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Management forecast credibility and underreaction to news

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Abstract In this paper, we first document evidence of underreaction to management forecast news. We then hypothesize that the credibility of the forecast influences the magnitude of this underreaction. Relying on evidence that more credible forecasts are associated with a larger reaction in the short window around the management forecasts and a smaller post-management forecast drift in returns, we show that the magnitude of the underreaction is smaller for firms that provide more credible forecasts. Our paper contributes to the literature by providing out-of-sample evidence of the drift in returns documented in the post-earnings-announcement drift literature, with the credibility of the news being one explanation for the phenomenon.

Keywords Market efficiency · Credibility · Voluntary disclosure

JEL Classification G12 · G14 · G30 · M41

1 Introduction

This paper studies whether the credibility of a disclosure is a determinant of the market underreaction to the news conveyed by the disclosure. Since Ball and Brown

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(1968), several papers have documented a market underreaction to news such as earnings announcements (Fama 1998). We hypothesize that news credibility can provide an explanation for underreaction to news. To test this hypothesis, we focus on management forecast news because prior research has highlighted that the voluntary and non-audited nature of management forecasts leads to concerns about the credibility of these forecasts (e.g., Jennings 1987; Skinner 1994; Hutton et al. 2003; Rogers and Stocken 2005; Hutton and Stocken 2009). Thus management forecasts provide a powerful setting to explore the role of credibility in explaining the underreaction to news.

Our study relies on the idea that investors' reaction to forecast news is a function of the new information about future cash flows and the credibility of the forecast (Jennings 1987). Thus we argue that investors are more likely to delay their reaction to less credible news until more credible information (e.g., announcement of actual earnings) appear to support the forecast. If that is the case, then we expect that, when credibility of the news is higher, there will be a stronger market reaction at the time of the forecast, which is then followed by a smaller post-management forecast drift in returns.

Using a sample of management forecasts from 1996 to 2008, we first document an underreaction to management forecast news. This is a necessary condition for us to be able to test the role of credibility on the market underreaction to forecast news. Using portfolio analyses, we document significant 3-month abnormal buy-and-hold returns of 3.65 % (−0.95 %) in the extreme good (bad) forecast news quintile. A hedge portfolio that is long (short) in the extreme good (bad) news quintiles results in abnormal returns of 4.60 % in the next 3 months; these returns are both statistically and economically significant.

We then test whether forecast credibility provides an explanation for the market underreaction to forecast news. Specifically, we examine how the reaction to the forecast and the subsequent return correction vary cross-sectionally with various proxies of credibility: prior forecasting accuracy, litigation risk, proprietary costs (proxied by R&D intensity and industry concentration), the extent to which analysts agree with the management forecast, and bad news versus good news. With regards to prior forecasting accuracy, we follow the literature and assume that managers develop a reputation for issuing credible forecasts when prior forecasts have proven to be more accurate (Williams 1996; Hirst et al. 1999). We treat forecasts of firms that are exposed to greater litigation risk and greater proprietary costs (i.e., more competition and higher R&D) as being more credible (Gigler 1994; Frankel et al. 1995; Rogers and Stocken 2005; Wang 2007). Analyst agreement is determined by whether the post-management-forecast analyst consensus forecast is close to the management forecast. Finally, we assume, based on findings in the prior literature (e.g., Rogers and Stocken 2005; Hutton et al. 2003) that bad news forecasts are more credible than good news forecasts.

We perform two sets of tests to examine whether credibility is associated with underreaction to news. The first set relies on the three-day abnormal returns around the management forecast. We provide some evidence that the market relies on the credibility of the management forecasts when reacting to management forecast news in the short-term. In particular, we show that the market reaction to forecast news is larger for more credible forecasts, with credibility proxied by prior management forecast accuracy, R&D, analyst agreement, and bad as opposed to good management forecast news. Overall these findings are consistent with prior research that documents a lower market response to forecasts with lower credibility.

The second set of tests—and the key innovation of our paper—examines whether the abnormal returns subsequent to the management forecasts vary cross-sectionally with forecast credibility. Consistent with this hypothesis, the post-management-forecast 3-month hedge abnormal returns is smaller for more credible forecasts, with credibility proxied by prior management forecast accuracy, litigation risk, competition, R&D, and bad (as opposed to good) management forecast news. For example, using prior forecast accuracy (R&D) as a proxy for credibility, our regression results show that the 3-month hedge abnormal returns are 3.01 % (3.96 %) lower for more credible forecasts. The results, however, are statistically insignificant when credibility is proxied by analyst agreement.

Overall, the evidence from both sets of tests suggests that, for more credible forecasts, the market reacts more strongly in the short-term and that the subsequent drift is smaller. Our findings also imply that the market overly discounts less credible forecasts, resulting in a greater underreaction and a subsequent correction. If the market's discount of the news based on the perception of credibility was appropriate, there would be no basis for a drift.

We then provide a series of tests to ensure that our results are not simply capturing factors related to post-earnings announcement drift (PEAD). First, in our main tests, we control for prior drift in returns (momentum), earnings surprises (PEAD), and analyst forecast revisions. Second, we show that credibility continues to explain the cross-sectional variation in the underreaction to management forecast news after controlling for earnings persistence, size, investor sophistication, and transaction costs, which have been shown in the prior literature to be cross-sectional determinants of the post-earnings-announcement drift (Bernard and Thomas 1989, 1990; Bartov et al. 2000; Ng et al. 2008). We also control for management underreaction to news, a phenomenon documented by Gong et al. (2011). Finally, we show that the post-management-forecast drift is distinct from the post-earnings-announcement drift. We sort the observations into earnings surprise and management forecast surprise portfolios and show that the underreaction to management forecast surprise is present among firms with positive, negative, or zero earnings surprise.

Our paper extends the management forecast literature by showing that credibility affects not only the short-window returns around management forecasts (e.g., Hutton et al. 2003; Rogers and Stocken 2005) but also the long-window returns subsequent to the forecasts. Specifically, we show that, in addition to the smaller reaction to less credible forecasts in the short-term, there is also an underreaction with a subsequent correction in the long-term that varies with the forecast credibility. In doing so, we also contribute to the literature on market underreaction to news by showing that the credibility of the news signal helps to drive the cross-sectional variation in the market underreaction to news.

The remainder of the paper proceeds as follows. Section 2 develops the hypotheses. Section 3 describes our data and variable measurement. Section 4 presents the results, and Sect. 5 describes our additional analyses. Section 6 concludes.

2 Hypothesis development

2.1 Market underreaction to management forecasts

The objective of this paper is to investigate whether credibility of news is a cross-sectional determinant of the market under-reaction to news. We test this hypothesis using management forecasts, as opposed to PEAD, because management forecasts are voluntary disclosures about which investors have significant credibility concerns. Thus management forecasts provide us with a powerful setting to explore capital market consequences of cross-sectional variation in credibility in disclosure.

A necessary condition to explore the role of credibility in the underreaction to management forecast news is to examine whether an underreaction exists in the first place. There is extensive evidence that investors underreact to earnings news, a phenomenon known as the post-earnings-announcement drift (PEAD) (e.g., Bernard and Thomas 1989, 1990). Specifically, prior research documents a positive (negative) drift in post-earnings-announcement abnormal returns after positive (negative) earnings news. The typical explanation is that investors underreact to earnings news at the time of the earnings announcement and that a drift in returns occurs due to a subsequent market correction in the longer term. An examination into whether there is a post-management-forecast drift is a natural extension of the PEAD literature.

The management forecast literature provides some indirect evidence of a drift in returns after forecast news. Using a sample of 548 forecasts from 1979 through 1983, McNichols (1989, Figure 2) documents a negative drift in returns for negative forecast news but no drift in returns after positive forecast news. In contrast, Anilowski et al. (2007, Figure 5) document a positive drift in returns after positive aggregate forecast news quarters but no drift after negative news quarters.[1] None of these papers, however, provide conclusive evidence as to whether there is an underreaction to forecast news. Hence, as a preliminary step to investigating the role of credibility to the underreaction, we will first establish the existence of the underreaction within our sample.

2.2 The role of credibility

Management earnings forecasts are a potentially valuable source of information for investors because they inform investors and other stakeholders about the prospects of a firm. Management forecasts represent one of the key voluntary disclosure mechanisms through which managers establish or alter market's earnings expectations, preempt litigation concerns, and influence their reputation for transparent

[1] Anilowski et al. (2007) measure aggregate management forecast news by aggregating the management forecast news for all firms in First Call for each quarter from 1990 to 2004.

and accurate reporting (Graham et al. 2005; Hirst et al. 2008). Investors' reaction to the news in the forecasts, however, is expected be a function of the new information about future cash flows *and* the credibility of the forecast (Jennings 1987), where credibility refers to the extent to which investors perceive the forecast to be believable. The concern about credibility arises because management forecasts are voluntary and unaudited disclosures over which managers have substantial discretion.

Early research even questions whether credibility concerns related to management forecasts would render the forecasts uninformative to investors (Patell 1976; Penman 1980). Since then, the literature has established that investors do react to management forecasts. Nevertheless, the concern about credibility remains. For example, Healy and Palepu (2001, 425) emphasize that "the extent to which voluntary disclosure mitigates resource misallocation in the capital market depends on the degree of credibility of information on the firm's economics that is not available from other sources, including required disclosures. Because managers have incentives to make self-serving voluntary disclosures, it is unclear whether management disclosures are credible."

If there is an underreaction to forecast news, we conjecture that the underreaction is likely to be greater when there are greater credibility concerns. In particular, investors are more likely to disregard the forecast news when the news is less credible and delay their reaction until more credible information (e.g., actual earnings) is disclosed that supports the forecast. Specifically, we expect that, when credibility of the news is higher, there will be a stronger market reaction at the time of the forecast, which is then followed by a smaller post-management forecast drift.

To illustrate, assume that prevailing expectations are 5 cents a share and management issues a forecast of 10 cents a share. In addition, assume that the forecast is unbiased (i.e., actual earnings are 10 cents a share). According to our conjecture, if the market considers the forecast credible, it will revise its expectation fully to management's estimate of 10 cents a share upon management forecast release, and there should be no post-forecast drift. However, if the market views the forecast as less than credible and therefore revises its expectation to only 7 cents a share, then there will be a delayed response when until the actual earnings of 10 cents are ultimately announced. The delayed response only happens because the market made the faulty assumption (based upon whatever information it used) that management's forecast was not credible.[2]

Therefore, for credibility to have a role in the post-management-forecast drift, it must be true that, while the market relies on credibility in responding to management forecasts, it overly discounts less credible forecasts when compared with their actual ability to predict actual earnings (i.e., 7 vs. 10 cents in the prior example). Prior literature suggests that this could be the case. For example, it has shown that the abnormal returns around management forecasts are larger for bad news forecasts than for good news forecasts (e.g., Jennings 1987; Hutton et al. 2003). However, Rogers and Stocken (2005) find no difference in the management

[2] The assumption that all forecasts are unbiased is simply for ease of exposition. The above example would hold as long as the actual earnings for the less credible forecast is more than 7 cents.

forecast bias (i.e., the difference between actual earnings and forecasted earnings) between bad news and good news forecasts. Thus the lack of difference in bias between good and bad news forecasts seems consistent with an investor over-discounting good news surprises, despite little difference in their actual forecasting ability.

To test our hypotheses, we examine the short-term and long-term reactions to forecast news as a function of forecast credibility. Our first hypothesis predicts that the short-term market reaction to the forecast news *increases* with the credibility of the forecast. Our second hypothesis focuses on whether the long-term market (under-)reaction to forecast news *decreases* with forecast credibility.[3]

H_1: The short-term market reaction around management forecast news is larger for more credible forecasts.

H_2: The underreaction to management forecast news is smaller for more credible forecasts.

3 Data description and variable measurement

3.1 Sample selection

We obtain from the Company Issued Guidelines (CIG) dataset in the First Call database all point and closed range management forecasts of annual and quarterly earnings per common share (EPS) that are issued between January 1, 1995, and December 31, 2008. We exclude the forecasts before 1995 because First Call provides little coverage of management forecasts before 1995. We restrict our sample to annual and quarterly EPS forecasts because these are the most common types of forecasts that firms issue. We then drop forecasts with confounding events that could lead to discontinuity in EPS (e.g., mergers and accounting changes), forecasts that might have erroneous forecast dates (specifically, forecast dates recorded as being after the data entry date), and forecasts with missing CUSIPs. Our sample contains only point and closed range forecasts because only these forecasts provide numerical estimates that are required to compute forecast surprises.

We drop all forecasts without the CUSIP-PERMNO link that is required to link the forecasts to stock returns from CRSP. We also restrict forecasts to those of firms with ordinary shares listed on NYSE, AMEX, or NASDAQ (i.e., CRSP share codes 10 and 11 and CRSP exchange codes 1, 2, and 3) on the forecast date.

Next, we retain all forecasts for which we can compute forecast news. Following prior research (e.g., Baginski et al. 1993; Clement et al. 2003; Cotter et al. 2006), we compute management forecast news, also known as forecast surprise, *Surprise*, as follows:

[3] Related to our prediction, prior research has shown that PEAD is smaller for firms with high quality accruals (Francis et al. 2007) and for firms that host conference calls (Kimbrough 2005). Likewise, the accruals anomaly is smaller for more reliable accruals (Richardson et al. 2005) and for firms with higher analyst disclosure quality ratings (Drake et al. 2009).

1. If the management EPS forecast is a point forecast (i.e., forecast description code is 'A', 'F', or 'Z'), then

$$Surprise = (X - AF)/P$$

2. If the management EPS forecast is a range forecast (i.e., forecast description code is 'B', 'G', or 'H'), then

$$Surprise = (((Y + Z)/2 - AF)/P \tag{1}$$

where X is the value of the forecast for a point forecast; Y and Z are the lower and upper bounds of the forecast, respectively, for a range forecast; P is the stock price 2 days before the forecast date.[4] X, Y, and Z are from First Call. AF is the pre-management-forecast analyst consensus median forecast from nonsplit-adjusted I/B/E/S Summary File. We are thus matching the nonsplit-adjusted (i.e., original) management forecasts from First Call with the nonsplit-adjusted analyst forecasts from I/B/E/S. Since the above computation involves per-share numbers and the management forecast and analyst forecast are made on different days, we ensure that both forecasts are based on the same number of outstanding shares by using the shares split factors from CRSP database to adjust EPS numbers, if necessary.

Next, we remove all forecasts for which we cannot compute our dependent variables—short-term and long-term abnormal returns—and our control variables: beta, size, book-to-market, momentum, prior quarterly earnings surprise, and prior analyst forecast revision. Details of the above variables are provided below. Finally, we remove all forecasts made within 3 days of an earnings announcement. Rogers and Van Buskirk (2009) show that forecasts bundled with earnings announcement releases are common, so we exclude them to mitigate concerns that our results are driven by the post-earnings-announcement drift.[5]

We then sort firms into quintile portfolios based on the management forecast surprises. We use the distribution of all the forecast surprises in the previous year to determine the cut-offs for the quintile portfolios to avoid a look-ahead bias when determining the relative magnitude of forecast surprises (Foster et al. 1984).[6] This procedure imposes the deletion of all forecasts in 1995, the first year in the sample. Our final sample consists of 23,822 management forecasts from 1996 to 2008.

3.2 Measures of market reaction

To study the short-term market reaction to management forecast surprises, we measure the size-adjusted return in the three-day window around the management

[4] Our results are robust to the use of the mean consensus (instead of the median) EPS forecast from the I/B/E/S Summary File. They are also robust to the use of unscaled forecast surprise and alternative scalars, namely the absolute value of the management EPS forecast and the absolute value of the analyst median consensus EPS forecast. .

[5] When we include in our sample management forecasts that are bundled with earnings announcement releases, we continue to find evidence that there is an underreaction to forecast news and that greater credibility mitigates this underreaction.

[6] The results are robust when we use the current year's distribution as an alternative way to assign firms into portfolios.

forecast date, *AbRet3d*. To study the long-term market reaction, we measure the post-management-forecast size-adjusted return, *AbRet3m* and *AbRet12m*. *AbRet3m* (*AbRet12m*) is the 3-month (12-month) size-adjusted returns beginning from the third day after the management forecast. The abnormal returns, which are in percentages, are computed as the buy-and-hold return of the stock minus the benchmark buy-and-hold return of the decile portfolio of NYSE, AMEX, and NASDAQ stocks of similar size as of the most recent June (i.e., the June before the management forecast date). The equal-weighted cut-off points for the size portfolios are obtained from Professor Kenneth French's website.[7]

3.3 Measures of credibility

From the investors' perspective, many factors could influence their evaluation of a forecast's credibility. In this paper, we rely on six credibility proxies to examine the role of credibility in market's reaction to forecast news. These measures follow from prior research, which uses forecast characteristics, firm characteristics, and market reaction to infer the credibility of a given forecast.

Our first measure of credibility is *forecast accuracy*. We expect managers to develop a reputation for credible forecasts if their prior forecasts have been accurate (Williams 1996). Graham et al. (2005) survey executives and find that managers issue voluntary disclosures such as management forecasts to develop and maintain a reputation for accurate and transparent reporting. To the extent that prior forecasts have been accurate, investors are likely to regard subsequent forecasts as being more credible. Thus we use prior forecast accuracy as a proxy for credibility based on the argument that managers are likely to be viewed as issuing more credible forecasts if they have been accurate in prior ones (Williams 1996; Hirst et al. 1999; Hutton and Stocken 2009).

We compute *Accuracy* as the average of the accuracy of all management forecasts of EPS announced prior to the current management forecast. Our use of the earnings announced prior to the current forecast ensures that the accuracies of all the forecasts used to compute *Accuracy* are known and measurable at the time of the current forecast. To compute *Accuracy*, we first retrieve the series of actual earnings before the current forecast. We then retrieve all the management forecasts that the firm has issued in relation to the actual earnings. By construction, these forecasts are made before the current forecast. We compute accuracy for each of these forecasts as the absolute value of the difference between actual earnings and management forecast, scaled by share price 2 days before the forecast date and multiplied by minus one.[8] *Accuracy* is then computed as the average of the forecast accuracies of all prior forecasts.

Our second measure of credibility is *litigation risk*. Managers of firms facing higher litigation risk are more likely to be more careful in issuing forecasts and are less likely to use earnings forecasts to opportunistically manipulate investors' expectations (Frankel et al. 1995; Rogers and Stocken 2005). To the extent that

7 http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

8 We use the single numerical estimate for a point forecast and the midpoint of the lower bound and upper bound for a range forecast.

litigation risk constrains opportunistic forecasting, it might increase investors' perception of a forecast's credibility. We measure *LitRisk* using the model in Rogers and Stocken (2005). (See "Appendix" for details.)

Our third and fourth measures of credibility use proprietary costs to proxy for credibility. Gigler (1994) highlights the tension between the benefit of providing investors with value-relevant voluntary information and the cost of revealing proprietary information to competitors and argues that higher cost reflects greater credibility. First, we expect proprietary cost to increase in the extent to which the firm faces competition within its industry because more competition increases the likelihood that competitors will use the disclosed information to their own advantage and to the firm's disadvantage, which is consistent with Gigler (1994).

We measure competition, *Competition,* as the negative of the Herfindahl Index, which is a measure of industry concentration. The formula for the Herfindahl index is $\sum_i^n s_i^2$, where s_i is the market share of firm i in the market, and n is the number of firms. The negative sign is added because a more competitive industry is a less concentrated industry. The *Competition* associated with each forecast is based on the competitiveness of the firm's industry in the prior calendar quarter.

In addition, we expect the proprietary cost of disclosing earnings forecasts to be higher when a firm engages in more research and development because these forecasts reveal to competitors the successes and failures of new projects undertaken by the firm (Wang 2007). We measure the *research and development intensity* (*R&D*) of a firm using research and development expenses scaled by total assets. The *R&D* associated with each forecast is based on the research and development that firm engaged in during the prior fiscal year.

Our fifth measure of credibility is *analyst agreement*. We argue that the extent to which analysts agree with a management forecast indicates analysts' perception of the credibility of the management forecast. To operationalize this measure, we construct an indicator variable, *AnalystAgree*. It equals one (1) if the management forecast is a point forecast and the post-management-forecast analyst consensus median forecast is within one penny of the management EPS forecast or (2) if the management forecast is a range forecast and the post-management-forecast analyst consensus median EPS forecast is within upper and lower bounds of the management forecast and zero otherwise.[9] Two caveats with this measure are in order: first, investors underreact to information provided by analysts (e.g., Givoly and Lakonishok 1980; Gleason and Lee 2003). Second, analysts themselves do not fully impound the implications of the firm's disclosures in their forecasts (e.g., Abarbanell and Bernard 1992; Bradshaw et al. 2002).

Our final proxy for credibility is whether the forecast conveys *good or bad news*. Prior literature has argued that there are managerial incentives to voluntarily disclose good news and withhold bad news and thus that good news forecasts are less credible than bad news forecasts (Hutton et al. 2003; Rogers and Stocken 2005). We also therefore examine whether there is any difference in the market reaction to

[9] We use one penny as the boundary to determine the credibility of point forecasts because point forecasts are typically preceded by modifiers such as "about" or "approximately." In untabulated analysis, we use zero or two pennies and find similar results.

good and bad news forecasts. To this end, we develop two variables, *Good News* and *Bad News*: (1) *Good News* is a dummy variable equalling one if *Surprise* is positive and zero otherwise, and (2) *Bad News* is a dummy variable equalling one if *Surprise* is negative and zero otherwise. We then compare the magnitude of the effects for good and bad news using forecasts of no news (about 10 % of our sample) as the benchmark.[10]

4 Empirical analyses

4.1 Analyses of market reaction by quintile portfolios

As discussed in Sect. 3.1, we assign firms into quintile portfolios based on the management forecast surprises, with quintile 1 (Q1) and quintile 5 (Q5) consisting of firms disclosing the most negative and most positive forecast surprises, respectively. Table 1 presents the means of various characteristics across all the observations, as well as by quintile portfolios.[11] The first column reports the means of the forecast surprises (*Surprise*), which increase, by construction, from Q1 to Q5. The three-day abnormal returns (*AbRet3d*) is −10.90 (3.79) for Q1 (Q5). This is consistent with prior research that shows that the investors react to management forecasts by revising the stock price in the direction of the management forecast (e.g., Ajinkya and Gift 1984; Waymire 1984). Further, consistent with prior research (e.g., Hutton et al. 2003), the market reaction to bad news is larger than the reaction to good news.

The last two columns of Table 1 present the analysis of the long-term market reaction, in terms of post-management-forecast 3-month and 12-month abnormal returns (*AbRet3m* and *AbRet12m*, respectively). For the extreme good forecast news quintile, there is a positive 3-month (12-month) abnormal returns of 3.65 % (4.03 %); these returns are both statistically and economically significant. In contrast, for extremely bad management forecast news quintile, there is a negative 3-month (12-month) abnormal returns of −0.95 % (−3.26 %). The middle quintiles are characterized by statistically (and economically) insignificant abnormal returns, arguably due to the lower variation in forecast surprise among these portfolios. The hedge portfolio 3-month (12-month) abnormal returns from buying (selling) the shares of firms in the extreme positive (negative) forecast news quintile equals 4.60 % (7.29 %) and are statistically and economically significant. Further, since more than half of the hedge portfolio abnormal returns appear to be generated in the first 3 months, our subsequent analysis will largely focus on the drift in returns in the 3 months after the management forecast.

[10] In untabulated analysis, we find that our measures of credibility are positively associated with current forecast accuracy, suggesting that they carry information about actual earnings.

[11] The number of observations differs across quintiles because we use cut-offs based on the distribution of the forecast surprises in the previous calendar year.

Table 1 Sample characteristics of management EPS forecast surprises

Quintile	OBS	*Surprise*	*AbRet3d*	*AbRet3m*	*AbRet12m*
All	23,822	−0.37	−2.80	1.10	0.69
1	4,503	−2.22	−10.90***	−0.95	−3.26*
2	4,716	−0.40	−7.29***	0.58	0.46
3	4,079	−0.09	−3.00***	−0.16	−0.73
4	5,477	0.02	0.08	0.35	−0.46
5	5,047	0.48	3.79***	3.65***	4.03***
Q5–Q1		2.70	14.69***	4.60***	7.29***

This table presents the quintile portfolio means of various characteristics that indicate market responses to management EPS forecast surprises. The sample contains 23,822 forecast surprises from management forecasts that were made between 1996 and 2008. *Surprise* is the difference between management forecast and the pre-management-forecast consensus analyst median forecast. *AbRet3d* is the 3-day size-adjusted buy-and-hold return, in percentage, in the 3-day window around the management forecast date. *AbRet3m* (*AbRet12m*) is the 3-month (12-month) size-adjusted buy-and-hold return, in percentage, in the three (twelve) months from the third day after the management forecast date. *t* statistics are computed for *AbRet3d*, *AbRet3m*, and *AbRet12m*, and *, **, and *** indicate two-tailed statistical significance at the 10, 5, and 1 percent levels, respectively

To further illustrate the patterns of returns in relation to the management forecasts, Fig. 1 plots the cumulative abnormal returns at monthly intervals of up to 12 months after the forecasts for the top, middle, and bottom quintiles of forecast surprises. Each number on the x-axis represents the end of a month, with month '0' being the third day after the management forecast. Figure 1a (b, c) presents the returns for all (quarterly, annual) forecasts. Overall, we observe from these figures that there is a positive (negative) drift in abnormal returns for firms in the top (bottom) quintile of forecast surprises. In addition, Fig. 2a (b) presents the 3-month (12-month) hedge portfolio abnormal returns by calendar quarter. The hedge portfolio returns are generally positive throughout the calendar quarters, although there are some quarters with economically significant negative returns.

In untabulated analyses, following Bernard and Thomas (1990) and Sloan (1996), we examine whether there is a concentration of hedge portfolio returns around the earnings announcements that occur after the management forecasts. Evidence of such concentration of returns is consistent with our arguments in Sect. 2 that investors delay their reaction until more credible information (e.g., announcement of actual earnings) appear to support the forecast. We find that there is indeed a concentration of hedge portfolio returns around the very next earnings announcement and around the announcement of the earnings being forecasted. The 3-day hedge portfolio return around the next earnings announcement and around the earnings announcement being forecasted is 0.91 % and 0.88 %, respectively. Assuming that there are 252 trading days in a year and assuming no concentration of returns, one might have expected, in any 3-day window, for the hedge portfolio returns to be about 0.087 % (3/252 × 7.29 %).

Overall the results in Table 1 and Figs. 1 and 2 are consistent with a market underreaction to management forecast news. We document a drift in abnormal

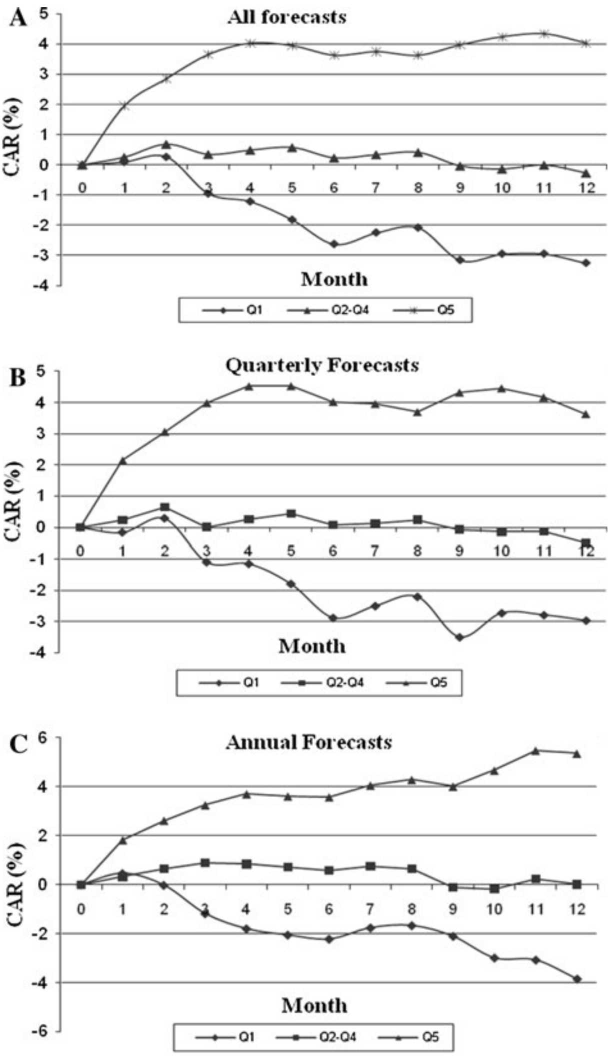

Fig. 1 Post-Management-Forecast Drift. This figure presents the post-management-forecast cumulative abnormal returns for the management forecast news. **a** presents the results for all forecasts, whereas **b** (**c**) presents the results for quarterly (annual) forecasts. The cumulation of the buy-and-hold returns begins from the third day after the management forecast and continues for up to 12 months. The forecast news of each firm in each year is sorted into quintile portfolios based on the prior year's distribution of all forecast news, *Surprise*. *Surprise* is the difference between management forecast and the pre-management-forecast consensus analyst median forecast. Q1 (Q5) refers to the quintile with the lowest (highest) forecast news. Q2–Q4 refers to the middle three quintiles of forecast news

returns in the direction of the forecast news for up to 12 months, although most of the returns appear to be generated during the first 3 months after the forecast. These findings are consistent with the literature on PEAD, which documents positive (negative) drift in returns subsequent to positive (negative) earnings news.

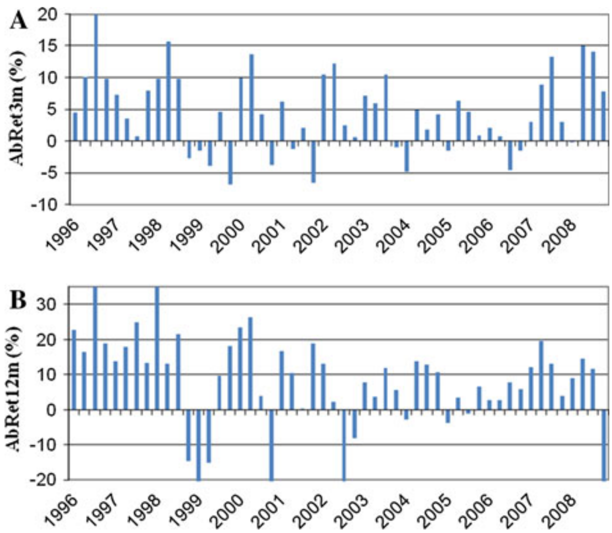

Fig. 2 Hedge Portfolio Returns by Calendar Quarter. **a** (**b**) presents, for each calendar quarter, the equal-weighted 3-month (12-month) abnormal returns of buying firms in the top quintile and selling firms in the bottom quintile of forecast surprises, with the trades being made on the third day after the management forecasts. *AbRet3m* (*AbRet12m*) is the 3-month (12-month) size-adjusted buy-and-hold return, in percentage, in the three (twelve) months from the third day after the management forecast date

4.2 The role of forecast credibility in the market reaction to forecast news

In this section, we examine the short-term and long-term reactions to forecast news as a function of forecast credibility. We begin by examining the role of forecast credibility in moderating the short-term market reaction around the management forecast. The two regression specifications that we rely on in the analyses are:

$$AbRet3d = \beta_0 + \beta_1 QSurprise + \beta_2 Credibility + \beta_3 QSurprise \times Credibility + \varepsilon \tag{2}$$

$$AbRet3d = \gamma_0 + \gamma_1 Bad\,News + \gamma_2 Good\,News + \varepsilon \tag{3}$$

where *AbRet3d* is the 3-day abnormal return around the management forecast; *QSurprise* is a quintile transformation of management forecast surprise (*Surprise*); *Credibility* is one of our proxies for credibility: *Accuracy*, *LitRisk*, *Competition*, *R&D*, or *AnalystAgree*. *Good News* and *Bad News* are indicator variables for good and bad news forecasts, respectively.

In all our regressions, we use scaled quintile ranks of *Surprise* (*QSurprise*) to address potential outliers and nonlinearities in the relation between earnings surprises and the dependent variables of interest. We re-scale the quintile ranks such that *QSurprise* ranges from zero to one to allow for the exposition of the results in terms of a hedge portfolio return from buying the top and shorting the bottom quintiles of management forecast news. Similarly, we also develop scaled quintile ranks of the measures of credibility that are continuous variables: *QAccuracy*, *QLitRisk*, *QCompetition*. For *R&D*, because this variable equals zero for 57 % of our sample, we assign these observations a *QR&D* value of zero and then assign the remaining firms to two groups coded as *QR&D* equalling 0.5 and 1. The other credibility proxies, *AnalystAgree*, *Good News*, and *Bad News*, are already indicator variables and thus are not further transformed. To mitigate cross-sectional and time-series dependence, we cluster the standard errors by firm and calendar quarter (Petersen 2009).

Our first hypothesis states that the short-term market reaction is expected to be stronger for more credible forecasts. Hence, we expect β_3 to be positive in Eq. (2) and γ_1 to be greater than γ_2 in Eq. (3).

Before we present the regression results, Table 2 presents descriptive statistics and pair-wise correlations for the credibility measures. The correlations among the credibility proxies are generally in the expected direction. (Note that all variables are coded so that they are increasing in credibility.) For instance, the Pearson correlation between *Accuracy* and *AnalystAgree* is a statistically significant 0.10, indicating that, when prior forecasts have been more accurate, post-management-forecast analyst forecasts are more likely to agree with the management forecasts. The positive (negative) correlation between *Accuracy* and *Bad News* (*Good News*) forecasts indicates that firms with higher prior forecast accuracy are more (less) likely to announce bad (good) management forecast news.[12]

Table 3 presents the regression results. The dependent variable is the 3-day abnormal return (*AbRet3d*). In the first column, the positive coefficient on *QSurprise* indicates that investors respond more positively to more positive management forecast news. Specifically, the coefficient on *QSurprise* implies that the difference in the short-term market response to top and bottom quintile of forecast surprise is 13.92 %, consistent with the finding in Table 1.

The next few columns provide some evidence that investors' response is stronger for more credible forecasts. In particular, the coefficients on the interaction term between *QSurprise* and *QAccuracy* in Column I, *QSurprise* and *QR&D* in Column IV, and *QSurprise* and *AnalystAgree* in Column V are positive and statistically significant. This implies that investors respond more strongly to forecasts associated with greater prior forecast accuracy, forecasts associated with higher proprietary costs as proxied by *R&D* intensity, as well as forecasts for which analysts agree with the management forecast. For example, the difference in the short-term market response to top and bottom quintile of forecast surprise is greater by 3.05 % for firms with more accurate forecasts.

In Column VII, we also find some evidence of that the magnitude of the market reaction to negative forecast news is greater than that to positive forecast news, suggesting the negative forecast news is more credible than positive forecast news; this finding is consistent with prior evidence (e.g., Hutton et al. 2003). We find no evidence, however, that litigation risk (Column II) and competition (Column III) influences the reaction to forecast news.

[12] We note that the correlation between *Bad News* and *Good News* is not mechanically equal to minus one because about 12 % of our sample has forecasts that provide no news. That is, for these observations, both *Bad News* and *Good News* are equal to zero.

Table 2 Descriptive statistics of credibility and related variables

Variables	OBS	Mean	STD	P1	Median	P99
Panel A: descriptive statistics						
Accuracy	19,978	−0.01	0.01	−0.05	0.00	0.00
LitRisk	23,822	−2.52	0.28	−3.07	−2.55	−1.70
Competition	23,822	−7.95	6.93	−36.72	−5.70	−1.78
R&D	23,822	0.03	0.05	0.00	0.00	0.24
AnalystAgree	20,956	0.73	0.44	0.00	1.00	1.00
Bad News	23,822	0.58	0.49	0.00	1.00	1.00
Good News	23,822	0.32	0.47	0.00	0.00	1.00

Table 2 continued

Variables	*Accuracy*	*LitRisk*	*Competition*	*R&D*	*AnalystAgree*	*Bad News*	*Good News*
Panel B: correlations							
Accuracy	–	0.14	0.05	0.02	0.10	0.03	−0.07
		<0.0001	*<0.0001*	*0.00*	*<0.0001*	*<0.0001*	*<0.0001*
LitRisk	0.15	–	0.06	0.19	0.06	0.04	−0.06
	<0.0001		*<0.0001*	*<0.0001*	*<0.0001*	*<0.0001*	*<0.0001*
Competition	0.02	0.14	–	0.22	0.00	−0.01	0.01
	0.02	*<0.0001*		*<0.0001*	*0.60*	*0.43*	*0.21*
R&D	0.07	0.23	0.34	–	−0.01	0.03	−0.04
	<0.0001	*<0.0001*	*<0.0001*		*0.18*	*<0.0001*	*<0.0001*
AnalystAgree	0.10	0.06	−0.01	−0.01	–	−0.04	−0.05
	<0.0001	*<0.0001*	*0.07*	*0.11*		*<0.0001*	*<0.0001*
Bad News	0.04	0.03	0.00	0.04	−0.04	–	−0.80
	<0.0001	*<0.0001*	*1.00*	*<0.0001*	*<0.0001*		*<0.0001*
Good News	−0.11	−0.05	0.00	−0.04	−0.05	−0.80	–
	<0.0001	*<0.0001*	*0.63*	*<0.0001*	*<0.0001*	*<0.0001*	

Panel A presents the descriptive statistics of the key variables used in the analyses. Panel B presents pair-wise correlations for the credibility proxies, with Pearson (Spearman) correlations above (below) the main diagonal. *Accuracy* is the prior forecasting accuracy based on the average of the accuracies of all management forecasts made before the current management forecast. *LitRisk* is the litigation risk exposure. *Competition* is the negative of the Herfindahl Index of the industry that the firm belongs to, and *R&D* is research and development expenses. *AnalystAgree* is an indicator variable equalling one (1) if the management forecast is a point forecast and the post-management-forecast analyst consensus mean forecast is within one penny of the management EPS forecast or (2) if the management forecast is a range forecast and the post-management-forecast analyst consensus mean EPS forecast is on or within upper and lower bounds of the management forecast and zero otherwise. *Bad News* (*Good News*) is an indicator variable equal to one if the management forecast surprise is negative (positive). *p* values are presented in italics below the correlations

Table 3 Effect of credibility on short-term reaction to the forecast

	Main Effect	*Credibility* measures: *QAccuracy* I	*QLitRisk* II	*QCompetition* III	*QR&D* IV	*AnalystAgree* V	*Good* versus *Bad News* VI
QSurprise	13.92***	11.88***	13.73***	14.51***	12.62***	10.87***	
	(21.38)	(16.09)	(23.15)	(20.18)	(19.68)	(17.74)	
Credibility		−2.79***	−1.74*	0.31	−3.29***	−2.71***	
		(−4.52)	(−1.90)	(0.39)	(−5.29)	(−6.79)	
QSurprise × *Credibility*		3.05***	0.47	−1.18	4.02***	3.77***	
		(3.23)	(0.43)	(−1.16)	(5.42)	(6.77)	
Bad News							−6.61***
							(−14.84)
Good News							2.16***
							(9.59)
Adj-R^2 (%)	22.13	22.34	22.34	22.16	22.56	22.14	16.79
OBS	23,822	19,978	23,822	23,822	23,822	20,956	23,822

This table presents regressions that investigate the effect of credibility on the short-term reaction to management EPS forecast surprises. The dependent variable is *AbRet3d*, which is the size-adjusted buy-and-hold return, in percentage, in the 3-day window around the management forecast. *QSurprise* is the quintile rank of *Surprise*, where *Surprise* is management forecast minus pre-management-forecast consensus analyst mean forecast, scaled by stock price 2 days before the management forecast; the quintile rank is scaled to range from zero to one. *Credibility* is measured using various individual proxies: *QAccuracy*, *QLitRisk*, *QCompetition*, *QR&D*, *AnalystAgree*, and *Good* versus *Bad News*. *Accuracy* is the prior forecasting accuracy based on the average of the accuracies of all management forecasts made before the current management forecast. *LitRisk* is the litigation risk exposure, *Competition* is the negative of the Herfindahl Index of the industry that the firm belongs, and *R&D* is research and development expenses. *QAccuracy*, *QLitRisk*, *QCompetition*, and *QR&D* are quintile ranks of *Accuracy*, *LitRisk*, *Competition*, and *R&D*, respectively. *AnalystAgree* is an indicator variable equalling one (1) if the management forecast is a point forecast and the post-management-forecast analyst consensus mean forecast is within one penny of the management EPS forecast or (2) if the management forecast is a range forecast and the post-management-forecast analyst consensus mean EPS forecast is on or within upper and lower bounds of the management forecast and zero otherwise. *Bad News* (*Good News*) is an indicator variable equal to one if the management forecast surprise is negative (positive). Year-quarter fixed effects and the intercept are included in the regressions, but, for parsimony, these coefficients are untabulated. *t* statistics, which are in parentheses, are obtained after the two-way clustering of the standard errors by firm and by calendar quarter. *, **, and *** indicate two-tailed statistical significance at the 10, 5, and 1 percent levels, respectively

Overall, the results in Table 3 indicate that the short-term market reaction to forecast news is generally stronger when the news is regarded to be of greater credibility. However, the findings are consistent for most, but not all, credibility proxies. Thus Table 3 provides only some support for our first hypothesis, which states that investors rely on the credibility of the forecasts when responding to forecast news.

Our second hypothesis predicts that the market underreaction to forecasts will be smaller for forecasts with higher credibility. To test this hypothesis we adapt Eqs. (2) and (3) to examine the long-term returns subsequent to (as opposed to short-term returns around) the management forecast. We also include controls for known risk factors and variables associated with market drift in returns. We rely on the following the two regression specifications:

$$AbRet3m = \beta_0 + \beta_1 QSurprise + \beta_2 Credibility + \beta_3 QSurprise \times Credibility + \Sigma\, \delta_m Control_m + \varepsilon \tag{4}$$

$$AbRet3m = \gamma_0 + \gamma_1 Bad\,News + \gamma_2 Good\,News + \Sigma\, \delta_m Control_m + \varepsilon \tag{5}$$

where *AbRet3m* is the 3-month abnormal return beginning from the second day after the management forecast; *QSurprise*, *Credibility*, *Good News* and *Bad News* are defined above; and *Control* is a set of control variables that includes three risk factors—firm beta (*Beta*), logarithm of size (*Log Size*), and book-to-market (*BEME*)—and three variables associated with drift in returns—momentum (*QMomentum*), earnings surprise (*QPEAD*), and analyst forecast revisions (*QAnalystDrift*). The inclusion of the last three control variables ensures that the post-management forecast returns that we document are not simply a continuation of the drift in returns due to prior events such as market returns, earnings announcements or analyst forecast revisions.[13] In untabulated analysis, we find that *QSurprise* has a Pearson correlation of 0.20 (0.23, 0.16) with *QPEAD* (*QMomentum*, *QAnalystDrift*). As before, to mitigate cross-sectional and time-series dependence, we cluster the standard errors by firm and calendar quarter (Petersen 2009).

Our control variables are measured as follows: *Beta* is estimated from a market model time-series regression of a firm's returns on market returns for firms with at least 18 months of returns in the 5 years before the month of the forecast. Size is the market value of equity at the beginning of the month of the management forecast. *BEME* is the ratio of the book value of equity to the market value of equity at the end of the previous fiscal year. *Momentum* is the 12-month cumulative raw return ending 2 months before the month of the management forecast. *PEAD* is the difference between the actual earnings announced on or just before the management forecast date and the most recent analysts' mean consensus EPS forecast, scaled by price 2 days before the earnings announcement date. *AnalystDrift* is the difference in the consensus analyst mean EPS forecast 1 and 2 months before the management

[13] We are not testing the existence of an underreaction to prior returns, to earnings surprises, or to analyst forecast revisions when *QMomentum*, *QPEAD*, and *QAnalystDrift* are included in the regressions. First, our sample differs substantially from those used in these literatures due to the requirement that a firm issue a management forecast. Second, the cumulation of the returns begins from the second day after the management forecast date.

forecast, scaled by price 2 days before the computation of the consensus forecast 1 month ago. For consistency with *QSurprise*, we also use quintile rank specifications for momentum, *PEAD*, and *AnalystDrift*; we label these variables *QMomentum*, *QPEAD*, and *QAnalystDrift*, respectively.

Hypothesis 2 states that we expect the underreaction to management forecast news to be smaller for more credible forecasts. Thus we expect β_3 to be negative in Eq. (4) and γ_1 to be smaller than γ_2 in Eq. (5).

Table 4 presents the results with *AbRet3m* as the dependent variable. In the first column, the coefficient on *QSurprise* can be interpreted as the estimate of the hedge portfolio abnormal returns from an investment strategy of buying (selling) firms in the top (bottom) quintile of forecast surprises. This coefficient indicates a hedge portfolio 3-month abnormal return of 3.13 %. This result is consistent with our earlier results in Table 1, specifically, that there is an underreaction to management forecasts.

In the subsequent columns, the coefficient of the interaction term on *QSurprise* × *Credibility* can be interpreted as the difference in the returns of *QSurprise* hedge portfolios between firms with high and low credibility. The coefficient on *QSurprise* × *QAccuracy* in Column I is a significant −3.01; this indicates that, compared with least credible forecasts in terms of prior forecast accuracy, the 3-month abnormal returns are 3.01 % lower for most credible forecasts. In other words, the coefficient on *QSurprise* indicates that the abnormal returns are 4.60 % for the least credible forecasts, whereas the sum of the coefficients on *QSurprise* and *QSurprise* × *Credibility* indicates that the abnormal returns are 1.59 % (= 4.60–3.01 %) for the most credible forecasts.

The remaining columns repeat the analyses with other measures of credibility. The results in Columns II (III, IV) indicate that, compared with firms with the least credible forecasts in terms of litigation risk (competition, R&D), those with the most credible forecasts have 3-month hedge portfolio abnormal returns that are smaller by a statistically significant 10.17 % (4.98, 3.96 %). In Column V, while the coefficient on *QSurprise* and *AnalystAgree* of −1.28 is in the expected direction, it is statistically insignificant. Finally, in the last column, we compare the difference in the underreaction between bad and good news forecasts. We find that there is a significant underreaction to good news but that the underreaction to bad news forecasts is statistically insignificant.

5 Additional analyses

5.1 Post-management-forecast drift versus post-earnings-announcement drift

Our results so far suggest a market underreaction to management forecasts that is a function of the credibility of the forecast. We now provide two sets of tests to increase the confidence that our results are indeed driven by the forecast and its credibility, as opposed to some other factor associated with the post-earnings announcement drift. We note, however, that all regressions in Table 4 already control for the prior stock price momentum, earnings surprise, and forecast revision.

Table 4 Effect of credibility on post-management-forecast drift

		Credibility measures					
	Main Effect	*QAccuracy* I	*QLitRisk* II	*QCompetition* III	*QR&D* IV	*AnalystAgree* V	*Good* versus *Bad News* VI
Beta	0.53	0.20	0.33	0.51	0.34	0.41	0.51
	(0.81)	(0.32)	(0.58)	(0.78)	(0.57)	(0.64)	(0.78)
Log Size	0.01	−0.06	−0.16	0.01	0.01	0.06	0.08
	(0.04)	(−0.42)	(−0.58)	(0.08)	(0.07)	(0.37)	(0.49)
BEME	0.18	−0.24	0.42	0.19	0.45	0.17	0.02
	(0.19)	(−0.24)	(0.45)	(0.20)	(0.51)	(0.17)	(0.02)
QMomentum	−0.24	−0.62	0.02	−0.28	−0.24	−0.02	−0.05
	(−0.32)	(−0.82)	(0.02)	(−0.37)	(−0.31)	(−0.02)	(−0.07)
QPEAD	0.05	0.02	0.01	0.03	0.03	−0.01	0.07
	(0.27)	(0.11)	(0.04)	(0.20)	(0.19)	(−0.07)	(0.43)
QAnalystDrift	−0.17	−0.12	−0.12	−0.17	−0.18	−0.16	−0.15
	(−1.06)	(−0.78)	(−0.79)	(−1.09)	(−1.14)	(−1.04)	(−0.92)
QSurprise	3.13***	4.60***	7.79***	5.62***	4.40***	3.66***	
	(4.48)	(4.95)	(7.09)	(6.21)	(5.10)	(3.66)	
Credibility		0.50	6.82***	2.37**	3.00**	0.97	
		(0.55)	(3.89)	(2.56)	(2.15)	(1.32)	
QSurprise × *Credibility*		−3.01**	−10.17***	−4.98***	−3.96**	−1.28	
		(−2.11)	(−5.56)	(−3.56)	(−2.01)	(−1.33)	
Bad News							−0.85
							(−1.39)
Good News							1.41***
							(2.82)
QSurprise + *QSurprise* × *Credibility*		1.59***	−2.38*	0.64**	0.54	2.38	
Adj-R^2 (%)	2.30	2.65	2.68	2.38	2.39	2.21	2.28
OBS	23,822	19,978	23,822	23,822	23,822	20,956	23,822

Table 4 continued

This table presents regressions that investigate the effect of credibility on the post-management-forecast drift. The dependent variable is *AbRet3m*, which is the size-adjusted buy-and-hold return, in percentage, beginning from the second day after the management forecast. *QSurprise* is the quintile rank of *Surprise*, where *Surprise* is management forecast minus pre-management-forecast consensus analyst mean forecast, scaled by stock price 2 days before the management forecast; the quintile rank is scaled to range from zero to one. *Credibility* is measured using various individual proxies: *QAccuracy*, *QLitRisk*, *QCompetition*, *QR&D*, *AnalystAgree*, and *Good* versus *Bad News*. *Accuracy* is the prior forecasting accuracy based on the average of the accuracies of all management forecasts made before the current management forecast. *LitRisk* is the litigation risk exposure. *Competition* is the negative of the Herfindahl Index of the industry that the firm belongs, and *R&D* is research and development expenses. *QAccuracy*, *QLitRisk*, *QCompetition*, and *QR&D* are quintile ranks of *Accuracy*, *LitRisk*, *Competition* and *R&D*, respectively. *AnalystAgree* is an indicator variable equalling one (1) if the management forecast is a point forecast and the post-management-forecast analyst consensus mean forecast is within one penny of the management EPS forecast or (2) if the management forecast is a range forecast and the post-management-forecast analyst consensus mean EPS forecast is on or within upper and lower bounds of the management forecast and zero otherwise. *Bad News* (*Good News*) is an indicator variable equal to one if the management forecast surprise is negative (positive). *QPEAD* is the quintile rank of the most recent quarterly earnings surprise, measured as the difference between the actual earnings announced on or just before the management forecast date and the pre-actual-earnings consensus analyst mean EPS forecast. *QAnalystDrift* is the quintile rank of the most recent analyst forecast revision, measured as the difference in the consensus analyst mean EPS forecast 2 months and 1 month before the management forecast. *Beta* is systematic risk, estimated as the coefficient on the market factor from a market model regression. *Log Size* is the natural logarithm of the market value of equity in billions. *BEME* is the ratio of the book value of equity to the market value of equity. *QMomentum* is the quintile rank of the 12-month cumulative raw return ending at the end of the second month before the month of the management forecast. Year-quarter fixed effects and the intercept are included in the regressions, but, for parsimony, these coefficients are untabulated. *t* statistics, which are in parentheses, are obtained after the two-way clustering of the standard errors by firm and by calendar quarter. *, **, and *** indicate two-tailed statistical significance at the 10, 5, and 1 percent levels, respectively

Table 5 Double-sorts on PEAD and management forecast surprises

PEAD Tercile	*Surprise* Quintile	*PEAD*	*Surprise*	*AbRet3m*	*AbRet12m*
1	1	−0.66	−2.46	−0.94	−5.39**
1	2	−0.23	−0.41	1.08	−0.42
1	3	−0.18	−0.10	−0.37	0.17
1	4	−0.22	0.02	0.21	−1.14
1	5	−0.50	0.60	2.98	0.77
	Hedge	0.16	3.06	3.92*	6.17*
2	1	0.02	−1.82	0.16	−2.45
2	2	0.02	−0.39	0.23	0.23
2	3	0.03	−0.09	0.04	−0.49
2	4	0.03	0.01	0.56	−0.61
2	5	0.03	0.36	3.83***	5.79**
	Hedge	0.01	2.17	3.67**	8.24*
3	1	0.40	−2.31	−2.03	−1.94
3	2	0.28	−0.41	0.94	4.15
3	3	0.24	−0.09	−0.40	−0.51
3	4	0.23	0.02	0.17*	0.65
3	5	0.36	0.50	4.30***	4.55*
	Hedge	−0.04	2.81	6.33***	6.49

This table examines the long-term abnormal returns in three-by-five portfolios. The portfolios are formed by independently sorting the observations into *PEAD* terciles and *Surprise* quintiles. *PEAD* is the most recent quarterly earnings surprise, measured as the difference between the actual earnings announced on or just before the management forecast date and the pre-actual-earnings consensus analyst mean EPS forecast. *Surprise* is the difference between management forecast and the pre-management-forecast consensus analyst median forecast. *AbRet3m* (*AbRet12m*) is the 3-month (12-month) size-adjusted buy-and-hold return, in percentage, in the three (twelve) months from the third day after the management forecast date. *t* statistics are computed for the dependent variables (*AbRet3m* and *AbRet12m*) using the Fama–MacBeth procedure. *, **, and *** indicate two-tailed statistical significance at the 10, 5, and 1 percent levels, respectively

Nonetheless, we perform dual sorts to explicitly control for earnings surprises. In addition, we check whether the effect of credibility is robust to controlling for other determinants of PEAD.

In our first set of analysis, we create dual-sort portfolios on the basis of the earnings surprise and the management forecast surprise. The objective is to evaluate the hedge portfolio based on the management forecast holding the earnings surprise constant. To do so, we sort firms in fifteen portfolios based *PEAD* terciles and *Surprise* quintiles.[14] We form these portfolios by independently sorting our observations into *PEAD* terciles and *Surprise* quintiles.

[14] The choice of three-by-five (instead of five-by-five) portfolios is to ensure a reasonable number of firms in each portfolio. This is particularly important in the earlier years of our sample for which the number of forecasts is relatively small. For example, the average number of firms in each portfolio in 1996 and 1997 is about 20–30 firms.

Table 5 presents these results. There are three sets of results, separated for firms in the bottom, middle, and top *PEAD* terciles respectively. For example, in the bottom (top) *PEAD* tercile, the average earnings surprise ranges from −0.66 to −0.18 (0.23 to 0.40). Then, for each *PEAD* tercile, we order firms in terms of *Surprise* quintiles. For example, in the bottom *PEAD* tercile, *Surprise* ranges from −2.46 to 0.60, whereas, in the top *PEAD* tercile, *Surprise* ranges from −2.31 to 0.50. Thus, despite of the earnings surprises, within each *PEAD* tercile, there is considerable variation in forecast surprise.

Most importantly, the future abnormal returns are also in the direction of the forecast surprise, regardless of the direction of *PEAD*. For instance, the hedge portfolio 3-month (12-month) abnormal returns from buying (selling) the shares of firms in the extreme positive (negative) forecast surprise quintile equals 3.92 % (6.17 %) among firms in the bottom tercile of *PEAD*. This pattern is also observed for the other *PEAD* terciles. For example, the hedge portfolio 3-month (12-month) abnormal returns from buying (selling) the shares of firms in the extreme positive (negative) forecast surprise quintile equals 3.67 % (8.24 %) among firms in the middle tercile of *PEAD* and 6.33 % (6.49 %) among firms in the top tercile of *PEAD*.

Our second analysis replicates the analysis in Table 4 but includes additional controls for some determinants of drift in returns: serial correlation in seasonally differenced earnings (Bernard and Thomas 1990), size (Bernard and Thomas 1989), institutional ownership (Bartov et al. 2000), and transaction costs (Bhushan 1994, Ng et al. 2008). Bernard and Thomas (1990) show that there is persistence, i.e., first-order serial autocorrelation, in seasonally differenced earnings and that this persistence is one explanation for the PEAD. To measure persistence in earnings surprises (*Persistence*), we obtain, for each management forecast of a firm, the prior 12 quarters (with a minimum requirement of eight quarters) of seasonally differenced quarterly actual earnings from Compustat and compute the first-order serial correlation in the these earnings. We proxy for size using the market value of equity at the beginning of the month of the management forecast (*Size*), institutional ownership using the percentage of shares held by institutional investors at the calendar quarter-end before the management forecast (*InstOwner*), and transaction cost using the closing bid-ask spread on the month before the management forecast (*Spread*). Data to compute *Size* and *Spread* is obtained from the CRSP database while that to compute *InstOwner* is obtained from the Institutional (13f) Holdings dataset in the Thomson Reuters database. Similar to our treatment of credibility proxies that were originally continuous variables, we transform these variables into quintile ranks (re-scaled to range from zero to one) and label them *QPersistence*, *QSize*, *QInstOwner*, and *QSpread*.

Gong et al. (2011) documents that there is positive serial correlation in management forecast errors. This evidence indicates that management forecasts themselves reflect managerial underreaction to prior information. An implication is that even management forecasts that the market views as 100 % credible could be associated with a drift to the extent the market's reaction to these forecasts simply reflects the underreaction implicit in management forecasts themselves. To control

Table 6 Controlling for other determinants of drift

	QAccuracy I	*QLitRisk* II	*QCompetition* III	*QR&D* IV	*AnalystAgree* V
Control for earnings surprise persistence					
QSurprise	4.69***	8.29***	5.99***	4.78***	4.34***
	(5.32)	(7.45)	(6.98)	(5.84)	(4.53)
QSurprise × *Credibility*	−2.51*	−9.93***	−4.56***	−3.46*	−1.49
	(−1.73)	(−5.12)	(−3.22)	(−1.79)	(−1.58)
QSurprise × *QEarnSurp*	0.92	−0.12	−0.05	−0.02	−0.01
	(0.65)	(−0.09)	(−0.03)	(−0.02)	(−0.01)
Control for size					
QSurprise	4.23***	8.55***	5.17***	4.18***	3.39***
	(4.55)	(6.66)	(5.48)	(4.70)	(3.43)
QSurprise × *Credibility*	−2.48*	−11.04***	−4.55***	−4.18**	−1.16
	(−1.76)	(−4.64)	(−3.14)	(−2.13)	(−1.19)
QSurprise × *QSize*	−5.08***	1.77	−4.72***	−5.35***	−4.98***
	(−3.22)	(0.86)	(−3.06)	(−3.56)	(−3.09)
Control for institutional ownership					
QSurprise	4.70***	7.63***	5.97***	4.52***	3.52***
	(4.99)	(6.92)	(6.29)	(5.13)	(3.51)
QSurprise × *Credibility*	−2.90**	−9.67***	−5.66***	−4.24**	−1.00
	(−2.11)	(−5.25)	−4.11)	(−2.20)	(−1.03)
QSurprise × *QInstOwner*	−4.54**	−3.58*	−5.11***	−4.55**	−4.64**
	(−2.52)	(−1.82)	(−2.68)	(−2.41)	(−2.36)
Control for bid-ask spread					
QSurprise	4.34***	7.28***	5.26***	4.20***	3.40***
	(4.85)	(6.23)	(5.62)	(4.96)	(3.36)
QSurprise × *Credibility*	−2.65*	−8.95***	−4.62***	−3.88**	−1.16
	(−1.85)	(−4.37)	(−3.29)	(−1.97)	(−1.15)
QSurprise × *QSpread*	6.01***	3.24	6.07***	6.12***	6.44***
	(3.08)	(1.55)	(3.24)	(3.24)	(3.48)
Control for prior management forecast error					
QSurprise	4.88***	8.55***	5.63***	5.01***	4.22***
	(4.85)	(6.92)	(5.23)	(5.27)	(3.71)
QSurprise × *Credibility*	−3.15**	−10.74***	−4.32***	−4.61**	−1.41
	(−2.15)	(−5.30)	(−2.85)	(−2.30)	(−1.33)
QSurprise × *QPrior_MFE*	−0.02	−0.18	0.22	−0.05	−0.47
	(−0.02)	(−0.12)	(0.15)	(−0.03)	(−0.28)
Control for current management forecast error					
QSurprise	4.34***	7.46***	5.52***	4.24***	4.82***
	(4.21)	(6.91)	(5.86)	(4.83)	(4.97)
QSurprise × *Credibility*	−2.35	−9.55***	−4.98***	−3.78*	−3.16***
	(−1.61)	(−5.32)	(−3.69)	(−1.93)	(−3.59)
QSurprise × *QCurr_MFE*	−5.74***	−6.01***	−6.52***	−6.57***	−7.27***
	(−4.44)	(−4.34)	(−4.83)	(−4.75)	(−5.27)

Table 6 continued

This table presents the regressions that investigate the effect of credibility on the post-management-forecast drift, after controlling for other potential determinants of the drift. The dependent variable is *AbRet3m*, the percentage three-month size-adjusted buy-and-hold return in the 3 months from the second day after the management forecast date. *QPersistence, QSize*, *QInstOwner*, *QSpread*, *QPrior_MFE*, and *QCurr_MFE* are the quintile ranks of *Persistence, Size*, *InstOwner*, *Spread*, *Prior_MFE*, and *Curr_MFE* respectively; the quintile ranks are scaled to range from zero to one. *Persistence* is the first-order serial correlation in prior seasonally differenced quarterly earnings. *Size* is the natural logarithm of the market value of equity in billions. *InstOwner* is the percentage of shares held by institutional investors. *Spread* is the relative bid-ask spread of the stock, measured as ask price minus bid price, divided by the mid-point of the ask and bid prices. *Prior_MFE* and *Curr_MFE* are the management forecast errors of all prior management forecasts and the current management forecast, respectively; management forecast error is management forecast minus actual earnings, scaled by stock price 2 days before the management forecast. All the other variables are defined in Table 4. The intercept, all control variables in Table 4 (including year-quarter fixed effects), as well as the main effects for *QPersistence, QSize*, *QInstOwner*, *QSpread*, *QPrior_MFE*, and *QCurr_MFE* are included in the regressions; for parsimony, the coefficients on these variables are not tabulated. *t* statistics which are in parentheses, are obtained after the two-way clustering of the standard errors by firm and by calendar quarter. *, **, and *** indicate two-tailed statistical significance at the 10, 5, and 1 percent levels, respectively

for this underreaction, we construct two variables: management forecast error of all forecasts before the current management forecast (*Prior_MFE*) and management forecast error of the current management forecast (*Curr_MFE*); management forecast error is management forecast minus actual earnings, scaled by stock price 2 days before the management forecast. As before, we transform these variables into quintile ranks (re-scaled to range from zero to one) and label them *QPrior_MFE* and *QCurr_MFE*.

Table 6 presents the results after controlling for various determinants of the drift. We introduce each of the determinants separately due to concerns about changes in sample sizes based on data requirements, multicollinearity between the variables, and the fact that our objective is not to run a horse race between these variables. In the majority of cases, the coefficients on *QSurprise* × *Credibility* remain negative and significant, the only exception being the coefficient on *QSurprise* × *AnalystAgree*, which is positive but statistically insignificant. Thus our earlier inference that there is a larger post-management-forecast drift for less credible forecasts appears to be robust controlling for these determinants. In addition, based on the additional interaction terms, there is evidence that the post-management-forecast drift is lower for firms that are larger, have a greater institutional ownership, and whose stocks have higher transaction costs. Interestingly, we find that the coefficient on the interaction term between *QSurprise* × *QCurr_MFE* is negative. Since higher values of *QCurr_MFE* indicate less understatement by managers, this means that the market correction to the underreaction to management forecast surprises is less when there is less understatement of actual earnings by managers.

Overall, the evidence in Tables 5 and 6 indicates that the post-management-forecast drift is a distinct phenomenon for which credibility is a mitigating factor. Table 5 shows that the management forecast drift continues to exist after controlling for the post-earnings announcement drift. Table 6 demonstrates that the role of credibility is also robust to controlling for other possible determinants of drift.

Table 7 Effect of credibility on the post-management-forecast drift: subsamples of quarterly and annual forecasts

		Credibility measures					
	Main Effect	*QAccuracy* I	*QLitRisk* II	*QCompetition* III	*QR&D* IV	*AnalystAgree* V	*Good* versus *Bad News* VI
Panel A: quarterly forecasts							
QSurprise	3.58***	7.60***	8.75***	6.36***	5.58***	5.12***	
	(3.53)	(3.97)	(6.37)	(5.28)	(5.20)	(3.37)	
QCredibility		1.71	8.05***	2.46**	4.05**	1.96*	
		(1.16)	(4.28)	(2.43)	(2.41)	(1.81)	
QSurprise × *Credibility*		−6.01**	−11.53***	−5.74***	−5.63**	−2.50	
		(−2.29)	(−5.11)	(−2.65)	(−2.29)	(−1.55)	
Bad News							−0.85
							(−1.17)
Good News							2.03***
							(3.11)
QSurprise + *QSurprise* × *Credibility*		1.59**	−2.78	0.62*	−0.05	2.62	
OBS	13,284	11,340	13,284	13,284	132,84	10,704	13,284

Table 7 continued

	Main Effect	*Credibility* measures: *QAccuracy* I	*QLitRisk* II	*QCompetition* III	*QR&D* IV	*AnalystAgree* V	*Good* versus *Bad News* VI
Panel B: annual forecasts							
QSurprise	2.69***	3.11***	6.39***	4.64***	3.02***	2.56**	
	(3.61)	(3.34)	(5.13)	(4.31)	(2.98)	(2.18)	
QCredibility		1.72	4.47**	1.68	1.21	0.27	
		(1.16)	(2.38)	(1.42)	(0.89)	(0.31)	
QSurprise × *Credibility*		−3.00	−7.95***	−3.76**	−1.19	−0.28	
		(−1.60)	(−4.03)	(−2.48)	(−0.58)	(−0.22)	
Bad News							−1.17
							(−1.38)
Good News							0.40
							(0.56)
QSurprise + *QSurprise* × *Credibility*		0.11	−1.56**	0.88**	1.83	2.28	
OBS	10,538	8,638	10,538	10,538	10,538	10,252	10,538

This table presents, for subsamples of quarterly and annual management forecasts, regressions that investigate the effect of credibility on the post-management-forecast drift. Panel A (B) presents the results for quarterly (annual) forecasts. The dependent variable is *AbRet3m*, the percentage 3-month size-adjusted buy-and-hold return in the 3 months from the second day after the management forecast date. All the other variables are defined in Table 4. All control variables in Table 4 (including the intercept and year-quarter fixed effects) are included in the regressions; for parsimony, the coefficients on these variables, as well as the intercept, are not tabulated. *t* statistics, which are in parentheses, are obtained after the two-way clustering of the standard errors by firm and by calendar quarter. *, **, and *** indicate two-tailed statistical significance at the 10, 5, and 1 percent levels, respectively

5.2 Decomposition of sample into quarterly and annual forecasts

The sample that we use in our earlier analyses consists of both quarterly and annual earnings per share forecasts. In this section, we examine whether our earlier results are robust across subsamples of quarterly and annual forecasts. Table 7 Panel A reports the results of the regressions that replicate the analysis in Table 4 with subsamples of quarterly forecasts, whereas Table 7 Panel B reports the results for the subsample of annual forecasts. The results in Table 7 are similar to those in Table 4. In particular, the results in the leftmost column (titled "Main Effect") of Panel A (B) indicate that there is an underreaction to quarterly (annual) forecasts. In Panel A (B), the coefficient on *QSurprise* indicates 3-month hedge portfolio abnormal returns of 3.58 % (2.69 %).

The remaining columns of both panels in Table 7 report the results of the regressions that examine the role of credibility on the underreaction to forecast news. As discussed earlier, to examine the role of credibility on the underreaction, we focus on the coefficient on the interaction term between *QSurprise* and *QCredibility*. The evidence that greater credibility reduces the underreaction appears somewhat stronger using quarterly (Panel A) than annual (Panel B) forecasts. In Panel A, we find that the coefficients on the interaction term between *QSurprise* and *QCredibility* are significantly negative for all proxies of credibility except *AnalystAgree*. We also find that the economic magnitude of the underreaction to good news to be greater than that to bad news. In Panel B, however, we only find statistically significant evidence for litigation risk and competition. For the remaining variables the estimated coefficients are in the correct direction but are statistically insignificant. Taken together, we conclude that the results in Table 7 provide some additional evidence that greater credibility reduces the underreaction to forecast news and the evidence appear to be stronger for quarterly forecasts.

6 Conclusion

The question of whether the market responds fully to the news in reported earnings and the explanation for this finding has been the subject of extensive research. We hypothesize that the market underreaction to news is a function of the news credibility. We test this hypothesis by using management forecast as a proxy for news because prior literature has emphasized that the voluntary and non-audited nature of forecasts creates credibility concerns. To the extent that credibility concerns lead to an underweighting of news and investors are more concerned about the credibility of voluntary disclosures than that of mandatory disclosures, management forecasts provide a powerful setting to test whether credibility has a role in explaining the underreaction to news.

We examine the abnormal returns around and subsequent to management forecasts to address two questions: i) whether the short-term reaction to forecast news increase with credibility and ii) whether credibility, by allowing a stronger short-term response, is associated with a lower long-term drift in returns. Using a variety of credibility measures, we provide evidence that the short-term reaction is stronger and the long-term underreaction is smaller when forecasts are deemed more credible. Further, we perform a battery of tests to mitigate the concerns that our findings are capturing market reaction to other forms of news (particularly earnings announcements) or are solely due to other determinants of market underreaction such as earnings persistence, investor sophistication, or transaction costs.

Our paper contributes to the literature by providing empirical evidence on the role that credibility plays in the market reaction to news. By showing that investors discount forecasts with lower credibility but that these forecasts have implications for future returns, our findings suggest that investors inappropriately weight credibility when reacting to management forecasts. Our findings raise the possibility that investors, by attempting to discount forecasts perceived as less credible, could be exacerbating the market underreaction to these forecasts.

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Appendix: Measuring litigation risk

We use the litigation risk model in Rogers and Stocken (2005) to compute litigation risk, *Litigation Risk*:

$$\begin{aligned} \mathit{Litigation\,Risk} &= -5.738 + 0.141 \times \mathit{Size} + 0.284 \times \mathit{Turn} + 0.012 \times \mathit{Beta} \\ &- 0.237 \times \mathit{Returns} - 1.340 \times \mathit{Std\_Ret} + 0.011 \times \mathit{Skewness} - 3.161 \times \mathit{Min\_Ret} \\ &- 0.025 \times \mathit{Bio\_Tech} + 0.378 \times \mathit{Computer\,Hardware} + 0.075 \times \mathit{Electronics} \\ &- 0.034 \times \mathit{Retailing} + 0.211 \times \mathit{Computer\,Software} \end{aligned} \tag{6}$$

where *Size* is the natural log of the average market value of equity measured in dollars; *Beta* is the slope coefficient from regressing daily returns on the CRSP equal-weighted index; *Returns* is defined as buy and hold returns; *Std_Ret* is the standard deviation of the daily returns; *Skewness* is the skewness of the daily returns; *Min_Ret* is the minimum of the daily returns; *Bio_Technology* is an industry indicator variable equalling one if the firm is in the bio-tech industry (SIC 2833–2836) and zero otherwise; *Computer Hardware* is an industry indicator variable equalling one if the firm is in the computer hardware industry (SIC 3570–3577) and zero otherwise; *Electronics* is an industry indicator variable equalling one if the firm is in the electronics industry (SIC 3600–3674) and zero otherwise; *Retailing* is an industry indicator variable equalling one if the firm is in the retail industry (SIC 5200–5961) and zero otherwise; *Computer Software* is an industry indicator variable equalling one if the firm is in the computer software industry (SIC 7371–7379) and zero otherwise. The above model provides the firm-specific litigation risk in each calendar quarter. The litigation risk associated with each forecast is based on the litigation risk of the firm in the prior calendar quarter.

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