Why do firms forecast earnings for multiple years simultaneously?

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Abstract

By issuing earnings forecasts for both current and future years simultaneously, managers provide the multi-year data required for many valuation models and help investors sort out transitory and permanent shocks. We find that firms that are overpriced and have more transitory earnings tend to issue multi-year forecasts simultaneously. Overpriced firms are more likely to issue both short- and long-term bad news than only short-term bad news forecasts. Mispricing tends to be corrected after firms' multi-year forecasts, especially when overpriced firms issue both long- and short-term bad news forecasts. We also find a more linear current period earnings–return relation when firms issue multi-year forecasts, which suggests that investors underreact less to extreme news because the future year forecasts embed earnings persistence information.

JEL Classification: D82; D83; G12; M40

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1. Introduction

Firms disclose more data in recent years, but investors still mis-value firms due to imprecise, inadequate, or excessive data. Managers can guide investors better by providing data that investors use in their valuation models, such as earnings forecasts for multiple years. We study whether firms' simultaneous issuance of forecasts for multiple years helps investors better assess firm value. Specifically, we examine the effect of mispricing and earnings persistence on managers' decisions to provide multi-year forecasts and the consequences of these forecasts on firms' valuations.

Some firms forecast earnings only for the current year, whereas other firms forecast earnings for both the current and future years. Earnings forecasts for multiple years (hereafter “management forecast sets” or “MF sets”) provide important inputs to investors' valuation models.¹ Short- and long-term earnings forecasts together help investor assess the persistence of current earnings surprises (Liu and Thomas, 2000). If earnings persistence is high, investors would predict higher dividends, leading to higher stock returns (Kormendi and Lipe 1986; Collins and Kothari, 1989). Since MF sets help investors predict future earnings better, equity mispricing is likely to be reduced.

Firms are more likely to be mispriced when managers withhold private information. Because firms and managers are often punished when this withholding is revealed, mispriced firms may want to commit to providing value-relevant data quickly. We argue that MF sets likely make firms' disclosures more credible by increasing the number of commitments and the time that they span. Moreover, overpriced firms have greater incentives to issue MF sets due to greater litigation risk from stock price crashes. Thus, we predict that overpriced firms are more likely to issue MF sets (especially bad news for both short- and long-term forecasts) than current-year forecasts.

¹ We use “Management forecast sets”, “MF sets”, and multiple-year (or multi-year) forecasts interchangeably.

We also predict that firms with more transitory items in current earnings are likely to guide investors by providing MF sets. Investors could overestimate earnings persistence if they assign too much weight to transitory items. Brown, Foster, and Noreen (1985) argue that analysts' one-year-ahead forecasts have more transitory components than two-year-ahead forecasts, because analysts adjust short-term forecasts to GAAP earnings but they base long-term forecasts on permanent earnings. Hence, investors can identify the transitory components of current earnings by treating future earnings as permanent. Similarly, MF sets can help separate the transitory and permanent items in earnings news, reducing investors' overextrapolation of recent transitory items.

We predict that investors reduce future mispricing by using the additional data in MF sets. Many valuation models require earnings forecasts for at least the first two years (e.g. Ohlson and Juettner-Nauroth, 2005), suggesting that using only one year's data is likely to cause misvaluation. We also expect that firms issuing MF sets are likely to mitigate the nonlinear earnings–return relation. Subramanyam (1996) argues that the earnings–return relation appears nonlinear because investors associate extreme earnings news with lower precision due to uncertainty stemming from transitory items and accrual estimates. Since MF sets contain persistence data, investors provided with MF sets are likely to have more precise information, reducing the extent of nonlinearity.

We use management forecasts from I/B/E/S Guidance between 2000 and 2016. We identify mispricing by summarizing 11 prominent anomalies, following Stambaugh, Yu, and Yuan (2012, 2015). We find that overpriced firms are more likely to issue MF sets, and that they tend to issue both short- and long-term bad news forecasts rather than only short-term bad news forecasts.

We use three proxies for transitory or nonrecurring items: non-GAAP earnings disclosures, special items, and extraordinary items and discontinued operations. We find that they are all positively associated with the issuance of MF sets. However, this association is found only in

overpriced firms. Using difference-in-difference tests, we use a 2007 Supreme Court decision to establish a litigation risk channel for the overpriced firms' disclosures, and brokerage mergers and closures to link reduction in information availability to MF set disclosure.

We find that mispricing falls after managers issue MF sets and reverts towards the mean. Specifically, firms' overpricing falls when they issue long-term bad news with short-term forecasts. We also find that firms with MF sets have a more linear earnings surprise-return relation, consistent with investors using MF set data to separate permanent and temporary components in earnings.

Our study contributes to management forecast research by differentiating between single-year forecasts and bundled multi-year forecasts. We show that MF sets are more likely to be provided when firms are overpriced and have more transitory items, which has broader implications for disclosure research. We also contribute to valuation research by showing that overpricing and underpricing have different effects on firm disclosures, likely due to higher litigation risk and the higher cost of arbitraging by short selling.

The remainder of this paper is organized as follows. We review prior studies and develop hypotheses in Section 2. We explain our research design and sample selection in Sections 3 and 4. We provide descriptive statistics and empirical results in Section 5. We conclude in Section 6.

2. Hypothesis development

2.1. The effect of mispricing on the issuance of management forecast sets

Firms' shares are often mis-valued because of excessive, inadequate or incorrect data; investors' limited understanding of financial data; etc. Mary Jo White (2013), a former SEC Chair, argues that "when disclosure gets to be too much or strays from its core purpose, ... ever-increasing

amounts of disclosure make it difficult for an investor ... to ferret out the information that is most relevant.” Managers disclose or withhold their private information based in part on their incentives. Managers with career or pay concerns often withhold bad news, hoping that their firms’ status improves before the news must be released or waiting for subsequent good news to overshadow the bad news (Graham, Harvey, and Rajgopal, 2005; Kothari, Shu, and Wysocki, 2009; Leuz and Wysocki, 2016; Bertomeu, Ma, and Marinovic, 2018; Bliss, Partnoy, and Furchtgott, 2018).

As information asymmetry between managers and outside investors increases, investors become more reluctant to invest or they require a higher premium for the information risk (Myers and Majluf, 1984; Barry and Brown 1985; Merton, 1987). In addition, overpriced firms can have a sudden revelation of bad news, causing a stock price crash (Jin and Myers, 2006). Firms lose credibility when the stock price decline reveals that managers withheld data. In such cases, firms can restore their credibility by committing to providing value-relevant information quickly.

MF sets are likely to enhance firms’ disclosure credibility because releasing both long- and short-term forecasts increases the number of commitments and the time that they span. Mercer (2004) reports that disclosure credibility is influenced by managers’ incentives to mislead when disclosing. To restore firms’ credibility and reduce information asymmetry, mispriced firms are likely to provide more accurate and detailed disclosures. If managers have less incentives to mislead investors, they will likely make disclosure commitments for longer periods, increasing credibility and reducing information asymmetry. While public earnings releases report on a firm’s short-term prospects, MF sets inform investors about both short- and long-term earnings.

Disclosure behaviors likely differ between overpriced and underpriced firms. Bergman and Roychowdhury (2008) find that firms increase (decrease) long-horizon forecasts during low- (high)-sentiment periods but these forecasts are not issued only to correct the bias. Seybert and

Yang (2012) show that managers' earnings guidance can correct optimistic market expectations. They find that managers' earnings forecasts, especially bad new forecasts, are associated with more negative market reactions in high-sentiment periods, suggesting that earnings guidance could correct sentiment-driven overvaluation. These studies do not consider different litigation risks for overvalued and undervalued firms, which likely also influence firms' disclosure policy.

Prior studies show that large stock price declines trigger shareholder class-action lawsuits accusing managers of withholding bad news, but large stock price increases have little effect (Kellogg, 1984; Alexander, 1991). Therefore, overpriced firms are likely to have greater litigation exposure than underpriced firms. This asymmetric loss function induces managers to promptly warn investors before large negative earnings surprises (Skinner, 1994; Kasznik and Lev, 1995). Francis, Philbrick, and Schipper (1994) find that sued firms disclose three times more than do "at risk" firms. Skinner (1997) shows that timely disclosures reduce the settlement costs once firms are sued. However, some studies find that early disclosures trigger litigation and sued firms decrease the amount they disclose (Francis et al., 1994; Rogers and Van Buskirk, 2009).

Although it is unclear how litigation affects managers' disclosures on average, we expect that overpriced firms are more likely to issue MF sets because of greater litigation risk. Overpriced firms are likely to use long-term forecasts to mitigate potential claims for withholding information about the future. Also, they could weaken the impact of negative surprises by providing early warnings of bad news via MF sets. Therefore, we hypothesize:

H1a: Firms are more likely to issue management forecast sets if they are overpriced.

H1b: Firms are more likely to issue bad news management forecast sets if they are overpriced.

2.2. The effect of transitory (nonrecurring) items on the issuance of management forecast sets

Prior studies document that short- and long-term analyst forecasts differ in persistence. Brown, Foster, and Noreen (1985) show that analysts' one-year-ahead earnings forecasts have more transitory components than their two-year-ahead forecasts. They argue that analysts adjust one-year-ahead forecasts to the GAAP earnings number, which includes both transitory and permanent components, but they forecast two-year-ahead earnings based on permanent components only because they cannot predict temporary components far in the future. Identifying the transitory and permanent components is crucial in forecasting earnings and valuing stocks because transitory earnings affect only one period while permanent earnings affect multiple periods (Beaver, 1970; Ramakrishnan and Thomas, 1998).

Investors find it difficult to estimate persistence because no accounting item can be classified as purely recurring or nonrecurring. Analysts rely on professional judgment for classification (Gu and Chen, 2004). Managers classify nonrecurring items in part based on their incentives to meet or beat market expectations. Doyle, Jennings, and Soliman (2013) find that firms define non-GAAP earnings opportunistically and firms with non-GAAP exclusions are more likely to meet or beat analysts' forecasts. Furthermore, analysts' incentives affect how they treat non-recurring items in "Street" earnings. Bradshaw and Sloan (2002) report that "Street" earnings reflect a strong bias to present numbers more favorably.

Because estimating earnings persistence is difficult, the market may mis-estimate persistence, especially when a firm's recent earnings have large transitory components. Since some investors fixate on earnings (Hand, 1990; Bushee, 2001; Graham, Harvey, and Rajgopal, 2005), they could incorrectly extrapolate transitory earnings to the future, i.e., overestimate earnings persistence. Elliott, Hobson, and Jackson (2011) find that earnings fixation is mitigated when firms provide

disaggregated management forecasts, suggesting that investors consider inputs other than earnings. We argue that investors' fixation on earnings can be mitigated if they are given forecasts for multiple years because they help avoid over-extrapolating recent earnings' transitory components. Thus, we expect that firms with more transitory earnings are more likely to provide MF sets to guide investors about earnings persistence. Accordingly, we propose the following hypothesis.

H2: Firms with more transitory earnings are more likely to issue management forecast sets.

2.3. The consequences of the issuance of management forecast sets: valuation and nonlinearity

MF sets can assist investors by providing multi-year inputs for valuation models. Many newer valuation models require forecasts for the next two periods (Lee, Myers, and Swaminathan, 1999; Gebhardt, Lee, and Swaminathan, 2001; Ohlson and Juettner-Nauroth, 2005), and are more accurate than valuation models using a one-period forecast like the Gordon growth model (Gordon and Shapiro, 1956). MF sets can reduce mispricing because investors can readily use managers' forecasts for multiple periods.

Furthermore, MF sets are likely to affect firms' earnings–return relation. Prior studies find a S-shaped relationship between unexpected earnings and returns (e.g. Freeman and Tse, 1992; Cheng, Hopwood and McKeown, 1992). Subramanyam (1996) shows in a model that uncertainty regarding information precision can cause a price response to information that is neither linear nor monotonic. Subramanyam (1996) argues that nonlinearity arises because transitory or nonrecurring items, changes in accounting methods, and accrual estimates lead to greater uncertainty and because investors associate extreme news with less precision. Since investors' response to information increases with its precision, extreme news is likely to induce less stock

price reaction per unit. Because MF sets embed persistence data, investors can extract more precise information for even extreme news from forecast sets, reducing the extent of nonlinearity.

Liu and Thomas (2000) show that nonlinearity is attenuated when revisions of analysts' future earnings forecasts are included in the regression. Their findings suggest that the estimated nonlinearity is driven by omitting available data (i.e., earnings forecast revisions) that investors use to separate transitory and permanent components in earnings news. Because management earnings forecasts are often more accurate than analysts' forecasts (Hutton, Lee and Shu 2012), including MF sets should mitigate the nonlinearity problem. We propose the following hypotheses:

H3a: Firms issuing management forecast sets are less likely to have future mispricing.

H3b: Firms issuing management forecast sets are less likely to have a nonlinear relation between earnings and returns.

3. Research Design

3.1. Tests of the effect of mispricing (H1) and transitory items (H2) on the issuance of management forecast sets

We jointly test H1 and H2 using the following models. The difference between equations (1) and (2) is that equation (1) uses the absolute value of nonrecurring items ($abs(NRI)$) and equation (2) allows different slopes for positive and negative nonrecurring items by introducing a dummy variable (DN) for negative nonrecurring items.

$$\begin{aligned}
 MFSET_{i,t} = & \alpha_0 + \alpha_1 MIS P_{i,t-1} + \alpha_2 abs(NRI)_{i,t-1} + \alpha_3 LITG_{i,t-1} + \alpha_4 MISSMF_{i,t-1} + \alpha_5 SIZE_{i,t-1} \\
 & + \alpha_6 BTM_{i,t-1} + \alpha_7 EVOL_{i,t-1} + \alpha_8 RET_{i,t-1} + \alpha_9 ISSUE_{i,t-1} + \alpha_{10} INST_{i,t-1} \\
 & + \alpha_{11} LOSS_{i,t-1} + \alpha_{12} NAF_{i,t-1} + \alpha_{13} AFSTD_{i,t-1} + IndustryFixed + YearFixed \\
 & + \varepsilon_{i,t}
 \end{aligned} \tag{1}$$

$$\begin{aligned}
MFSET_{i,t} = & \alpha_0 + \alpha_1 MISP_{i,t-1} + \alpha_2 NRI_{i,t-1} + \alpha_3 DN_{i,t-1} + \alpha_4 DN * NRI_{i,t-1} + \alpha_5 LITG \\
& + \alpha_6 MISSMF_{i,t-1} + \alpha_7 SIZE_{i,t-1} + \alpha_8 BTM_{i,t-1} + \alpha_9 EVOL_{i,t-1} + \alpha_{10} RET_{i,t-1} \\
& + \alpha_{11} ISSUE_{i,t-1} + \alpha_{12} INST_{i,t-1} + \alpha_{13} LOSS_{i,t-1} + \alpha_{14} NAF_{i,t-1} + \alpha_{15} AFSTD_{i,t-1} \\
& + IndustryFixed + YearFixed + \varepsilon_{i,t}
\end{aligned} \tag{2}$$

MFSET is an indicator variable that equals one if a firm simultaneously (i.e., on the same day) issues a short-term forecast (e.g., forecast for year t) and long-term forecasts (e.g., forecasts for years $t+1$, $t+2$, and so on, if available), and zero if a firm issues single-year forecasts.

We construct a mispricing measure (*MISP*) from 11 prominent anomalies (Stambaugh, Yu, and Yuan 2012, 2015).² To compute the degree of mispricing, we rank firms on each anomaly so that higher rankings indicate overpricing and lower rankings indicate underpricing.³ *MISP* is the average ranking percentile for each of the 11 anomalies each year. We find similar results (untabulated) when we use a monthly *MISP* rather than an annual *MISP*. To study how MF set issuance differs between overpriced and underpriced firms, we divide the full sample into five quintiles based on $MISP_{t-1}$, where *Quintile1* and *Quintile5* represent the most underpriced and the most overpriced firms, respectively. We find similar results when we use book-to-market (*BTM*) instead of *MISP* to form the five mispricing quintiles. For H1a, we expect to find a significantly positive α_1 for overpriced firms (i.e., *Quintile5*) if they are more likely to issue MF sets.

For H1b, we use two different MF sets as the dependent variable in model (1) instead of *MFSET*: MF sets that are short-term good news and long-term good news (SGLG) and short-term

² The eleven anomalies cover a stock's various stock characteristics that capture potential mispricing. The anomalies used by Stambaugh, Yu, and Yuan (2012, 2015) are as follows: Financial distress (Campbell, Hilscher, and Szilagyi, 2008), O-Score bankruptcy probability (Ohlson, 1980), net stock issues (Ritter, 1991; Loughran and Ritter, 1995; Fama and French, 2008), composite equity issues (Daniel and Titman, 2006), total accruals (Sloan, 1996), net operating assets (Hirshleifer, Hou, Teoh, and Zhang, 2004), momentum (Jegadeesh and Titman, 1993), gross profitability (Novy-Marx, 2013), asset growth (Cooper, Gulen, and Schill, 2008), return on assets (Fama and French, 2006; Chen, Novy-Marx, and Zhang, 2011) and investment-to-assets (Titman, Wei, and Xie, 2004; Xing, 2008).

³ For example, high asset growth is followed by a low return in the subsequent period (Cooper et al., 2008), indicating that higher asset growth tends to be overpriced. Therefore, stocks with the highest rank are the most overpriced, and stocks with the lowest rank are the most underpriced (Stambaugh et al., 2015).

bad news and long-term bad news (SBLB).⁴ Short-term good (bad) news is defined as management earnings forecasts that are greater (less) than the most recent analyst consensus for the current year.⁵ Similarly, long-term good (bad) news is defined as management earnings forecasts that are greater (less) than the most recent analyst consensus for long-term news.

We restrict our analysis to firms whose actual news is close to what managers forecasted and compare each type of MF set with single-period forecasts. For example, to examine why firms provide SGLG forecasts, we first restrict the analysis to firms whose actual EPS for the forecasted periods are greater than the issued consensus forecasts. Conditional on having the actual earnings be SGLG, we compare SGLG and SG (i.e., only short-term good news) forecasts to examine why some firms issue SGLG while others issue SG forecasts when both groups likely expect SGLG. Thus, *SGLG* (*SBLB*) is an indicator variable that equals one for MF sets of SGLG (*SBLB*) and zero for SG (*SB*) forecasts, conditional on having actual earnings be SGLG (*SBLB*). For H1b, we expect a significantly positive α_1 for overpriced firms (i.e., *Quintile5*) when *SBLB* is used as the dependent variable if overpriced firms are likely to issue bad news MF sets.

To measure transitory or nonrecurring items (*NRI*), we use three proxies: non-GAAP measures (Bentley, Christensen, Gee, and Whipple, 2018), special items, and extraordinary items and discontinued operations. Non-GAAP measures (*NGAAP*) are constructed from all available non-GAAP earnings disclosures from the Bentley et al. (2018) data set.⁶ We subtract quarterly non-

⁴ We exclude neutral news (i.e., management forecasts = analyst consensus forecasts) because the frequency of management forecast sets having neutral news in either short-term or long-term forecasts is less than 5% of the frequency of the total management forecast sets. Moreover, introducing neutral news will lead to nine different types of management forecast sets rather than four types of these forecasts.

⁵ For range forecasts (i.e., two-sided), we use the upper value that Ciconte, Kirk, and Tucker (2014) find represents managers' true expectations and investors' interpretation of managers' expectations.

⁶ This data set includes all firms in the Compustat-CRSP-I/B/E/S universe that provide manager-disclosed non-GAAP earnings between 2003 and 2016. Bentley et al. (2018) identify and collect the information from firms' 8-K filings on EDGAR. <https://sites.google.com/view/kurthgee/data>.

GAAP EPS from quarterly GAAP EPS and sum over the fiscal year to analyze on an annual basis. Special items (*SPI*) and extraordinary items and discontinued operation (*XIDO*) are scaled by total assets.⁷ For H2, we expect to find a significantly positive α_2 if firms that had greater transitory earnings in the previous year tend to issue MF sets.

Also, a dummy variable (*DN*) for negative nonrecurring items is interacted with nonrecurring items (*NRI*). We expect α_4 to be significantly positive if negative nonrecurring items have a greater slope than positive items (i.e., firms tend to issue MF sets to a greater extent when they have negative transitory items than when they have positive transitory items).

To control for lawsuits, we use *LITG*, an indicator variable that equals one if a firm was sued in the previous year and zero otherwise.⁸ We include *MISSMF*, the number of times a firm missed its management forecasts during the year, to control for managers' incentives to provide supplementary disclosures to increase credibility (Hutton et al., 2003). We also include *SIZE*, the natural log of total assets, to control for firm size and book-to-market ratio (*BTM*) to control for firms' growth opportunity. To control for earnings volatility, we include *EVOL*, the standard deviation of the firm's earnings over the previous 12 quarters. *RET*, the past 12-month return adjusted for the value-weighted market return, is included to control for firms' recent stock performance. We include *ISSUE*, the natural log of the equity issuance amount, to control for firms' equity issues. We include *INST*, the percentage of institutional ownership, to control for corporate governance. To control for firms' poor earnings performance, we include a loss indicator (*LOSS*). We include the number of analysts following the firm (*NAF*) and the standard deviation of analyst

⁷ Since FASB eliminated the concept of extraordinary items from 2015 (Accounting Standards Update (ASU) 2015-01), *XIDO* represents the sum of extraordinary items and discontinued operations before the start of 2015 and only discontinued operations from 2015 onwards.

⁸ Instead of the actual litigation event, we also estimate the litigation risk following Kim and Skinner (2012). Our main results are qualitatively similar using the estimated litigation risk.

forecasts (*AFSTD*) to control for the information environment. We include year and industry fixed effects to control for any time-series or cross-industry variation.

3.2. Tests of the effect of management forecast sets on mispricing

To test H3a, we use model (3) to test whether mispricing is mitigated after MF sets are issued.

$$MISP_{i,t+1} - MISP_{i,t} = \alpha_0 + \alpha_1 MFSET_{i,t} + \alpha_2 SIZE_{i,t} + \alpha_3 IVOL_{i,t} + \alpha_4 R2_{i,t} + \alpha_5 ZERO_{i,t} + \alpha_6 NAF_{i,t} + \alpha_7 AFSTD_{i,t} + \alpha_8 \Delta MISP_{i,t} + \varepsilon_{it} \quad (3)$$

$MISP_{t+1} - MISP_t$ is the change in mispricing (*MISP*) from year t to $t+1$. *MFSET* again indicates the firms' issuance of MF sets. Alternatively, we use the level of mispricing, $MISP_{t+1}$, instead of the change in mispricing, as the dependent variable. For H3a, we expect to find a significantly negative α_1 if firms issuing MF sets experience a decrease in mispricing in the following year.

We control for other factors that could influence mispricing following Jacobs (2016). Chari, Jagannathan, and Ofer (1988) find that small firms have greater returns around earnings releases than large firms. Thus, we control for firm size (*SIZE*). We also include idiosyncratic volatility (*IVOL*) to control for firm-specific risk. Following Fu (2009), we regress daily excess returns on the daily Fama-French (1993, 1996) three factors for each month. Then, we compute the standard deviation of the daily residuals over the year to proxy for idiosyncratic risk.

We also add two variables associated with market efficiency, *R2* and *ZERO*. *R2* is the average R^2 obtained from regressing excess returns on the Fama-French three factors to measure idiosyncratic volatility.⁹ *ZERO* is the average fraction of days with zero returns, controlling for

⁹ Prior studies argue that a lower R^2 could indicate either informed trading or noise trading (Roll, 1988; Morck, Yeung, and Yu, 2000; Campbell, Lettau, Malkiel, and Xu, 2001; Durnev, Morck, Yeung, and Zarowin, 2003). If high firm-specific return variation reflects informed investors' active trading, a lower R^2 could indicate greater market efficiency. However, if firm-specific return volatility reflects noise trading, a lower R^2 could indicate greater market inefficiency.

trading activity (Lesmond, Ogden and Trzcinka, 1999).¹⁰ We also add *NAF* and *AFSTD* to control for information uncertainty and the dispersion of investor beliefs.

Additionally, we add $\Delta MIS P_t$ to control for mean reversion of mispricing because overpricing and underpricing are likely to revert to the mean in the following period, especially if mispricing increases or decreases to a greater extent in the current period. Alternatively, when we use the level of mispricing, $MIS P_{t+1}$, as the dependent variable, we replace $\Delta MIS P_t$ with $MIS P_t$ and $MIS P_{t-1}$ on the right-hand side of the equation. $MIS P_t$ controls for the mean reverting tendency when mispricing is very high or low in the current period. $MIS P_{t-1}$ controls for the potential confounding effect of past mispricing on current changes in mispricing.

3.3. Tests of the effect of management forecast sets on nonlinearity

Prior studies model the nonlinear earnings-return relation using symmetric quadratic or arctan functions (Freeman and Tse, 1992; Das and Lev, 1994; Beneish and Harvey, 1998). We use a quadratic function that allows different curvatures for negative and positive unexpected earnings to test H3b.

$$UR_{i,t} = \alpha_0 + \alpha_1 D_{i,t} + \alpha_2 UE_{i,t} + \alpha_3 D * UE_{i,t} + \alpha_4 UE^2_{i,t} + \alpha_5 D * UE^2_{i,t} + \varepsilon_{i,t} \quad (4)$$

$$UR_{i,t} = \alpha_0 + \alpha_1 D_{i,t} + \alpha_2 UE_{i,t} + \alpha_3 D * UE_{i,t} + \alpha_4 UE^2_{i,t} + \alpha_5 D * UE^2_{i,t} + \alpha_6 STnews_{i,t} + \varepsilon_{i,t} \quad (5)$$

$$UR_{i,t} = \alpha_0 + \alpha_1 D_{i,t} + \alpha_2 UE_{i,t} + \alpha_3 D * UE_{i,t} + \alpha_4 UE^2_{i,t} + \alpha_5 D * UE^2_{i,t} + \alpha_6 STnews_{i,t} + \alpha_7 LTnews_{i,t} + \varepsilon_{i,t} \quad (6)$$

Unexpected returns (*UR*) are measured as annual stock returns adjusted for value-weighted returns starting three months after the end of the fiscal year. Unexpected earnings (*UE*) is the difference between a firm's actual earnings-per-share (EPS) and the median EPS analyst forecast

¹⁰ High trading activity could be associated with less mispricing if the trading activity reflects small transaction costs or arbitrage (McLean and Pontiff, 2016). However, high trading activity could imply greater mispricing in cases where the activity indicates noise trading (Baker and Stein, 2004; Baker and Wurgler, 2006).

in the last month of the firm's fiscal year. D is an indicator variable that equals one if UE is negative and zero otherwise. We estimate model (4) separately for firms that issued MF sets at least once during the year (i.e., $MFSET=1$) and firms that issued only single-period forecasts throughout the year (i.e., $MFSET=0$). We predict that α_4 and α_5 will be smaller for firms with $MFSET=1$ than those with $MFSET=0$.

For models (5) and (6), we add short-term news ($STnews$), which is the difference between management forecasts and the latest analyst consensus forecasts for the current year, and long-term news ($LTnews$), which is the difference between management forecasts and the latest analyst consensus forecasts for the aggregated forecasts beyond the current year. Short-term news is available for firms with $MFSET=1$ or 0, whereas long-term news is only available for firms with $MFSET=1$. We estimate model (5) separately for both groups but estimate model (6) only for firms with $MFSET=1$.

We also test whether managers' short- and long-term forecasts are informative. We expect α_6 in model (5) and α_6 and α_7 in model (6) to be significantly positive if the unexpected returns are associated with managers' short- and long-term surprises. In addition, the adjusted R^2 is expected to increase from model (4) to (5) if short-term surprises from management forecasts can explain the unexpected returns. We also expect to find an increase in the adjusted R^2 from model (5) to (6) if the unexpected returns can be further explained by long-term surprises.

4. Sample selection

Table 1 summarizes the sample selection. We collect EPS management forecasts between 2000 and 2016 from the I/B/E/S Guidance Database. We restrict the sample to U.S. firms because countries vary in reporting frequency requirements. We exclude preannouncements, which are

management forecasts after the fiscal year-end but before the earnings announcement, because preannouncements are more likely to be reporting the actual earnings like earnings announcements. We exclude observations that do not have analyst forecast data from I/B/E/S.

We make several adjustments for management forecasts that are disclosed on the same day. First, we aggregate quarterly or semiannual management forecasts over the same fiscal year to make all forecasts on an annual basis. For example, if quarterly forecasts are provided simultaneously for the third and fourth quarters of the same year, we add these forecasts as one annual forecast. We sum corresponding analyst forecasts similarly.¹¹

Second, we exclude quarterly or semiannual management forecasts if they are provided simultaneously with an annual forecast for the same year. When an annual forecast is provided with quarterly forecasts for the same year, the quarterly forecasts are somewhat redundant because an annual forecast consists of quarterly forecasts.

Third, we sum long-term management forecasts beyond the current year. When multi-year forecasts are provided on the same day, we condense them to one short-term forecast (i.e., forecast for year t) and one long-term forecast (e.g., aggregated forecast for year $t+1$ and $t+2$).

We collect financial statement data from Compustat, stock market data from CRSP, analysts' forecast data from I/B/E/S, and institutional ownership from Thomson Reuters Institutional Holdings. For litigation, we use the class action lawsuit data from the Stanford Securities Class Action Clearinghouse and collect equity offering data from the SDC database. The final sample consists of 67,546 management forecasts from 2,987 firms.

¹¹ Aggregating a subset of quarterly or semiannual forecasts over the same fiscal year still informs the news for the entire year because certain quarters with no updated forecasts imply that previous forecasts for these quarters are still valid and updates for the entire year are coming from the quarters with new forecasts.

5. Empirical results

5.1. Descriptive statistics

Table 2 provides descriptive statistics for the regression variables. Continuous variables are winsorized at the 1st and 99th percentile to reduce the impact of outliers. The mean value of *MFSET* is 0.053, indicating that approximately 5% of EPS management forecasts are multiple-year forecasts. The mean *NGAAP* is -0.231, suggesting that the average non-GAAP exclusions increase EPS by 0.231. The mean *SPI* is -0.014 and the mean *XIDO* is 0.0005. The mean *MISP* is 53.39, which is around 50 by construction because *MISP* is the average ranking percentile of 11 anomalies. The mean *LITG* is 0.039, meaning that approximately 4% of the sample experience litigation. The mean value of *MISSMF* is 2.051, suggesting that on average, firms miss their forecasts twice per year. The mean unexpected return (*UR*) is 0.9% and the mean unexpected earnings (*UE*) is -0.015. The mean value of *STnews* is 0.003 and that of *LTnews* is 0.022, indicating that the managers' and analysts' expectations differ more for long-term than short-term earnings.¹²

5.2. The effect of past mispricing on the issuance of management forecast sets

We divide the full sample into five quintiles based on $MISP_{t-1}$, where *Quintile1* and *Quintile5* represent the most underpriced and the most overpriced firms, respectively. Panel A in Table 3 shows the frequency and column percentages of MF sets for each quintile. MF sets are issued least (most) often for the most underpriced (overpriced) firms. The column percentage for firms with *MFSET*=1 increases from 16.1% for *Quintile1* to 26.1% for *Quintile5*.¹³

¹² Because the unit of analysis becomes the firm-year for the nonlinearity tests, the number of observations decreases for *UR*, *UE*, *STnews*, and *LTnews*.

¹³ Untabulated results show a similar frequency distribution across quintiles to that in Panel A of Table 3 when quintiles are formed based on $MISP_{t-2}$.

Panel B of Table 3 shows the frequency of MF sets by three different proxies for nonrecurring items. We divide the full sample into five quintiles based on $NGAAP_{t-1}$, SPI_{t-1} , and $XIDO_{t-1}$, respectively. The frequency and percentage of MF sets are much higher for *Quintile1* and *Quintile5* of $NGAAP_{t-1}$ than *Quintile2*, *Quintile3*, and *Quintile4*. However, the frequency of MF sets is quite even across SPI_{t-1} quintiles. The frequency distribution for $XIDO_{t-1}$ is like that for $NGAAP_{t-1}$, suggesting that firms with greater non-GAAP exclusions and those with greater extraordinary items and discontinued operations tend to provide more multi-year forecast sets concurrently.

Panel C of Table 3 presents OLS results of model (1). The results are similar using a logit regression instead of OLS. In addition to the full sample results, we also present the results for the most overpriced firms (i.e., *Quintile5*) and the most underpriced firms (i.e., *Quintile1*) based on $MISP_{t-1}$. Columns (1), (4), and (7) use $abs(NGAAP)$, columns (2), (5), and (8) use $abs(SPI)$, and columns (3), (6), and (9) use $abs(XIDO)$ for nonrecurring items (*NRI*). The *MISP* coefficients are significantly positive for the full sample, indicating that firms are more likely to issue MF sets if their firm values are mispriced at the start of the year. Consistent with the prediction for H1a, these results are driven by the overpriced firms but not by the underpriced firms because the *MISP* coefficients are significantly positive for only overpriced firms.

Similarly, the coefficients on nonrecurring items (*NRI*) are significantly positive for the overpriced but insignificant for the underpriced firms, indicating that overpriced firms tend to issue more forecast sets if they have greater transitory earnings. A greater likelihood of issuing MF sets for overpriced firms could be due to the high litigation risk they face (e.g. Kellogg, 1984). The coefficients on *LITG* are significantly positive for overpriced firms (column [6]) but insignificant for underpriced firms, indicating that only overpriced firms issue MF sets when they are being sued. *MISSMF* has significantly positive coefficients for only overpriced firms, suggesting that

firms that missed their forecasts try to restore their credibility by providing MF sets. The coefficients on *SIZE* and *BTM* are significantly positive and negative, respectively, suggesting that larger and growing firms are more likely to issue MF sets.

We address a concern that all the underpriced firms in *Quintile1* might have equally strong incentives to issue MF sets, which would be indicated by a flat slope in *Quintile1* (as opposed to a steeper slope in *Quintile5* which suggests that the probability of issuing MF sets increases with *MISP* for top quintile firms). If both underpriced and overpriced firms are more likely to issue MF sets than more accurately priced firms, the probability of issuing MF sets will be higher for *Quintile1* and *Quintile5* and lower for *Quintile2*, *Quintile3*, and *Quintile4*, that is, an overall U-shape. We re-estimate model (1) by replacing *MISP* with four quintile dummy variables (*Quintile2*, *Quintile3*, *Quintile4*, and *Quintile5*) created based on $MISP_{t-1}$. Untabulated results show that the quintile coefficients increase from *Quintile2* to *Quintile5*, indicating that the likelihood of issuing MF sets increases from the most underpriced to the most overpriced firms. The results do not support a U-shape; rather, they suggest a monotonic increase in MF set issuances from underpriced to overpriced firms, consistent with Panel A of Table 3.

5.3. The effect of past mispricing on the issuance of different types of management forecasts

Panel A of Table 4 reports the frequency of six different types of management forecasts for each quintile formed based on $MISP_{t-1}$. Most management forecasts are short-term forecasts (*SG* and *SB*). Among MF sets, *SGLG* has the highest frequency, followed by *SBLB*, *SGLB* and *SBLG*. Single-period forecasts (i.e., *SG* and *SB*) are more equally distributed at around 20% across quintiles compared to the distribution of MF sets. *Quintile5* has the highest percentage of *SGLG*,

SBLG, and *SBLB* issuances, indicating that overpriced firms tend to issue more MF sets than single-period forecasts.

Panel B of Table 4 shows the results for model (1) using *SGLG* and *SBLB* as the dependent variables in the first four and the last four columns, respectively.¹⁴ *LOSS* has significantly positive coefficients in columns (1) and (2) and negative coefficients in columns (3) and (4), indicating that overpriced firms tend to issue *SGLG* more than *SG* forecasts but underpriced firms tend to issue more *SG* forecasts than *SGLG* if they had losses in the past. These results also suggest that overpriced firms have higher incentives to issue multiperiod forecasts. Consistent with the prediction of H1b, *MISP* has a positive but weakly significant coefficient in column (6), indicating that highly overpriced firms are more likely to issue *SBLB* than only *SB* forecasts.

To further investigate the effect of mispricing on the issuance of *SBLB* forecasts, we replace *MISP* in the model (1) with four quintile dummy variables (i.e., *Quintile2*, *Quintile3*, *Quintile4*, and *Quintile5*) and use *SBLB* as the dependent variable. In Panel C of Table 4, *Quintile5* has the largest and highly significant coefficients while other quintile dummies have much smaller and insignificant or weakly significant coefficients. These results also indicate that overpriced firms are more likely to issue long-term bad news than short-term bad news forecasts.

5.4. The effect of nonrecurring items on the issuance of management forecast sets

Table 5 presents the piecewise-linear regression results of model (2) in columns (4), (5), and (6). For comparison, we also provide the results of model (1) in the first three columns (i.e., the same results as the first three columns of Table 3, Panel B). Consistent with the prediction of H2, coefficients on nonrecurring items (*NRI*) are significantly positive in columns (1) and (2),

¹⁴ Because *abs(NGAAP)* is provided after 2003, we only report the results using *abs(SPI)* and *abs(XIDO)* as *NRI* in Table 4. The results using *abs(NGAAP)* are similar to the tabulated results.

suggesting that firms with greater transitory earnings issue more MF sets. In columns (4) and (5), the coefficients on *DN* are significantly positive, suggesting that negative non-GAAP exclusions and negative special items in the previous year are associated with the issuance of MF sets. In column (6), the coefficient on *NRI* is significantly positive, indicating that firms are more likely to issue MF sets if they have greater positive extraordinary items and discontinued operations in the previous year. However, the coefficients of 0.564 on *NRI* and -0.557 on *DN*NRI* indicate a greater slope for positive *XIDO* than for negative *XIDO*. Overall, the results suggest that positive transitory items have a greater effect on firms' decision to provide multiperiod forecasts than negative transitory items, likely to avoid overpricing if investors overextrapolate temporary positive items.

5.5. Consequences of management forecast set issuance on future mispricing

Panel A of Table 6 provides the descriptive statistics for the change in mispricing from year t to $t+1$ ($MISP_{t+1} - MISP_t$). The average one-year decrease in *MISP* of firms that issue MF sets ($MFSET=1$) is approximately three times more than that of firms that issue single-period forecasts ($MFSET=0$). The different average changes in mispricing for firms with and without MF sets suggest that multiperiod forecasts could be effective in correcting mispriced firms' valuation.

Panel B of Table 6 shows the changes in mispricing by the number of MF sets per year. When firms provide MF sets only once a year, the average change in *MISP* is -1.697. The decrease in *MISP* is the greatest when firms provide MF sets twice a year.¹⁵ Firms providing MF sets five times or more experience little decrease in *MISP*, suggesting that frequent issuances do not have much effect on mitigating mispricing or that these firms are initially more accurately priced.

Panel A of Table 7 reports the results of the OLS estimation of model (3). Consistent with our

¹⁵ The average two-year change ($MISP_{t+2} - MISP_t$) is -2.514 for firms providing MF sets once a year. The two-year decrease in *MISP* is the greatest when firms provide MF sets three times a year.

expectation of H3a, $MFSET_t$ is significantly negative in column (1), indicating that firms issuing MF sets tend to experience declines in overpricing. However, when we use the levels of mispricing in year t and $t+1$ in column (2), $MFSET_t$ becomes insignificant. The coefficient of 0.108 on $MISP_t$ (i.e., a coefficient less than 1) implies that mispricing reverts toward the mean in the following period. From columns (3) to (6), $MFSET_t$ is not highly significant.

Panel B of Table 7 shows the estimation results of model (3) with four different types of MF sets ($SGLG_t$, $SGLB_t$, $SBLG_t$, and $SBLB_t$). In this test, $SGLG_t$ ($SGLB_t$, $SBLG_t$, and $SBLB_t$) is an indicator variable that equals one for MF sets of SGLG ($SGLB$, $SBLG$, and $SBLB$) in year t and zero otherwise.¹⁶ $SBLB_t$ has significantly negative coefficients in both columns (3) and (4), indicating that overpriced firms issuing SBLB forecasts are likely to experience declines in overpricing in the next period. Also, $SGLB_t$ has significantly negative coefficients in column (3) and (4), suggesting that long-term bad news is likely to correct overpricing. Overall, these findings imply that overpriced firms are likely to experience a bigger reduction in overpricing when they issue short-term and long-term bad news forecasts.

5.6. Consequences of management forecast set issuance on nonlinearity in the earnings–return relation

To examine whether nonlinearity in the earnings–return relation is mitigated if firms provide MF sets, we partition the firms with only single-period forecasts into 20 equal-size groups ranked based on unexpected earnings (UE) and plot the mean UR against the mean UE for each group. We also construct 20 equal-size groups for the firms that issue MF sets at least once during the year and plot the mean UE against the mean UR . Figure 1 shows the extent of nonlinearity of firms

¹⁶ The variable definitions for these four variables are different from those in Section 3.1 (results reported in Table 4). The control group (which takes the value of zero) is all the other management forecasts (including single-period and multiperiod forecasts) except for the specified type of MF sets (e.g., SGLG).

without and with MF sets. Panel A shows the nonlinear earnings–return relation (i.e., “S-shape”) for firms with only single-period forecasts. This shape is like that reported in prior studies, having a smaller slope and a longer tail for the negative earnings (Liu and Thomas, 2000). However, Panel B shows a more linear earnings–return relation for firms with MF sets. This figure suggests that investors are less likely to underreact to extreme news when firms issue MF sets.

Table 8 presents the OLS estimation results of models (4), (5), and (6). Columns (1) and (3) show the results of estimating model (4) for firms with only single-period forecasts ($MFSET=0$) and firms with MF sets ($MFSET=1$), respectively. Consistent with H3b, the coefficients on UE^2 and $D*UE^2$ are significant in column (1) but become insignificant in column (3). These results indicate that the quadratic model fits better for firms with single forecasts than firms with MF sets, because the latter have a more linear earnings–return relation. Columns (2) and (4) show the model (5) estimation results for firms with $MFSET=0$ and $MFSET=1$, respectively. UE^2 and $D*UE^2$ have significant coefficients in column (2) but not in column (4). The coefficients on $STnews$ are significantly positive in columns (2) and (4). The adjusted R^2 increases from column (1) to (2) and from column (3) to (4). These findings suggest that unexpected returns are better explained by $STnews$. When $LTnews$ is included, only $LTnews$ has a significant coefficient in column (5), suggesting that long-term news explains unexpected returns better than short-term news.¹⁷

To test whether the coefficients in column (1) and (3) (column (2) and (4)) are different from each other, we interact the variables with $MFSET$ and present the results in column (6) (column (7)). In column (6), the coefficients on $UE^2*MFSET$ and $D*UE^2*MFSET$ indicate that the coefficient differences between firms with and without MF sets are weakly significant.

¹⁷ To correctly examine how much the adjusted R^2 increases by adding $LTnews$, we estimate model (5) again using the same observations in column (5). The adjusted R^2 increases from 3.6% to 4.5% by adding $LTnews$, suggesting that long-term news in MF sets better explains the unexpected returns.

Overall, we find that firms with only single-period forecasts have more quadratic earnings–return relations and those with multiperiod forecasts have more linear relations. These findings suggest that investors better understand the persistence of current news and associate greater precision with extreme news when they receive MF sets rather than single-period forecasts.

6. Validation tests

6.1. Explanation for the asymmetric results: Changes in litigation risk

To further investigate the asymmetric results for overpriced and underpriced firms, we use the 2007 Supreme Court decision in the case *Tellabs, Inc. v. Makor Issues & Rights*, which increased litigation risk for firms located in the Ninth Circuit states. These firms faced less litigation risk after 1999 when the Ninth Circuit Court in the *Silicon Graphics* case adopted a more stringent interpretation of the pleading standards. However, a U.S. Supreme Court decision in 2007 reversed the litigation risk for the Ninth Circuit because a more uniform standard on securities class actions was instituted across circuit courts. Therefore, we expect an increase in the issuance of MF sets for firms located in the Ninth Circuit states after 2007, especially for overpriced firms because their litigation risks are higher than before. However, underpriced firms' MF set issuances are unlikely to be affected by the Supreme Court decision because their litigation risks are still low.

Following Houston, Lin, Liu, and Wei (2019), we conduct an untabulated difference-in-difference analysis which includes four years before and after the 2007 Supreme Court decision. We find that firms located in the Ninth Circuit states are more likely to issue MF sets after 2007 only if they are overpriced. These results support our explanation of litigation risks regarding the asymmetric results in Panel C of Table 3 because we predicted that overpriced firms would be affected more by the Supreme Court decision increasing litigation exposure.

6.2. Alternative explanation for the asymmetric results

6.2.1. The effect of short-selling demand on issuing management forecast sets

We examine alternative explanations for why overpriced firms are more likely to issue MF sets. Stambaugh et al. (2015) note that shorting a stock is more difficult than taking a long position, hence overpricing, which is costlier to arbitrage, is likely deeper than underpricing. Investors are more likely to demand more information to short overpriced stocks (Chen et al., 2020) than to take a long position in underpriced stocks, leading to more issuance of MF sets for overpriced firms.

We use short transaction data to test the association between MF set issuances and the short-selling demand. We create a variable, *SHORT*, which is the average monthly short interest divided by the number of shares outstanding for year *t*. Short interest is the total number of shares sold short for transactions settling on or before the 15th of the month.¹⁸ In untabulated tests, we find that overpriced firms are more likely to issue MF sets if they have more short transactions but underpriced firms' MF set issuances are not significantly associated with short transactions.¹⁹ This finding is consistent with the alternative explanation, that is, short investors' greater information demand for overpriced stocks.

6.2.2. The effect of option grants on issuing management forecast sets

Managers' incentives related to option grants is another explanation for why overpriced firms are more likely to issue MF sets. Prior studies find that firms manage earnings downwards and miss earnings targets before option grants to lower the share price at the grant date and to increase the value of their stock options (Baker et al., 2003; Balsam et al., 2003; McAnally et al., 2008).

¹⁸ Short interest data is available from Compustat for the entire sample period for NYSE and AMEX stocks but only from July 2003 for NASDAQ firms.

¹⁹ Untabulated descriptive statistics also show that overpriced firms have, on average, greater short transactions than underpriced firms (average *SHORT* of 6.5% for overpriced firms and 5.1% for underpriced firms).

Therefore, firms are likely to issue both short- and long-term bad news MF sets before option grants to reduce the share price.

Using option grant dates from ExecuComp, we test whether managers issue more bad news MF sets (i.e., SBLB) during the 10 days before option grants.²⁰ However, we do not find significant results for both overpriced and underpriced firms (untabulated), suggesting that managers' option-related incentives do not explain why only overpriced firms issue more MF sets.

6.3. The effect of brokerage closures and mergers on issuing management forecast sets

We also exploit a natural experiment that reduces information supply. Specifically, we use brokerage closures and mergers as exogenous shocks to analyst coverage. Both brokerage closures and mergers lead to a decrease in the number of analysts covering a firm. Because retail investors rely on publicly available information including the information provided by analysts, brokerage firms' closures and mergers are likely to reduce the pool of public signals related to a firm. The decrease in information supply could worsen the information asymmetry of the previously covered firms, which could lead to firms disclosing more information such as MF sets.

Using Kelly and Ljungqvist's (2012) list of brokerage closures and mergers between the first quarter of 2000 and the first quarter of 2008, we examine whether firms that were covered by closed or acquired brokerage houses are more likely to provide MF sets. First, we test whether the cumulative number of a firm's associated brokerage closures and mergers is associated with MF set issuances. Second, we compare the periods before and after brokerage closures and mergers for the affected firms. Untabulated results indicate that firms affected by brokerage closures or

²⁰ Changing the event window from 10 days to 5 days or 15 days does not significantly change the results.

mergers are likely to issue MF sets. These findings support our previous findings that managers tend to issue MF sets for firms with greater mispricing because brokerage closures or mergers could lead to greater mispricing due to less publicly available information.

7. Conclusion

We examine the effects of mispricing and earnings persistence on managers' decisions to provide multiple-year earnings forecasts and the consequences of these forecasts on firms' future mispricing and earnings-return relation. We use simultaneously issued management EPS forecasts consisting of a current-year forecast and one or more future-year forecasts between 2000 and 2016.

We find that firms that are overpriced, are experiencing decreases in analyst coverages due to brokerage closures and mergers, have more transitory earnings, and are facing litigation are more likely to issue multiperiod forecasts simultaneously. Also, overpriced firms tend to issue bad news forecasts for both current and future years rather than only current-year bad news forecasts. After firms issue MF sets, mispricing tends to decrease and reverts toward the mean in the next year. Specifically, overpriced firms experience decreases in overpricing when they issue both short-term and long-term bad news forecasts. In addition, we find that firms issuing MF sets have a more linear earnings–return relation than those issuing only single-period forecasts, indicating that investors better understand the persistence of current news if they receive MF sets.

Overall, we show that multi-year earnings forecasts provide more information and help disentangle transitory or permanent earnings components, and ultimately price more accurately. Our findings suggest that firms' incentives to provide MF sets differ between overpriced and underpriced firms. Therefore, investigating firms' disclosure behavior for mispriced firms all together could obscure their different incentives.

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APPENDIX

Variable definition

Variables	Definitions
<i>MFSET</i>	An indicator variable that equals one if the firm simultaneously (i.e., on the same day) issues management forecasts comprised of a short-term forecast (e.g., forecast for year t) and long-term forecasts (e.g., forecasts for years $t+1$, $t+2$, and so on, if available), and zero if a firm issues a single-year forecast.
<i>SG</i>	Current-year management forecasts that are short-term good news (i.e., management forecasts are greater than the latest analyst consensus forecast for the current year).
<i>SB</i>	Current-year management forecasts that are short-term bad news (i.e., management forecasts are smaller than the latest analyst consensus forecast for the current year).
<i>SGLG</i>	An indicator variable that equals one if the firm simultaneously issued management forecasts that are short-term good news (i.e., management forecasts are greater than the latest analyst consensus forecast for the current year) and long-term good news (i.e., the aggregated management forecasts beyond the current year are greater than the aggregated latest analyst consensus forecast for the corresponding period), and zero otherwise.
<i>SGLB</i>	An indicator variable that equals one if the firm simultaneously issued management forecasts that are short-term good news (i.e., management forecasts are greater than the latest analyst consensus forecast for the current year) and long-term bad news (i.e., the aggregated management forecasts beyond the current year are smaller than the aggregated latest analyst consensus forecast for the corresponding period), and zero otherwise.
<i>SBLG</i>	An indicator variable that equals one if the firm simultaneously issued management forecasts that are short-term bad news (i.e., management forecasts are smaller than the latest analyst consensus forecast for the current year) and long-term good news (i.e., the aggregated management forecasts beyond the current year are greater than the aggregated latest analyst consensus forecast for the corresponding period), and zero otherwise.
<i>SBLB</i>	An indicator variable that equals one if the firm simultaneously issued management forecasts that are short-term bad news (i.e., management forecasts are smaller than the latest analyst consensus forecast for the current year) and long-term bad news (i.e., the aggregated management forecasts beyond the current year are smaller than the aggregated latest analyst consensus forecast for the corresponding period), and zero otherwise.
<i>NRI</i>	Nonrecurring items, using one of three proxies: <i>NGAAP</i> , <i>SPI</i> , or <i>XIDO</i> .
<i>abs(NRI)</i>	Absolute value of each of three proxies for nonrecurring items (<i>NRI</i>).
<i>NGAAP</i>	Quarterly GAAP earnings per share minus quarterly non-GAAP earnings per share provided by Bentley et al. (2018), which is then aggregated (i.e., sum) over the fiscal year.
<i>SPI</i>	Annual special items provided by Compustat, scaled by the total assets.
<i>XIDO</i>	Annual extraordinary items and discontinued operation provided by Compustat, scaled by the total assets.
<i>DN</i>	An indicator variable that equals one if <i>NRI</i> is negative, and zero otherwise.

<i>MISP</i>	A mispricing measure based on 11 anomalies, following Stambaugh, Yu, and Yuan (2015). Firms are ranked based on each anomaly and then average the ranking percentile for each of 11 anomalies each year. 11 anomalies used by Stambaugh, Yu, and Yuan (2012, 2015): Financial distress (Campbell, Hilscher, and Szilagyi, 2008), O-Score bankruptcy probability (Ohlson, 1980), net stock issues (Ritter, 1991; Loughran and Ritter, 1995; Fama and French, 2008), composite equity issues (Daniel and Titman, 2006), total accruals (Sloan, 1996), net operating assets (Hirshleifer, Hou, Teoh, and Zhang, 2004), momentum (Jegadeesh and Titman, 1993), gross profitability (Novy-Marx, 2013), asset growth (Cooper, Gulen, and Schill, 2008), return on assets (Fama and French, 2006; Chen, Novy-Marx, and Zhang, 2011) and investment-to-assets (Titman, Wei, and Xie, 2004; Xing, 2008).
<i>MISSMF</i>	The number of times a firm missed its management forecast during the year.
<i>LITG</i>	An indicator variable that equals one if a firm was sued in the previous year, and zero otherwise.
<i>SIZE</i>	The natural log of total assets.
<i>BTM</i>	Book value of equity divided by market value of equity.
<i>EVOL</i>	The standard deviation of the firm's earnings over the previous 12 quarters.
<i>RET</i>	The past 12-month return adjusted for the value-weighted market return.
<i>ISSUE</i>	The natural logarithm of the equity issuance amount during the year.
<i>INST</i>	The percentage of the firm's shares held by institutional investors.
<i>PLOSS</i>	An indicator variable that equals one if earnings for more than half of the previous eight consecutive quarters are losses, and zero otherwise.
<i>NAF</i>	The number of analysts following the firm.
<i>AFSTD</i>	The standard deviation of analysts' EPS forecasts.
<i>SHORT</i>	The average monthly short interest divided by the number of shares outstanding for year t.
<i>ZERO</i>	The average fraction of days with zero returns (%).
<i>IVOL</i>	The standard deviation of the daily residuals from regressing daily excess returns on the daily Fama-French (1993, 1996) three factors for each month.
<i>R2</i>	The average R^2 obtained from regressing excess returns on Fama-French three factors to measure idiosyncratic volatility (<i>IVOL</i>) (%).
<i>UR</i>	The stock returns adjusted for CRSP value-weighted returns over the 12 months from April 1 of the fiscal year through March 31 following it.
<i>UE</i>	Actual earnings-per-share (EPS) minus the median EPS analyst forecasts in the last month of the firm's fiscal year.
<i>D</i>	An indicator variable that equals one if <i>UE</i> is negative, and zero otherwise.
<i>STnews</i>	Management forecasts minus the latest analyst forecast consensus for short-term news (i.e., forecasts for the current year).
<i>LTnews</i>	Management forecasts minus the latest analyst forecast consensus for long-term news (i.e., aggregated forecasts beyond the current year).

Figure 1.

Earnings-return relation for 20 equal-sized groups of firms without and with management forecast sets

Panel A. Mean unexpected returns and mean unexpected earnings for firms with only single-period forecasts

Panel B. Mean unexpected returns and mean unexpected earnings for firms with management forecast sets

This figure presents the extent of nonlinearity in earnings–return relations for firms without and with MF sets. Panel A presents the earnings–return relation for firms with only single-period management forecasts. Firms with only single-period forecasts are partitioned into 20 equal-size groups ranked based on the unexpected earnings (UE) and plot the mean unexpected returns (UR) against the mean UE for each group. Panel B presents the earnings–return relation for firms that issue MF sets at least once during the year. These firms are partitioned into 20 equal-size groups ranked based on UE and plot the mean UR against the mean UE .

TABLE 1
Sample Selection

Details of sample formation	Number of forecasts	Number of firms
EPS management forecasts for US firms from I/B/E/S Guidance (2000-2016)	119,193	3,988
Less preannouncements (i.e., forecasts after fiscal year-end but before earnings announcement)	(9,539)	(392)
Less observations with no analyst forecast data from I/B/E/S	(2,277)	(165)
Adjustments for management forecast sets on the same day:		
Aggregation of quarterly or semi-annual management forecasts over the same fiscal year	(604)	
Exclusion of quarterly or semi-annual management forecasts if their forecasting periods overlap with annual forecasts	(23,548)	
Aggregation of long-term management forecasts (i.e., forecasts for periods beyond the current fiscal year)	(206)	
Less observations with insufficient data from other databases (Compustat, CRSP, and Thomson Reuters Institutional Holdings)	(15,473)	(444)
Final Sample	67,546	2,987

TABLE 2
Descriptive statistics

	n	mean	sd	min	p50	max
<i>MFSET</i>	67,546	0.053	0.225	0.000	0.000	1.000
<i>NGAAP</i>	36,929	-0.231	0.650	-4.260	0.000	0.890
<i>SPI</i>	51,985	-0.014	0.038	-0.253	-0.001	0.039
<i>XIDO</i>	52,731	0.0005	0.007	-0.050	0.000	0.034
<i>MISP</i>	52,731	53.391	10.080	7.635	53.073	88.866
<i>LITG</i>	52,731	0.039	0.194	0.000	0.000	1.000
<i>MISSMF</i>	52,731	2.051	2.818	0.000	1.000	23.000
<i>SIZE</i>	52,731	7.324	1.770	3.639	7.175	11.695
<i>BTM</i>	52,731	0.484	0.437	-8.166	0.405	12.280
<i>EVOL</i>	52,731	0.402	0.549	0.027	0.216	3.572
<i>RET</i>	52,731	0.061	0.434	-0.718	-0.005	2.182
<i>ISSUE</i>	52,731	0.416	1.437	0.000	0.000	6.775
<i>INST</i>	52,731	0.619	0.356	0.000	0.727	1.203
<i>PLOSS</i>	52,731	0.142	0.349	0.000	0.000	1.000
<i>NAF</i>	52,731	14.067	8.998	1.000	12.000	65.000
<i>AFSTD</i>	52,731	0.212	0.356	0.011	0.113	2.639
<i>R2</i>	67,546	0.865	0.529	0.302	0.705	2.311
<i>ZERO</i>	67,546	1.785	2.140	0.000	1.190	12.903
<i>IVOL</i>	67,546	0.032	0.044	0.009	0.023	0.400
<i>UR</i>	16,125	0.009	0.414	-0.784	-0.034	1.840
<i>UE</i>	16,125	-0.015	0.254	-1.740	0.010	0.650
<i>STnews</i>	16,125	0.003	0.237	-1.210	0.010	1.094
<i>LTnews</i>	1,947	0.022	0.356	-2.190	0.020	1.739

TABLE 3
The effect of past mispricing on issuing management forecast sets

Panel A. Frequency of management forecast sets for each quintile of $MISP_{t-1}$

Quintiles of $MISP_{t-1}$	Mean of $MISP_{t-1}$	$MFSET$ (Freq)			$MFSET$ (Col%)	
		0	1	Total	0	1
<i>Quintile1</i>	39.56	10,104	443	10,547	20.2%	16.1%
<i>Quintile2</i>	47.53	10,034	512	10,546	20.1%	18.6%
<i>Quintile3</i>	53.05	10,012	534	10,546	20.0%	19.4%
<i>Quintile4</i>	58.98	9,996	550	10,546	20.0%	19.9%
<i>Quintile5</i>	67.83	9,827	719	10,546	19.7%	26.1%
Total		49,973	2,758	52,731	100%	100%

Panel B. Frequency of management forecast sets for each quintile of non-GAAP ($NGAAP_{t-1}$), special items (SPI_{t-1}), and extraordinary items and discontinued operations ($XIDO_{t-1}$)

Quintiles based on	Quintile	Quintile Mean	$MFSET$ (freq)			$MFSET$ (col%)	
			0	1	Total	0	1
$NGAAP_{t-1}$	<i>Quintile1</i>	-1.121	7,009	377	7,386	19.90%	23.10%
	<i>Quintile2</i>	-0.171	7,084	302	7,386	20.10%	18.50%
	<i>Quintile3</i>	-0.014	7,114	272	7,386	20.20%	16.70%
	<i>Quintile4</i>	0	7,086	300	7,386	20.10%	18.40%
	<i>Quintile5</i>	0.148	7,004	381	7,385	19.80%	23.30%
	Total		35,297	1,632	36,929	100%	100%
SPI_{t-1}	<i>Quintile1</i>	-0.063	9,875	522	10,397	20.00%	19.20%
	<i>Quintile2</i>	-0.009	9,887	510	10,397	20.10%	18.80%
	<i>Quintile3</i>	-0.002	9,838	559	10,397	20.00%	20.60%
	<i>Quintile4</i>	0	9,828	569	10,397	19.90%	21.00%
	<i>Quintile5</i>	0.005	9,843	554	10,397	20.00%	20.40%
	Total		49,271	2,714	51,985	100%	100%
$XIDO_{t-1}$	<i>Quintile1</i>	-0.006	9,906	641	10,547	19.80%	23.20%
	<i>Quintile2</i>	0	10,050	496	10,546	20.10%	18.00%
	<i>Quintile3</i>	0	10,074	472	10,546	20.20%	17.10%
	<i>Quintile4</i>	0	10,061	485	10,546	20.10%	17.60%
	<i>Quintile5</i>	0.004	9,882	664	10,546	19.80%	24.10%
	Total		49,973	2,758	52,731	100.00%	100%

Panel A shows the distribution of $MFSET$ (management forecast sets) by past mispricing. $MFSET$ of one represents simultaneously issued management forecasts comprised of both short- and long-term forecasts and $MFSET$ of zero represents single-period forecasts. Panel A presents the frequency and column percentage of management forecast sets for each quintile formed based on $MISP_{t-1}$. *Quintile1* and *Quintile5* represent the most underpriced and the most overpriced firms, respectively. Panel B shows the distribution of $MFSET$ by three different proxies of nonrecurring items. Each panel shows the frequency and column percentage of MF sets for each quintile that is formed based on $NGAAP_{t-1}$, SPI_{t-1} , and $XIDO_{t-1}$, respectively.

Panel C. The effect of past mispricing on issuing management forecast sets: Overpriced and underpriced firms

VARIABLES	Exp.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Full Sample			Overpriced			Underpriced		
		<i>abs(NGAAP)</i>	<i>abs(SPI)</i>	<i>abs(XIDO)</i>	<i>abs(NGAAP)</i>	<i>abs(SPI)</i>	<i>abs(XIDO)</i>	<i>abs(NGAAP)</i>	<i>abs(SPI)</i>	<i>abs(XIDO)</i>
<i>MISP</i>	+	0.001*** (7.02)	0.001*** (8.07)	0.001*** (8.17)	0.002** (2.29)	0.002** (2.40)	0.002*** (2.67)	0.000 (0.34)	-0.000 (-0.84)	-0.000 (-0.59)
<i>NRI</i>	+	0.009*** (5.13)	0.057** (2.06)	0.174 (1.27)	0.022*** (4.59)	0.463*** (4.94)	-0.254 (-0.58)	0.003 (0.86)	-0.037 (-0.93)	0.145 (0.64)
<i>LITG</i>	+	-0.007 (-1.11)	-0.009* (-1.71)	-0.008 (-1.56)	0.018 (1.04)	0.024 (1.49)	0.034** (2.16)	0.010 (0.98)	-0.000 (-0.00)	0.000 (0.02)
<i>MISSMF</i>	+	0.003*** (8.42)	0.002*** (6.97)	0.003*** (7.15)	0.005*** (4.81)	0.003*** (2.64)	0.003*** (3.04)	0.000 (0.42)	0.001 (1.42)	0.001 (1.35)
<i>SIZE</i>	+	0.006*** (6.44)	0.007*** (8.47)	0.007*** (8.26)	0.009*** (3.54)	0.008*** (3.38)	0.008*** (3.62)	0.009*** (4.58)	0.008*** (4.53)	0.007*** (4.21)
<i>BTM</i>	-	-0.012*** (-3.45)	-0.010*** (-4.14)	-0.010*** (-4.00)	-0.034*** (-3.51)	-0.023*** (-2.87)	-0.021*** (-2.65)	-0.010 (-1.31)	-0.009** (-2.27)	-0.010** (-2.52)
<i>EVOL</i>	?	0.005** (2.00)	0.005*** (2.76)	0.005*** (2.71)	-0.006 (-1.02)	-0.003 (-0.64)	-0.001 (-0.19)	0.015*** (3.06)	0.016*** (4.07)	0.015*** (3.85)
<i>RET</i>	+	0.004 (1.50)	0.007*** (2.87)	0.007*** (2.74)	-0.007 (-1.18)	-0.003 (-0.55)	-0.005 (-0.90)	-0.005 (-0.60)	-0.003 (-0.39)	-0.002 (-0.25)
<i>ISSUE</i>	+	-0.000 (-0.36)	-0.001 (-1.33)	-0.001 (-1.00)	0.002 (1.05)	0.000 (0.37)	0.001 (0.68)	0.005* (1.68)	0.004 (1.48)	0.004 (1.39)
<i>INST</i>	+	-0.007** (-2.19)	-0.002 (-0.61)	-0.002 (-0.63)	-0.016** (-1.97)	-0.008 (-1.07)	-0.009 (-1.25)	-0.023*** (-3.30)	-0.013** (-2.18)	-0.012** (-2.04)
<i>LOSS</i>	-	-0.001 (-0.42)	0.002 (0.64)	0.002 (0.67)	0.009 (1.02)	0.008 (1.07)	0.011 (1.43)	-0.014** (-2.03)	-0.014** (-2.32)	-0.015** (-2.53)
<i>NAF</i>	+	-0.000 (-0.22)	-0.000 (-1.29)	-0.000 (-1.10)	-0.001** (-2.43)	-0.001 (-1.55)	-0.001 (-1.56)	-0.000 (-1.14)	-0.001* (-1.91)	-0.001* (-1.80)
<i>AFSTD</i>	?	-0.013*** (-3.56)	-0.012*** (-3.99)	-0.011*** (-3.96)	-0.035*** (-4.39)	-0.034*** (-4.72)	-0.033*** (-4.70)	-0.012* (-1.72)	-0.011** (-2.08)	-0.011** (-2.21)
Constant		-0.091*** (-5.20)	-0.077*** (-5.34)	-0.075*** (-5.28)	-0.047 (-0.56)	-0.073 (-0.88)	-0.083 (-1.01)	-0.081 (-1.53)	-0.025 (-0.55)	-0.019 (-0.41)
Adj. R ²		0.030	0.034	0.034	0.050	0.037	0.036	0.044	0.045	0.044
Year/Ind FE		yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations		36,929	51,985	52,731	7,385	10,397	10,546	7,386	10,397	10,547

This table presents the OLS regression results of the following model:

$$\begin{aligned}
 MFSET_{i,t} = & \alpha_0 + \alpha_1 MISP_{i,t-1} + \alpha_2 abs(NRI)_{i,t-1} + \alpha_3 LITG_{i,t-1} + \alpha_4 MISSMF_{i,t-1} + \alpha_5 SIZE_{i,t-1} + \alpha_6 BTM_{i,t-1} \\
 & + \alpha_7 EVOL_{i,t-1} + \alpha_8 RET_{i,t-1} + \alpha_9 ISSUE_{i,t-1} + \alpha_{10} INST_{i,t-1} + \alpha_{11} LOSS_{i,t-1} + \alpha_{12} NAF_{i,t-1} \\
 & + \alpha_{13} AFSTD_{i,t-1} + IndustryFixed + YearFixed + \varepsilon_{i,t}
 \end{aligned} \tag{1}$$

MFSET is an indicator variable that equals one for MF sets and zero for single-period forecasts. *MISP* is a mispricing measure based on 11 anomalies. *NRI* is nonrecurring items, using one of three proxies: *NGAAP* (GAAP EPS minus non-GAAP EPS), *SPI* (special items, scaled by the total assets), or *XIDO* (extraordinary items and discontinued operation, scaled by the total assets). Other control variables are defined in Appendix. Columns (1), (2), and (3) report the estimation results for the full sample. Columns (4), (5), and (6) report the results for the most overpriced sample (i.e., *Quintile5*). Columns (7), (8), and (9) report the results for the most underpriced sample (i.e., *Quintile1*). Quintiles are formed based on *MISP*_{t-1}. Columns (1), (4), and (7) use *abs(NGAAP)*, columns (2), (5), and (8) use *abs(SPI)*, and columns (3), (6), and (9) use *abs(XIDO)* for nonrecurring items (*NRI*).

***, **, * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

TABLE 4

The effect of past mispricing on issuing different types of management forecast sets

Panel A. Frequency and percentage of different types of management forecast sets by mispricing

Quintiles of <i>MISP_{t-1}</i>	<i>SG</i>	<i>SGLG</i>	<i>SGLB</i>	<i>SB</i>	<i>SBLG</i>	<i>SBLB</i>
<i>Quintile1</i>	7,972	278	80	4,203	77	109
<i>Quintile2</i>	8,084	352	89	4,069	83	115
<i>Quintile3</i>	8,032	300	120	3,976	79	129
<i>Quintile4</i>	7,879	336	80	4,060	104	124
<i>Quintile5</i>	7,699	423	87	4,000	100	165
Total	39,666	1,689	456	20,308	443	642

Quintiles of <i>MISP_{t-1}</i>	<i>SG</i>	<i>SGLG</i>	<i>SGLB</i>	<i>SB</i>	<i>SBLG</i>	<i>SBLB</i>
<i>Quintile1</i>	20%	16%	18%	21%	17%	17%
<i>Quintile2</i>	20%	21%	20%	20%	19%	18%
<i>Quintile3</i>	20%	18%	26%	20%	18%	20%
<i>Quintile4</i>	20%	20%	18%	20%	23%	19%
<i>Quintile5</i>	19%	25%	19%	20%	23%	26%
Total	100%	100%	100%	100%	100%	100%

Panel A reports the frequency of six different types of management forecasts for each quintile formed based on $MISP_{t-1}$ ($MISP_{t-2}$). *SG* represents short-term good news management forecasts and *SB* represents short-term bad news management forecasts. *SGLG* (*SGLB*) is MF sets comprised of short-term good news and long-term good (bad) news forecasts. *SBLB* (*SBLG*) is MF sets comprised of short-term bad news and long-term bad (good) news forecasts. Good/bad news is determined by comparing management forecasts and the latest analyst consensus forecasts. The frequency of neutral news (i.e., management EPS forecasts = analysts' consensus EPS forecasts) is not tabulated.

Panel B. Determinants of the issuance of management forecast sets for overpriced and underpriced firms: Short-term good news & long-term good news (SGLG) and short-term bad news & long-term bad news (SBLB)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<i>SGLG</i>				<i>SBLB</i>			
	Overpriced		Underpriced		Overpriced		Underpriced	
VARIABLES	<i>abs(SPI)</i>	<i>abs(XIDO)</i>	<i>abs(SPI)</i>	<i>abs(XIDO)</i>	<i>abs(SPI)</i>	<i>abs(XIDO)</i>	<i>abs(SPI)</i>	<i>abs(XIDO)</i>
<i>MISP</i>	-0.000 (-0.18)	-0.000 (-0.11)	0.000 (0.36)	0.001 (0.58)	0.002 (1.44)	0.003* (1.87)	0.001 (0.53)	0.001 (0.74)
<i>NRI</i>	0.150 (0.74)	0.033 (0.03)	0.021 (0.30)	0.746 (1.58)	1.200*** (5.58)	1.420 (1.40)	-0.084 (-1.00)	-0.280 (-0.59)
<i>LITG</i>	0.023 (0.65)	0.026 (0.64)	0.008 (0.46)	0.007 (0.41)	0.007 (0.20)	0.035 (1.09)	0.008 (0.49)	0.005 (0.28)
<i>MISSMF</i>	-0.003 (-1.35)	-0.003 (-1.26)	0.000 (0.31)	0.000 (0.17)	0.003 (1.41)	0.005** (2.15)	0.001 (0.41)	0.000 (0.27)
<i>SIZE</i>	0.002 (0.33)	0.001 (0.18)	0.008** (2.45)	0.007** (2.18)	0.015*** (2.97)	0.018*** (3.61)	0.001 (0.23)	0.003 (0.66)
<i>BTM</i>	-0.007 (-0.34)	-0.006 (-0.23)	-0.004 (-0.49)	-0.006 (-0.63)	-0.034* (-1.65)	-0.033 (-1.63)	-0.011* (-1.80)	-0.011* (-1.83)
<i>EVOL</i>	-0.004 (-0.42)	-0.004 (-0.39)	0.007 (1.07)	0.006 (0.94)	0.014 (1.29)	0.023** (2.13)	0.009 (1.06)	0.005 (0.61)
<i>RET</i>	-0.014 (-1.34)	-0.016 (-1.42)	0.004 (0.34)	0.001 (0.05)	-0.009 (-0.83)	-0.012 (-1.11)	-0.029** (-2.10)	-0.026* (-1.80)
<i>ISSUE</i>	-0.001 (-0.58)	-0.001 (-0.38)	-0.002 (-0.36)	-0.002 (-0.30)	-0.005* (-1.94)	-0.006** (-2.30)	0.006 (1.49)	0.005 (1.14)
<i>INST</i>	-0.024 (-1.63)	-0.027 (-1.63)	-0.014 (-1.13)	-0.012 (-0.97)	0.010 (0.65)	0.017 (1.03)	0.007 (0.63)	0.012 (0.97)
<i>LOSS</i>	0.040** (2.34)	0.040* (1.66)	-0.024** (-2.05)	-0.023** (-1.97)	-0.004 (-0.23)	0.008 (0.50)	-0.011 (-0.94)	-0.009 (-0.79)
<i>NAF</i>	-0.000 (-0.11)	-0.000 (-0.02)	-0.000 (-0.55)	-0.000 (-0.34)	-0.002* (-1.84)	-0.002* (-1.95)	-0.001 (-1.17)	-0.001 (-1.44)
<i>AFSTD</i>	-0.035** (-2.12)	-0.035** (-2.05)	-0.005 (-0.43)	-0.006 (-0.56)	0.002 (0.16)	0.002 (0.14)	-0.005 (-0.56)	-0.005 (-0.52)
Constant	0.107 (0.55)	0.101 (0.90)	-0.011 (-0.12)	-0.013 (-0.14)	-0.260** (-2.08)	-0.320** (-2.54)	-0.023 (-0.30)	-0.018 (-0.22)
Adj. R ²	0.074	0.072	0.070	0.070	0.128	0.110	0.051	0.048
Year/Ind FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	2,686	2,731	2,687	2,732	1,347	1,364	1,347	1,365

This table presents the OLS regression results of the following model with *SGLG* and *SBLB* as the dependent variable instead of *MFSET*.

$$\begin{aligned}
 MFSET_{i,t} = & \alpha_0 + \alpha_1 MISP_{i,t-1} + \alpha_2 abs(NRI)_{i,t-1} + \alpha_3 LITG_{i,t-1} + \alpha_4 MISSMF_{i,t-1} + \alpha_5 SIZE_{i,t-1} + \alpha_6 BTM_{i,t-1} \\
 & + \alpha_7 EVOL_{i,t-1} + \alpha_8 RET_{i,t-1} + \alpha_9 ISSUE_{i,t-1} + \alpha_{10} INST_{i,t-1} + \alpha_{11} LOSS_{i,t-1} + \alpha_{12} NAF_{i,t-1} \\
 & + \alpha_{13} AFSTD_{i,t-1} + IndustryFixed + YearFixed + \varepsilon_{i,t} \quad (1)
 \end{aligned}$$

Panel B reports the results using *SGLG* and *SBLB* as the dependent variables in the first four columns and the last four columns, respectively. For the first (last) four columns, the estimation is restricted to firms whose actual EPS is greater (smaller) than the consensus forecasts at the time of management forecast issuance for both short- and long-term periods (i.e., firms with actual *SGLG* [*SBLB*]). *SGLG* is an indicator variable that equals one for MF sets of *SGLG* and zero for only SG forecasts, conditional on having the actual *SGLG*. *SBLB* is an indicator variable that equals one for MF sets of *SBLB* and zero for SB forecasts, conditional on having the actual *SBLB*.

For Panel B, columns (1), (2), (5) and (6) report the estimation results for the most overpriced sample (i.e., *Quintile5* from the quintiles formed based on $MISP_{t-1}$). Columns (3), (4), (7) and (8) report the results for the most underpriced sample (i.e., *Quintile1* from the quintiles formed based on $MISP_{t-1}$). Columns (1), (3), (5) and (7) use *abs(SPI)*, and columns (2), (4), (6) and (8) use *abs(XIDO)* for nonrecurring items (*NRI*). Other variables are defined in Appendix.

***, **, * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel C. The effect of mispricing on the issuance of short-term and long-term bad news forecasts (*SBLB*)

VARIABLES	(1) <i>abs(NGAAP)</i>	(2) <i>abs(SPI)</i>	(3) <i>abs(XIDO)</i>
<i>Quintile2</i>	0.012* (1.84)	0.007 (1.13)	0.005 (0.84)
<i>Quintile 3</i>	0.011 (1.61)	0.011* (1.69)	0.009 (1.42)
<i>Quintile 4</i>	0.007 (1.02)	0.009 (1.48)	0.008 (1.23)
<i>Quintile 5</i>	0.031*** (4.32)	0.029*** (4.21)	0.028*** (4.10)
<i>NRI</i>	0.012*** (2.97)	0.103* (1.73)	0.621** (2.13)
Constant	-0.047 (-1.22)	-0.035 (-0.99)	-0.028 (-0.80)
Adj. R ²	0.023	0.026	0.027
Controls	yes	yes	yes
Year/Ind FE	yes	yes	yes
Observations	4,710	6,738	6,824

Panel C reports the estimation results for model (1), replacing *MISP* with four quintile dummy variables (i.e., *Quintile2*, *Quintile3*, *Quintile4*, and *Quintile5*) that are formed based on $MISP_{t-1}$ and using *SBLB* as the dependent variable. *SBLB* is an indicator variable that equals one for MF sets of *SBLB* and zero for SB forecasts, conditional on having the actual *SBLB*. *Quintile2* and *Quintile5* represent the second most underpriced and the most overpriced firms, respectively. *Quintile1* (the most underpriced) is excluded as it is the base group. Columns (1), (2), and (3) use *abs(NGAAP)*, *abs(SPI)*, and *abs(XIDO)* for nonrecurring items (*NRI*), respectively. Control variables are not tabulated.

***, **, * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

TABLE 5

The effect of non-recurring items on the issuance of management forecast sets

VARIABLES	Exp.	(1) <i>abs(NGAAP)</i>	(2) <i>abs(SPI)</i>	(3) <i>abs(XIDO)</i>	(4) <i>NGAAP</i>	(5) <i>SPI</i>	(6) <i>XIDO</i>
<i>MISP</i>	+	0.001*** (7.03)	0.001*** (8.07)	0.001*** (8.16)	0.001*** (7.10)	0.001*** (8.13)	0.001*** (8.20)
<i>NRI</i>	+	0.009*** (5.13)	0.057** (2.07)	0.174 (1.27)	0.010 (1.07)	0.297 (1.44)	0.564** (2.31)
<i>DN</i>	?				0.009*** (3.51)	0.005** (2.07)	0.001 (0.25)
<i>DN*NRI</i>	?				-0.017* (-1.76)	-0.337 (-1.61)	-0.557* (-1.82)
Adj. R ²		0.030	0.034	0.034	0.034	0.034	0.034
Controls		yes	yes	yes	yes	yes	yes
Year/Ind FE		yes	yes	yes	yes	yes	yes
Observations		36,929	51,985	52,731	36,929	51,985	52,731

This table presents the OLS regression results of the following model:

$$\begin{aligned}
 MFSET_{i,t} = & \alpha_0 + \alpha_1 MISP_{i,t-1} + \alpha_2 NRI_{i,t-1} + \alpha_3 DN_{i,t-1} + \alpha_4 DN * NRI_{i,t-1} + \alpha_5 LITG + \alpha_6 MISSMF_{i,t-1} \\
 & + \alpha_7 SIZE_{i,t-1} + \alpha_8 BTM_{i,t-1} + \alpha_9 EVOL_{i,t-1} + \alpha_{10} RET_{i,t-1} + \alpha_{11} ISSUE_{i,t-1} + \alpha_{12} INST_{i,t-1} \\
 & + \alpha_{13} LOSS_{i,t-1} + \alpha_{14} NAF_{i,t-1} + \alpha_{15} AFSTD_{i,t-1} + IndustryFixed + YearFixed + \varepsilon_{i,t} \quad (2)
 \end{aligned}$$

MFSET is an indicator variable that equals one for MF sets, and zero for single-period forecasts. *MISP* is a mispricing measure based on 11 anomalies. *NRI* is nonrecurring items, using one of three proxies: *NGAAP* (GAAP eps minus non-GAAP eps), *SPI* (annual special items, scaled by the total assets), or *XIDO* (annual extraordinary items and discontinued operation, scaled by the total assets). *DN* is an indicator variable that equals one for negative nonrecurring items, and zero otherwise. Control variables are not tabulated as the results are similar to the results in Panel B of Table 3. Columns (1), (2), and (3) use *abs(NGAAP)*, *abs(SPI)*, and *abs(XIDO)* for *NRI*, respectively. Columns (4), (5), and (6) use *NGAAP*, *SPI*, and *XIDO* for *NRI*.

***, **, * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

TABLE 6
Changes in mispricing by the issuance of management forecast sets

Panel A. Descriptive Statistics of ($MISP_{t+1} - MISP_t$)

<i>MFSET</i>	Variable	N	Mean	Median	Std Dev
0	$MISP_{t+1} - MISP_t$	63,939	-0.718	-0.402	11.128
1	$MISP_{t+1} - MISP_t$	3,607	-2.138	-1.461	11.296
Diff			1.420***	1.059***	

Panel B. ($MISP_{t+1} - MISP_t$) by the number of management forecast sets per year

Number of MF sets per year	$MISP_{t+1} - MISP_t$		
	N	Mean	Median
1	1,899	-1.697	-1.185
2	382	-3.594	-2.990
3	109	-2.532	-1.528
4	58	-2.856	-2.719
5 or more	64	-0.392	0.777
Total	17,054	-0.747	-0.419

These tables present summary statistics of the changes in mispricing after firms issue MF sets (*MFSET* of one) or firms issue only single-period forecasts (*MFSET* of zero). Panel A provides the descriptive statistics of the changes in mispricing from year *t* to *t*+1 ($MISP_{t+1} - MISP_t$). Panel B shows the changes in mispricing by the number of MF sets provided per year.

TABLE 7

The effect of issuing management forecast sets on the changes in mispricing

Panel A. The effect of management forecast sets (*MFSET*) on the changes in mispricing

VARIABLES	Exp.	(1)	(2)	(3)	(4)	(5)	(6)
		Full sample		Overpriced		Underpriced	
		$\Delta MISP_{t+1}$	$MISP_{t+1}$	$\Delta MISP_{t+1}$	$MISP_{t+1}$	$\Delta MISP_{t+1}$	$MISP_{t+1}$
$MFSET_t$	-	-1.270*** (-5.72)	-0.087 (-0.50)	-0.767* (-1.83)	-0.222 (-0.60)	0.042 (0.08)	0.337 (0.75)
$SIZE_t$	-	0.286*** (3.21)	-1.230*** (-10.93)	-0.524** (-2.52)	-1.070*** (-4.51)	-0.593*** (-3.31)	-0.541*** (-2.79)
$IVOL_t$	?	-6.319*** (-2.67)	-1.504 (-0.68)	6.664 (1.23)	6.289 (1.12)	-2.532 (-0.49)	-0.816 (-0.16)
$R2_t$	?	1.072*** (6.29)	0.759*** (5.31)	1.166*** (2.62)	0.723 (1.58)	0.915** (2.21)	1.010** (2.58)
$ZERO_t$	?	0.512*** (10.37)	0.258*** (5.73)	0.341*** (2.95)	0.364*** (3.42)	0.040 (0.37)	-0.055 (-0.50)
NAF_t	-	-0.036** (-2.04)	-0.125*** (-6.86)	-0.112*** (-2.92)	-0.128*** (-3.05)	-0.089** (-2.45)	-0.125*** (-3.21)
$AFSTD_t$	+	0.056 (0.16)	-1.073*** (-3.22)	-2.171** (-2.50)	-1.391* (-1.74)	-0.700 (-1.31)	-1.118** (-2.16)
$\Delta MISP_t$	-	-0.423*** (-61.76)		-0.076*** (-3.20)		-0.008 (-0.40)	
$MISP_t$	+		0.108*** (11.66)		0.001 (0.02)		0.096* (1.81)
$MISP_{t-1}$	?		-0.023*** (-2.75)		-0.117*** (-4.89)		-0.133*** (-6.71)
Constant		-5.354*** (-8.71)	55.446*** (53.32)	-8.286*** (-5.98)	67.949*** (15.72)	13.476*** (10.09)	55.671*** (21.56)
Within R ²		0.194	0.058	0.050	0.116	0.019	0.059
Overall R ²		0.165	0.047	0.022	0.002	0.023	0.005
Observations		67,546	67,546	13,509	13,509	13,510	13,510

This table presents the OLS regression results of the following model:

$$MISP_{i,t+1} - MISP_{i,t} = \alpha_0 + \alpha_1 MFSET_{i,t} + \alpha_2 SIZE_{i,t} + \alpha_3 IVOL_{i,t} + \alpha_4 R2_{i,t} + \alpha_5 ZERO_{i,t} + \alpha_6 NAF_{i,t} + \alpha_7 AFSTD_{i,t} + \alpha_8 \Delta MISP_{i,t-1} + \varepsilon_{it} \quad (3)$$

$MISP_{t+1} - MISP_t (= \Delta MISP_{t+1})$ is the changes in mispricing from year t to $t+1$ where $MISP$ is a mispricing measure based on 11 anomalies. $MFSET$ is an indicator variable that equals one for MF sets, and zero for single-period forecasts. Other control variables are defined in Appendix. Columns (1) and (2) report the estimation results for the full sample. Columns (3) and (4) report the results for the most overpriced sample (i.e., *Quintile5*). Columns (5) and (6) report the results for the most underpriced sample (i.e., *Quintile1*). These quintiles are formed based on $MISP_t$. Columns (1), (3), and (5) show the results using $\Delta MISP_{t+1}$ and columns (2), (4), and (6) show the results using $MISP_{t+1}$ as the dependent variable.

***, **, * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel B. The effect of different types of management forecast sets (*SGLG*, *SGLB*, *SBLG*, and *SBLB*) on the changes in mispricing

		(1)	(2)		(3)	(4)		(5)	(6)
		Full sample			Overpriced			Underpriced	
VARIABLES	Exp.	$MISP_{t+1} - MISP_t$	$MISP_{t+1}$	Exp.	$MISP_{t+1} - MISP_t$	$MISP_{t+1}$	Exp.	$MISP_{t+1} - MISP_t$	$MISP_{t+1}$
$SGLG_t$	?	-1.188*** (-3.54)	0.127 (0.47)	?	-0.412 (-0.71)	0.224 (0.43)	+	0.123 (0.14)	0.605 (0.80)
$SGLB_t$	?	-0.683 (-1.41)	-0.116 (-0.31)	?	-2.194*** (-2.93)	-1.327* (-1.87)	?	-0.275 (-0.34)	0.282 (0.36)
$SBLG_t$	?	-1.402** (-2.32)	-0.166 (-0.34)	?	-1.190 (-0.89)	-1.136 (-0.95)	?	1.745 (1.55)	1.717 (1.51)
$SBLB_t$	?	-0.983** (-2.03)	-0.466 (-1.27)	-	-2.133** (-2.57)	-1.704** (-2.10)	?	0.276 (0.36)	0.111 (0.14)
Within R ²		0.193	0.058		0.051	0.116		0.016	0.059
Overall R ²		0.165	0.047		0.023	0.002		0.024	0.005
Controls		yes	yes		yes	yes		yes	yes
Observations		67,546	67,546		13,502	13,502		13,503	13,503

This table presents the OLS regression results of the following model:

$$MISP_{i,t+1} - MISP_{i,t} = \alpha_0 + \alpha_1 SGLG_{i,t} + \alpha_2 SGLB_{i,t} + \alpha_3 SBLG_{i,t} + \alpha_4 SBLB_{i,t} + \alpha_5 SIZE_{i,t} + \alpha_6 IVOL_{i,t} + \alpha_7 R2_{i,t} + \alpha_8 ZERO_{i,t} + \alpha_9 NAF_{i,t} + \alpha_{10} AFSTD_{i,t} + \alpha_{11} MISP_{i,t} + \alpha_{12} MISP_{i,t-1} + \varepsilon_{it}$$

$MISP_{t+1} - MISP_t$ is the changes in mispricing from year t to t+1 where $MISP$ is a mispricing measure based on 11 anomalies. $SGLG_t$ ($SGLB_t$, $SBLG_t$, and $SBLB_t$) is an indicator variable that equals one for MF sets of $SGLG$ ($SGLB$, $SBLG$, and $SBLB$) in year t and zero otherwise (i.e., all the other types of management forecasts including both short- and long-term forecasts). Other control variables are defined in Appendix. Columns (1) and (2) report the estimation results for the full sample. Columns (3) and (4) report the results for the most overpriced sample (i.e., *Quintile5* from the quintiles formed based on $MISP_t$). Columns (5) and (6) report the results for the most underpriced sample (i.e., *Quintile1* from the quintiles formed based on $MISP_t$). Columns (1), (3), and (5) show the results using $\Delta MISP_{t+1}$ ($= MISP_{t+1} - MISP_t$) as the dependent variable. Columns (2), (4), and (6) show the results using $MISP_{t+1}$ as the dependent variable. Control variables are not tabulated since the estimated coefficients for control variables are the same as those in Panel A of Table 7.

***, **, * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

TABLE 8

The effect of management forecast sets on nonlinearity in the earnings-return relations

VARIABLES	(1) <i>MFSET</i> =0	(2) <i>MFSET</i> =0	(3) <i>MFSET</i> =1	(4) <i>MFSET</i> =1	(5) <i>MFSET</i> =1	(6) Diff: (1) & (3)	(7) Diff: (2) & (4)
<i>D</i>	-0.088*** (-9.48)	-0.087*** (-9.49)	-0.058** (-2.47)	-0.057** (-2.45)	-0.037 (-1.32)	-0.088*** (-9.67)	-0.087*** (-9.51)
<i>UE</i>	0.672*** (7.08)	0.642*** (6.78)	0.267 (1.18)	0.248 (1.10)	-0.032 (-0.12)	0.636*** (6.82)	0.642*** (6.79)
<i>D*UE</i>	-0.276** (-2.54)	-0.273** (-2.52)	0.340 (1.22)	0.300 (1.08)	0.551* (1.68)	-0.250** (-2.34)	-0.273** (-2.52)
<i>UE</i> ²	-1.175*** (-6.87)	-1.155*** (-6.77)	-0.366 (-0.86)	-0.449 (-1.06)	0.001 (0.00)	-1.129*** (-6.70)	-1.155*** (-6.78)
<i>D*UE</i> ²	1.318*** (7.57)	1.291*** (7.43)	0.557 (1.28)	0.618 (1.42)	0.136 (0.26)	1.270*** (7.40)	1.291*** (7.45)
<i>STnews</i>		0.117*** (8.61)		0.151*** (3.96)	0.076 (1.55)		0.117*** (8.63)
<i>LTnews</i>					0.126*** (4.33)		
<i>MFSET</i>						0.025* (1.89)	0.023* (1.72)
<i>D*MFSET</i>						0.024 (0.96)	0.030 (1.19)
<i>UE*MFSET</i>						-0.373 (-1.53)	-0.394 (-1.58)
<i>D*UE*MFSET</i>						0.582** (1.96)	0.573* (1.90)
<i>UE</i> ² <i>MFSET</i>						0.810* (1.80)	0.706 (1.53)
<i>D*UE</i> ² <i>MFSET</i>						-0.764* (-1.65)	-0.674 (-1.42)
<i>STnews*MFSET</i>							0.034 (0.82)
Constant	0.035*** (6.53)	0.034*** (6.45)	0.060*** (4.94)	0.058*** (4.75)	0.072*** (5.05)	0.037*** (7.05)	0.034*** (6.46)
Adj R ²	0.044	0.049	0.035	0.040	0.045	0.042	0.048
Observations	16,125	16,125	2,631	2,631	1,947	19,315	18,756

This table presents the OLS regression results of the following model:

$$UR_{i,t} = \alpha_0 + \alpha_1 D_{i,t} + \alpha_2 UE_{i,t} + \alpha_3 D * UE_{i,t} + \alpha_4 UE^2_{i,t} + \alpha_5 D * UE^2_{i,t} + \varepsilon_{i,t} \quad (4)$$

$$UR_{i,t} = \alpha_0 + \alpha_1 D_{i,t} + \alpha_2 UE_{i,t} + \alpha_3 D * UE_{i,t} + \alpha_4 UE^2_{i,t} + \alpha_5 D * UE^2_{i,t} + \alpha_6 STnews_{i,t} + \varepsilon_{i,t} \quad (5)$$

$$UR_{i,t} = \alpha_0 + \alpha_1 D_{i,t} + \alpha_2 UE_{i,t} + \alpha_3 D * UE_{i,t} + \alpha_4 UE^2_{i,t} + \alpha_5 D * UE^2_{i,t} + \alpha_6 STnews_{i,t} + \alpha_7 LTnews_{i,t} + \varepsilon_{i,t} \quad (6)$$

UR is the stock returns adjusted for CRSP value-weighted returns. *UE* is the actual EPS minus the median analyst EPS forecasts in the last month of the fiscal year. *D* equals 1 if *UE* < 0 and 0 otherwise. Columns (1) and (3) (columns [2] and [4]) show the estimation results of model (4) (model [5]) for firms issuing only single-period forecasts and for firms issuing MF sets at least once during the year, respectively. Column (5) shows the estimation results of model (6) for *MFSET*=1. In columns (6) and (7), *MFSET* (which equals 1 for MF sets and 0 for single-period forecasts) is added to model (4) and (5), respectively, and interacted with the variables.

***, **, * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.