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Management Forecast Consistency

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ABSTRACT

We posit that management forecasts, which are predictable transformations of realized earnings without random errors, are more informative than unbiased forecasts, which manifest small but unpredictable errors, even if biased forecasts are less accurate. Consistent with this intuition, we find that managers who make consistent forecasting errors have a greater ability to influence investor reactions and analyst revisions, even after controlling for the effect of accuracy. This effect is more economically significant and statistically robust than that of forecast accuracy. More sophisticated investors and experienced analysts are found to have a better understanding of the benefits of consistent management forecasts.

1. *Introduction*

Managers issue earnings forecasts to set or alter market earnings expectations, to preempt litigation concerns, and to be seen as a source of transparent and accurate reporting. Indeed, the voluntary disclosure of financial information through management forecasts is an important part of the information environment surrounding the firm and its managers (Hirst, Koonce, and Venkataraman [2008]). The extent to which management forecast characteristics affect price formation as well as managers' career

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development has been extensively researched. Many studies use forecast accuracy (the absolute value of the difference between the forecast and realized earnings) to assess forecast quality or even management ability, concluding that more accurate managers/firms exert a greater influence on price and analyst opinions (Williams [1996], Yang [2012]), and experience lower CEO turnover (Lee, Matsunaga, and Park [2012]).

This is a very intuitive starting point. However, we argue that forecasts that are a predictable transformation of realized earnings without random error are more informative than unbiased forecasts with a small unpredictable error even if biased forecasts are less accurate. Specifically, if investors are Bayesian, a forecast's usefulness will be based on the volatility of forecast errors (i.e., the precision of the signal to use the Bayesian terminology). In other words, the usefulness of a management forecast is based not on its accuracy but its consistency.[1]

To illustrate our point, consider two managers issuing earnings forecasts. Manager A's forecasts are consistently three cents below realized earnings, whereas Manager B's forecasts are one cent below realized earnings half of the time, and one cent above the other half of the time. We contend that investors will prefer Manager A's forecasts because they have more predictable forecast errors, even though Manager B's forecasts are more accurate than A's.

Consistent with our predictions, we find that managers who make consistent forecast errors have a greater ability to move prices and analyst forecast revisions, even after controlling for the effect of accuracy. This result is both economically and statistically significant. Consistent with prior research, we find that forecast accuracy increases management's ability to move prices and analyst forecasts when we fail to control for the effect of consistency. However, the statistical significance of accuracy typically disappears when we control for consistency. The economic significance of the effect of consistency is approximately two to five times greater than that of accuracy. Similarly, the statistical significance of the effect of consistency is stronger than that of accuracy. The difference between the point estimates of the two effects is statistically significant. Our findings are robust to the adjustment to alternative definitions of systematic bias in management and analyst forecasts (e.g., Rogers and Stocken [2005]), to the identification of non-ExecuComp executives (Rogers and Van Buskirk [2009]), and to the use of forecasts that were "bundled" with earnings announcements (Rogers and Van Buskirk [2013]). They also hold after controlling for a host of potential confounds (e.g., Jennings [1987], Baginski, Conrad, and Hassell [1993], Rogers, Skinner, and Van Buskirk [2009], Kross, Ro, and Suk [2011]). Further, consistent with a Bayesian framework, we establish that investors and analysts filter systematic bias in management forecasts more easily when they are more consistent.

[1] Hilary and Hsu [2013] advance a similar argument in the context of analyst forecasts.

We next consider cross-sectional differences in reactions to a management forecast by examining whether the degree of users' sophistication affects their understanding of forecast properties. Our empirical results indicate that this is indeed the case and that sophisticated users behave in a way that is closer to the one predicted by a Bayesian framework. Specifically, institutional investors and experienced analysts react more to consistent forecasts than retail investors and inexperienced analysts. The opposite is true for accurate forecasts. We then examine the effect of the size of the bias. To the extent that users are more likely to detect and correct for biases that are larger (in absolute value), and hence more visible, we expect investors and analysts to value consistency rather than accuracy in the presence of large but predictable deviations from realized earnings. Our empirical results confirm this. Specifically, the effect of consistency on investor reactions and analyst revisions is more significant when bias is more visible (i.e., larger).

Our study contributes to the field in several ways. First, while existing research on management earnings forecasts mainly focuses on absolute forecast error when assessing the quality of management guidance, we shift the focus from the *magnitude* of error (accuracy) to the *volatility* of error (consistency). We posit that, if forecast users are Bayesian, consistency should be a key dimension for measuring the quality of a management forecast. Indeed, our evidence supports the notion that consistency is an important (and incremental) measure of the influence of management forecasts (i.e., the capacity to move the recipient's prior), one that has been largely ignored so far. Our findings extend prior research, which shows that the market predicts and filters bias from management earnings forecasts (Rogers and Stocken [2005]).

Second, although our results suggest that user behavior is consistent with a Bayesian model on average, it may be that less sophisticated subgroups behave in a different way. Our results indicate that this is indeed the case: less sophisticated users, such as retail investors and inexperienced analysts, value accuracy more than consistency in forecasts. These findings are potentially valuable for regulators interested in understanding the tradeoffs associated with biased forecasts among different types of users. This issue is particularly pertinent given the findings of Rogers and Stocken [2005, p. 1234] that, "extant market forces are insufficient to deter managers from offering self-serving forecasts."

Third, our study contributes to the literature on downward biases in management forecasts. We note that the large majority of managers are downward biased in their quarterly forecasts. While previous studies have shown that managers guide analysts' expectations downwards by issuing pessimistic quarterly forecasts (Matsumoto [2002], Kross, Ro, and Suk [2011]), there is scant research on how managers trade off forecast accuracy for "lowballing" without compromising the quality of their forecasts. We show that the bias is not necessarily detrimental to the influence of their forecasts as long as it is identifiable and predictable, where users are concerned. Indeed, our comparative statistics suggest that managers skilled enough to be consistent in their forecast errors may have an incentive to prompt a large (downward) bias to signal their type more clearly.

The remainder of the paper is organized as follows. In section 2, we develop our hypotheses. Section 3 describes the empirical design and the sample. In section 4, we present our main empirical results, whereas section 5 examines cross-sectional differences in user reactions to management forecasts. Section 6 offers our conclusions on the study.

2. *Hypotheses Development*

Previous research postulates that more accurate managers have a greater ability to move price and analyst opinions (Williams [1996], Yang [2012]). Tan, Libby, and Hunton [2002] suggest that forecast accuracy captures management's ability to process information. These studies suggest that management's reputation is based on the accuracy of its forecasts and that the accuracy of prior earnings forecasts serves as an indicator of the "believability" of a current management forecasts.

Accuracy, bias, and consistency, while all related to forecast error, represent different properties of management forecasts, with various implications for forecast informativeness. Accuracy is the absolute forecast error and does not consider uncertainty in management forecasts that arises from the volatility of past error; bias is the (average) signed forecast error, and consistency is the standard deviation of the signed forecast error. Consistency (i.e., the precision of the signal to use the Bayesian terminology) can mitigate the limitations of forecast accuracy by capturing the uncertainty in a management forecast. Therefore, if users of management forecasts can identify and correct for systematic bias, then it should be irrelevant when updating earnings forecasts. Hence, "Bayesian" investors and analysts will consider management forecasts of higher consistency to be more informative since they are a more predictable estimate of realized earnings than their less consistent counterparts.

To illustrate this intuition, let us revisit our earlier example. Manager A's forecasts are always three cents below realized earnings, while those of Manager B are either one cent below or above realized earnings. The two sets of forecasts have the same accuracy but different implications for earnings predictability. Intuitively, Manager A will introduce less noise in assessing management forecast quality than Manager B even though Manager A is more biased. Now, let us assume that prior to a management forecast, investors and analysts expect earnings to be $0.50 per share in the current quarter. Manager A issues a forecast of $0.48 per share, and "rational" users update their own forecasts to $0.51, with a degree of confidence in their earnings estimate. In contrast, when users respond to a similar forecast by Manager B, they are working with the classic signal-to-noise problem. They will revise their own forecast downward but dampen their negative response to the forecast and have less confidence in their estimate compared to a manager who has a reputation for being more consistent.

This discussion leads to testable hypotheses. Specifically, we expect consistent estimates to have a greater impact on investors' and analysts' prior expectations than estimates with inconsistent random errors, and hence to prompt larger price reactions and analyst revisions (given the distance between the new forecast, adjusted for the predictable bias, and prior expectations). This leads to our main hypotheses:

H1a: Earnings forecasts (adjusted for the predictable bias) made by managers who are more consistent in their forecast errors have a greater effect on prices than forecasts made by managers who are less consistent.

H1b: Earnings forecasts (adjusted for the predictable bias) made by managers who are more consistent in their forecast errors have a greater effect on analyst revisions than forecasts made by managers who are less consistent.

We note that, if investors are Bayesian, any systematic bias in the forecast is irrelevant after, perhaps, a learning period. The choice of the bias is a priori arbitrary and there is a multiplicity of possible equilibria in which an arbitrary bias is chosen by managers and undone by users. However, managers may want to demonstrate a bias that is aligned with the initial prior of the users. We note that very few managers issue quarterly forecasts with an upward bias. This may prompt users to expect new managers to issue a downward bias, and, in turn, lead to the marginal manager issuing a downward bias to conform to expectations.[2]

3. *Empirical Design and Sample*

3.1 EMPIRICAL DESIGN

To test our hypotheses, we estimate the following regressions:

$$\begin{aligned} ARET_{i,t} = a_0 + a_1 NEWS_{i,t} + a_2 CONS_{i,t} + a_3 ACCU_{i,t} + a_4 CONS_{i,t} \\ \times NEWS_{i,t} + a_5 ACCU_{i,t} \times NEWS_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

$$\begin{aligned} AFREV_{i,j,t} = b_0 + b_1 NEWS_{i,t} + b_2 CONS_{i,t} + b_3 ACCU_{i,t} + b_4 CONS_{i,t} \\ \times NEWS_{i,t} + b_5 ACCU_{i,t} \times NEWS_{i,t} + \varepsilon_{i,t}. \end{aligned} \tag{2}$$

[2] The reason the system evolves to this specific equilibrium is beyond the scope of this study. However, we note that, if managers derived some benefits out of exceeding their forecasts when forecasts were first issued, the starting point for the system may be a downward bias. This could be the case, for example, if users of management forecasts were unsophisticated and functionally fixated on the forecasts when these forecasts first appeared.

We test H1a using model (1) and H1b using model (2). In model (1), $ARET_{i,t}$ is the three-day size-adjusted stock return around the management forecast announcement by CEO i for quarter t.[3] In model (2), $AFREV_{i,j,t}$ is analyst j's forecast revision scaled by the stock price at the beginning of quarter t. An individual forecast revision is defined as the difference between the first forecast of an analyst issued within 30 days after the management forecast date and the last one issued by the same analyst up to 90 days before that date.[4]

To measure forecast consistency and accuracy, we construct two variables: *CONS* and *ACCU*. Following Williams [1996] and Hutton, Lee, and Shu [2012], we benchmark managerial forecast relative to the analyst forecasts. We define *CONS* as an indicator variable that equals one if the standard deviation of the management forecast errors (*STDMFE*) is less than the standard deviation of the consensus analyst forecast errors over the last two years before the current management forecast (*STDAFE*), and zero otherwise. A higher *CONS* score thus implies that the CEO is more consistent.

We define *ACCU* as an indicator variable that equals one if the absolute value of the management forecast error is less than the absolute value of the consensus analyst forecast error more than half of the time in the two prior years, and zero otherwise. A higher *ACCU* score thus implies that the CEO is more accurate. We use a two-year period to calculate *CONS* and *ACCU* to be consistent with Hilary and Hsu [2013].

Forecast news, *NEWS*, represents the information contained in the management forecast. We consider alternative definitions of this variable. We start with *NEWS_Raw*, which is equal to the management forecast of earnings-per-share (EPS) less the median analyst estimate prevailing on the day of the management forecast scaled by the stock price at the beginning of the quarter. However, we mainly use *NEWS_Raw* for descriptive statistics because prior research suggests that management forecasts are systematically biased (Rogers and Stocken [2005], Kross, Ro, and Suk [2011]).

To adjust for this bias, we next define *NEWS_FixAdj*. As a starting point, we estimate the management forecast bias *MF_FixBias* using the averaged value of management forecast error (*MFE*, defined as the managerial forecast minus realized earnings, scaled by price at the beginning of the quarter) for a given CEO.[5] We subtract *MF_FixBias* from *NEWS_Raw* to obtain *NEWS_FixAdj*, that is, $NEWS\_FixAdj = NEWS\_Raw - MF\_FixBias$.

[3] Our results are not affected if we use market-adjusted returns instead of size-adjusted returns.

[4] Our empirical results are unaffected when we deflate an individual analyst's revision by the stock price at two days before the current management forecast, or two days after the prior quarter's earnings announcement, or when we use the (–90, 10) window instead of the (–90, 30) window to define the revision. Results from model (2) also hold if we further control for contemporaneous events besides the management forecasts by including *ARET* in the specification.

[5] This approach implicitly assumes that CEOs are the individuals making the forecasts or at least that they play a significant role in the process. Bamber, Jiang, and Wang [2010] suggest this assumption is a reasonable approximation.

Hilary and Hsu [2013] show that using a fixed effect is a good approximation of analysts bias, while Bamber, Jiang, and Wang [2010] and Yang [2012] imply that manager fixed effects may capture systematic differences in managers' unique disclosure styles. However, Rogers and Stocken [2005] suggest that certain variables can provide cross-sectional and time-series variations in management bias. To address this point, we estimate *MF_Bias* as the fitted value of a specification regressing management forecast error on a vector of explanatory variables (Rogers and Stocken [2005]). We subtract *MF_Bias* from *NEWS_Raw* to obtain *NEWS_Adj*. We provide additional details on the methodology to obtain *MF_Bias* in appendix A. Although we treat this specification as our baseline, results typically hold across the different definitions of *NEWS*.

Rogers and Van Buskirk [2013] argue that "nonbundled" forecasts make up a small fraction of all forecasts and have substantially different properties from "bundled" forecasts (i.e., management earnings forecasts issued concurrently with earnings announcements). To address this issue, we follow the approach described in their study when we calculate *NEWS_Raw*, *NEWS_FixAdj*, and *NEWS_Adj*. In essence, we adjust the forecasts for the fact that the choice of issuing "bundled" or "nonbundled" forecast is not random by predicting the likelihood of issuing a bundled forecast based on a vector of observable characteristics (we provide additional details on this methodology in appendix A). Our main conclusions are not affected if we do not use this adjustment (untabulated results).

We interact *NEWS* with *CONS* and *ACCU*. Our main hypothesis is that investors and analysts react more to consistent forecasts. We, therefore, predict that the coefficient associated with the interaction between *CONS* and *NEWS* should be significantly positive. H1a predicts that a_4 is positive in model (1), and H1b predicts that b_4 is positive in model (2). We do not have formal hypotheses regarding the effect of *ACCU* once we have controlled for the effect of consistency. However, it is not clear what the role of accuracy should be in this context if investors are Bayesian.

Except for the indicator variables, all of the variables are winsorized at 1% in either tail of the distribution to remove the effects of outliers and extreme misrecorded data. We adjust the standard errors for heteroskedasticity and the clustering observations by CEO and quarter in model (1), and by CEO, analyst, and quarter in model (2) (Cameron, Gelbach, and Miller [2011]).

3.2 DATA

Our sample is taken from the management forecasts of quarterly EPS in the First Call database over the 2002–2010 period. To obtain a reliable measure of forecast consistency, we further require that each manager issue forecasts for at least six quarters over the previous two years, and that the firm's CEO is the same manager during the period when these forecasts were made.[6] Chuk, Matsumoto, and Miller [2013] document the presence of several problems with the First Call's Company Issued Guidance (CIG) database, but these are mitigated by both the time-series and cross-sectional characteristics of our sample. First, Chuk, Matsumoto, and Miller [2013] indicate that the problems in the First Call database are largely concentrated in the pre-1997 period, whereas our sample period starts in 2002.[7] Second, we require at least six management forecasts for each CEO—it is unlikely that CIG omits a given CEO, who issues a series of forecasts (Christensen et al. [2011] make a similar point).

We obtain CEO information from the ExecuComp database. In addition, we follow Rogers and Van Buskirk [2009] and extract CEO information from the Thomson Financial Insider Trading database and the Securities and Exchange Commission's (SEC) EDGAR database (we provide additional details on this procedure in appendix A).[8] We match our forecast data with the corresponding First Call reported earnings and analyst forecasts, where we use the same split-adjusted basis to calculate forecasts and realized earnings per share. Our initial sample consists of 37,286 CEO-quarter observations (including forecasts that were "bundled" with earnings announcements). We next deleted forecasts issued after the forecasting period ends (Ajinkya, Bhojraj, and Sengupta [2005], Rogers [2008], Hilary and Hsu [2011]; 5,597 observations). Our sample includes point, range, and confirming qualitative forecasts (deleting nonconfirming qualitative and open-ended forecasts leads to the further loss of 1,418 observations). Following Roger and Stocken [2005], we removed duplicate forecasts for the same fiscal quarter-end (6,259). We also delete observations for which earnings or consensus forecasts were missing (5,519),[9] for which CEO information was missing (152), for which we have fewer than six quarters of forecasts issued by the same CEO (11,245), and for which data were missing in CRSP (283). Our final sample contains 6,813 CEO-quarters to estimate model (1) and 59,105 CEO-analyst-quarters to estimate model (2). Table 1 summarizes the attrition in our sample.

[6] Our results do not change if we use at least five or seven quarters over the previous two years to calculate forecast consistency and accuracy.

[7] Although our initial sampling period starts in 1994, when the management forecast become available in the First Call database, our sample requirements are such that we do not get any observations before 1997. In addition, we would only gain 25 observations by adding observations from 1997 to 2001. We have deleted these 25 observations to increase data consistency. Our results are very similar if these observations are included (untabulated results). To further increase data consistency and mitigate the potential bias introduced via the different distribution of earlier forecasts, we focus on the last forecast made by a given manager before the end of the fiscal period (Hilary and Hsu [2011]).

[8] Our results hold when we use only the ExecuComp sample.

[9] Following Hilary and Hsu [2011], we require that there be at least two analysts who issued forecasts in the previous 90 days but our results are not affected by this requirement (untabulated result).

TABLE 1

Sample Selection Procedures

Management earnings forecasts issued for fiscal quarter-end from January 2002 to December 2010		37,286
Less:	Forecasts issued after the forecasting period end (preannouncements)	(5,597)
	Nonconfirming qualitative and open-range forecasts	(1,418)
	Number of duplicate forecasts for the same fiscal quarter-end	(6,259)
	Missing actual earnings and consensus analyst forecast with at least two analysts	(5,519)
	Missing CEO information in ExecuComp, Thomson Reuters, and SEC filings	(152)
	Missing at least six quarters of previous forecasts from the same CEO	(11,245)
	Missing return data in CRSP	(283)
Number of CEO quarters		6,813

TABLE 2

Summary Statistics

Variables	*N*	Mean	SD	25%	Median	75%
CONS	6,813	0.845	0.362	1.000	1.000	1.000
ACCU	6,813	0.486	0.500	0.000	0.000	1.000
ARET	6,813	0.002	0.084	−0.039	0.002	0.046
AFREV	59,105	−0.001	0.003	−0.001	0.000	0.001
NEWS_Raw	6,813	−0.000	0.004	−0.001	0.000	0.002
NEWS_FixAdj	6,813	−0.000	0.004	−0.001	0.001	0.002
NEWS_Adj	6,162	0.001	0.004	0.000	0.001	0.003

CONS is the management forecast consistency and *ACCU* is the management forecast accuracy (see appendix B for details). *ARET* is the three-day, size-adjusted stock return around the management forecast announcement. *AFREV* is an individual analyst's forecast revision scaled by the stock price at the beginning of quarter *t*. *NEWS_Raw* is the difference between management forecast and consensus analyst forecast issued up to 90 days before the management forecast date, scaled by the stock price at the beginning of quarter *t*. *NEWS_FixAdj* is the difference between the management forecast (adjusted for *MF_FixBias*, see appendix B) and the most recent consensus analyst forecast up to 90 days before the management forecast date, scaled by the stock price at the beginning of quarter *t*. *NEWS_Adj* is the difference between the management forecast (adjusted on *MF_Bias*; see appendix A) and the most recent consensus analyst forecast up to 90 days before the management forecast date, scaled by the stock price at the beginning of quarter *t*. *NEWS_Raw*, *NEWS_FixAdj*, and *NEWS_Adj* are adjusted for "bundle" effect (Rogers and Van Buskirk [2013], in appendix A).

4. *Empirical Results*

4.1 DESCRIPTIVE STATISTICS

Table 2 provides descriptive statistics for the main variables used in our analysis. The mean value of *CONS* is 0.85, suggesting a reasonably large degree of consistency in management forecasts compared to analyst forecasts. This result is consistent with the notion that managers have an information advantage over analysts when they forecast earnings for their own firms. In contrast, the mean value of *ACCU* is only 0.49, consistent with Hutton, Lee, and Shu [2012], who find that managers are not more accurate than analysts on average. The mean *ARET* and *AFREV* are close to zero (0.002 and –0.001) and the standard deviations are comparatively high (0.084 and 0.003). Similarly, *NEWS_Raw*, *NEWS_FixAdj*, and *NEWS_Adj* are on average close to zero (–0.000, –0.000, and 0.001, respectively, with a standard deviation of 0.004 in all three cases). We lose 651 additional observations when we calculate *NEWS_Adj* due to the additional data requirement to estimate *MF_Bias*. Untabulated results indicate that only 20% of forecasts are issued with an upward bias (i.e., $MFE > 0$). Untabulated results also show that the mean absolute value of the difference between actual management forecast error (*MFE*) and predicted bias (*MF_Bias*) is 25% smaller for highly consistent managers ($CONS = 1$) than for low consistent ones ($CONS = 0$). The average difference is statistically significant at less than 1% (one-sided test). This preliminary result suggests that it is easier to predict the bias when managers are more consistent.

The Pearson correlation matrix in table 3 indicates that the degree of correlation between *ACCU* and *CONS* is reasonably low (0.26). Similarly, the correlation of *NEWS_Raw*, *NEWS_FixAdj*, and *NEWS_Adj* with *ARET* (0.29, 0.33, and 0.28, respectively) and *AFREV* (0.36, 0.53, and 0.43, respectively) is moderate. Finally, the three measures of *NEWS* are positively correlated as expected (between 0.56 and 0.84). Panel B of table 3 provides the correlation between the three measures of *NEWS* and *ARET* or *AFREV*, conditionally on the value of *CONS*. Results indicate that the correlation between the news contained in the management forecasts and the reaction by users is approximately two to three times as large when *CONS* equals one than when *CONS* equals zero. The difference is statistically significant at less than 0.001 in all cases (one sided). These preliminary results are consistent with our main hypotheses that users of forecasts react more (per unit of "news") when the consistency of the forecasts is greater. Panel C provides a similar analysis conditionally on the value of *ACCU*. We observe that the correlation between the news contained in the management forecasts and the reaction by users is greater when *ACCU* equals one than when *ACCU* equals zero. However, the magnitude of the difference is smaller in panel C than in panel B in all six cases (at the 1% level in all six cases). In addition, the difference in the correlation between *ARET* and *NEWS_FixAdj* (between $ACCU = 1$ and $ACCU = 0$) is insignificantly different from zero in panel C.

4.2 INVESTOR REACTION

Table 4 presents results from model (1). Column (1) tabulates the results when we use *NEWS_FixAdj*, while column (2) reports those when we use *NEWS_Adj*. The results indicate that the market reaction to management forecasts is positively associated with management forecast consistency in both cases. The coefficients on *CONS* × *NEWS_FixAdj* and *CONS* × *NEWS_Adj* are 4.151 and 4.367, respectively. They are both significant at the 1% level (*z*-statistics equal 5.66 and 4.21, respectively). Untabulated analysis shows that our results continue to hold when we remove *ACCU* × *NEWS* from the regression. The economic effect of *CONS* × *NEWS_FixAdj*

TABLE 3
Correlations Matrix

Panel A: Unconditional analysis

Variables	*CONS*	*ACCU*	*ARET*	*AFREV*	*NEWS_Raw*	*NEWS_FixAdj*
ACCU	**0.26**					
ARET	0.01	**−0.03**				
AFREV	−0.01	**−0.02**	**0.31**			
NEWS_Raw	**0.06**	**0.03**	**0.29**	**0.36**		
NEWS_FixAdj	**0.07**	**0.04**	**0.33**	**0.53**	**0.64**	
NEWS_Adj	**0.05**	**0.03**	**0.28**	**0.43**	**0.84**	**0.56**

Panel B: Conditional analysis based on *CONS*

Correlations	*CONS* = 1	*CONS* = 0	*p*-value for equality of correlations
Corr (*ARET*, *NEWS_Raw*)	**0.31**	**0.16**	0.000***
Corr (*AFREV*, *NEWS_Raw*)	**0.63**	**0.24**	0.000***
Corr (*ARET*, *NEWS_FixAdj*)	**0.31**	**0.17**	0.000***
Corr (*AFREV*, *NEWS_FixAdj*)	**0.62**	**0.22**	0.000***
Corr (*ARET*, *NEWS_Adj*)	**0.30**	**0.18**	0.000***
Corr (*AFREV*, *NEWS_Adj*)	**0.63**	**0.28**	0.000***

Panel C: Conditional analysis based on *ACCU*

Correlations	*ACCU* = 1	*ACCU* = 0	*p*-value for equality of correlations
Corr (*ARET*, *NEWS_Raw*)	**0.32**	**0.25**	0.003***
Corr (*AFREV*, *NEWS_Raw*)	**0.62**	**0.31**	0.000***
Corr (*ARET*, *NEWS_FixAdj*)	**0.31**	**0.28**	0.197
Corr (*AFREV*, *NEWS_FixAdj*)	**0.60**	**0.36**	0.000***
Corr (*ARET*, *NEWS_Adj*)	**0.31**	**0.26**	0.033**
Corr (*AFREV*, *NEWS_Adj*)	**0.60**	**0.31**	0.000***

CONS is the management forecast consistency and *ACCU* is the management forecast accuracy (see appendix B for details). *ARET* is the three-day, size-adjusted stock return around the management forecast announcement. *AFREV* is an individual analyst forecast revision scaled by the stock price two days before the issuance of the management forecast. *NEWS_Raw* is the difference between management forecast and consensus analyst forecast issued up to 90 days before the management forecast date, scaled by the stock price at the beginning of quarter *t*. *NEWS_FixAdj* is the difference between the management forecast (adjusted for *MF_FixBias*, see appendix B) and the most recent consensus analyst forecast up to 90 days before the management forecast date, scaled by the stock price at the beginning of quarter *t*. *NEWS_Adj* is the difference between the management forecast (adjusted on *MF_Bias*, see appendix A) and the most recent consensus analyst forecast up to 90 days before the management forecast date, scaled by the stock price at the beginning of quarter *t*. *NEWS_Raw*, *NEWS_FixAdj*, and *NEWS_Adj* are adjusted for the "bundle" effect (Rogers and Van Buskirk [2013], in appendix A). The Pearson correlations in bold are significant at the 5% level or less. In panels B and C, the Pearson correlations that are significant at the 10%, 5%, and 1% levels are marked with *, **, and ***, respectively (two-tailed).

or *CONS* × *NEWS_Adj* is such that increasing *CONS* from 0 to 1 increases the effect of *NEWS_FixAdj* or *NEWS_Adj* by approximately 50%.[10] These results are consistent with H1a. In contrast, the coefficient on *ACCU* × *NEWS_FixAdj* (*ACCU* × *NEWS_Adj*, respectively) is insignificant and the point estimate of the coefficient is only 30% (20%, respectively) of the estimate for *CONS* × *NEWS_FixAdj* (*CONS* × *NEWS_Adj*, respectively). However,

[10] We multiply the coefficients on *CONS* × *NEWS_FixAdj* and *CONS* × *NEWS_Adj* (4.151 and 4.367) by 1 and divide the product by the coefficient on *NEWS* (1.873 and 2.789, respectively).

TABLE 4
The Effect of Consistency on the Market Reactions

	(1) $ARET_{i,t}$ *NEWS_FixAdj*	(2) $ARET_{i,t}$ *NEWS_Adj*	(3) $ARET_{i,t}$ *NEWS_Both*	(4) $ARET_{i,t}$ *NEWS_Both*
$NEWS_{i,t}$	1.873***	2.789***	2.718***	8.393***
	(3.097)	(3.838)	(3.610)	(2.717)
$CONS_{i,t}$	0.001	−0.004	0.002	0.002
	(0.410)	(−1.105)	(0.726)	(0.468)
$ACCU_{i,t}$	−0.006**	−0.007*	−0.008***	−0.008***
	(−2.148)	(−1.975)	(−2.966)	(−2.944)
$CONS_{i,t} \times NEWS_{i,t}$	4.151***	4.367***	4.393***	3.354***
	(5.658)	(4.214)	(5.411)	(3.074)
$ACCU_{i,t} \times NEWS_{i,t}$	1.437	0.849	1.421	0.399
	(1.370)	(0.801)	(1.533)	(0.413)
$\|NEWS_{i,t}\| \times NEWS_{i,t}$				−5.566***
				(−6.169)
$DA_{i,t-1} \times NEWS_{i,t}$				5.626
				(0.461)
$MTB_{i,t-1} \times NEWS_{i,t}$				−0.121
				(−0.450)
$MFLOSS_{i,t} \times NEWS_{i,t}$				3.408***
				(3.025)
$HOR_{i,t} \times NEWS_{i,t}$				−0.056
				(−0.098)
$RANGE_{i,t} \times NEWS_{i,t}$				1.799
				(1.340)
$MBESTREAK_{i,t} \times NEWS_{i,t}$				1.868
				(0.935)
$BAD_{i,t} \times NEWS_{i,t}$				−0.556
				(−0.485)
Adjusted R^2	0.093	0.087	0.105	0.121
Number of observations	6,813	6,162	5,957	5,957

This table reports the effects of management forecast consistency on the market reactions to the management forecasts (*ARET*). All of the variables are defined in appendix B. The constant terms are included, but not tabulated. All of the continuous variables are winsorized at the 1st and 99th percentiles. *Z*-statistics (reported in parentheses) are corrected for heteroskedasticity and clustering of observations by CEO and quarter. Coefficients that are significant at the 10%, 5%, and 1% levels are marked with *, **, and ***, respectively (two-tailed).

ACCU × *NEWS_Adj* becomes significant with a *z*-statistic of 3.07 when *CONS* and its interaction with *NEWS* are removed from the regression. The difference between *CONS* × *NEWS_FixAdj* and *ACCU* × *NEWS_FixAdj* or *CONS* × *NEWS_Adj* and *ACCU* × *NEWS_Adj* is statistically significant (the one-sided *p*-value is less than 0.05 and 0.001, respectively).

A recent study by Hilary and Hsu [2013] shows that analysts also care more about consistency than accuracy, and thus issue forecasts that may be systematically biased to maintain good relations with managers. To address this issue, we compute a measure of news, *NEWS_Both*, which is adjusted simultaneously for both the predictable bias in management forecasts and in analyst forecasts.[11] Our approach to estimate the predicted analyst bias, *AF_Bias*, is described in appendix A. We then reestimate model (1). Results presented in column (3) of table 4 do not change our conclusions. *CONS* × *NEWS_Both* remains significant and *ACCU* × *NEWS_Both* remains insignificant.[12]

Finally, we estimate an extended model that controls for various potential confounding effects. Our vector of control variables contains those identified in previous studies that influence price formation (Rogers and Stocken [2005], in particular). Specifically, we control for growth opportunities (*MTB*; Bamber and Cheon [1998], Rogers and Stocken [2005]), the predicted loss (*MFLOSS*; Hayn [1995], Rogers and Stocken [2005]), forecast range (*RANGE*; Baginski, Conrad, and Hassell [1993], Rogers and Stocken [2005]), consistency in meeting-or-beating consensus analyst forecast (*MBESTREAK*; Kross, Ro, and Suk [2011]), the amount of discretionary accruals (*DA*; Rogers and Stocken [2005]), forecast horizon (*HOR*; Kasznik [1999], Rogers and Stocken [2005]), the sign of management forecast news (*BAD*; Jennings [1987], Rogers, Skinner, and Van Buskirk [2009]), and the importance of the news (|*NEWS*|; Lipe, Bryant, and Widener [1998], Rogers and Stocken [2005]). All of these control variables are defined in greater detail in appendix B.

Again, results in column (4) of table 4 indicate that our conclusions are not affected and *CONS* × *NEWS_Both* remains significant.[13] However, we note that the average variation inflation factors (VIF) are approximately 13 in the last column of table 4 (with a maximum value over 64), suggesting the presence of strong multicollinearity in this specification. Thus, we focus on the specification reported in the first two columns as our baseline model. Our results hold if we examine several additional specifications (untabulated results), for example, if we include the vector of control variables (*BAD*, *RANGE*, *HOR*, *MBESTREAK*, |*NEWS*|, *DA*, *MTB*, and *MFLOSS*) without the interactions. They also hold if we add firm size (*SIZE*; Baginski, Conrad, and Hassell [1993]), leverage (*LEV*; Collins and Kothari [1989]), analyst following (*COVER*; Lang and Lundholm [1996]), and earnings volatility (*EARNVOL*; Imhoff and Lobo [1992]) to the vector of control variables and interact these variables with *NEWS_Both*. Similarly, they hold if we include earnings announcement news (*EANEWS*) and its interactions with |*EANEWS*|, *DA*, *MTB*, and *BAD_EA* (Rogers and Stocken [2005]).

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[11] We also adjust *NEWS_Both* for the "bundle" effect by following Rogers and Van Buskirk [2013].

[12] We reach similar conclusions if we use *NEWS_FixBoth* instead of *NEWS_Both* (untabulated result). *NEWS_FixBoth* is similar to *NEWS_Both* but we use *MF_FixBias* and *AF_FixBias* instead of *MF_Bias* and *AF_Bias* to adjust *NEWS*. *AF_FixBias* is calculated as the averaged value of analyst forecast error (*AFE*) for a given CEO.

[13] Untabulated results indicate that *CONS* × *NEWS_FixAdj*, *CONS* × *NEWS_Adj*, or *CONS* × *NEWS_FixBoth* is also significant if we substitute them for *CONS* × *NEWS_Both* in this extended model.

TABLE 5
The Effect of Consistency on the Analyst Revisions

	(1) $AFREV_{i,j,t}$ $NEWS\_FixAdj$	(2) $AFREV_{i,j,t}$ $NEWS\_Adj$	(3) $AFREV_{i,j,t}$ $NEWS\_Both$	(4) $AFREV_{i,j,t}$ $NEWS\_Both$
$NEWS_{i,t}$	0.085*	0.017	0.176***	0.253**
	(1.858)	(0.849)	(2.731)	(3.065)
$CONS_{i,t}$	−0.000	−0.001***	−0.000	−0.000
	(−1.329)	(−6.168)	(−0.874)	(−1.415)
$ACCU_{i,t}$	−0.000***	−0.000**	−0.000***	−0.000***
	(−3.332)	(−2.629)	(−5.228)	(−4.479)
$CONS_{i,t} \times NEWS_{i,t}$	0.387***	0.595***	0.326***	0.339***
	(7.920)	(15.784)	(5.232)	(4.862)
$ACCU_{i,t} \times NEWS_{i,t}$	0.022	−0.008	0.086**	0.071**
	(0.789)	(−0.351)	(2.360)	(2.064)
$\lvert NEWS_{i,t}\rvert \times NEWS_{i,t}$				−0.048
				(−0.775)
$DA_{i,t-1} \times NEWS_{i,t}$				−0.099
				(−0.469)
$MTB_{i,t-1} \times NEWS_{i,t}$				−0.000
				(−0.425)
$MFLOSS_{i,t} \times NEWS_{i,t}$				0.073**
				(2.514)
$HOR_{i,t} \times NEWS_{i,t}$				−0.023**
				(−1.989)
$RANGE_{i,t} \times NEWS_{i,t}$				−0.075*
				(−1.949)
$MBESTREAK_{i,t} \times NEWS_{i,t}$				0.018
				(0.440)
$BAD_{i,t} \times NEWS_{i,t}$				0.124***
				(3.644)
Adjusted R^2	0.345	0.373	0.366	0.380
Number of observations	59,105	54,098	52,305	52,305

This table reports the effects of management forecast consistency on the analyst responses to the management forecasts (*AFREV*). All of the variables are defined in appendix B. The constant terms are included, but not tabulated. All of the continuous variables are winsorized at the 1st and 99th percentiles. *Z*-statistics (reported in parentheses) are corrected for heteroskedasticity and clustering of observations by analyst, CEO, and quarter. Coefficients that are significant at the 10%, 5%, and 1% levels are marked with *, **, and ***, respectively (two-tailed).

Although our conclusions are not affected, these different specifications further exacerbate the multicollinearity (the average VIF becomes 16 with a maximum of 95).

4.3 ANALYST REACTION

Table 5 presents results from model (2). Column (1) tabulates the results when we use *NEWS_FixAdj*, whereas column (2) reports those when we use *NEWS_Adj*. The results indicate that the analyst forecast revision to management forecasts is positively associated with management forecast consistency in both cases. The coefficients on $CONS \times NEWS\_FixAdj$ and $CONS \times NEWS\_Adj$ are 0.387 and 0.595, respectively. They are significant at the 1% level (*z*-statistics are 7.92 and 15.78, respectively). Untabulated analysis shows that our results continue to hold when we remove *ACCU* × *NEWS* from the regression. These results are consistent with H1b. In contrast, the coefficients on *ACCU* × *NEWS_FixAdj* and *ACCU* × *NEWS_Adj* are insignificant (with *z*-statistics of 0.79 and –0.35), but become significant with a *z*-statistic of 4.39 when *CONS* and its interaction with *NEWS* are removed from the regression. The difference between *CONS* × *NEWS_FixAdj* and *ACCU* × *NEWS_FixAdj* or *CONS* × *NEWS_Adj* and *ACCU* × *NEWS_Adj* is statistically significant (the one-sided *p*-value is less than 0.001 in both cases).

We then substitute *NEWS_Both* for *NEWS_Adj* and reestimate model (2). The results, presented in column (3) of table 5, do not change our conclusions. *CONS* × *NEWS_Both* is significantly positive (the *z*-statistic is 4.86). The point estimate of the coefficient is approximately four times the value of the estimate of the coefficient for *ACCU* × *NEWS_Both* (the difference is significant with a one-sided *p*-value lower than 0.001).[14]

Finally, we estimate the same extended model described in section 4.2. We report the results in column (4) of table 5. Again, our conclusions are not affected when we include a vector of control variables (*BAD*, *RANGE*, *HOR*, *MBESTREAK*, |*NEWS*|, *DA*, *MTB*, and *MFLOSS*) and their interactions with *NEWS_Both*. *CONS* × *NEWS_Both* remains significant.[15] However, the average VIFs are approximately 11 in the last column of table 5 (with a maximum value of 67), again suggesting the presence of multicollinearity in this specification. Adding the vector of the aforementioned control variables without the interactions, further controlling for *SIZE*, *LEV*, *COVER*, and *EARNVOL* (and their interaction with *NEWS_Both*), or including earnings announcement news (*EANEWS*, and its interactions with |*EANEWS*|, *DA*, *MTB*, and *BAD_EA* as in Rogers and Stocken [2005]) does not affect our conclusions (untabulated results), but including the additional control variables further exacerbates the multicollinearity (the average VIF becomes 12 with a maximum of 83).

4.4 ADDITIONAL ROBUSTNESS CHECKS

We then perform different robustness checks (untabulated results). First, there may be a concern that the documented stock price reactions and analysts' forecast revisions might be the result of earnings announcement news (Atiase, Rees, and Tse [2010]). To address this concern, we delete management forecasts made within –1 to +1 days of an earnings announcement, using the Compustat quarterly file to identify the earnings announcement dates. This procedure results in a large number of observations being removed from our sample and a much smaller sample size (1,485 vs. 6,162 in the *ARET* specification; 35,524 vs. 54,098 in the *AFREV* one). However, this truncation does not affect our conclusions (untabulated result).

[14] We reach similar conclusions if we use *NEWS_FixBoth* instead of *NEWS_Both* (untabulated result).

[15] Untabulated results indicate that *CONS* × *NEWS_FixAdj*, *CONS* × *NEWS_Adj*, or *CONS* × *NEWS_FixBoth* is also significant if we substitute it for *CONS* × *NEWS_Both*.

CONS × *NEWS_Adj* remains significant (with *z*-statistics of 3.95 and 12.39 for *ARET* and *AFREV*, respectively) and *ACCU* × *NEWS_Adj* remains insignificant (with *z*-statistics of 0.88 and –0.28 for *ARET* and *AFREV*, respectively).

Second, our results continue to hold when we use *NEWS_Raw* (instead of *NEWS_FixAdj* or *NEWS_Adj*) to estimate models (1) and (2), as well as when we use either the averaged value of *MFE* over the last two years (instead of over the CEO's tenure) or the Kross, Ro, and Suk [2011] specification (instead of Rogers and Stocken [2005] specification) to debias *NEWS* in our baseline models.

Third, Rogers and Stocken [2005] find that the market predicts and filters bias from management earnings forecasts. We implicitly rely on this finding when we use debiased versions of the forecasts. However, if investors and analysts only cared about accuracy, they would not adjust the forecast for the predicted bias and, therefore, *ACCU* should be interacted with *NEWS_Raw*. To investigate this possibility, we reestimate models (1) and (2) substituting *ACCU* × *NEWS_Raw* for *ACCU* × *NEWS_Adj*, adding *NEWS_Raw*, and keeping *CONS* × *NEWS_Adj* and *NEWS_Adj*. *CONS* × *NEWS_Adj* remains significant (at the 1% level) and the difference between *ACCU* × *NEWS_Raw* and *CONS* × *NEWS_Adj* is significant at the 5% level or better (one sided).

Fourth, one could argue that we should measure consistency relative to a debiased forecast. This is not an issue if the bias is constant but it could be one if the bias is time varying. To investigate this question, we calculate the standard deviation of the adjusted management forecast errors (i.e., actual error, *MFE*, minus the estimated management bias, *MF_Bias*) and calculate *CONS_Adj* based on the standard deviation of the adjusted management forecast errors relative to the standard deviation of adjusted consensus analyst forecast errors (i.e., actual error, *AFE*, minus the estimated analyst bias, *AF_Bias*). Untabulated results indicate that our conclusions are not affected. *CONS_Adj* × *NEWS_Adj* remains significant (with a *z*-statistic of 4.75 in the *ARET* specification and 2.15 in the *AFREV* one).[16]

Fifth, we examine other alternative measures of management forecast consistency. For example, we define *CONS_50*, measured as one if *STDAFE* exceeds *STDMFE* by more than the median value of the difference between *STDAFE* and *STDMFE*. That is, we construct a consistency measure that is equal to one only half of the time. The mean value of *CONS_50* is 0.506 and the median value (by construction) is 0.500. Our conclusions are not affected. The *z*-statistics for *CONS_50* × *NEWS_Adj* are 3.12 in the *ARET* specification and 4.74 in the *AFREV* one. Alternatively, we rank all of the CEOs by industry (four-digit SIC codes) in quarter *t* based on the standard deviation of forecast errors scaled by the stock price at the beginning of

[16] We also define *ACCU_Adj* based on the absolute value of the adjusted management forecast errors relative to the absolute value of the adjusted analyst forecast errors. *ACCU_Adj* × *NEWS_Adj* remains insignificant in the *AFREV* specification but becomes significant in the *ARET* specification with a *z*-statistic of 2.42.

the quarter. We then compute a consistency ranking score using the formula (Hong and Kubik [2003], Hilary and Hsu [2013]): $CONS\_Rk = 1 -$ (rank – 1)/(number of CEOs within the industry – 1). Similarly, we estimate *ACCU_Rk* by ranking all of the CEOs within the same industry in each quarter based on accuracy and calculate the mean of the ranking scores over the last two years.[17] Our conclusions are not affected. $CONS\_Rk \times NEWS\_Adj$ remains significant in our baseline regressions (with *z*-statistics of 2.66 for *ARET* and 2.51 for *AFREV*) and $ACCU\_Rk \times NEWS\_Adj$ remains insignificant (with *z*-statistics of –0.33 for *ARET* and –0.23 for *AFREV*).

Sixth, we delete observations that are both accurate and consistent (i.e., those for which both *CONS* and *ACCU* are equal to one). In this case, the correlation between *CONS* and *ACCU* becomes –0.38. Again, our conclusions are not affected. $CONS \times NEWS\_Adj$ remains significant (with a *z*-statistic of 3.82 for *ARET* and 4.61 for *AFREV*) and $ACCU \times NEWS\_Adj$ remains insignificant or only weakly significant (with a *z*-statistic of –0.40 for *ARET* and 2.04 for *AFREV*).

5. *Conditional User Reactions*

In this last section, we examine whether users are aware of the systematic bias and whether this awareness depends on the consistency of the forecast. Further, we examine if the degree of sophistication of forecast users or the visibility of the bias influences their reactions.

5.1 TYPES OF NEWS AND PREDICTED BIAS

Our preliminary results in section 4.1 suggest that it is easier to predict management bias when forecasts are more consistent. Following Rogers and Stocken [2005], we posit that users filter bias more easily when forecasts are more consistent. We estimate two models similar to that in Rogers and Stocken [2005] (i.e., their model (2)), but we partition the sample based on the median value of *STDMFE*. Specifically, we estimate:

$$\begin{aligned} ARET_{i,t} = {} & a_0 + a_1 NEWS\_Raw_{i,t} + a_2 NEWS\_Raw_{i,t} \times MF\_Bias_{i,t} \\ & \times GOOD_{i,t} + a_3 NEWS\_Raw_{i,t} \times MF\_Bias_{i,t} \times BAD_{i,t} \\ & + \sum a_k CONTROLS_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{3}$$

$$\begin{aligned} AFREV_{i,j,t} = {} & b_0 + b_1 NEWS\_Raw_{i,t} + b_2 NEWS\_Raw_{i,t} \times MF\_Bias_{i,t} \\ & \times GOOD_{i,t} + b_3 NEWS\_Raw_{i,t} \times MF\_Bias_{i,t} \times BAD_{i,t} \\ & + \sum b_k CONTROLS_{i,t} + \varepsilon_{i,t}. \end{aligned} \tag{4}$$

If investors and analysts do indeed filter bias more easily when managerial forecasts are more consistent, we expect the coefficient (in absolute value) associated with $NEWS\_Raw \times MF\_Bias \times GOOD$ and *NEWS_Raw*

[17] This method of defining *ACCU* is similar to that used in Hong and Kubik [2003], except that we rank all CEOs within an industry based on quarterly forecast accuracy instead of ranking all analysts within a firm based on annual forecasts.

TABLE 6

Test of Rogers and Stocken [2005] Conditional on the Consistency of Management Forecasts

	$ARET_{i,t}$		$AFREV_{i,j,t}$	
	(1) Low *STDMFE*	(2) High *STDMFE*	(3) Low *STDMFE*	(4) High *STDMFE*
$NEWS\_Raw_{i,t}$	3.330	0.508	0.592***	0.647***
	(3.433)	(2.803)	(4.454)	(7.475)
$NEWS\_Raw_{i,t} \times MF\_Bias_{i,t} \times GOOD_{i,t}$	−3.323*	−1.442***	−1.123**	0.250
	(−1.809)	(−4.556)	(−2.451)	(0.934)
$NEWS\_Raw_{i,t} \times MF\_Bias_{i,t} \times BAD_{i,t}$	3.089***	0.157***	0.673**	0.304***
	(2.850)	(4.271)	(2.055)	(2.801)
$NEWS\_Raw_{i,t} \times \|NEWS\_Raw_{i,t}\|$	−0.000	−0.000***	−0.047	−0.002
	(−0.204)	(−2.841)	(−0.645)	(−1.336)
$NEWS\_Raw_{i,t} \times DA_{i,t-1}$	−3.810	0.289	−1.431*	−0.001
	(−0.116)	(0.035)	(−1.949)	(−0.005)
$NEWS\_Raw_{i,t} \times MTB_{i,t-1}$	−0.066	0.707***	−0.000*	−0.013
	(−0.129)	(2.613)	(−1.662)	(−1.259)
$NEWS\_Raw_{i,t} \times MFLOSS_{i,t}$	0.000	0.610	0.441***	0.147***
	(0.000)	(0.656)	(2.597)	(2.922)
$NEWS\_Raw_{i,t} \times HOR_{i,t}$	−5.613***	−0.791**	−0.002	0.018
	(−2.585)	(−2.326)	(−0.044)	(1.011)
$NEWS\_Raw_{i,t} \times RANGE_{i,t}$	1.567	−0.274	0.053	−0.112***
	(0.557)	(−0.160)	(0.552)	(−2.335)
$NEWS\_Raw_{i,t} \times MBESTREAK_{i,t}$	3.279	0.395	−0.090	−0.012
	(0.844)	(0.507)	(−1.518)	(−0.169)
Adjusted R^2	0.091	0.089	0.398	0.431
Number of observations	3,094	3,098	27,664	26,384

This table reports the estimation results based on the model (2) in Rogers and Stocken [2005]. We partition the sample based on the median management forecast consistency (*STDMFE*). Columns (1) and (2) report the estimation results of the market reactions (*ARET*). Columns (3) and (4) report the estimation results of analyst revisions (*AFREV*). All of the variables are defined in appendix B. The constant terms are included, but not tabulated. All of the continuous variables are winsorized at the 1st and 99th percentiles. *Z*-statistics (reported in parentheses) in columns (1) and (2) are corrected for heteroskedasticity and clustering of observations by CEO and quarter and those in columns (3) and (4) are by CEO, analyst, and quarter. Coefficients that are significant at the 10%, 5%, and 1% levels are marked with *, **, and ***, respectively (two-tailed).

× *MF_Bias* × *BAD* to be larger in a sample of high consistency.[18] Results in table 6 are consistent with our conjecture and with Rogers and Stocken [2005]. Specifically, we find that the magnitude of coefficients on $NEWS\_Raw_{i,t} \times MF\_Bias_{i,t} \times GOOD_{i,t}$ and $NEWS\_Raw_{i,t} \times MF\_Bias_{i,t} \times BAD_{i,t}$ are larger (in absolute value) in the sample of consistent forecasts than in the sample of inconsistent forecasts. The difference in the estimates for these coefficients across the two samples is statistically significant (with one-sided *p*-values approximately equal to 0.008 and 0.058 in the *ARET* specification and to 0.085 and 0.003 in the *AFREV* specification).[19]

[18] *GOOD* (*BAD*) is an indicator variable that equals one if *NEWS* is positive (negative), zero otherwise. The results are not affected if we use *MF_FixBias* instead of *MF_Bias* in the test.

[19] Our results are not affected if we follow Rogers and Stocken [2005] to further include earnings announcement news (*EANEWS*) and its interactions with |*EANEWS*|, *DA*, *MTB*, and

5.2 USER SOPHISTICATION

Our basic intuition is that investors and analysts should prefer biased but consistent forecasts rather than unbiased forecasts that are relatively more accurate but inconsistent if they can detect systematic bias. Therefore, the effect of consistency on the usefulness of management forecasts should be affected by the ability (sophistication) of investors and analysts to understand the systematic bias introduced by managers. Prior research suggests that institutional investors are more sophisticated than retail investors (Boehmer and Kelley [2009], Campbell, Ramadorai, and Schwartz [2009], Puckett and Yan [2011]), and that analysts with greater experience forecast earnings more accurately (Mikhail, Walther, and Willis [1997], Clement [1999], Jacob, Lys, and Neale [1999]) and are less overoptimistic regarding accruals (Drake and Myers [2011]). Our hypotheses rely on the assumption that users behave in a Bayesian fashion and understand the importance of consistency in forecasting, an ability that we would expect to be more common among sophisticated, experienced users.[20] To test this conjecture, we estimate model (1) conditional on the percentage of institutional investors (*INTO*) in the shareholding of the firm. Similarly, we estimate model (2) conditional on the amount of experience (*EXP*) analysts have.

Our results are reported in table 7. They indicate that sophisticated investors focus on consistent forecasts. In column (1), *CONS* × *NEWS_Adj* is significantly positive with a *z*-statistic of 3.94 in the sample of high institutional ownership, while *ACCU* × *NEWS_Adj* is insignificant (with a *z*-statistic of –0.71). In contrast, column (2) shows that *CONS* × *NEWS_Adj* is insignificant in the sample of low institutional ownership (with a *z*-statistic of –0.51), while *ACCU* × *NEWS_Adj* is significantly positive (with a *z*-statistic of 10.58). The differences between the estimates for *CONS* × *NEWS_Adj* and *ACCU* × *NEWS_Adj* across the two samples are significantly different with *p*-values lower than 0.001 (one sided) in both cases.

Similarly, results in table 7 indicate that experienced analysts focus on consistent forecasts. In column (3), *CONS* × *NEWS_Adj* is significantly positive in the sample of experienced analysts (with a *z*-statistic of 6.82), but insignificant in the sample of inexperienced analysts (with a *z*-statistic of 1.17), tabulated in column (4). The difference between the estimates across the two samples is significant with a *p*-value less than 0.001 (one sided). Column (4) shows that the point estimate of the coefficient of *ACCU* × *NEWS_Adj* is twice as large in the sample of inexperienced analysts as in the

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BAD_EA in model (3) (untabulated results), but this further exacerbates the multicollinearity (the average VIF becomes 30 with a maximum of 140).

[20] If investors are unable to debias forecasts, managers may try to manipulate investors' expectations. However, if investors are able to debias forecasts, manipulation is futile. In this case, as discussed in section 2, we expect the bias to exist because users expect it to occur. The prior literature (e.g., Rogers and Stocken [2005], Hilary and Hsu [2013]) suggests that the market reaction to the bias is efficient on average but that users in certain subsamples may be functionally fixated.

TABLE 7
Partition Tests Conditional on Investor Sophistication and Analyst Experience

	$ARET_{i,t}$		$AFREV_{i,j,t}$	
	(1) High *INTO*	(2) Low *INTO*	(3) High *EXP*	(4) Low *EXP*
$NEWS\_Adj_{i,t}$	3.279***	0.003	0.133**	0.513
	(3.284)	(0.048)	(2.273)	(3.637)
$CONS_{i,t}$	−0.002	0.001	−0.001***	−0.000
	(−0.407)	(0.192)	(−4.072)	(−1.248)
$ACCU_{i,t}$	−0.006	−0.013***	−0.000***	−0.001***
	(−1.639)	(−3.568)	(−4.430)	(−3.271)
$CONS_{i,t} \times NEWS\_Adj_{i,t}$	5.043***	−0.212	0.397***	0.049
	(3.937)	(−0.506)	(6.820)	(1.186)
$ACCU_{i,t} \times NEWS\_Adj_{i,t}$	−0.812	8.822***	0.144***	0.290**
	(−0.713)	(10.584)	(3.046)	(2.462)
Adjusted R^2	0.093	0.061	0.380	0.260
Number of observations	3,017	2,872	25,202	25,466

This table reports the effects of management forecast consistency on the market reactions and analysts' forecast revisions to the management forecasts. We partition the sample by the median institutional ownership (*INTO*) and report the estimation results of market reactions (*ARET*) in columns (1) and (2). We partition the sample by the median analyst experience (*EXP*) and report the estimation results of analyst revisions (*AFREV*) in columns (3) and (4). We adjust *NEWS* for *MF_Bias*. All of the variables are defined in appendix B. The constant terms are included, but not tabulated. All of the continuous variables are winsorized at the 1st and 99th percentiles. *Z*-statistics (reported in parentheses) in columns (1) and (2) are corrected for heteroskedasticity and clustering of observations by CEO and quarter and those in columns (3) and (4) are by CEO, analyst, and quarter. Coefficients that are significant at the 10%, 5%, and 1% levels are marked with *, **, and ***, respectively (two-tailed).

sample of experienced analysts. However, the coefficients are statistically significant in both samples and the difference across the two samples is not significant.

5.3 SIZE OF THE BIAS

Finally, we partition our sample into two subsamples based on the size of the bias using the median of *AbsMF_Bias* (i.e., absolute value of *MF_Bias*), although our results are not affected if we use the absolute value of *MF_FixBias* instead (untabulated result). We then reestimate the effect of consistency on forecast informativeness separately for each subsample. This allows us to better distinguish between consistency and accuracy by investigating whether consistency is more relevant to investors when stated accuracy is low. We expect this to be true because users should value consistency rather than accuracy in the presence of large systematic deviations from realized earnings. In other words, we expect forecast users to detect and correct for biases that are larger (in absolute value) and hence more visible.

Results reported in table 8 are consistent with this intuition. They indicate that investors focus on the consistent forecasts when the size of the systematic bias is large. In column (1), $CONS \times NEWS\_Adj$ is significantly positive with a *z*-statistic of 4.93 in the sample of high *AbsMF_Bias*, while $ACCU \times NEWS\_Adj$ is insignificant (with a *z*-statistic of 0.84). In contrast, column (2) shows that $CONS \times NEWS\_Adj$ is insignificant in the sample of

TABLE 8
Partition Tests Conditional on the Size of Bias

	$ARET_{i,t}$		$AFREV_{i,j,t}$	
	(1) High *AbsMF_Bias*	(2) Low *AbsMF_Bias*	(3) High *AbsMF_Bias*	(4) Low *AbsMF_Bias*
$NEWS\_Adj_{i,t}$	1.595**	0.687	0.162**	0.354***
	(2.780)	(0.415)	(2.164)	(7.725)
$CONS_{i,t}$	−0.006	0.007	−0.001***	0.000**
	(−1.484)	(1.304)	(−2.904)	(2.013)
$ACCU_{i,t}$	−0.006	−0.017***	−0.001***	−0.000**
	(−1.329)	(−4.964)	(−3.835)	(−2.417)
$CONS_{i,t} \times NEWS\_Adj_{i,t}$	3.939***	−0.876	0.389***	−0.008
	(4.925)	(−0.526)	(5.625)	(−0.701)
$ACCU_{i,t} \times NEWS\_Adj_{i,t}$	0.897	8.244***	0.198**	0.179***
	(0.835)	(7.291)	(2.340)	(2.973)
Adjusted R^2	0.111	0.074	0.444	0.263
Number of observations	3,151	3,011	27,253	26,829

This table reports the effects of management forecast consistency on the market reactions and analysts' forecast revisions to the management forecasts. We partition the samples based on the size of management forecast bias (*AbsMF_Bias*). Columns (1) and (2) report the estimation results of the market reactions (*ARET*) and columns (3) and (4) report the estimation results of analyst revisions (*AFREV*). We adjust *NEWS* for *MF_Bias*. All of the variables are defined in appendix B. The constant terms are included, but not tabulated. All of the continuous variables are winsorized at the 1st and 99th percentiles. *Z*-statistics (reported in parentheses) in columns (1) and (2) are corrected for heteroskedasticity and clustering of observations by CEO and quarter and those in columns (3) and (4) are by CEO, analyst, and quarter. Coefficients that are significant at the 10%, 5%, and 1% levels are marked with *, **, and ***, respectively (two-tailed).

low *AbsMF_Bias* (with a *z*-statistic of –0.53), whereas *ACCU* × *NEWS_Adj* is significantly positive (with a *z*-statistic of 7.29). The differences between the estimates for *CONS* × *NEWS_Adj* and *ACCU* × *NEWS_Adj* across the two samples are significantly different, with *p*-values lower than 0.003 (one sided) in both cases.

Similarly, our results in table 8 indicate that analysts focus on consistency of forecasts when the size of the systematic bias is large. In column (3), *CONS* × *NEWS_Adj* is significantly positive in the sample of high *AbsMF_Bias* (with a *z*-statistic of 5.63) but insignificant in the sample of small *AbsMF_Bias* (with a *z*-statistic of –0.70) tabulated in column (4). The differences between the estimates across the two samples are significant with a *p*-value less than 0.001 (one sided). In contrast, our results indicate that the size of the bias does not affect the importance of forecast accuracy for analysts.

6. Conclusions

We examine the role of management forecast consistency in the capital markets. We show that managers with higher forecast consistency have a greater ability to move prices and influence analyst revisions. The effect is both economically and statistically significant. Consistent with previous work, we find some support for the notion that accuracy influences market reactions and analyst revisions, but its effects are generally weaker than those of consistency. Indeed the effect of accuracy often disappears once we control for consistency. In contrast, the effect of consistency is robust to a host of specification checks. For example, the effect persists when we adjust for systematic biases in management and analyst forecasts (Rogers and Stocken [2005]), identify non-ExecuComp executives (Rogers and Van Buskirk [2009]), and use "bundled" forecasts (Rogers and Van Buskirk [2013]). The effect also persists after controlling for a host of potential confounds (e.g., Jennings [1987], Baginski, Conrad, and Hassell [1993], Kross, Ro, and Suk [2011]).

We also find that it is easier to predict the bias when managers are more consistent and that investors and analysts filter systematic bias in management forecasts more easily when the forecasts are more consistent. We next consider if the degree of user sophistication and of bias visibility affects the understanding of the forecast properties. Our empirical results suggest that this is indeed the case. Specifically, institutional investors and experienced analysts react more to consistent forecasts than retail investors and inexperienced analysts. Finally, the effect of consistency on investor reactions and analyst revisions is more significant when bias is more visible.

APPENDIX A

Additional Details on Methodology and Sampling Procedure

A.1 THE ESTIMATION OF MANAGEMENT FORECAST BIAS (MF_BIAS)

We follow Rogers and Stocken [2005] to calculate management forecast bias (*MF_Bias*) as the fitted value of management forecast error from the following regression estimated with quarterly data for management forecasts (firm and time subscripts omitted):

$$\begin{aligned} MFE = {} & a_0 + a_1 Difficulty + a_2 Litigation + a_3 Litigation \times Difficulty \\ & + a_4 Inside\_Trade + a_5 Inside\_Trade \times Difficulty + a_6 Distress \\ & + a_7 Distress \times Difficulty + a_8 Concen + a_9 Concen \times Difficulty \\ & + a_{10} Bad\_News + a_{11} News\_Raw \times Good\_News \\ & + a_{12} News\_Raw \times Bad\_News + a_{13} Horizon + a_{14} CAR_{-120,-1} \\ & + a_{15} Size + a_{16} M/BRank + a_{17} DAccruals \\ & + \text{year and industry fixed effects} + \varepsilon. \end{aligned} \tag{A.1}$$

MFE is the management forecast error, defined as the difference between management forecast and actual earnings, scaled by stock price. *Difficulty* is forecasting difficulty, combining the effects of lack of analyst consensus (*STD_AF*), the difficulty analysts experienced when predicting earnings (*STD_AFE*), lagged loss (*Lagged_Loss*), predicted loss (*MFLOSS*), volatility in a firm's stock price (*STD_RET*), bid-ask spread (*Spread*), and manager-revealed uncertainty (*RANGE*) by using principal axis factoring (PAF). *Litigation* is the probability of litigation. *Inside_Trade* is the ranked value of the net insider purchases over the 10-trading-day window beginning on the day of the forecast. *Distress* is financial distress, defined as *Z*-score. *Concen* is industry concentration, measured by the Herfindahl index, which equals the sum of the squares of the market shares of the firms within a four-digit SIC industry. *News_Raw* is the management forecast news, measured as the difference between management forecast and consensus analyst forecast, scaled by the stock price. *Bad_News* is an indicator variable that equals one if *News_Raw* is negative, and zero otherwise. *Good_News* is an indicator variable that equals one if *NEWS_Raw* is equal to or greater than zero, and zero otherwise. *Horizon* is forecast horizon, measured as the number of calendar days between the forecast release date and the firm's fiscal year-end. $CAR_{-120,-1}$ is the cumulative daily return less the size-decile-matched CRSP value-weighted index over the period 120 days before to one day before the forecast date. *Size* is firm size, measured as the natural log of the firm's market capitalization one day prior to the forecast. *M/B Rank* is the decile rank of the market-to-book ratio, which is the market value of equity divided by the book value of equity at the end of the prior quarter. *DAccruals* is discretionary accruals estimated using the cross-sectional modified Jones model (Brown and Pinello [2007]) scaled by the stock price.

A.2 THE ESTIMATION OF "BUNDLED FORECAST EFFECTS"

Rogers and Van Buskirk [2013] suggest that evaluating management forecast news based on preforecast (and, therefore, preearnings) estimates is likely to yield a measure of forecast news that is both downwardly biased and spuriously correlated with the contemporaneous earnings surprise. Therefore, we consider earnings announcement effect on bundled forecast news by estimating the following two-stage regressions (Rogers and Van Buskirk [2013]):

First stage regression:

$$\begin{aligned}\text{Prob}(Bundled = 1) = {} & a_0 + a_1 ConferenceCall + a_2 MFIssued \\ & + a_3 LastBundled + a_4 GoodEANews \\ & + a_5 BadEANews + a_6 AbsEANews + a_7 Loss \\ & + a_8 STD\_AF + a_9 Ret + a_{10} SIZE + a_{11} COVER \\ & + a_{12} FreqAFLowball + \text{ year and industry} \\ & \quad \text{fixed effects} + \varepsilon. \end{aligned} \tag{A.2}$$

Bundled is an indicator variable that equals one if there is a management forecast issued in the three-day window (–1, 1) around an earnings announcement date. *ConferenceCall* equals one for earnings announcements issued with a contemporaneous conference call, and zero otherwise. We collect conference call data from LexisNexis, Bloomberg, and CapitalIQ. *MFIssued* equals one for earnings announcements for which management had previously issued an earnings forecast, zero otherwise. *LastBundled* equals one if the firm issued a forecast at the prior quarter's earnings announcement date, and zero otherwise. *GoodEANews* equals one for earnings surprises (actual earnings minus analyst estimates, scaled by stock price) greater than 0.0001, and zero otherwise. *BadEANews* equals one for earnings surprises less than –0.0001, and zero otherwise. *AbsEANews* is the absolute value of the actual earnings minus analyst estimates, scaled by the stock price. *Loss* equals one for negative actual earnings, and zero otherwise. *STD_AF* is the standard deviation of analyst estimates for the current period's earnings. *Ret* is the cumulative stock return over the 90-day period ending 3 trading days prior to the firm's earnings announcement. *SIZE* is firm size, measured as the natural log of the firm's market capitalization. *COVER* is analyst coverage, measured as the natural log of one plus the number of analysts following. *FreqAFLowball* is the proportion of the previous four quarters that the firm's reported earnings met or exceeded analysts' consensus earnings estimates.

Second stage regression:

$$\begin{aligned} AR_{NF} = {} & b_0 + b_1 GoodEANews + b_2 BadEANews + b_3 GoodEANews \\ & \times EANews + b_4 BadEANews \times EANews + b_5 Ret + b_6 EANews \\ & \times AbsEANews + b_7 EANews \times MVRank + b_8 EANews \\ & \times E/PRank + b_9 \mathrm{Prob}(Bundled = 1) + \varepsilon_{NF}. \end{aligned} \tag{A.3}$$

AR_{NF} is analyst revisions for the nonforecasting group, measured as to the mean analyst estimate five trading days after the current period's earnings announcement minus the mean analyst estimate outstanding immediately prior to the current period's earnings announcement, scaled by lagged stock price. *MVRank* is the decile rank of the firm's preearnings announcement market value. *E/PRank* is the decile rank of the firm's preearnings announcement earnings/price ratio. $\mathrm{Prob}(Bundled = 1)$ is the predicted probability of the firm issuing a forecast with the earnings announcement estimated from the first stage regression.

We obtain $\widehat{b_k}$, the vector of the coefficients from model (c) by estimating the regression using a nonforecasting group. We use $\widehat{b_k}$ to obtain $\widehat{AF_F}$, a fitted value of the proportion of earnings announcement news from an analyst revision of bundle forecast in the forecasting group. We define the conditional consensus analyst forecast after adjusting for the "bundle effect" as the unconditional consensus analyst forecast minus $\widehat{AF_F}$. Therefore, *NEWS_Raw* (after adjusting for the "bundle effect") is equal to the management forecast minus the conditional consensus analyst forecast.

A.3 THE PROCEDURE TO IDENTIFY ADDITIONAL CEOS FROM THOMSON FINANCIAL INSIDER TRADING DATABASE AND EDGAR

We follow Rogers and Van Buskirk [2009] to extract CEO information from the Thomson Financial Insider Trading Database and the SEC's EDGAR database. First, we approximate CEO tenure by identifying the dates of first and last insider trades (either stock or options) by a CEO as the pseudo-beginning and pseudo-ending dates of her tenure. We use the pseudo-dates to supplement the CEO information extracted from ExecuComp. Finally, we manually compile the starting date of CEOs directly from SEC filings (e.g., proxies, quarterly, and annual reports) when we are unable to obtain machine-readable data sets (ExecuComp and Thomson Financial Insider Trading).

A.4 THE ESTIMATION OF ANALYST FORECAST BIAS (AF_BIAS)

We calculate analyst forecast bias (*AF_Bias*) as the fitted value of *AFE* from the following regression estimated with quarterly data for firm characteristics (firm and time subscripts omitted):

$$AFE = a_0 + a_1 SIZE + a_2 MTB + a_3 LEV + a_4 COVER + a_5 EARNVOL + \text{year and industry fixed effects} + \varepsilon. \tag{A.4}$$

AFE is the analyst forecast error, defined as the difference between the analyst consensus forecast and actual earnings, scaled by stock price. We identify a list of independent variables following prior literature (e.g., Brown and Rozeff [1979], Kross, Ro, and Schroeder [1990]). *SIZE* is firm size, measured as the natural log of the firm's market capitalization. *MTB* is the market-to-book ratio, which is the market value of equity divided by book value of equity at the end of the prior quarter. *LEV* is the leverage ratio, which is the book value of debt divided by the book value of equity. *COVER* is analyst coverage, measured as the natural log of one plus the number of analysts following. *EARNVOL* is the standard deviation of the quarterly return on assets over the preceding eight quarters.

APPENDIX B

Data Definition

Variables	Definitions
CONS	Measure of management forecast consistency, defined as an indicator variable that equals one if the standard deviation of the management forecast errors is less than the standard deviation of the consensus analyst forecast errors over last two years before the current management forecast, otherwise zero.
ACCU	Measure of management forecast accuracy, defined as an indicator variable that equals one if more than half of the time the absolute management forecast errors are less than the absolute consensus analyst forecast errors over last two years before the current management forecast, otherwise zero.
AFE	Analyst forecast error, calculated as the difference between the analyst consensus forecast and actual earnings, scaled by stock price.
AF_Bias	Analyst forecast bias, calculated as the fitted value of analyst forecast error (*AFE*) from the regression in the appendix.
AFREV	Individual analyst forecast revision scaled by the stock price at the beginning of quarter *t*. An individual forecast revision is defined as the difference between the first forecast of an analyst issued within 30 days after the management forecast date, and the latest one issued by the same analyst up to 90 days before the management forecast date.
ARET	Three-day, size-adjusted stock return around the management forecast announcement.
BAD	An indicator variable that equals one if *NEWS* is negative, zero otherwise.
BAD_EA	An indicator variable that equals one if *EANEWS* is negative, zero otherwise.
COVER	Analyst following measured as the natural logarithm of one plus the number of analysts following the firm before the management forecast date.

(Continued)

Variables	Definitions
DA	Discretionary accruals, measured as the residual from a specification that regresses total accruals on assets; change in sales minus change in accounts receivables; and plant, property, and equipment (Brown and Pinello [2007]).
EANEWS	The earnings announcement news issued within (–1, 1) around the management forecast date. It is equal to the realized earnings minus the most recent consensus analyst forecast, scaled by stock price. If there is no earnings announcement issued within (–1, 1) around the management forecast, it is equal to zero.
|*EANEWS*|	The absolute value of *EANEWS*.
EARNVOL	The standard deviation of the quarterly return on assets over the preceding eight quarters.
EXP	Individual forecast experience of an analyst, measured as the natural logarithm of one plus the number of quarters in which an analyst has issued forecasts for a given CEO, before the current management forecast.
F_EXP	Firm-level analyst experience, measured as the averaged value of *EXP* across analysts for a firm quarter.
GOOD	An indicator variable that equals one if *NEWS* is positive, zero otherwise.
HOR	Management forecast horizon, measured as the natural logarithm of one plus the number of days between the issuance of the forecast and the earnings announcement.
INTO	Institutional ownership, measured as the averaged percentage of shares owned by institutional investors for a given firm over the last two years.
LEV	Leverage ratio, measured as total liability over book value of equity.
MBESTREAK	Meet-or-beat market expectation (*MBE*) consistency, defined as an indicator variable that equals one if *MBE* string runs for eight consecutive quarters before the current management forecast date, and zero otherwise. *MBE* string is the consecutive preceding *MBE*s (Kross, Ro, and Suk [2011]).
MFLOSS	Indicator variable that equals one if the management forecast is negative, and zero otherwise.
MF_Bias	Management forecast bias, calculated as the fitted value of management forecast error (*MFE*) from the regression using a vector of control variables estimated with quarterly data for management forecasts (see appendix A).
MF_FixBias	Management forecast bias, calculated as the averaged value of management forecast error (*MFE*) for a given CEO.
AbsMF_Bias	The absolute value of *MF_Bias*.
MFE	Management forecast errors, measured as quarter t management forecast minus realized earnings per share, scaled by the stock price at the beginning of quarter t.
MTB	Market-to-book ratio, measured as market value of equity divided by book value of equity.
NEWS	Management forecast news, calculated as management forecast minus consensus analyst forecast and adjusted for bundle effect (Rogers and Van Buskirk [2013]), denoted as *NEWS_Raw*, *NEWS_Adj*, *NEWS_FixAdj*, and *NEWS_Both*.
|*NEWS*|	Absolute value of *NEWS*.
NEWS_FixAdj	The difference between the management forecast (adjusted on *MF_Biass*) and the most recent consensus analyst forecast up to 90 days before the management forecast date, scaled by the stock price at the beginning of quarter t.

(Continued)

Variables	Definitions
NEWS_Adj	The difference between the management forecast (adjusted on *MF_Bias*, see appendix A) and the most recent consensus analyst forecast up to 90 days before the management forecast date, scaled by the stock price at the beginning of quarter *t*.
NEWS_Both	The difference between the management forecast (adjusted for *MF_Bias*, see appendix A) and the most recent consensus analyst forecast (adjusted for *AF_Bias*; see appendix A) up to 90 days before the management forecast date, scaled by the stock price at the beginning of quarter *t*.
NEWS_FixAdj	The difference between the management forecast (adjusted for *MF_FixBias*) and the most recent consensus analyst forecast) up to 90 days before the management forecast date, scaled by the stock price at the beginning of quarter *t*.
NEWS_Raw	The difference between the management forecast and the most recent consensus analyst forecast up to 90 days before the management forecast date, scaled by the stock price at the beginning of quarter *t*.
RANGE	An indicator variable that equals one if the management forecast is not point forecast, zero otherwise.
SIZE	The natural logarithm of market value of equity.
STDAFE	The standard deviation of the forecast errors of an analyst, scaled by the stock price.
STDMFE	The standard deviation of the management forecast errors, scaled by the stock price.

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