just versus all	beat (1) tother (0)	Meet/just versus mi	
	Coeff.	z-stat	Coeff.	z-stat	Coeff.	z-stat
Panel A: Earnings ma	anagement as	s moderating fac	ctor based o	n AAERs		
ln(DISP)	-0.565	-22.48***	-0.882	-52.63***	-1.122	-52.48***
AAER	-0.078	-0.61	0.208	2.18**	0.093	0.81
ln(DISP)*AAER	-0.203	-1.30	0.035	0.33	-0.027	-0.20
Control variables		Included		Included		Included
Quarter fixed effects		Included		Included		Included
n		28,287		78,101		45,898
Pseudo R ²		0.079		0.137		0.218
Panel B: Expectation	s managemen	nt as moderating	g factor base	ed on public ear	rnings guida	nce
ln(DISP)	-0.456	-14.71***	-0.811	-41.91***	-0.993	-33.37***
GUIDE	0.166	4.01***	0.137	5.34***	0.379	10.25***
ln(DISP)*GUIDE	-0.191	-4.89***	-0.008	-0.31	-0.106	-2.84***
Control variables		Included		Included		Included
Quarter fixed effects		Included		Included		Included
n		26,137		83,103		43,689
Pseudo R ²		0.057		0.131		0.207

See Table 1 for sample selection details and the "Appendix" for variable descriptions. In Panel A, AAER is an indicator variable capturing whether or not the firm-quarter had a material misstatement as identified in an SEC Accounting and Auditing Enforcement Release (AAER). The AAER data are based on misstatements which originally resulted in an overstatement of net income. AAER is set to missing for fiscal quarters after 2007 due to limited data coverage. In Panel B, GUIDE is an indicator capturing whether management issues earnings guidance for the fiscal-quarter end. This variable is used only for fiscal quarters ending in the post-Reg FD period (i.e., fiscal quarters ending in November 2000 and later) in order to capture public guidance. The interaction variables in Panels A and B are computed based on mean-adjusted main effects to reduce the influence of multicollinearity. Test statistics are calculated using standard errors adjusted for two-way clustering by firm and quarter. ****, ***, and * reflect statistical significance at the level of 0.01, 0.05, and 0.10, respectively

consistent with the conjecture that our documented negative relation between dispersion and small earnings surprise incidence is explained by earnings management.²⁵

²⁵ In untabulated analyses, we also used alternative earnings-management variables based on restatements. Specifically, we used indicator variables that capture whether the firm-quarter was misstated as identified in a subsequent restatement, based on the Audit Analytics Non-Reliance Restatement database. The key difference between the two variables is that the first captures all restatements, while the second captures more severe restatements as indicated by SEC investigation, indications of fraud, and class action lawsuits. For both restatement variables, we also find no significant negative coefficients.



5.3 The role of expectations management

Our study relates to research that suggests managers try to walk down analyst expectations with guidance (i.e., expectations management). For instance, Cotter et al. (2006) find that guidance reduces forecast dispersion and increases the likelihood that firms meet or beat analyst expectations. Note, however, that our prediction and findings should also hold in the absence of guidance. Uncertainty before earnings announcements varies for reasons other than guidance, leading to the same conceptual prediction that high uncertainty impairs analysts' ability to slightly understate their forecasts. Moreover, many firms do not issue guidance. Nevertheless, we explore the role of earnings guidance in this section.

We examine the moderating effect of a variable that captures public guidance. If guidance explains our findings, we should observe (1) a more negative association between dispersion and our dependent variables when earnings guidance occurs, and (2) no relation between dispersion and our dependent variables when earnings guidance does not occur. To examine these predictions, we obtain data on public guidance from the I/B/E/S Guidance database. Given data coverage and the importance of public guidance post-Reg FD, we restrict the analyses to the period starting in November 2000 (n = 83,103). ²⁶ Indicator variable *GUIDE* equals 1 for firm-quarters for which earnings guidance was issued and 0 otherwise.

Panel B of Table 6 presents the results of running our main analyses with an interaction term between dispersion and *GUIDE*. The negative and significant coefficient on the interaction term is consistent with earnings guidance contributing to our findings and suggests that guidance could be viewed as one of the mechanisms through which forecast uncertainty predicts the likelihood of a small positive earnings surprise. The coefficient on the interaction term is insignificant in the specification that predicts firms' incidence of zero and small positive surprises. More importantly, the coefficient on dispersion remains strongly negative and significant, which suggests that our results remain strong in cases where guidance is not observed. We conclude that our findings are unlikely to be explained solely by expectations management.

5.4 Other sensitivity analyses

5.4.1 Dispersion as proxy for a moving earnings target

Dispersion could also proxy for the difficulty managers face in managing earnings to meet expectations. If lower dispersion captures a more stable earnings target that is easier to identify, it could be associated with a greater ability to manage earnings.

²⁶ Chuk et al. (2013) investigate the reliability of the widely used I/B/E/S (previously "CIG") data for public guidance and find that these data suffer from coverage biases. They recommend that researchers limit the use of data from years before 1998 and that they examine subsets of data to determine whether results using the data are driven by coverage bias. Our focus is on post-Reg FD, which is consistent with the first recommendation. Following the second recommendation, we find our results to be qualitatively similar if we split our sample based on median analyst coverage. This suggests our results are not likely to be driven by data coverage biases.



To test this conjecture, we construct a new variable based on the variability in the consensus forecast in the period before each firm-quarter's earnings announcement. Specifically, we compute a daily consensus for each of the 360 days before the earnings announcement based on individual forecasts outstanding prior to that day. We construct a variable *TARGETVAR* as a firm-quarter's time series coefficient of variation in the daily changes in the consensus forecast.

If ability to manage earnings explains our findings, we should observe a negative association between *TARGETVAR* and the incidence of small positive earnings surprises. Moreover, this relation should subsume the effect of dispersion. The first regression in Panel A of Table 7 shows that dispersion and *TARGETVAR* are significantly positively related. The second regression confirms the existence of a significant negative association between *TARGETVAR* and the incidence of small positive earnings surprises. However, after including dispersion in the rightmost column, we find the coefficient on dispersion remains strongly negative, while the coefficient on *TARGETVAR* switches from negative to positive. We therefore conclude that it is unlikely that the ability to manage earnings, as a result of variability in the earnings target to meet or beat, explains our main findings.

5.4.2 Dispersion and future firm performance

Minton et al. (2002) show that higher forecast uncertainty firms tend to have lower future operating cash flows and earnings. To the extent that such lower performance is not fully anticipated in analysts' earnings forecasts, our findings could capture the relation between uncertainty and ex post performance. To test this possibility, we split our sample into quartile portfolios, each calendar quarter, based on ex post earnings performance, and estimate our regressions for each of these portfolios. Panel B of Table 7 presents results of these estimations and suggests our findings are robust to partitioning on performance and are not driven by any particular portfolio of performance. We conclude that our findings are not explained by the link between forecast uncertainty and future performance.

5.4.3 Earnings forecast uncertainty and forecast optimism

Prior related research presents evidence on a relation between forecast uncertainty and optimism in longer-horizon forecasts (Ackert and Athanassakos 1997; Das et al. 1998; Lim 2001). With longer-horizon forecasts, managers prefer analysts to be overly optimistic (see the discussion in Sect. 2), and these prior studies conjecture that analysts have more to gain from pleasing managers with forecast optimism when uncertainty is relatively high. To test whether our findings are simply an outcome of the previously documented empirical relation between uncertainty and analysts' forecast optimism, we use the same daily consensus forecasts as in subsection 5.4.1 and analyze the correlation between dispersion and just beating versus just missing over the forecast horizon.

Our prediction on forecast uncertainty and forecast pessimism implies that the negative association between dispersion and small positive earnings surprise incidence should be strongest based on forecasts measured just before the earnings



Table 7 Additional sensitivity tests

	OLS regression	ssion		Logit regression				
Dependent variable	$\ln(DISP)$]	Just beat (1) versus just miss (0)	st miss (0)	Just b	Just beat (1) versus just miss (0)	just miss (0)
	Coeff.	t-stat]	Coeff.	z-stat	Coeff.		z-stat
Panel A: Dispersion a In(TARGETVAR)	Panel A: Dispersion as proxy for a moving earnings target In(TARGETVAR) 0.226 40.53*	arnings target 40.53***	**	-0.029	-2.62***	0.050	20	4.18***
$\ln(DISP)$						-0.544	44	-22.45***
Control variables		Included	led		Included			Included
Quarter fixed effects		Included	led		Included			Included
u		118,730	30		39,227			39,227
Adjusted R ² Pseudo R ²	\mathbb{R}^2	0.311	_		0.041			0.068
Logit regression	Performance quartile 1		Performance quartile 2	quartile 2	Performance quartile 3	quartile 3	Performance quartile 4	e quartile 4
Dependent variable	Just beat (1) versus just miss (0)	tst miss (0)	Just beat (1)	Just beat (1) versus just miss (0)	Just beat (1)	Just beat (1) versus just miss (0)	Just beat (I	Just beat (1) versus just miss (0)
	Coeff. z-stat		Coeff.	z-stat	Coeff.	z-stat	Coeff.	z-stat
Panel B: Dispersion a	Panel B: Dispersion and the role of actual future performance	ture performa	ınce					
$\ln(DISP)$	-0.411 -11.9	-11.92***	-0.608	-14.93***	-0.546	-14.39***	-0.553	-13.06***
Control variables	Included	led		Included		Included		Included
Quarter fixed effects	Included	led		Included		Included		Included
u	9928			11,651		10,995		7815
Pseudo R ²	0.0	0.071		0.087		0.065		0.063
		* 10				2200		

(TARGETVAR). Panel B presents tests partitioned by the firm-quarter's earnings performance, where earnings performance is measured as the actual earnings per share used to construct the earnings surprise, scaled by share price at the end of the previous fiscal quarter. Quartiles are formed each calendar quarter. Test statistics are calculated using standard errors adjusted for two-way clustering by firm and quarter. ***, ***, and * reflect statistical significance at the level of 0.01, 0.05, and 0.10, Panel A presents tests on whether dispersion is merely a proxy for firms' difficulty to manage earnings, based on the variability in the consensus forecast target respectively



announcement. This is because forecast pessimism is desirable for managers *only* for those short-horizon forecasts. If, instead, the negative association between dispersion and small positive earnings surprise incidence is simply an artifact of the positive relation between uncertainty and forecast optimism, we should observe the negative correlation to be driven by longer-horizon forecasts.

Figure 2 plots the cross-sectional correlation between dispersion and an indicator variable for small positive versus small negative earnings surprise incidence for each of the 360 days before the quarterly earnings announcement. The figure shows that the relation between dispersion and small positive earnings surprise incidence is driven by short-horizon forecasts. For longer-horizon forecasts, the correlation is virtually zero. Shortly before the earnings announcement, however, the correlation strengthens to around -0.23. These results are more consistent with the predicted link between uncertainty and pessimism than with a link between uncertainty and optimism. In addition, a plot of the indicator variable for small positive surprise incidence itself reveals that the temporal pattern in small positive earnings surprise frequency virtually mirrors that of the cross-sectional correlations. Overall, we conclude that our findings are not an artifact of the previously documented association between uncertainty and forecast optimism.

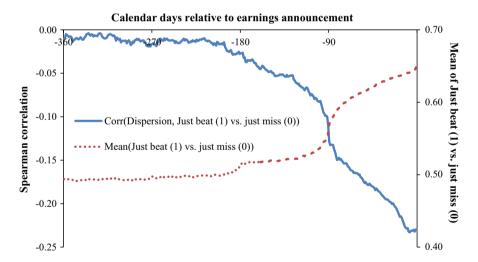


Fig. 2 Additional sensitivity test: Relation between forecast dispersion and small earnings surprises over the forecast horizon. For each day in the period from 360 days to 1 day before the quarterly earnings announcement date, a consensus (mean) forecast is computed based on outstanding individual forecasts. For this purpose, we additionally use individual forecasts with "FPI" equal to 7 (two quarters ahead), 8 (three quarters ahead), 9 (four quarters ahead), and N (five quarters ahead), in order to construct a daily consensus. At each point in time, we remove stale forecasts by including only forecasts made in the most recent 180 days when computing the daily consensus. If multiple forecasts are found by the same analyst for the same firm-quarter, only the last forecast is retained. The figure displays the daily Spearman correlation between dispersion and an indicator variable for small positive earnings surprises of 1 or 2 cents ("just beat") versus small negative earnings surprises of -1 or -2 cents ("just miss")



6 Conclusions

Prior studies link variation in the incidence of zero and small positive earnings surprises to earnings management. We examine an alternative explanation based on strategic analyst forecast pessimism. We argue that earnings forecast uncertainty (i.e., lack of precision in analysts' information signals about a firm's earnings) is negatively associated with analysts' ability to slightly understate their forecasts and help firms meet or just beat expectations. Consistent with this prediction, we show that firms with relatively low forecast uncertainty are significantly more likely to report earnings that just beat rather than just miss analyst expectations. Our results are robust to the inclusion of an array of control variables, the use of an alternative measure of forecast uncertainty, and tests of potential alternative explanations.

Our study contributes to the literature on the interpretation of the asymmetry around zero in the frequency distribution of earnings surprises and provides evidence on a relatively unexplored explanation for the asymmetry based on analysts' forecasts. We highlight the importance of our findings for studies that employ small earnings surprises to measure constructs related to earnings management, and show that controlling for dispersion can materially change inferences in settings where a variable of interest is correlated with uncertainty. Overall, our findings are consistent with the notion that strategic analyst forecast pessimism plays a key role in explaining zero and small positive earnings surprises. These findings matter for researchers that select firms suspected of earnings management based on zero and small positive earnings surprises. Our study suggests that their samples are more likely sorted based on variation in forecast uncertainty than on earnings management.

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Appendix: variable definitions

SURPRISE	Quarterly earnings surprise in cents per share, calculated as the difference between actual earnings per share (EPS) and the mean consensus forecast based on individual analysts' latest EPS forecasts before the quarterly earnings announcement (I/B/E/S fiscal period indicator "FPI" = 6), where actual and forecasts of EPS are both obtained from the I/B/E/S unadjusted detail files and at least three analysts are required to contribute to the consensus; to account for stock splits between the analyst forecast and earnings announcement dates, cumulative stock split factors are obtained from CRSP and merged separately with the forecast and announcement dates; if the cumulative split factor at the forecast date is different from the cumulative split factor at the earnings announcement date, the forecast of earnings per share is multiplied by the ratio of the cumulative price adjustment factor at the announcement date to the cumulative price adjustment factor at the forecast date
Just beat versus just miss	Indicator variable set equal to 1 if <i>SURPRISE</i> equals 1ϕ or 2ϕ per share, 0 if <i>SURPRISE</i> is -1ϕ or -2ϕ per share
Meet/just beat versus all other	Indicator variable set equal to 1 if <i>SURPRISE</i> equals 0¢ or 1¢ per share, 0 otherwise
Meet/just beat versus miss	Indicator variable set equal to 1 if <i>SURPRISE</i> equals 0¢ or 1¢ per share, 0 if <i>SURPRISE</i> is negative
DISP	Standard deviation of individual analysts' latest EPS forecasts before the earnings announcement, in cents per share
MV	Market value of equity at the end of the previous fiscal quarter (COMPUSTAT Fundamentals Quarterly data items "PRCCQ" x "CSHOQ")
BTM	Book-to-market ratio at the end of the previous fiscal quarter, calculated as the book value of equity (COMPUSTAT Fundamentals Quarterly data item "SEQQ") divided by the market value of equity (MV)
GROWTH	Variable capturing the proportion of the most recent eight firm-quarters in which the firm reported positive seasonally-differenced earnings per share (COMPUSTAT Fundamentals Quarterly data item "EPSPXQ" adjusted for "AJEXQ")
ERC	Firm-specific sensitivity of stock price to earnings news, calculated as the ERC (slope coefficient) obtained from rolling time-series regressions of announcement-window abnormal returns (three-day cumulative size-adjusted returns centered around the earnings announcement date from CRSP) on earnings surprise scaled by the stock price 2 days prior to the earnings announcement date (CRSP) using the past 20 firm-quarters (requiring a minimum of eight firm-quarter observations)
MNA	Indicator variable set equal to 1 if an M&A announcement is observed in the 90-day window prior to the quarterly earnings announcement, 0 otherwise (source: Thomson One (formerly SDC Platinum))
SEO	Variable capturing the proportion of the most recent eight firm-quarters in which the firm engaged in seasoned equity offerings (source: Thomson One (formerly SDC Platinum))
INSELL	Variable capturing the proportion of the most recent eight firm-quarters in which the firm's insiders (officers and directors) were net sellers of the firm's stock (source: Thomson Reuters Insider Filing database)
INST	Percentage of outstanding shares held by institutional investors based on 13-F filings (Source: Thomson Reuters Institutional Holdings database)



LAGRET	Prior abnormal stock returns, computed as 60-day cumulative size-adjusted return prior to the earnings announcement (source: CRSP's "erdport1" file)
LAGDQEPS	Quarter <i>t-1</i> seasonally-differenced earnings per share (COMPUSTAT Fundamentals Quarterly data item "EPSPXQ" adjusted for "AJEXQ")
SHRS	Number of shares outstanding at the end of the previous fiscal quarter (COMPUSTAT Fundamentals Quarterly data item "CSHOQ")
PRICE	Stock price at the end of the previous fiscal quarter (COMPUSTAT Fundamentals Quarterly data item "PRCCQ")
SPLIT	Indicator variable set equal to 1 if the company split its stock in the 365 days prior to the earnings announcement (source: CRSP)
NUMEST	Number of analysts contributing to the consensus forecast (source: I/B/E/S)
HORIZON	Age of the consensus forecast, calculated as the mean of the number of days between the earnings announcement date and the individual analyst earnings forecast
AAER	Indicator variable set equal to 1 if the firm-quarter's net income is identified as materially overstated in an AAER, based on the extended sample of Dechow et al. (2011), 0 otherwise; variable is set to missing for fiscal quarters after 2007 due to limited data coverage
GUIDE	Indicator variable set equal to 1 if public earnings guidance is observed for the firm-quarter, 0 otherwise (source: I/B/E/S); variable is used only for fiscal quarters ending in the period after Reg FD (2000:11 through 2013:12)
BLOAT	Variable capturing balance sheet bloat, calculated as the ratio of previous quarter net operating assets (NOA) to lagged sales (COMPUSTAT Fundamentals Quarterly data item "SALEQ"), where NOA equals shareholders' equity (COMPUSTAT Fundamentals Quarterly data item "SEQQ") less cash and cash equivalents (COMPUSTAT Fundamentals Quarterly data item "CHEQ") plus total debt (sum of COMPUSTAT Fundamentals Quarterly data items "DLCQ" and "DLTTQ")
Q4	Indicator variable set equal to 1 for the fourth quarter in the fiscal year, 0 otherwise
CFF	Indicator variable set equal to 1 if at fiscal-quarter-end at least one analyst forecast of quarterly or annual cash flow per share is available in the I/B/E/S summary file, 0 otherwise
INACCR	Quarterly decile rank of a firm-quarter measure of the average past (relative) forecast inaccuracy of analysts that contribute to the current consensus forecast, calculated as the firm-quarter mean of a variable that captures the fraction of all forecast errors by an individual analyst over the preceding five-year period (excluding the firm of interest) which are greater in absolute value than the median firm-quarter individual forecast error
TARGETVAR	Firm-quarter specific measure of earnings target variability, measured as the time series coefficient of variation in daily changes in the consensus forecast, where the consensus forecast is constructed for each day in the 360-day period prior to the firm-quarter's earnings announcement; we additionally use individual forecasts with "FPI" equal to 7 (two quarters ahead), 8 (three quarters ahead), 9 (four quarters ahead), and N (five quarters ahead) to construct a daily consensus; at each point in time, we remove stale forecasts by including only forecasts made in the most recent 180 days when computing the daily consensus; if multiple forecasts are found by the same analyst for the same firm-quarter, only the most recent forecast is retained



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