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Do management EPS forecasts allow returns to reflect future earnings? Implications for the continuation of management's quarterly earnings guidance

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Abstract Using 18,253 firm-year observations from 1998 through 2003, we build on literature suggesting that more informative disclosures allow returns to better reflect future earnings and test whether management earnings per share forecasts and their characteristics influence the future earnings response coefficient (FERC). We find that FERCs are greater for forecasting firms and when forecasts are more frequent or precise. We suggest that more frequent and more precise forecasts assist investors in better predicting future earnings. Importantly, we find that quarterly and short-term forecasts incrementally increase the association between returns and future earnings beyond annual and long-term forecasts; thus, even short-term, quarterly forecasts allow investors to form better expectations about future earnings. This suggests a benefit of quarterly earnings forecasts possibly overlooked in recommendations from the United States Chamber of Commerce, CFA Institute, Business Roundtable Institute for Corporate Ethics, and The Conference Board to eliminate quarterly earnings guidance.

Data availability: All data are available from public sources identified in the paper.

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1 Introduction

Earnings forecasts are voluntary disclosures, and managers have considerable discretion when issuing these forecasts. For example, they choose the frequency, precision, and horizon of their forecasts. These choices can influence the market's ability to interpret the forecasts and to reflect the implications of the forecasts in current stock prices. In addition, the forecast characteristics may provide a signal about managers' confidence in their forecasts, assisting investors in better understanding the relation between the forecasts and future earnings and allowing them to price securities accordingly. In this study, we examine whether management earnings per share (EPS) forecasts and forecast characteristics are associated with the ability of current period returns to reflect information in future earnings. We follow prior literature in calling this relation the future earnings response coefficient (FERC) or the informativeness of stock price. Studying this association is important because more informative stock prices can lead to more efficient resource allocation (Durnev et al. 2003; Fishman and Hagerty 1989).[1]

Our study is motivated by recent calls for the permanent elimination of quarterly earnings guidance by the US Chamber of Commerce, the CFA Institute, the Business Roundtable Institute for Corporate Ethics, and The Conference Board (which we collectively call "the Chamber of Commerce and others") (CFA Institute 2006; Chamber of Commerce 2007; McCafferty 2007).[2] In addition, the Center for Audit Quality, a nonprofit group affiliated with the American Institute of Certified Public Accountants, has announced its support for the elimination of quarterly guidance (Burns 2007). Moreover, a recent survey by the Financial Executives International shows that chief financial officers strongly favour annual forecasts over quarterly earnings forecasts (Johnson 2007). Concerns about management incentives resulting from quarterly earnings guidance also appear regularly in the business press.[3]

[1] Fishman and Hagerty (1989) show that the information efficiency of a firm's stock price is linked to the efficiency of its investment and production decisions, suggesting that improved stock price informativeness benefits both the firm and the economy.

[2] Interestingly, some companies, including Berkshire Hathaway, Coca-Cola, McDonald's, Pfizer, and The Washington Post Co., have discontinued the practice of forecasting quarterly earnings.

[3] For example, a story in the March 19, 2007 edition of *InvestmentNews* states: "[i]f public companies adopted the policy of no quarterly guidance, the result might well be a dramatic improvement in the long-term performance of American corporations and the economy. Studies have shown that pressure to provide quarterly guidance …distorts investment decisions and policies of corporate management teams and imposes a short-term mind-set on them." Also see "The market game" in *The Wall Street Journal* (May 8, 2002), "The last quarter of the guidance game" in *CFO.com* (March 17, 2006), "Ditch guidance" in *CFO.com* (March 30, 2006), "Dump quarterly guidance" in *CFO.com* (July 25, 2006), "Stop playing the guidance game" in *Directorship* (September 2007), and "Corporations should stop giving quarterly earnings guidance" in the *Idaho Business Review* (September 24, 2007).

Opponents of quarterly guidance claim that the practice is harmful because of the pressure that managers feel to meet or beat their forecasts. Because the market assumes that a company is doing poorly when a forecast is missed, investors lose confidence (McCafferty 2007), placing management under intense pressure to meet their forecasts (Barsky 2002; Fuller and Jensen 2002; Oakley 2002; Taub 2006). Thus, managers may sacrifice long-term company health to meet short-term earnings goals (Donohue 2005; Fuller and Jensen 2002; Horowitz 2005; Koller and Rajan 2006; Chamber of Commerce 2007). Opponents also believe that it is costly for managers to provide and meet quarterly earnings targets. The costs include wasted effort in preparing forecasts, neglect of long-term growth opportunities, investor overreactions to missed forecasts, incentives for firm privatization to avoid the pressure to provide guidance, the temptation to manage earnings, and ongoing pressure to update previously released information (CFA Institute 2006; Chamber of Commerce 2007; Institute of Management & Administration (IOMA) 2003).[4,5]

Proponents of quarterly guidance counter that its discontinuance will not eliminate management pressure to meet quarterly earnings targets because analyst EPS forecasts will continue to influence investor expectations. Eliminating quarterly guidance will also restrict management's ability to correct inappropriate analyst forecasts (Johnson 2007). Because at least half of all public firms systematically or occasionally issue quarterly guidance, the elimination of quarterly guidance would affect many firms (National Investor Relations Institute [NIRI] 2007).

We suggest a benefit that might arise from earnings guidance by examining the impact of management forecasts on the FERC. Accordingly, we study both quarterly and annual forecasts because quarterly forecasts have been criticized but annual forecasts are generally considered useful (CFA Institute 2006; Chamber of Commerce 2007). Thus, we compare the benefits of quarterly versus annual forecasts and compare these with cases where no forecast is issued. We also consider short- and long-term forecasts because this forecast characteristic may affect the FERC and because concern about short-term forecasts (rather than quarterly forecasts) may in fact underlie the objections of opponents of earning guidance.[6] Much of the management forecast literature studies outcomes of forecast characteristics but how these characteristics affect the ability of forecasts to allow future earnings news to be reflected in returns has not been addressed. Thus, we also

4 Consistent with significant costs for forecasting firms, Cheng et al. (2005) find that frequent forecasters invest less in research and development and experience lower long-term earnings growth than firms that infrequently forecast. Moreover, Krehmeyer et al. (2006) report that among a group of over 400 financial executives, 80% state that they would decrease discretionary spending, and 50% state that they would sacrifice value creation to meet earnings forecasts.

5 Opponents also suggest that, if managers stop providing quarterly guidance, analysts and investors will seek information elsewhere, and managers may disclose better quality (other) information (Harbert 2003; Nolan 2006). Moreover, according to a CFA Institute survey, 76% of investment analysts would prefer more in-depth disclosures about long-term plans than continuing quarterly earnings guidance (Krehmeyer et al. 2006; Pozen 2007).

6 We distinguish between four forecast types. Short-term quarterly forecasts are of quarterly EPS for upcoming quarters in the current fiscal year; long-term quarterly forecasts are of quarterly EPS for quarters in a future fiscal year; short-term annual forecasts are of annual EPS in the current fiscal year; and long-term annual forecasts are of annual EPS in a future fiscal year.

study management forecast precision and frequency because they are important in determining investor responses to management forecasts and should be especially helpful in informing market participants about future earnings.

Although prior studies examine short-window market reactions (for example, Ajinkya and Gift 1984; Anilowski et al. 2007; Han and Wild 1991; Hutton et al. 2003; Pownall et al. 1993) and analyst reactions (for example, Baginski and Hassell 1990; Jennings 1987) to management forecasts, investigating the impact of management forecasts and their characteristics on the FERC provides insights beyond those available from existing studies. Rather than assessing whether (and how) investors and analysts react to management forecasts, we ask whether these forecasts allow investors to adjust securities prices in a way that is consistent with future earnings realizations. Here, managers must provide relatively accurate information in their forecasts (so that prices move to reflect future earnings realizations), and investors must view the forecasts as credible (so that they act on the forecasts). Our analyses can be thought of as a joint test of whether managers provide relatively accurate information and whether investors view this information as credible.[7]

We expect FERCs to be greater for forecasting firms, for firms issuing more frequent and more precise forecasts, for firms issuing annual forecasts, and for firms issuing long-term forecasts. In addition, we expect that even quarterly and short-term forecasts will result in greater FERCs relative to nonforecasts. Empirical tests, using 18,253 firm-year observations (7,353 observations with forecasts and 10,900 observations with no forecasts) from 1998 through 2003 (through 2006 for data on future earnings and returns), strongly support our predictions. First, FERCs are greater for firms that forecast earnings; current returns are more strongly positively associated with future earnings for forecasting firms than for nonforecasting firms. Second, FERCs are greater when firms issue more frequent or more precise forecasts (for example, point or range forecasts versus minimum/maximum or qualitative forecasts). Third, FERCs are greater for firms issuing annual or quarterly forecasts than for nonforecasting firms, even when the forecast horizon is short. Fourth, FERCs are greater for firms issuing short-term forecasts than for nonforecasting firms, even when the forecasts are of quarterly-only EPS. In contrast, forecast characteristics rarely influence the degree to which returns reflect current-period earnings (that is, the earnings response coefficient (ERC)). Thus, it is important to consider the FERC, and not just the ERC, when examining the effects of a management forecast. We perform various sensitivity analyses controlling for firm characteristics and endogeneity and find that our results are robust.

Our findings reveal that management forecasts affect the ability of returns to reflect future earnings. In related work, Gelb and Zarowin (2002) and Lundholm and Myers (2002) show that FERCs increase with the informativeness of firm

[7] Note that the ERC measures how much the market values one dollar of current earnings on average, so the ERC is unable to inform us about *how well* investors can predict future earnings. Our goal is to determine whether the market's future earnings expectations, as implied in stock returns, reflect the future earnings realizations more when managers forecast (and whether this varies with the forecast characteristics). Thus, the FERC is a means to address a question that cannot be addressed using short-window ERC tests.

disclosures. While these studies address the informativeness of disclosures in general, to our knowledge, no studies have demonstrated a relation between management forecasts and FERCs. In our study we document evidence regarding benefits of management earnings guidance and advocate that managers forecast earnings and issue more frequent and more precise forecasts. Because quarterly forecasts allow returns to better reflect future earnings, quarterly forecasts are beneficial in this regard. This benefit should not be overlooked in the debate about whether to eliminate quarterly earnings guidance. In addition, we suggest that managers can affect the amount of information asymmetry through their choice of forecast characteristics.

Next, we present our theoretical development and hypotheses. Section 3 discusses our sample selection and models. Section 4 presents empirical results, and the last section concludes.

2 Theory and hypotheses

Prior work on the association between ERCs and management forecasts focuses on past ERCs (that is, on prior year associations between earnings and contemporaneous returns). Lennox and Park (2006) find that forecasting firms have greater past ERCs than nonforecasting firms and argue that firms with greater past ERCs are more likely to issue earnings forecasts. However, their research addresses management's decision to issue forecasts rather than the consequences of that decision. In contrast, we investigate whether current returns better reflect future earnings when firms issue forecasts. Focusing on the FERC, rather than the current or past ERC, is informative for our research question because, "The change in (expected) future earnings may be due to a shock that has no effect on current earnings" (Tucker and Zarowin 2006, 252). These shocks would not be captured by current earnings (or by the ERC) but will be reflected in returns and would be captured by the FERC.

2.1 The effect of forecast issuances on the FERC

Research suggests that managers forecast earnings when their expectations for future performance differ from those of investors (Ajinkya and Gift 1984; Kasznik and Lev 1995; Penman 1980; Skinner 1994) so the market reacts to EPS forecasts (Ajinkya and Gift 1984; Han and Wild 1991; Hutton et al. 2003; Pownall et al. 1993). Analysts then revise their forecasts in response to management forecasts (Baginski and Hassell 1990; Jennings 1987). Thus, investors and analysts use information in management forecasts to assess firm values.

When disclosure quality is high, analysts and investors should be better able to predict performance. Consistent with this, Lang and Lundholm (1996) find that analyst forecasts become more accurate and forecast dispersion decreases as analyst ratings of disclosure quality increase. Gelb and Zarowin (2002) and Lundholm and Myers (2002) suggest that expanded disclosure helps investors to better predict future performance by "bringing the future forward," and thus FERCs are greater when disclose quality is higher. To measure disclosure quality, they use analyst ratings of disclosure quality as reported by the Association for Investment Management and Research (AIMR).[8] AIMR scores, which are based on analyst perceptions, are meant to reflect the quality information in annual and quarterly reports and other sources. However, "The AIMR rankings are probably a poor measure of management earnings forecasts since there is no mention of them in the documentation of the AIMR scoring system and the AIMR has opposed any requirement that management forecast earnings" (Lundholm and Myers 2002, 820). AIMR scores are based on relative rankings within an industry and thus do not reflect the amount of disclosure during the year (Lundholm and Myers 2002). Finally, the AIMR scores only relatively large firms, so prior results may not be generalizable to smaller firms.[9]

We first test whether FERCs are greater for forecasting firms relative to nonforecasting firms. Forecasts are one of the most efficient ways that managers can communicate their expectations to the market. Because they have private information about future business plans, EPS forecasts may help investors to better predict future earnings. Thus, future earnings should be more accurately reflected in returns and, as a result, FERCs should be greater, for forecasting firms. Our first alternative hypothesis is:

> **H1a:** Firms issuing earnings forecasts will have greater FERCs than those not issuing forecasts, all else equal.

2.2 The effect of forecast frequency on the FERC

Regulators passed the Safe Harbour Rule in 1979 and the Private Securities Litigation Reform Act (PSLRA) in 1995 to protect managers from litigation related to forecast errors and to induce them to release more frequent and more precise forward-looking information (Hirst et al. 2008).[10] However, evidence on whether forecast frequency has increased over time is mixed. Johnson et al. (2001) find more firms issue forecasts and firms issue more forecasts since the passage of the PSLRA, but Warner (2006) finds that forecast frequency decreased following the Sarbanes–Oxley Act of 2002.

Forecast frequency can affect the market's reaction to management forecasts. Hutton and Stocken (2007) find that investor reactions to EPS forecasts are stronger for managers issuing more frequent and accurate prior forecasts. They suggest that frequency matters for forecast credibility. King et al. (1990) argue that more frequent forecasts should results in larger ERCs. We argue that forecast frequency

[8] Similarly, Ettredge et al. (2005) find that the adoption of SFAS No. 131 on segment reporting increased FERCs, and Orpurt and Zang (2009) find that FERCs are greater when firms prepare their cash flow statements using the direct approach.

[9] The median market value of equity for the firms in Lundholm and Myers (2002) is \$1.27 billion versus \$483 million in our study. Their sample includes approximately 300 firms per year versus our approximately 3,000 firms per year.

[10] Increasing disclosure frequency can alter the timing and the content of disclosures (Botosan and Harris 2000).

should also influence FERCs because higher frequency should improve perceived forecast credibility and help investors to update their future earnings expectations. Our second alternative hypothesis is:

H2a: Firms issuing more frequent earnings forecasts will have greater FERCs than those issuing less frequent forecasts, all else equal.

2.3 The effect of forecast precision on the FERC

Managers also choose forecast precision, presumably by comparing the benefits and costs of disclosing precise information (Baginski and Hassell 1997). Managers issue less precise forecasts when they are more uncertain about the accuracy of their forecasts (Baginski et al. 1993; Choi et al. 2010). Thus, investors are likely less able to interpret the information in imprecise forecasts and are less likely to understand their implications for future earnings. If investors understand that precision is related to uncertainty, their reactions to less precise forecasts will be weaker.[11]

Kim and Verrecchia (1991) and Subramanyam (1996) show the magnitude of the market's response to a disclosure is positively related to its precision. Consistent with this, Skinner (1994) and Baginski and Hassell (1997) suggest that managers issue less precise forecasts to dampen the market reaction to bad forecast news. Thus, more precise forecasts should reveal more about management's expectations (Choi et al. 2010; Karamanou and Vafeas 2005) and allow investors to better predict future earnings. Our third alternative hypothesis is:

H3a: Firms issuing more precise earnings forecasts will have greater FERCs than those issuing less precise forecasts, all else equal.

2.4 The effect of forecast type (annual vs. quarterly) on the FERC

The Chamber of Commerce and others call for eliminating quarterly forecasts but continuing annual forecasts. This implies that annual forecasts are beneficial but quarterly earnings forecasts are not. We test these implications with the following (alternative) hypotheses:

H4(i)a: Firms issuing annual earnings forecasts will have greater FERCs than those not issuing forecasts, all else equal.
H4(ii)a: Firms issuing quarterly earnings forecasts will have greater FERCs than those not issuing forecasts, all else equal.

Some of the quarterly forecasts in our sample are of long-term earnings. Since forecast horizon could be responsible for any observed relation between FERCs and the issuance of quarterly forecasts, we also compare FERCs of firms issuing only short-term quarterly forecasts with FERCs of nonforecasting firms:

[11] Atiase et al. (2005) and Pownall et al. (1993) do not find a relation between forecast precision and the magnitude of the market reaction, but Baginski et al. (1993) find that the market reaction to a forecast surprise is increasing in forecast precision.

H4(iii)a: Firms issuing short-term quarterly earnings forecasts will have greater FERCs than those not issuing forecasts, all else equal.

This is the most conservative test of the benefits associated with quarterly earnings guidance.

2.5 The effect of forecast horizon (long- vs. short-term) on the FERC

Managers have incentives to make forecasts with varying horizons. They might make long-term forecasts to decrease the cost of capital[12] but make short-term forecasts to guide expectations to achievable levels.[13] Choi and Ziebart (2004) suggest that managers use long-term forecasts (which are usually optimistic) to increase earnings expectations and use short-term forecasts (which are usually pessimistic) to guide expectations downward.

We posit that, while short-term forecasts (that is, quarterly and annual forecasts within the current year) should help investors to predict short-term earnings, they may or may not help them to better predict long-term earnings. However, long-term forecasts should help investors to predict long-term earnings.[14] Thus, we expect greater FERCs when long-term forecasts (annual, quarterly, or both) are issued. Our fifth alternative hypothesis is:

H5(i)a: Firms issuing long-term earnings forecasts will have greater FERCs than those not issuing forecasts, all else equal.

Finally, we ask whether FERCs are greater for firms that issue only short-term forecasts relative to nonforecasting firms. Thus, we examine whether short-term forecasts result in greater FERCs after ruling out the possibility that greater FERCs are due to managers disclosing their long-term earnings expectations. Because earnings are serially correlated (Bernard and Thomas 1990), even short-term forecasts could provide information about long-term earnings, allowing investors to price securities so that future earnings news is brought forward. The resulting alternative hypothesis is:

H5(ii)a: Firms issuing short-term earnings forecasts will have greater FERCs than those not issuing forecasts, all else equal.

H4(iii) and H5(ii) rely on the ability of current earnings to predict future earnings and cash flows (Dechow et al. 1998; Drake et al. 2009; Finger 1994; Kim and Kross 2005; Sloan 1996). We expect short-term forecasts to allow stock prices to incorporate more information about (long-term) future earnings to the extent that the forecasts help investors to better predict future earnings.

[12] See, for example, Botosan (1997), Botosan and Plumlee (2002), Frankel et al. (1995), Healy et al. (1999), Healy and Palepu (2001), Lang and Lundholm (2000), Leuz and Verrecchia (2000), Marquardt and Wiedman (1998), and Welker (1995).

[13] See, for example, Cotter et al. (2006), Kasznik and McNichols (2002), Matsumoto (2002), and Richardson et al. (2004).

[14] This assumes that long-term forecasts are informative about long-term earnings realizations (i.e., that realizations are closer to forecasts than to pre-forecast market expectations).

3 Methodology

3.1 Model

The ability of returns to reflect future earnings can be tested using a model adapted by Lundholm and Myers (2002) from Collins et al. (1994):

$$R_t = b_0 + b_1 X_{t-1} + b_2 X_t + \sum_{i=1}^{3} (b_{3i} X_{t+i} + b_{4i} R_{t+i}) + \varepsilon_t \tag{1}$$

where for years t and i:

R_t = the cumulative return for fiscal year t; and

X_t = income available to common shareholders before extraordinary items deflated by the market value of equity at the beginning of fiscal year t.

Following Lundholm and Myers (2002), we include 3 years of future earnings and estimate a condensed version of model (1). We combine 3 years of future returns (R_{t+1}, R_{t+2}, and R_{t+3}) to form R_{t3} and combine the next three years of earnings (X_{t+1}, X_{t+2}, and X_{t+3}) to form X_{t3}:

$$R_t = b_0 + b_1 X_{t-1} + b_2 X_t + b_3 X_{t3} + b_4 R_{t3} + \varepsilon_t \tag{2}$$

where for year t:

R_{t3} = the cumulative return for fiscal years $t + 1$ through $t + 3$;

X_{t3} = the sum of income available to common shareholders before extraordinary items for years $t + 1$ through $t + 3$ deflated by the market value of equity at the beginning of fiscal year t; and all other variables are as previously defined.

We follow Collins et al. (1994) and Tucker and Zarowin (2006) and measure returns over the fiscal year.[15] The change in earnings, ΔX_t, often appears in the price-earnings relation under the assumption that earnings follow a random walk. Rather than restrict our specification by this assumption, we follow Lundholm and Myers (2002) and include X_{t-1} and X_t.[16] Consistent with the interpretation in Ettredge et al. (2005) and Tucker and Zarowin (2006), b_2 is the ERC, where b_2 reflects the relation between returns and contemporaneous earnings,[17] and b_3 is the FERC, which reflects the relation between returns and future earnings. Based on prior studies, we expect b_1 to be negative and b_2 and b_3 to be positive.

To test our hypotheses, we extend model (2):

$$R_t = b_0 + b_1 X_{t-1} + b_2 X_t + b_3 X_{t3} + b_4 R_{t3} + b_5 D_t + b_6 D_t * X_{t-1} + b_7 D_t * X_t + b_8 D_t * X_{t3} + b_9 D_t * R_{t3} + \varepsilon_t \tag{3}$$

where for year t:

[15] Our results are robust to measuring returns with a three-month lag as in Lundholm and Myers (2002).

[16] If $b_1 = -b_2$, earnings follow a random walk.

[17] See footnote 5 in Lundholm and Myers (2002) for a discussion of the alternative ERC definition and note that the inclusion of future earnings may confound the traditional interpretation of the ERC (Lundholm and Myers 2002).

D_t = a variable representing the characteristics of the forecast; D_t is either *DF*, *LNF, PREC*, *DQF, DAF, DQF_ONLY, DAF_ONLY, DQA_JOINT, DCF*, *DLF, DCF_ONLY, DLF_ONLY,* or *DCL_JOINT*;
DF_t = 1 if a management EPS forecast is issued during fiscal year *t*, 0 otherwise;
LNF_t = the natural log of (1 plus the number of forecasts issued during fiscal year *t*);
$PREC_t$ = the average precision of the forecasts issued in fiscal year *t*;
DQF_t = 1 if a (short- or long-term) quarterly forecast is issued during fiscal year *t*, 0 otherwise;
DAF_t = 1 if a (short- or long-term) annual forecast is issued during fiscal year *t*, 0 otherwise;
DQF_ONLY_t = 1 if a (short- or long-term) quarterly forecast, but no annual forecast, is issued during fiscal year *t*, 0 otherwise;
DAF_ONLY_t = 1 if a (short- or long-term) annual forecast, but no quarterly forecast, is issued during fiscal year *t*, 0 otherwise;
DQA_JOINT_t = 1 if a (short- or long-term) quarterly forecast *and* a (short- or long-term) annual forecast are issued during fiscal year *t*, 0 otherwise;
DCF_t = 1 if a short-term (quarterly or annual) forecast (that is, a forecast for the current fiscal year) is issued during fiscal year *t*, 0 otherwise;
DLF_t = 1 if a long-term (quarterly or annual) forecast (that is, a forecast for a future fiscal year) is issued during fiscal year *t*, 0 otherwise;
DCF_ONLY_t = 1 if a short-term (quarterly or annual) forecast, but no long-term (quarterly or annual) forecast, is issued during fiscal year *t*, 0 otherwise;
DLF_ONLY_t = 1 if a long-term (quarterly or annual) forecast, but no short-term (quarterly or annual) forecast, is issued during fiscal year *t*, 0 otherwise;
DCL_JOINT_t = 1 if a (quarterly or annual) short-term forecast *and* a (quarterly or annual) long-term forecast are issued during fiscal year *t*, 0 otherwise; and all other variables are as previously defined.

In model (3), D_t is either *DF*, *LNF, PREC*, *DQF, DAF, DQF_ONLY, DAF_ONLY, DQA_JOINT, DCF*, *DLF, DCF_ONLY, DLF_ONLY,* or *DCL_JOINT*.

DF is an indicator variable for the issuance of a management forecast; if FERCs are greater for firms that forecast earnings (see H1a), b_8 will be positive. *LNF* is increasing in the number of forecasts; if FERCs increase with forecast frequency (see H2a), b_8 will be positive. We classify all forecasts into point, range, minimum/maximum, or qualitative forecasts using First Call's codes for Company Issued Guidelines (CIGCODEQ) following Anilowski et al. (2007). *PREC* is the average forecast precision, calculated by awarding a score of 4 to point forecasts, 3 to range forecasts, 2 to minimum/maximum forecasts, and 1 to qualitative statements, and averaging the score for each firm-year observation.[18] If FERCs increase with forecast precision (see H3a), b_8 will be positive.

[18] Thus, if a firm makes a point forecast and a minimum forecast in a given year, the value of *PREC* is 3 (i.e., [4 + 2]/2). In untabulated analyses, we alternatively measure forecast precision as the proportion of forecasts made in the year that are quantitative (i.e., point and range forecasts). Our results and inferences are qualitatively unchanged.

DQF, DAF, DQF_ONLY, DAF_ONLY, and *DQA_JOINT* are forecast type variables. We form indicator variables for observations with forecasts of quarterly EPS, annual EPS, quarterly-only EPS, annual-only EPS, and both quarterly and annual EPS, respectively. We test whether the coefficient estimates on the interactions between these variables and X_{t3} are different from zero to determine whether forecast type matters to the FERC.

DCF, *DLF, DCF_ONLY, DLF_ONLY,* and *DCL_JOINT* are the forecast horizon variables. We form indicator variables for observations with forecasts of short-term EPS, long-term EPS, short-term-only EPS, long-term-only EPS, and both short- and long-term EPS, respectively. We test whether the coefficient estimates on the interactions between these variables and X_{t3} are different from zero to determine whether forecast horizon matters to the FERC.

We also follow prior literature (Ettredge et al. 2005; Lundholm and Myers 2002; Orpurt and Zang 2009; Tucker and Zarowin 2006) and extend model (3) to include additional explanatory variables related to FERCs:

$$\begin{aligned} R_t = {} & b_0 + b_1 X_{t-1} + b_2 X_t + b_3 X_{t3} + b_4 R_{t3} + b_5 D_t + b_6 D_t * X_{t-1} + b_7 D_t * X_t + b_8 D_t * X_{t3} \\ & + b_9 D_t * R_{t3} + c_1 SIZE_t + c_2 SIZE_t * X_{t3} + c_3 LOSS_t + c_4 LOSS_t * X_{t3} + c_5 GROWTH_t \\ & + c_6 GROWTH_t * X_{t3} + c_7 EARNSTD_t + c_8 EARNSTD_t * X_{t3} + c_9 NANAL_t \\ & + c_{10} NANAL_t * X_{t3} + \varepsilon_t \end{aligned} \tag{4}$$

where for year t:

$SIZE_t$ = the natural log of the market value of equity at the beginning of fiscal year t;

$LOSS_t = 1$ if X_{t3} is negative, 0 otherwise;

$GROWTH_t$ = the percentage growth in total assets from year $t-1$ to year $t+1$;

$EARNSTD_t$ = the standard deviation of X for years t through $t+3$;

$NANAL_t$ = the natural log of (one plus the number of analysts following the firm in the month prior to the earnings announcement for fiscal year t), from the First Call Analyst Forecast database; and all other variables are as previously defined.

We add $SIZE_t$ and the number of analysts, $NANAL_t$, to control for differences in the information environment across firms. We include an indicator variable, $LOSS_t$, because negative future earnings may be more difficult than positive future earnings to predict. We include $GROWTH_t$ because high-growth firms tend to have greater FERCs. Lastly, we include the volatility of future earnings, $EARNSTD_t$, since volatile earnings are more difficult to predict.[19]

Finally, we note that self-selection and endogeneity are important concerns because managers choose whether to issue a forecast, as well as the forecast characteristics. We address these concerns by (1) employing a Heckman self-selection model, (2) performing subsample analyses to alleviate self-selection concerns, and (3) using a two-stage least-squares (2SLS) estimation procedure

[19] As a robustness test, we convert these raw continuous control variables to fractional rankings in their (two-digit SIC) industries and years. The results are qualitatively similar. We tabulate results using raw values because the first-stage of our two-stage least-squares model (explained later) uses raw values.

based on prior studies (for example, Ajinkya et al. 2005; Chen et al. 2008; Karamanou and Vafeas 2005). We discuss these tests in Sect. 4.

3.2 Sample and data

Our sample comes from the intersection of the 2007 Annual Industrial Compustat files, the Center for Research in Securities Prices (CRSP) database, and the 2007 First Call Analyst Forecast Database. Management EPS forecasts for the current and future fiscal years come from First Call's Issued Guidelines Database. We begin with forecasts made in 1998 because data in First Call appears to be incomplete before 1998 (Anilowski et al. 2007) and end with forecasts made in 2003 because we require stock returns and earnings data for 3 years following the forecasts. We include only those firms appearing in the First Call Analyst Forecast Database during the same fiscal year, so if First Call has analyst forecast data but no management forecast data in a given year, we assume that management did not issue a forecasts in the year. To minimize the effect of outliers, we follow Tucker and Zarowin (2006) and delete observations that are in the top or bottom 1 percent of the distributions of past, current, and future earnings, and of current and future returns. The final sample consists of 18,253 firm-year observations; 7,353 firm-year observations issued a total of 27,767 management forecasts during our sample period, and the remaining 10,900 firm-year observations did not issue management forecasts in the year but are covered by First Call. We label the 7,353 observations that provided forecasts "the restricted sample" and perform subsample analyses with these observations.

3.3 Sample description

Table 1, panel A, reports the number of observations by year. The average sample firm issues approximately 1.5 forecasts per year, and the average forecasting firms (in the restricted sample) issue more than three forecasts per year. The average number of forecasts is increasing over the sample period.

To investigate whether trends in forecast precision exist, we assign point, range, minimum/maximum, and qualitative statements scores of 4, 3, 2, and 1, respectively and calculate average forecast precision as the mean firm score in each year. *PREC* averages 2.885 overall and tends to increase over our sample period.

Table 1, panel B, describes the distribution of annual versus quarterly forecasts by year. More firms issue quarterly-only forecasts than annual-only forecasts, and the number of firms that issue both quarterly and annual forecasts is increasing, suggesting that eliminating earnings guidance would affect many firms.

Table 1, panel C, describes forecast precision of individual forecasts by forecast type (annual versus quarterly). Range forecasts are most frequent: 17,334 (or 62 percent) are range forecasts, 6,145 (22 percent) are point forecasts, 2,211 (8 percent) are qualitative forecasts, and 2,077 (7 percent) are minimum/maximum forecasts. The distributions of forecast precision are similar for annual and quarterly forecasts except that a greater proportion of quarterly forecasts are minimum/maximum rather than qualitative.

Table 1 Sample description

Panel A: Sample distribution by year

Fiscal year	Full sample		Restricted sample		
	# of obs.	Avg. # of forecasts	# of obs.	Avg. # of forecasts	Avg. forecast precision
1998	3,014	0.621	881	2.125	2.816
1999	3,002	0.741	961	2.314	2.595
2000	3,179	0.960	1,145	2.667	2.666
2001	3,181	1.982	1,553	4.060	2.934
2002	3,170	2.330	1,492	4.951	3.022
2003	2,707	2.559	1,321	5.243	3.002
Total	18,253	1.521	7,353	3.776	2.885

Panel B: Number of firm-years with quarterly and annual forecasts in the restricted sample

Fiscal year	Quarterly forecasts only	Annual forecasts only	Both quarterly and annual forecasts	Total
1998	386	219	276	881
1999	366	295	300	961
2000	438	244	463	1,145
2001	483	316	754	1,553
2002	387	385	720	1,492
2003	275	421	625	1,321
Total	2,335	1,880	3,138	7,353

Panel C: Precision of individual forecasts

	Point forecasts	Range forecasts	Min/max forecasts	Qualitative forecasts	Total
Number of annual forecasts	2,973	8,924	847	1,003	13,747
Number of quarterly forecasts	3,172	8,410	1,230	1,208	14,020
Number of total forecasts	6,145	17,334	2,077	2,211	27,767

Panel A The restricted sample consists of observations with at least one management forecast made during the fiscal year. Forecast precision refers to whether the management forecast is a point estimate of expected earnings (e.g., we expect EPS to be $1.02), a range of expected earnings (e.g., we expect EPS to be between $0.95 and $1.05), a maximum level of expected earnings (e.g., EPS will be below $1.10), a minimum level of expected earnings (e.g., EPS will be at least $0.93), or a qualitative statement about earnings (e.g., we expect a good year. We are OK with expected earnings). To calculate the average forecast precision for an observation, we use an ordinal coding scheme for each forecast that gives the highest values to the most precise forecasts: point, range, minimum/maximum, and qualitative forecasts are coded 4, 3, 2, and 1, respectively, following the classifications in the appendix of Anilowski et al. (2007). The average forecast specificity for each firm-year in the restricted sample is calculated as [(4 × the number of point forecasts) + (3 × the number of range forecasts) + (2 × the number of minimum/maximum forecasts) + (1 × the number of qualitative forecasts)]/(the number of forecasts issued during the fiscal year)

Panel B The restricted sample firm-years (n = 7,353) consist of observations (n = 2,335) that issued only quarterly forecasts, observations (n = 1,880) that issued only annual forecasts, and observations (n = 3,138) that issued both quarterly and annual forecasts

Panel C The restricted sample (n = 7,353) issued a total of 27,767 EPS forecasts (13,747 annual forecasts and 14,020 quarterly forecasts). This table presents precision of individual forecasts

3.4 Descriptive statistics and correlations

Table 2, panel A, presents descriptive statistics for the full and restricted samples. Approximately 40 percent of all firm-year observations issue at least one forecast (mean $DF = 0.4028$). For the restricted sample, approximately 32 percent issue only quarterly forecasts (*DQF_ONLY*), 26 percent issue only annual forecasts (*DAF_ONLY*), and 43 percent issue both quarterly and annual forecasts (*DQA_JOINT*).[20] The full (restricted) sample issues an average of 1.521 (3.776) forecasts per year [mean $LNF = 0.5497$ (1.3645)].[21] Untabulated tests show that the median market value and number of analysts following for our restricted sample (at $837 million and six analysts) are greater than for our full sample (at $483 million and four analysts). We control for size and the number of analysts following the firm in our multivariate analyses.

Table 2, panel B, presents Pearson correlations for our full sample. X_{t-1}, X_t, and X_{t3} are highly correlated, as expected, as are R_{t3} and X_{t3}. Among the control variables, analyst following (*NANAL*) is highly correlated with *SIZE* ($p = 0.700$), but no other correlations are very high.[22] Untabulated results show that *PREC* is not highly correlated with R_t, X_{t-1}, X_t, X_{t3}, or R_{t3} in the restricted sample. Moreover, the largest correlation between *PREC* and the control variables is small ($p = -0.1050$ with *LOSS*). Correlations for the restricted sample are qualitatively similar (untabulated).

4 Empirical results

4.1 The effect of forecast issuances on the FERC (H1)

Using models (2) through (4), we perform ordinary least square (OLS) regression analyses to test whether firms that issue forecasts have greater FERCs than nonforecasting firms (see H1a). In all analyses, we correct for heteroskedasticity following White (1980) and perform firm-level clustering to control for correlation that may exist because multiple observations from the same firm are in our dataset (Petersen 2009). Results using the full sample appear in Table 3. Column 1 presents the traditional FERC model (model (2)), and column 2 presents our basic FERC model that tests for the effects of forecasts (model (3)). Finally, column 3 presents the full FERC model that tests for effects of forecasts and includes control variables (model (4)).

[20] Untabulated results indicate that in the restricted sample, most forecasts are only for the current fiscal year or for a quarter in the current year (mean $DCF\_ONLY = 0.7796$), and approximately 20 percent are for both current and future years (mean $DCL\_JOINT = 0.2025$). Long-term forecasts only for future years or for quarters in future years are rare (mean $DLF\_ONLY = 0.0178$).

[21] The average of *LNF* is calculated after the values are logged. The raw average number of forecasts is reported in Table 1, panel A.

[22] The correlation between *LNF* and *DF* is very high ($p = 0.878$), but these variables do not enter the same regression.

Table 2 Descriptive statistics and correlations

Panel A: Descriptive statistics

Variable	Mean	SD	5%	25%	Median	75%	95%
Full sample (n = 18,253)							
DF_t	0.4028	0.4905	0	0	0	1	1
DQF_ONLY_t	0.1279	0.3340	0	0	0	0	1
DAF_ONLY_t	0.1030	0.3040	0	0	0	0	1
DQA_JOINT_t	0.1719	0.3773	0	0	0	0	1
LNF_t	0.5497	0.7708	0	0	0	1.0986	2.1972
R_t	0.1437	0.7658	−0.6899	−0.2713	0.0197	0.3512	1.3315
X_{t-1}	0.0091	0.1505	−0.2112	0.0039	0.0426	0.0705	0.1225
X_t	0.0164	0.1234	−0.2194	−0.0031	0.0456	0.0768	0.1393
X_{t3}	0.1160	0.3615	−0.5136	−0.0222	0.1520	0.2853	0.6287
R_{t3}	0.5906	1.5738	−0.7710	−0.1835	0.3140	0.9126	2.7574
$SIZE_t$	6.3111	1.8683	3.5385	4.9308	6.1802	7.4646	9.6588
$LOSS_t$	0.2621	0.4398	0	0	0	1	1
$GROWTH_t$	39.7413	133.4308	−34.9366	−0.8619	17.9210	46.4463	165.7805
$EARNSTD_t$	0.0647	0.0752	0.0065	0.0174	0.0371	0.0811	0.2233
$NANAL_t$	1.5382	0.8627	0	0.6931	1.6094	2.1972	2.9444
Restricted sample (n = 7,353)							
DQF_ONLY_t	0.3176	0.4656	0	0	0	1	1
DAF_ONLY_t	0.2557	0.4363	0	0	0	1	1
DQA_JOINT_t	0.4268	0.4946	0	0	0	1	1
LNF_t	1.3645	0.6026	0.6931	0.6931	1.3863	1.7918	2.4849
$PREC_t$	2.8848	0.7835	1	2	3	3.25	4

Table 2 continued

Panel B: Pearson correlations (full sample)

Variable	DF_t	LNF_t	R_t	X_{t-1}	X_t	X_{t3}	R_{t3}	$SIZE_t$	$LOSS_t$	$GROWTH_t$	$EARNSTD_t$
LNF_t	0.868 (<0.001)										
R_t	−0.043 (<0.001)	−0.023 (<0.001)									
X_{t-1}	0.077 (<0.001)	0.080 (<0.001)	−0.073 (<0.001)								
X_t	0.059 (<0.001)	0.073 (<0.001)	0.147 (<0.001)	0.547 (<0.001)							
X_{t3}	0.056 (<0.001)	0.078 (<0.001)	0.102 (<0.001)	0.315 (<0.001)	0.504 (<0.001)						
R_{t3}	−0.017 (0.018)	−0.014 (0.058)	−0.148 (<0.001)	−0.059 (<0.001)	−0.061 (<0.001)	0.293 (<0.001)					
$SIZE_t$	0.249 (<0.001)	0.291 (<0.001)	−0.106 (<0.001)	0.176 (<0.001)	0.142 (<0.001)	0.090 (<0.001)	−0.130 (<0.001)				
$LOSS_t$	−0.067 (<0.001)	−0.090 (<0.001)	−0.151 (<0.001)	−0.319 (<0.001)	−0.495 (<0.001)	−0.587 (<0.001)	−0.070 (<0.001)	−0.169 (<0.001)			
$GROWTH_t$	−0.038 (<0.001)	−0.038 (<0.001)	0.233 (<0.001)	−0.034 (<0.001)	0.066 (<0.001)	−0.038 (<0.001)	−0.066 (<0.001)	0.009 (0.239)	0.015 (0.038)		
$EARNSTD_t$	−0.064 (<0.001)	−0.083 (<0.001)	0.172 (<0.001)	−0.352 (<0.001)	−0.429 (<0.001)	−0.209 (<0.001)	0.150 (<0.001)	−0.304 (<0.001)	0.270 (<0.001)	0.071 (<0.001)	
$NANAL_t$	0.344 (<0.001)	0.373 (<0.001)	0.059 (<0.001)	0.119 (<0.001)	0.136 (<0.001)	0.092 (<0.001)	−0.133 (<0.001)	0.700 (<0.001)	−0.147 (<0.001)	0.070 (<0.001)	−0.185 (<0.001)

Panel A $DF_t = 1$ if a management earnings per share (EPS) forecast is issued during fiscal year t, 0 otherwise; $DQF\_ONLY_t = 1$ if only quarterly management EPS forecasts are issued during fiscal year t, 0 otherwise; $DAF\_ONLY_t = 1$ if only annual management EPS forecasts are issued during fiscal year t, 0 otherwise; $DQA\_JOINT_t = 1$ if both quarterly and annual management EPS forecasts are issued during fiscal year t, 0 otherwise; LNF_t = the natural log of (1 plus the number of management EPS forecasts issued during fiscal year t); R_t = the cumulative (monthly compounded) return for fiscal year t; X_{t-1} = income available to common shareholders before extraordinary items in fiscal year $t-1$ deflated by the market value of equity at the beginning of fiscal year t; X_t = income available to common shareholders before extraordinary items deflated by the market value of equity at the beginning of fiscal year t; X_{t3} = the sum of income available to common shareholders before extraordinary items for years $t+1$ through $t+3$ deflated by the market value of equity at the beginning of fiscal year t; R_{t3} = the cumulative return for fiscal years $t+1$ to $t+3$; $SIZE_t$ = the natural log of the market value of equity at the beginning of fiscal year t; $LOSS_t = 1$ if X_{t3} is negative, 0 otherwise; $GROWTH_t$ = the percentage growth in total assets from year $t-1$ to year $t+1$; $EARNSTD_t$ = the standard deviation of X for year t through $t+3$; $NANAL_t$ = the natural log of (1plus the number of analysts following the firm in the month before the earnings announcement for fiscal year t), from the First Call Analyst Forecast database; and $PREC_t$ = the average forecast precision of management EPS forecasts in fiscal year t, calculated by awarding a score of 4 to all point forecasts, 3 to all range forecasts, 2 to all minimum/maximum forecasts, and 1 to all qualitative forecasts, and calculating the average score for the firm-year observation

Panel B Two-tailed p-values are presented in parentheses. Variable definitions appear in panel A

Table 3 Regression analyses on the effect of forecast issuance on the FERC

Panel A: Effect of management forecasts

Variable	Full sample OLS (n = 18,253) Column 1 Model (2)	Column 2 Model (3)	Column 3 Model (4)	Heckman two-stage (n = 13,420) Column 4
Intercept	0.1562*** (.0001)	0.2022*** (.0001)	0.2281*** (.0001)	0.9041*** (.0001)
X_{t-1}	−1.1835*** (.0001)	−1.0615*** (.0001)	−0.7640*** (.0001)	−1.0915*** (.0001)
X_t	1.2202*** (.0001)	1.1921*** (.0001)	1.2001*** (.0001)	1.0474*** (.0001)
X_{t3}	0.2780*** (.0001)	0.1216*** (.0001)	0.4016*** (.0001)	0.7109*** (.0001)
R_{t3}	−0.0915*** (.0001)	−0.0922*** (.0001)	−0.1143*** (.0001)	−0.1760*** (.0001)
DF_t		−0.1434*** (.0001)	−0.1085*** (.0001)	−0.1348** (.0215)
$DF_t * X_{t-1}$		−0.1998 (.2253)	−0.2750* (.0629)	−0.0331 (.7543)
$DF_t * X_t$		0.0880 (.6240)	0.1498 (.3473)	0.1321 (.3406)
$\boldsymbol{DF_t * X_{t3}}$	**0.5513*** (.0001)**			
$DF_t * R_{t3}$		−0.0026 (.8873)	0.0093 (.6756)	0.0259 (.3107)
$Mills_t$				−0.1967** (.0175)
$DF_t*Mills_t$				0.1292 (.3046)
$SIZE_t$			−0.0886*** (.0001)	−0.0984*** (.0001)
$SIZE_t* X_{t3}$			0.1001*** (.0001)	0.0920*** (.0001)
$LOSS_t$			−0.2092*** (.0001)	−0.1982*** (.0001)
$LOSS_t* X_{t3}$			−0.8319*** (.0001)	−0.8760*** (.0001)
$GROWTH_t$			0.0010*** (.0001)	0.0026*** (.0001)
$GROWTH_t* X_{t3}$			0.0004*** (.0002)	0.0009*** (.0001)
$EARNSTD_t$			2.2622*** (.0001)	2.3290*** (.0001)
$EARNSTD_t* X_{t3}$			−0.7933*** (.0021)	−1.0648*** (.0021)
$NANAL_t$			0.1929*** (.0001)	0.1023*** (.0001)
$NANAL_t* X_{t3}$			0.2789*** (.0001)	0.2441*** (.0001)
Adjusted R^2	0.0868	0.1021	0.2671	0.3280

Panel B: Subsample analyses for self-selection

Variable	Within SMF firms, OLS (n = 9,085) Column 1, $F1 = DF_t$	SMF vs. NMF firms, OLS (n = 7,946) Column 2, $F1 = DSMF_t$
Intercept	0.2741*** (.0001)	0.1527*** (.0001)
X_{t-1}	−0.8758*** (.0001)	−0.7706*** (.0001)
X_t	1.0765*** (.0001)	1.0088*** (.0001)
X_{t3}	0.8746*** (.0001)	0.7887*** (.0001)
R_{t3}	−0.1858*** (.0001)	−0.1133*** (.0001)
$F1$	−0.1407*** (.0001)	0.0782*** (.0001)
$F1* X_{t-1}$	−0.0896 (.4656)	−0.1587* (.0604)

Table 3 continued

Panel B: Subsample analyses for self-selection		
Variable	Within SMF firms, OLS (n = 9,085) Column 1, $F1 = DF_t$	SMF vs. NMF firms, OLS (n = 7,946) Column 2, $F1 = DSMF_t$
$F1^{*} X_t$	0.2360 (.2399)	0.0432 (.8065)
$F1^{*} X_{t3}$	**0.2443*** (.0001)**	**0.1479 (.1304)**
$F1^{*} R_{t3}$	0.0354 (.2010)	−0.0681 (.1102)
$SIZE_t$	−0.0951*** (.0001)	−0.0816*** (.0001)
$SIZE_t{}^{*} X_{t3}$	0.0173 (.4264)	0.0678*** (.0001)
$LOSS_t$	−0.1376*** (.0001)	−0.1658*** (.0001)
$LOSS_t{}^{*} X_{t3}$	−0.6816*** (.0001)	−0.8879*** (.0001)
$GROWTH_t$	0.0023*** (.0001)	0.0024*** (.0001)
$GROWTH_t{}^{*} X_{t3}$	0.0003** (.0312)	0.0003** (.0236)
$EARNSTD_t$	3.2222*** (.0001)	2.6126*** (.0001)
$EARNSTD_t{}^{*} X_{t3}$	−1.6193*** (.0001)	−1.1126*** (.0001)
$NANAL_t$	(.0001)	0.1593*** (.0001)
$NANAL_t{}^{*} X_{t3}$	(.0583)	0.2680*** (.0001)
Adjusted R^2	0.3286	0.2825

When estimating the coefficient standard errors, we use White's (1980) method to correct for heteroskedasticity as well as a clustering procedure that accounts for serial dependence across years for a given firm (Petersen 2009). Two-tailed p-values are presented in the parentheses. *, **, and *** denote p-values <10, 5, and 1%, respectively. In panel A, the sample size in Heckman model is smaller due to additional data requirements for the first-stage regression. In panel B, $DSMF_t = 1$ if the firm issues management EPS forecasts in other years during our sample period but does not issue a forecast in year t, and 0 otherwise. See Table 2, panel A, for definitions of the other variables

In model (2) in column 1, we test whether our results are similar to those in prior studies. The coefficient on X_t (the ERC) is positive ($b_2 = 1.2202$, $p = 0.0001$), so returns are increasing in current earnings. In addition, the coefficient on X_{t3} (the FERC) is positive ($b_3 = 0.2780$, $p = 0.0001$), so returns are increasing in future earnings, consistent with Lundholm and Myers (2002).

Model (3) in column 2 includes the interaction between DF and the other variables in our basic FERC model. The coefficient of interest (that is, the estimate on $DF_t{}^{*}X_{t3}$) is positive ($b_8 = 0.5513$, $p = 0.0001$), implying that the returns of forecasting firms more strongly reflect future earnings than do returns of nonforecasting firms. The results strongly support H1a and suggest that earnings forecasts provide information that investors can use to adjust securities prices to better reflect future earnings news.

Model (4) in column 3 includes control variables. Our main result remains: the coefficient on $DF_t{}^{*}X_{t3}$ is positive (0.3712, $p = 0.0001$), so management forecasts allow returns to reflect future earnings. Among the control variables, we find that FERCs are greater for larger firms, growing firms, and firms followed by more analysts, and are smaller for loss firms and for firms with higher earnings variability, consistent with prior studies.

Note that in columns 2 and 3, the coefficients on $DF_t{*}X_t$ are not significant, suggesting that the management forecasts do not influence the ERC. Thus, it is important to consider the FERC when assessing the impact of management forecasts because the ERC does not fully capture their informativeness.

4.2 Self-selection issues for H1

Since management forecasts are voluntary, our tests of H1 are subject to self-selection bias. To address this potential endogeneity, we conduct the following analyses.

First, we follow Heckman (1979) and model the decision to issue forecasts in a first-stage model. Our first-stage probit model follows Ajinkya et al. (2005) and Chen et al. (2008):

$$\begin{aligned} DF_t = {} & d_0 + d_1 INST_t + d_2 BDIND_t + d_3 D\_CAP_t + d_4 DISP_t + d_5 BETA_t + d_6 LIT_t + d_7 ROA_t \\ & + d_8 SIZE_t + d_9 LOSS_t + d_{10} GROWTH_t + d_{11} EARNSTD_t + d_{12} NANAL_t \\ & + YearDummies + IndustryDummies + \varepsilon_t \end{aligned} \tag{5}$$

where for year t:

$INST_t$ = the percentage of institutional ownership at the beginning of fiscal year t;

$BDIND_t$ = the percentage of independent directors at the beginning of fiscal year t; we define independent directors as those who are not corporate executives and have no business relationship with the firm;

D_CAP_t = 1 if the sum of debt or equity issued during the year t is greater than 5 percent of total assets and 0 otherwise;

$DISP_t$ = analyst forecast dispersion in year t, measured as the standard deviation of one-year-ahead EPS forecasts, scaled by the absolute mean forecast, using the most recent consensus forecast before the end of year t;

$BETA_t$ = equity beta for fiscal year t;

LIT_t = 1 for firms in high litigation risk industries (SIC codes 2833-2836, 3570-3577, 7370-7374, 3600-3674, 5200-5961, 8731-8734) and 0 otherwise;

ROA_t = return on assets for fiscal year t; and

all other variables are as previously defined.

To improve the efficacy of the first-stage selection model, we add variables that are not in the second-stage model. Prior studies find that the likelihood of management forecasts increases with institutional ownership ($INST_t$), board independence ($BDIND_t$), and substantial external financing (D_CAP_t) (Ajinkya et al. 2005; Chen et al. 2008; Karamanou and Vafeas 2005). We find that these variables are very weakly associated with the FERC.[23]

[23] We add these variables and their interactions with X_{t3} to model (3), and find that the coefficient on $INST_t{*}X_{t3}$ is marginally significant ($p = 0.0457$), but the coefficients on $BDIND_t{*}X_{t3}$ and $D\_CAP_t{*}X_{t3}$ are not significant. When the other control variables (*SIZE, LOSS, GROWTH*, *EARNSTD*, and *NANAL*) and their interactions with X_{t3} are included (as in model (4)), $INST_t{*}X_{t3}$, $BDIND_t{*}X_{t3}$, and $D\_CAP_t{*}X_{t3}$ are all insignificant.

The first-stage estimation results appear in the appendix. Using 13,420 firm-year observations with available data, we obtain the inverse Mills ratio ($Mills_t$). In the second-stage, we follow prior studies where the group indicator variable (DF_t in our case) is endogenous (for example, Ball and Shivakumar 2005; Orpurt and Zang 2009; Oswald and Zarowin 2007) and include $Mills_t$ and its interaction with DF_t to allow the coefficient on $Mills_t$ to vary between the forecast and nonforecast groups. The results from this second-stage model appear in column 4 of Table 3, panel A. Although the coefficient on $Mills_t$ is significant, the coefficient on $Mills_t*DF_t$ is not, indicating that self-selection bias, to the extent that it exists, does not significantly affect our results. Moreover, the coefficient on DF_t*X_{t3} remains positive ($p = 0.0001$).[24]

Second, we perform two additional subsample analyses to explore the potential impact of self-selection.[25] We first limit our sample to firms that forecast in some years but not in others ("SMF firms") and test whether FERCs are greater in years where SMF firms issue forecasts than in years where SMF firms do not issue forecasts.[26] This test requires a sufficiently long period to allow for both forecasting and nonforecasting years, so our sample consists of 1,723 unique firms with at least four years of data (number of firm-years = 9,085; 4,690 with forecasts and 4,395 without). The results in column 1 of Table 3, panel B, are similar to those previously reported; FERCs are greater when SMF firms issue forecasts.

Next, we limit the sample to SMF firms and nonforecasting firms ("NMF firms") and compare FERCs of SMF firms in nonforecasting years to FERCs of NMF firms. In column 2 of Table 3, panel B, *DSMF* is an indicator set to 1 when an SMF firm does not forecast earnings in the year and zero otherwise. The coefficient on $DSMF_t*X_{t3}$ is not significant. Thus, the FERCs of SMF firms are not greater than the FERCs of NMF firms in years when SMF firms do not issue forecasts. Taken together, these analyses reveal that FERCs are not different for SMF versus NMF firms when SMF firms do not issue forecasts. However, FERCs are greater when SMF firms issue forecasts. These results alleviate self-selection concerns.

4.3 The effect of forecast frequency on the FERC (H2)

H2a predicts that FERCs increase with forecast frequency. To test this, we replace *DF* with *LNF* (the natural log of 1 plus the number of forecasts issued in the year) in Table 4. The coefficient on LNF_t*X_{t3} is positive [$p = 0.0001$ in column 1 (full sample); $p = 0.0001$ in column 2 (restricted sample)] and the results qualitatively unchanged using the Heckman two-stage approach in the full sample (untabulated). Thus FERCs increase with forecast frequency, suggesting that the issuance of

[24] Results from the Heckman two-stage approach for all other analyses using the full sample are robust. For parsimony, we report only OLS results in subsequent tables.

[25] We thank the reviewer for suggesting this approach.

[26] This test limits the sample to firms that forecast at least once so it provides some control for self-selection.

Table 4 Regression analyses on the effect of number of forecasts and forecast precision on the FERC

Variable	Full sample OLS (n = 18,253)	Restricted sample OLS (n = 7,353)		Restricted sample 2SLS (n = 6,482)	
	Column 1	Column 2	Column 3	Column 4	Column 5
Intercept	0.2148*** (.0001)	0.0614 (.1975)	0.0723 (.2463)	−0.1420*** (.0039)	0.3295* (.0740)
X_{t-1}	−0.7635*** (.0001)	−0.5419** (.0392)	−0.6378** (.0474)	−0.8815*** (.0060)	−0.7439** (.0238)
X_t	1.2547*** (.0001)	1.7524*** (.0001)	1.1904*** (.0001)	1.1509*** (.0029)	1.1763*** (.0001)
X_{t3}	0.3931*** (.0001)	0.6791*** (.0039)	0.8962*** (.0029)	0.9074*** (.0001)	0.8763** (.0138)
R_{t3}	−0.1016*** (.0001)	−0.0045 (.6701)	−0.0819 (.1129)	−0.0670** (.0364)	−0.0461 (.1259)
LNF_t	−0.0541*** (.0001)	0.0637*** (.0001)	0.0645*** (.0001)	0.2837*** (.0001)	0.3619*** (.0001)
$LNF_t * X_{t-1}$	−0.2409** (.0324)	−0.3780** (.0307)	−0.3938** (.0403)	−0.1937* (.0721)	−0.2866* (.0832)
$LNF_t * X_t$	−0.0036 (.9626)	−0.4090* (.0587)	−0.4538** (.0393)	0.0739 (.8086)	0.1348 (.2253)
$\boldsymbol{LNF_t * X_{t3}}$	**0.3314*** (.0001)**	**0.3868*** (.0001)**	**0.3974*** (.0001)**	**0.1712*** (.0028)**	**0.1625** (.0272)**
$LNF_t * R_{t3}$	−0.0218** (.0336)	−0.0993*** (.0001)	−0.1022*** (.0001)	−0.0696*** (.0033)	−0.0908*** (.0008)
$PREC_t$			−0.0050 (.1980)		−0.0596 (.1197)
$PREC_t * X_{t-1}$			0.0444 (.5815)		−0.1671 (.6398)
$PREC_t * X_t$			−0.1143 (.2451)		−0.1027 (.1838)
$\boldsymbol{PREC_t * X_{t3}}$			**0.0746** (.0253)**		**0.0895* (.0501)**
$PREC_t * R_{t3}$			0.0269 (.2432)		0.0372 (.5369)
$SIZE_t$	−0.0876*** (.0001)	−0.0861*** (.0001)	−0.0860*** (.0001)	−0.0875*** (.0001)	−0.1065*** (.0001)
$SIZE_t * X_{t3}$	0.0971*** (.0001)	0.0079 (.7286)	0.0084 (.7108)	0.0824 (.2018)	−0.0724** (.0194)
$LOSS_t$	−0.2128*** (.0001)	−0.1632*** (.0001)	−0.1627*** (.0001)	−0.1535*** (.0001)	−0.1786*** (.0001)
$LOSS_t * X_{t3}$	−0.8309*** (.0001)	−0.5010*** (.0001)	−0.5018*** (.0001)	−0.4954*** (.0001)	−0.4845*** (.0001)
$GROWTH_t$	0.0011*** (.0001)	0.0018*** (.0001)	0.0018*** (.0001)	0.0021*** (.0001)	0.0021*** (.0001)
$GROWTH_t * X_{t3}$	0.0004*** (.0002)	0.0010** (.0431)	0.0010** (.0390)	0.0005* (.0652)	0.0006 (.1376)
$EARNSTD_t$	2.2512*** (.0001)	2.6296*** (.0001)	2.6554*** (.0001)	2.6038*** (.0001)	2.4148*** (.0001)

Table 4 continued

Variable	Full sample OLS (n = 18,253)	Restricted sampleOLS (n = 7,353)		Restricted sample2SLS (n = 6,482)	
	Column 1	Column 2	Column 3	Column 4	Column 5
$EARNSTD_t * X_{t3}$	−0.7715*** (.0027)	−1.5677*** (.0002)	−1.5930*** (.0001)	−1.7213*** (.0002)	−1.8657*** (.0001)
$NANAL_t$	0.1888*** (.0001)	0.1488*** (.0001)	0.1488*** (.0001)	0.1094*** (.0001)	0.1279*** (.0001)
$NANAL_t * X_{t3}$	0.2799*** (.0001)	0.0319 (.4913)	0.0334 (.4714)	−0.1133 (.2968)	−0.0501 (.4609)
Adjusted R^2	0.2676	0.3490	0.3528	0.3457	0.3646

When estimating the coefficient standard errors, we use White's (1980) method to correct for heteroskedasticity as well as a clustering procedure that accounts for serial dependence across years for a given firm (Petersen 2009). Two-tailed p-values are presented in the parentheses. *, **, and *** denote p-values <10, 5, and 1%, respectively. LNF_t and $PREC_t$ in 2SLS (columns 4 and 5) are the fitted values from the first-stage regressions in the appendix. The sample size in 2SLS is smaller due to additional data requirements for the first-stage regressions. See Table 2, panel A, for definitions of the other variables multiple forecasts in a period enhances the market's ability to bring future earnings news into current stock prices.[27]

4.4 The effect of forecast precision on the FERC (H3)

We also test whether FERCs increase with forecast precision (see H3a) in Table 4, column 3.[28] In column 3, the coefficient on $PREC_t{*}X_{t3}$ is positive ($p = 0.0253$), and the coefficient on $LNF_t{*}X_{t3}$ remains positive. Thus providing frequent, precise forecasts enhances the ability of current returns to reflect future earning news.

Since frequency and precision are endogenous given the decision to forecast, we also employ 2SLS on the restricted sample. We follow Ajinkya et al. (2005) and include variables similar to those in the Heckman first-stage model and estimate fitted values of *LNF* and *PREC* in the first-stage regressions (see the Appendix). Columns 4 and 5 present the second-stage estimations, which are largely consistent with the previous results; the coefficients on $LNF_t{*}X_{t3}$ and $PREC_t{*}X_{t3}$ remain positive.[29]

4.5 The effect of forecast type (annual vs. quarterly) on the FERC (H4)

Since recommendations to reduce earnings guidance focus on eliminating quarterly forecasts, by implication, annual forecasts are assumed to be beneficial and quarterly forecasts are assumed to be detrimental. To investigate the effect of forecast type on FERCs, we estimate the following model in Table 5, panel A:

$$\begin{aligned} R_t = {} & b_0 + b_1X_{t-1} + b_2X_t + b_3X_{t3} + b_4R_{t3} + c_1F_{ti} + c_2F_{ti} * X_{t-1} + c_3F_{ti} * X_t + c_4F_{ti} * X_{t3} \\ & + c_5F_{ti} * R_{t3} + f_1SIZE_t + f_2SIZE_t * X_{t3} + f_3LOSS_t + f_4LOSS_t * X_{t3} + f_5GROWTH_t \\ & + f_6GROWTH_t * X_{t3} + f_7EARNSTD_t + f_8EARNSTD_t * X_{t3} + f_9NANAL_t \\ & + f_{10}NANAL_t * X_{t3} + \varepsilon_t \end{aligned} \tag{6}$$

where:

in column 1, $F_{ti} = DAF_t = 1$ if annual forecasts are issued during fiscal year t, 0 otherwise;

in column 2, $F_{ti} = DQF_t = 1$ if quarterly forecasts are issued during fiscal year t, 0 otherwise;

in column 3, $F_{ti} = DAF\_ONLY_t$, DQF_ONLY_t, and DQA_JOINT_t; and all other variables are as previously defined.

[27] In contrast, the coefficient on $LNF_t{*}X_t$ is not significant for the full sample, suggesting that, on average, how investors respond to current earnings (the ERC) is not influenced by management forecast frequency. However, when we limit our analyses to the restricted sample (columns 2, 3, and 4), the coefficient on $LNF_t{*}X_t$ is negative. The negative coefficients on $LNF_t{*}X_t$ and positive coefficients on $LNF_t{*}X_{t3}$ suggest that investors focus more on forecasted future earnings than on current earnings in setting stock prices as forecast frequency increases.

[28] The results are qualitatively similar when we do not control for the number of forecasts issued (*LNF*).

[29] Using two fitted variables in the same second-stage regression does not cause econometric problems even if the two fitted variables are estimated using similar variables in the first-stage regression (Gul et al. 2009). In addition, the Pearson correlation between the fitted values of *LNF* and *PREC* is only 0.1684.

Table 5 Regression analyses on the effect of forecast type (annual vs. quarterly) on the FERC

Panel A: Effect of annual and quarterly forecasts

Variable	Full sample OLS ($n = 18{,}253$)			Restricted sample OLS ($n = 7{,}353$)	Restricted sample 2SLS ($n = 6{,}482$)
	Column 1 $F1 = DAF_t$	Column 2 $F1 = DQF_t$	Column 3 $F1 = DQF\_ONLY_t$ $F2 = DAF\_ONLY_t$ $F3 = DQA\_JOINT_t$	Column 4 $F1 = DQA\_JOINT_t$	Column 5 $F1 = DQA\_JOINT_t$
Intercept	0.2166*** (.0001)	0.2248*** (.0001)	0.2282*** (.0001)	0.1082** (.0135)	0.0450 (.3072)
X_{t-1}	−0.8524*** (.0001)	−0.7631*** (.0001)	−0.7620*** (.0001)	−0.9518*** (.0001)	−1.0572*** (.0001)
X_t	1.2658*** (.0001)	1.2351*** (.0001)	1.2052*** (.0001)	1.4035*** (.0001)	1.1957*** (.0001)
X_{t3}	0.4078*** (.0001)	0.4120*** (.0001)	0.4089*** (.0001)	1.0370*** (.0001)	1.0734*** (.0001)
R_{t3}	−0.1072*** (.0001)	−0.1114*** (.0001)	−0.1145*** (.0001)	−0.0903*** (.0001)	−0.2933*** (.0001)
$F1$	−0.0650*** (.0001)	−0.1139*** (.0001)	−0.1283*** (.0001)	0.0011 (.9474)	0.2275*** (.0020)
$F1 * X_{t-1}$	−0.0964 (.3458)	−0.1139** (.0233)	−0.0919* (.0654)	−0.1915* (.0635)	0.2297 (.1319)
$F1 * X_t$	0.0095 (.9441)	0.0702 (.5530)	0.0863 (.4827)	0.0520 (.4369)	0.0297 (.9614)
$\boldsymbol{F1 * X_{t3}}$	**0.4333*** (.0001)**	**0.4143*** (.0001)**	**0.2417*** (.0001)**	**0.2993*** (.0001)**	**0.1362** (.0134)**
$F1 * R_{t3}$	−0.0138 (.1025)	−0.0001 (.9905)	0.0250 (.5249)	−0.0679*** (.0001)	−0.1135* (.0762)
$F2$			−0.0672*** (.0168)		
$F2 * X_{t-1}$			0.0859 (.5580)		
$F2 * X_t$			0.3131 (.1208)		
$\boldsymbol{F2 * X_{t3}}$			**0.2631** (.0011)**		
$F2 * R_{t3}$			0.0265 (.1633)		
$F3$			−0.1086*** (.0001)		
$F3 * X_{t-1}$			−0.4247*** (.0014)		
$F3 * X_t$			−0.0478 (.7785)		

Table 5 continued

Panel A: Effect of annual and quarterly forecasts

Variable	Full sample OLS ($n = 18{,}253$) Column 1 $F1 = DAF_t$	Column 2 $F1 = DQF_t$	Column 3 $F1 = DQF\_ONLY_t$ $F2 = DAF\_ONLY_t$ $F3 = DQA\_JOINT_t$	Restricted sample OLS ($n = 7{,}353$) Column 4 $F1 = DQA\_JOINT_t$	Restricted sample 2SLS ($n = 6{,}482$) Column 5 $F1 = DQA\_JOINT_t$
***F3* * X_{t3}**			**0.5655*** (.0001)**		
F3 * R_{t3}			−0.0396 (.1235)		
$SIZE_t$	−0.0886*** (.0001)	−0.0893*** (.0001)	−0.0891*** (.0001)	−0.0833*** (.0001)	−0.0828*** (.0001)
$SIZE_t$* X_{t3}	0.1011*** (.0001)	0.0999*** (.0001)	0.0992*** (.0001)	0.0065 (.7766)	0.0706 (.2272)
$LOSS_t$	−0.2157*** (.0001)	−0.2062*** (.0001)	−0.2078*** (.0001)	−0.1591*** (.0001)	−0.1470*** (.0001)
$LOSS_t$* X_{t3}	−0.8598*** (.0001)	−0.8562*** (.0001)	−0.8331*** (.0001)	−0.5327*** (.0001)	−0.5219*** (.0001)
$GROWTH_t$	0.0011*** (.0001)	0.0011*** (.0001)	0.0011*** (.0001)	0.0018*** (.0001)	0.0019*** (.0001)
$GROWTH_t$*X_{t3}	0.0003*** (.0001)	0.0004*** (.0002)	0.0004*** (.0001)	0.0010*** (.0001)	0.0006*** (.0004)
$EARNSTD_t$	2.2294*** (.0001)	2.2585*** (.0001)	2.2797*** (.0001)	2.6139*** (.0001)	2.6936*** (.0001)
$EARNSTD_t$*X_{t3}	−0.7300*** (.0019)	−0.7695*** (.0022)	−0.7899*** (.0065)	−1.5837*** (.0001)	−1.8745*** (.0001)
$NANAL_t$	0.1832*** (.0001)	0.1923*** (.0001)	0.1938*** (.0001)	0.1546*** (.0001)	0.1356*** (.0001)
$NANAL_t$* X_{t3}	0.2549*** (.0001)	0.2665*** (.0001)	0.2808*** (.0001)	0.0245 (.5990)	−0.0779 (.2531)
Adjusted R^2	0.2629	0.2671	0.2701	0.3391	0.3420

Table 5 continued

Panel B: Effect of issuance, number, and precision of quarterly forecasts

Variable	Full sample 2 OLS (n = 13,235)		Restricted sample 2 OLS (n = 2,335)		Restricted sample 2 2SLS (n = 1,996)	
	Column 1 $F1 = DQF\_ONLY_t$	Column 2 $F1 = LNF_t$	Column 3 $F1 = LNF_t$	Column 4 $F1 = LNF_t$	Column 5 $F1 = LNF_t$	Column 6 $F1 = LNF_t$
Intercept	0.2226*** (.0045)	0.2142*** (.0001)	0.0334 (.6434)	0.0172 (.8371)	−0.0935 (.3012)	0.9082** (.0127)
X_{t-1}	−0.7670*** (.0001)	−0.7741*** (.0001)	−0.7030*** (.0067)	−0.3955* (.0502)	−1.0689** (.0271)	−0.8402** (.0216)
X_t	1.1903*** (.0001)	1.2157*** (.0001)	1.4762*** (.0001)	0.7757*** (.0006)	0.8303*** (.0035)	0.7944*** (.0060)
X_{t3}	0.3168*** (.0001)	0.3130*** (.0001)	0.2364** (.0264)	0.2651** (.0388)	0.2618** (.0362)	0.2497** (.0318)
R_{t3}	−0.1131*** (.0001)	−0.1059*** (.0001)	−0.1033** (.0325)	−0.0464 (.1527)	−0.0655* (.0657)	−0.0614 (.1133)
$F1$	−0.1270*** (.0001)	−0.0872*** (.0001)	0.1851 (.2322)	0.1832 (.1774)	0.3732** (.0301)	0.3316** (.0415)
$F1 * X_{t-1}$	−0.3987** (.0235)	−0.3534** (.0421)	−0.4047* (.0754)	−0.3499* (.0815)	−0.4876 (.9130)	−0.2591 (.1338)
$F1 * X_t$	0.1639 (.2905)	0.0362 (.7990)	−0.3312 (.3092)	−0.4651 (.1609)	0.4528 (.4171)	0.3498 (.2913)
$\boldsymbol{F1 * X_{t3}}$	**0.3372*** (.0001)**	**0.3908*** (.0001)**	**0.6807*** (.0001)**	**0.4253*** (.0003)**	**0.4132** (.0296)**	**0.2607** (.0334)**
$F1 * R_{t3}$	0.0248 (.1065)	−0.0061 (.5630)	−0.2389*** (.0001)	−0.2439*** (.0001)	−0.1284*** (.0056)	−0.1607*** (.0082)
$PREC_t$				−0.0061 (.6854)		−0.0040 (.2265)
$PREC_t * X_{t-1}$				−0.1412 (.2437)		−0.0798 (.3325)
$PREC_t * X_t$				−0.1005 (.2569)		−0.1177 (.6581)
$\boldsymbol{PREC_t * X_{t3}}$				**0.0868** (.0322)**		**0.0429* (.0842)**
$PREC_t * R_{t3}$				0.0583 (.3067)		−0.0308 (.4306)
$SIZE_t$	−0.0892*** (.0001)	−0.0886*** (.0001)	−0.1200*** (.0001)	−0.1198*** (.0001)	−0.1328*** (.0001)	−0.1592*** (.0001)
$SIZE_t * X_{t3}$	0.1227*** (.0001)	0.1221*** (.0001)	0.1867*** (.0001)	0.1852*** (.0001)	0.1033* (.0595)	0.1027* (.0782)
$LOSS_t$	−0.2153*** (.0001)	−0.2158*** (.0001)	−0.1218*** (.0009)	−0.1241*** (.0008)	−0.1009** (.0113)	−0.1468*** (.0005)
$LOSS_t * X_{t3}$	−0.9164*** (.0001)	−0.9223*** (.0001)	−0.9078*** (.0001)	−0.9048*** (.0001)	−0.8513*** (.0001)	−0.8964*** (.0001)
$GROWTH_t$	0.0011*** (.0001)	0.0011*** (.0001)	0.0029*** (.0001)	0.0029*** (.0001)	0.0029*** (.0001)	0.0029*** (.0001)

Table 5 continued

Panel B: Effect of issuance, number, and precision of quarterly forecasts

Variable	Full sample 2 OLS (n = 13,235)		Restricted sample 2 OLS (n = 2,335)		Restricted sample 2 2SLS (n = 1,996)	
	Column 1 $F1 = DQF\_ONLY_t$	Column 2 $F1 = LNF_t$	Column 3 $F1 = LNF_t$	Column 4 $F1 = LNF_t$	Column 5 $F1 = LNF_t$	Column 6 $F1 = LNF_t$
$GROWTH_t * X_{t3}$	0.0005*** (.0001)	0.0005*** (.0001)	0.0020*** (.0005)	0.0020*** (.0004)	0.0019** (.0216)	0.0018** (.0327)
$EARNSTD_t$	2.1082*** (.0001)	2.0888*** (.0001)	2.2754*** (.0001)	2.3154*** (.0001)	2.3294*** (.0001)	2.0622*** (.0001)
$EARNSTD_t * X_{t3}$	−0.5990*** (.0023)	−0.6027*** (.0041)	−0.9942** (.0148)	−1.0023** (.0140)	−0.9635** (.0359)	−1.0167** (.0331)
$NANAL_t$	0.2013*** (.0001)	0.1985*** (.0001)	0.1906*** (.0001)	0.1906*** (.0001)	0.1631*** (.0001)	0.1845*** (.0001)
$NANAL_t * X_{t3}$	0.3139*** (.0001)	0.3133*** (.0001)	0.1985** (.0227)	0.2024** (.0202)	−0.0144 (.1128)	0.0327 (.7829)
Adjusted R^2	0.2537	0.2562	0.3694	0.3784	0.3794	0.3877

Panel A When estimating the coefficient standard errors, we use White's (1980) method to correct for heteroskedasticity as well as a clustering procedure that accounts for serial dependence across years for a given firm (Petersen 2009). Two-tailed p-values are presented in the parentheses. *, **, and *** denote p-values <10, 5, and 1%, respectively. The sample size in 2SLS is smaller due to additional data requirements for the first-stage regressions. $DAF_t = 1$ if annual management EPS forecasts are issued during fiscal year t, 0 otherwise; $DQF_t = 1$ if quarterly management EPS forecasts are issued during fiscal year t, 0 otherwise; $DQA\_JOINT_t = 1$ if both quarterly and annual management EPS forecasts are issued during fiscal year t, 0 otherwise; and DQA_JOINT_t in the 2SLS model (column 5) is the fitted value from the first-stage regression in the appendix. See Table 2, panel A, for definitions of the other variables

Panel B When estimating the coefficient standard errors, we use White's (1980) method to correct for heteroskedasticity as well as a clustering procedure that accounts for serial dependence across years for a given firm (Petersen 2009). Two-tailed p-values are presented in the parentheses. *, **, and *** denote p-values <10, 5, and 1%, respectively. Full sample 2 includes DQF_ONLY (n = 2,335) firm-year observations and no-forecast (n = 10,900) firm-year observations and excludes any observations with annual forecasts. Restricted sample 2 includes only DQF_ONLY firm-year observations. LNF_t and $PREC_t$ in the 2SLS models (columns 5 and 6) are the fitted values from the first-stage regressions in the appendix. The sample size in the 2SLS models is smaller due to additional data requirements for the first-stage regressions. See Table 2, panel A, for definitions of the other variables

Column 1 of Table 5, panel A, supports H4(i)a. The coefficient on $DAF_t{*}X_{t3}$ is positive ($p = 0.0001$), confirming that returns reflect future earnings to a greater extent when managers forecast annual EPS. More important, column 2 supports H4(ii)a. The coefficient on $DQF_t{*}X_{t3}$ is positive ($p = 0.0001$), confirming that returns reflect future earnings to a greater extent even when managers forecast quarterly EPS. Thus even quarterly forecasts appear to provide information about future earnings news, allowing this to be reflected in stock prices.

Since some firms making quarterly forecasts also make annual forecasts, we perform two additional tests. First, in untabulated analyses, we add an indicator for quarterly-only forecasts (*DQF_ONLY*) and appropriate interaction terms in column 2. The coefficient on $DQF\_ONLY_t{*}X_{t3}$ is positive ($p = 0.0023$). Second, in column 3, we form separate indicator variables for quarterly-only forecasts (*DQF_ONLY*), annual-only forecasts (*DAF_ONLY*), and both quarterly and annual forecasts (*DQA_JOINT*). Again, the coefficient on $DQF\_ONLY_t{*}X_{t3}$ is positive ($p = 0.0001$). These two tests confirm that returns reflect future earnings to a greater extent even when managers issue only quarterly forecasts. A test of equality cannot reject that the coefficient estimate on $DQF\_ONLY_t{*}X_{t3}$ equals that on $DAF\_ONLY_t{*}X_{t3}$ (F-value $= 0.31$, $p = 0.5777$), suggesting that quarterly EPS forecasts may be as informative as annual EPS forecasts with respect to future earnings.

In column 4 (restricted sample), results suggest that issuing both quarterly and annual EPS forecasts provides more information than issuing either quarterly- or annual-only forecasts ($p = 0.0001$). Finally, because the decision to issue both quarterly and annual forecasts could be endogenous, we use 2SLS on the restricted sample in column 5. Again, our inferences remain unchanged.

In panel B, we test the effect of issuing quarterly-only forecasts relative to not forecasting (H4(ii)). Here, FERCs are greater when managers issue quarterly-only forecasts (column 1: $p = 0.0001$) and when quarterly-only forecasts are more frequent (column 2: $p = 0.0001$). Using a restricted sample of firms issuing quarterly-only forecasts, we confirm our findings for H2a and H3a: FERCs are greater when managers issue more quarterly-only forecasts (column 3: $p = 0.0001$ and column 4: $p = 0.0003$) and when quarterly-only forecasts are more precise (column 4: $p = 0.0322$). The results are qualitatively unchanged using 2SLS (columns 5 and 6).

Since some of the quarterly forecasts in our sample are of long-term earnings, we perform more conservative analyses by limiting our restricted sample to short-term quarterly-only forecasts ($n = 2{,}265$); here, we eliminate 70 observations with forecasts for quarters in future fiscal years (that is, long-term quarterly forecasts). Untabulated results reveal that FERCs are greater for firms issuing short-term quarterly-only forecasts ($p = 0.0001$) than for those not issuing forecasts (H4(iii)), and when short-term quarterly-only forecasts are more frequent ($p = 0.0001$). Moreover, within the restricted sample, FERCs are greater when managers issue more frequent short-term quarterly-only forecasts ($p = 0.0002$) and when short-term quarterly-only forecasts are more precise ($p = 0.0315$). Untabulated results using 2SLS are similar ($n = 1{,}942$). Thus these results suggest that even short-term quarterly-only forecasts allow investors to adjust stock prices so that returns reflect future earnings.

4.6 The effect of forecast horizon (long- vs. short-term) on the FERC (H5)

Finally, in Table 6, we perform tests using forecast horizon because concerns expressed by the Chamber of Commerce and others may be directed at short-term quarterly guidance. We estimate the following model:

$$\begin{aligned} R_t = {} & b_0 + b_1 X_{t-1} + b_2 X_t + b_3 X_{t3} + b_4 R_{t3} + c_1 F_{ti} + c_2 F_{ti} * X_{t-1} + c_3 F_{ti} * X_t \\ & + c_4 F_{ti} * X_{t3} + c_5 F_{ti} * R_{t3} + f_1 SIZE_t + f_2 SIZE_t * X_{t3} + f_3 LOSS_t \\ & + f_4 LOSS_t * X_{t3} + f_5 GROWTH_t + f_6 GROWTH_t * X_{t3} + f_7 EARNSTD_t \\ & + f_8 EARNSTD_t * X_{t3} + f_9 NANAL_t + f_{10} NANAL_t * X_{t3} + \varepsilon_t \end{aligned} \tag{7}$$

where:

in column 1, $F_{ti} = DLF_t = 1$ if a forecast for a future fiscal year (or quarter in a future fiscal year) is issued during the fiscal year t, 0 otherwise;

in column 2, $F_{ti} = DCF_t = 1$ if a forecast for the current fiscal year (or quarter in the current fiscal year) is issued during the fiscal year t, 0 otherwise;

in column 3, $F_{ti} = DCF\_ONLY_t$, DLF_ONLY_t, and DCL_JOINT_t, where $DCF\_ONLY_t, = 1$ if only a forecast for the current fiscal year (or quarters in the current fiscal year) is issued during the fiscal year t, 0 otherwise; $DLF\_ONLY_t, = 1$ if only a forecast for a future fiscal year (or quarter in a future fiscal year) is issued during the fiscal year t, 0 otherwise; $DCL\_JOINT_t = 1$ if both a forecast for the current fiscal year (or quarters in the current fiscal year) and a forecast for a future fiscal year (or a quarter in a future fiscal year) are issued during the fiscal year t, and 0 otherwise; and all other variables are as previously defined.

Column 1 of Table 6 supports H5(i)a. The coefficient on $DLF_t{*}X_{t3}$ is positive ($p = 0.0001$), confirming that returns reflect future earnings to a greater extent when managers issue long-term forecasts. Moreover, in column 2, the coefficient on $DCF_t{*}X_{t3}$ is positive ($p = 0.0001$) confirming that returns reflect future earnings to a greater extent when managers issue short-term forecasts.

Since some firms make short- and long-term forecasts, we perform three additional tests. First, we add *DCF_ONLY* and appropriate interaction terms in column 2 (untabulated); the coefficient on $DCF\_ONLY_t{*}X_{t3}$ is positive ($p = 0.0001$). Second, in column 3, we form *DCF_ONLY*, *DLF_ONLY*, and *DCL_JOINT*. Again, the coefficient on $DCF\_ONLY_t{*}X_{t3}$ is positive ($p = 0.0001$). Third, we compare FERCs of firms issuing short-term-only forecasts and those of firms issuing no forecasts, after we eliminate 1,620 observations making any long-term forecasts from the full sample (untabulated). Here, we continue to find that the coefficient on $DCF\_ONLY_t{*}X_{t3}$ is positive ($p = 0.0001$). These tests confirm that returns reflect future earnings to a greater extent even when managers issue only short-term EPS forecasts, supporting H5(ii)a.

When we separate X_{t3} into X_{t+1}, X_{t+2}, and X_{t+3} in column 3 of Table 6, the coefficients on $DCF\_ONLY_t{*}X_{t+1}$ and $DCF\_ONLY_t{*}X_{t+2}$ are positive ($p = 0.0001$ and 0.0001, respectively), but the coefficient on $DCF\_ONLY_t{*}X_{t+3}$ ($p = 0.2690$) is not significant. This suggests that short-term forecasts are more informative about near-term future earnings. However, the coefficient on $DLF\_ONLY_t{*}X_{t+2}$ is marginally significant ($p = 0.0611$), but the coefficients on the other two

Table 6 Regression analyses on the effect of forecast horizon (short-vs. long-term) on the FERC

Variable	Full sample OLS ($n = 18{,}253$)			Restricted sample OLS ($n = 7{,}353$)	Restricted sample 2SLS ($n = 6{,}482$)
	Column 1 $F1 = DLF_t$	Column 2 $F1 = DCF_t$	Column 3 $F1 = DCF\_ONLY_t$ $F2 = DLF\_ONLY_t$ $F3 = DCL\_JOINT_t$	Column 4 $F1 = DCL\_JOINT_t$	Column 5 $F1 = DCL\_JOINT_t$
Intercept	0.2193*** (.0001)	0.2274*** (.0001)	0.2304*** (.0002)	0.1167*** (.0011)	0.0837** (.0356)
X_{t-1}	−0.8646*** (.0001)	−0.7736*** (.0001)	−0.7645*** (.0001)	−1.0054*** (.0001)	−1.1019*** (.0001)
X_t	1.2619*** (.0001)	1.2088*** (.0001)	1.1946*** (.0001)	1.3086*** (.0001)	1.2545*** (.0001)
X_{t3}	0.4340*** (.0001)	0.4033*** (.0001)	0.4116*** (.0001)	1.1256*** (.0001)	1.1392*** (.0001)
R_{t3}	−0.1070*** (.0001)	−0.1143*** (.0001)	−0.1144*** (.0001)	−0.0979*** (.0001)	−0.0693*** (.0001)
$F1$	0.0115 (.5902)	−0.1147*** (.0001)	−0.1208*** (.0001)	0.0614*** (.0034)	0.0519*** (.0002)
$F1 * X_{t-1}$	−0.3837* (.0570)	−0.2529*** (.0025)	−0.2537*** (.0035)	0.0025 (.9902)	−0.1080 (.8527)
$F1 * X_t$	−0.0781 (.7176)	0.1288 (.2465)	0.1701 (.1505)	0.3465 (.1383)	0.2518 (.2180)
$\boldsymbol{F1 * X_{t3}}$	**0.2928*** (.0001)**	**0.3903*** (.0001)**	**0.3889*** (.0001)**	**0.2304** (.0383)**	**0.1738** (.0383)**
$F1 * R_{t3}$	−0.1065*** (.0001)	0.0097 (.1594)	0.0195*** (.0057)	−0.1310*** (.0001)	−0.1508** (.0001)
$F2$			0.0852 (.1687)		
$F2 * X_{t-1}$			−1.0006** (.0402)		
$F2 * X_t$			0.8369 (.1614)		
$\boldsymbol{F2 * X_{t3}}$			**0.1992 (.3306)**		
$F2 * R_{t3}$			−0.0192 (.6923)		
$F3$			−0.0566** (.0146)		
$F3 * X_{t-1}$			−0.3697* (.0937)		
$F3 * X_t$			0.0996 (.6678)		
$\boldsymbol{F3 * X_{t3}}$			**0.5172*** (.0001)**		
$F3 * R_{t3}$			−0.1127*** (.0001)		

Table 6 continued

Variable	Full sample OLS (n = 18,253) Column 1 $F1 = DLF_t$	Column 2 $F1 = DCF_t$	Column 3 $F1 = DCF\_ONLY_t$ $F2 = DLF\_ONLY_t$ $F3 = DCL\_JOINT_t$	Restricted sample OLS (n = 7,353) Column 4 $F1 = DCL\_JOINT_t$	Restricted sample 2SLS (n = 6,482) Column 5 $F1 = DCL\_JOINT_t$
$SIZE_t$	−0.0908*** (.0001)	−0.0883*** (.0001)	−0.0890*** (.0001)	−0.0859*** (.0001)	−0.0907*** (.0001)
$SIZE_t * X_{t3}$	0.1041*** (.0001)	0.0994*** (.0001)	0.0994*** (.0001)	0.0051 (.8227)	−0.0399 (.7208)
$LOSS_t$	−0.2141*** (.0001)	−0.2094*** (.0001)	−0.2091*** (.0001)	−0.1582*** (.0001)	−0.1467*** (.0001)
$LOSS_t * X_{t3}$	−0.9071*** (.0001)	−0.8272*** (.0001)	−0.8319*** (.0001)	−0.5533*** (.0001)	−0.5858*** (.0001)
$GROWTH_t$	0.0011*** (.0001)	0.0011*** (.0001)	0.0011*** (.0001)	0.0018*** (.0001)	0.0018*** (.0001)
$GROWTH_t * X_{t3}$	0.0003*** (.0001)	0.0004*** (.0001)	0.0004*** (.0001)	0.0001*** (.0001)	0.0004** (.0021)
$EARNSTD_t$	2.2012*** (.0001)	2.2644*** (.0001)	2.2561*** (.0001)	2.5554*** (.0001)	2.7062*** (.0001)
$EARNSTD_t * X_{t3}$	−0.7161*** (.0001)	−0.8046*** (.0001)	−0.8326*** (.0001)	−1.6368*** (.0001)	−1.9448*** (.0001)
$NANAL_t$	0.1795*** (.0001)	0.1932*** (.0001)	0.1930*** (.0001)	0.1547*** (.0001)	0.1604*** (.0001)
$NANAL_t * X_{t3}$	0.2325*** (.0001)	0.2796*** (.0001)	0.2782*** (.0001)	0.0147 (.7524)	−0.0716 (.8887)
Adjusted R^2	0.2614	0.2676	0.2693	0.3396	0.3518

When estimating the coefficient standard errors, we use White's (1980) method to correct for heteroskedasticity as well as a clustering procedure that accounts for serial dependence across years for a given firm (Petersen 2009). Two-tailed p-values are presented in the parentheses. *, **, and *** denote p-values <10, 5, and 1%, respectively. $DLF_t = 1$ if a management EPS forecast for a future fiscal year (or for quarters in future fiscal year) is issued during fiscal year t, 0 otherwise; $DCF_t = 1$ if a management EPS forecast for the current fiscal year t (or for quarters in fiscal year t) is issued during fiscal year t, 0 otherwise; $DLF\_ONLY = 1$ if only a management EPS forecast for a future fiscal year (or for quarters in future fiscal year) is issued during fiscal year t, 0 otherwise, (so if $DCF = 0$ and $DLF = 1$, then $DLF\_ONLY = 1$); $DCF\_ONLY_t = 1$ if only a management EPS forecast for the current fiscal year t (or for quarters in fiscal year t) is issued during fiscal year t, 0 otherwise, (so if $DCF = 1$ and $DLF = 0$, then $DCF\_ONLY = 1$); $DCL\_JOINT_t = 1$ if both a management EPS forecast for the current fiscal year (or for quarters in the current fiscal year) and a management EPS forecast for a future fiscal year (or for a quarter in the future fiscal year) are issued during fiscal year t and 0 otherwise; and DCL_JOINT_t in 2SLS (column 5) is the fitted value from the first-stage regressions in appendix. The sample size in 2SLS is smaller due to additional data requirements for the first-stage regressions. See Table 2, panel A, for definitions of the other variables interactions with DLF_ONLY_t (that is, $DLF\_ONLY_t*X_{t+1}$ and $DLF\_ONLY_t*X_{t+3}$) are not significant.[30] Finally, columns 4 (OLS results) and 5 (2SLS results) suggest that issuing both short and long-term forecasts provides more information than issuing either only short-term or long-term forecasts.

Finally, we perform additional analyses regarding the effect of the number and precision of forecasts within a restricted sample of short-term-only forecasts ($n = 5{,}733$) by eliminating 1,620 observations with any long-term forecasts from the previous restricted sample. Untabulated results reveal that FERCs are greater when managers issue more frequent short-term-only forecasts ($p = 0.0001$) and when short-term-only forecasts are more precise ($p = 0.0155$). Untabulated results using 2SLS are similar ($n = 4{,}978$). Thus, our inferences regarding H2a and H3a do not change when we consider the number and precision of short-term-only forecasts.

4.7 Other robustness checks

We perform additional sensitivity analyses to check the robustness of our results. First, in our main analyses, we interact our control variables with X_{t3} and with the intercept following Orpurt and Zang (2009) and Tucker and Zarowin (2006). Other studies (for example, Ettredge et al. 2005) interact each of the control variables with all X_ts and with R_{t3}. Untabulated results remain unchanged when we add these interactions.

Second, since the percentage of firms issuing forecasts and forecast characteristics can vary over time and industry, the effects of industry and year could bias our results. To address this, following Tucker and Zarowin (2006), we convert all continuous control variables (that is, *SIZE, GROWTH, EARNSTD, NANAL*) into fractional rankings within their (two-digit SIC code) industry-years. Untabulated results remain unchanged. Next, we include year and industry indicators in the first-stage Heckman model and 2SLS regressions, and we alternatively include year and industry indicators in the pooled OLS and all second-stage regressions. Again, our untabulated results remain unchanged.

Lastly, we conduct Fama and MacBeth (1973)-type tests on our main OLS regressions by first running annual regressions and estimating coefficients and then calculating the mean and *t*-statistics over time. Although there are only 6 years in our sample period, our main results remain robust.

5 Conclusion

In this study, we examine whether management EPS forecasts and their characteristics are associated with the ability of returns to reflect future earning news. We posit that information in these forecasts will affect the association

[30] This lack of significance may be due to low power resulting from a small number of observations with only long-term forecasts. Among our 7,353 restricted sample observations, 131 issue long-term-only forecasts while 5,733 (1,489) observations issued short-term-only forecasts (both short- and long-term forecasts). Another possibility is that long-term forecasts are perceived as less credible when short-term forecasts are not provided.

between returns and future earnings if the forecasts are more accurate than are extant expectations and if investors view these forecasts as credible. We posit that forecast characteristics should be important in revising investor expectations since more frequent, more precise, and longer-term (or more timely) forecasts may increase credibility and allow investors to form more accurate expectations of future earnings.

Our analyses reveal that FERCs are greater for firms issuing (1) forecasts, (2) more frequent forecasts, and (3) more precise forecasts. FERCs are also greater for firms issuing annual or quarterly forecasts, even when the forecast horizon is short. In addition, FERCs are greater for firms issuing short-term forecasts than for nonforecasting firms even when they forecast only quarterly EPS (that is, when they provide short-term "earnings guidance"). Finally, FERCs are greater for firms issuing both long- and short-term forecasts than for firms that issue only short-term forecasts or no forecasts.

Our findings have implications for managers, investors, and regulators by confirming that managers can influence investors' ability to predict future earnings by providing forecasts that are longer-term, more frequent, and more precise. This is especially important in situations where managers want to decrease information asymmetry and mispricing of their firms' stocks. While recent calls for the elimination of quarterly earnings guidance suggest that this guidance has detrimental effects, our findings indicate that even short-term quarterly EPS forecasts help investors to form better expectations about future earnings. To the extent that regulators believe that investors' ability to anticipate future earnings is valuable for efficient resource allocation, this study implies that the discontinuation of quarterly guidance will be harmful.

We acknowledge some limitations of this study. First, while the issuance and characteristics of management forecasts are endogenous in our models, we cannot be sure that we have controlled for all sources of endogeneity. Second, our analyses focus on the benefits of earnings guidance, and we do not provide a measurement of the associated costs. Anecdotal evidence suggests that these costs can include increased pressure to manage earnings to meet earnings forecasts, as well as costs of preparing and revising these forecasts, and neglect of long-term growth opportunities. Since we do not measure *net* benefits of quarterly guidance, we make no assertions as to whether the continuation of quarterly guidance is socially beneficial. We hope that future research can shed light on this issue.

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Appendix

First-stage models for Heckman self-selection and 2SLS models

Following prior studies (for example, Ajinkya et al. 2005; Chen et al. 2008; Karamanou and Vafeas 2005), we model management's decision to issue EPS forecasts using the following probit model:

$$\begin{aligned} DF_t = {} & d_0 + d_1 INST_t + d_2 BDIND_t + d_3 D\_CAP_t + d_4 DISP_t + d_5 BETA_t + d_6 LIT_t \\ & + d_7 ROA_t + d_8 SIZE_t + d_9 LOSS_t + d_{10} GROWTH_t + d_{11} EARNSTD_t \\ & + d_{12} NANAL_t + Year\ Dummies + Industry\ Dummies + \varepsilon_t \end{aligned} \quad (8)$$

where for year t, all variables are previously defined.

We add a number of variables to the model based on prior literature. Ajinkya et al. (2005) and Karamanou and Vafeas (2005) find that institutional ownership ($INST_t$) and board independence ($BDIND_t$) are positively associated with the likelihood of management forecasts.[31] Frankel et al. (1995) find that firms raising significant amounts of external capital (D_CAP_t) voluntarily disclose more information. Ajinkya and Gift (1984) and Miller (2002) find that firms with greater analyst following ($NANAL_t$) and greater information asymmetry ($DISP_t$ and $EARNSTD_t$) are more likely to issue voluntary disclosures. Alternatively, $DISP_t$ and $EARNSTD_t$ can proxy for uncertainties or difficulties that managers face in generating EPS forecasts. Skinner (1994) finds that firms in high litigation risk industries (LIT_t) are more likely to voluntarily disclose bad news. Miller (2002) finds that contemporaneous firm performance ROA_t and $LOSS_t$ (proxied by ROA_t and $LOSS_t$) affect voluntary disclosure. Equity beta ($BETA$), the log of total assets ($SIZE_t$), and growth in total assts ($GROWTH_t$) control for market risk, size, and firm growth, respectively. Finally, we include year and (two-digit SIC code) industry indicators to control for differences in EPS forecasts over time and across industries.

Once a manager decides to issue a forecast, frequency, precision, and whether to issue both annual and quarterly forecasts (or whether to issue both short- and long-term forecasts) may be endogenous.[32] Thus, we employ 2SLS using the following first-stage regressions:

[31] We obtain board independence ($BDIND_t$) data from the Board Analytics and Investor Responsibility Research Center (IRRC) databases. This data item is missing for 4,973 of 13,420 sample observations. Due to a large number of missing data observations, we use the 'modified zero-order regression' method suggested by Maddala (1977) and Greene (2003), which substitutes a zero for missing values and adds an indicator variable coded 1 if the corresponding variable is missing. That is, we set $BDIND_t$ to zero if it is missing and set $MISSING_t$ to 1 if $BDIND_t$ is set to zero because it is missing, and we set $MISSING_t$ to zero if $BDIND_t$ is not missing. Our main results are qualitatively unchanged if we exclude observations missing data, but we tabulate the results with modified zero-order regressions because this method requires fewer assumptions about the missing values.

[32] When we perform the Hausman (1978) test for endogeneity for each model in our restricted samples, we find that endogeneity is significant only when both forecast frequency and precision are jointly included in the model (as in column 3 in Table 4 ($p = 0.0251$)). Although we find endogeneity for only this specification of the models, to enhance comparability, we employ 2SLS procedures for all restricted sample models.

Table 7 First-stage Models for Heckman and Two-stage Least-squares (2SLS) Estimation

Variable	First-stage of Heckman Full Sample ($n = 13{,}420$)	First-stage of 2SLS Restricted sample ($n = 6{,}482$)			
	Column 1 *Dep. Var.* = DF_t	Column 2 *Dep. Var.* = LNF_t	Column 3 *Dep. Var.* = $PREC_t$	Column 4 *Dep. Var.* = DQA_JOINT_t	Column 5 *Dep. Var.* = DCL_JOINT_t
Intercept	−0.9174*** (.0001)	0.7259*** (.0001)	2.7428*** (.0035)	0.2273** (.0201)	0.0869 (.2821)
$INST_t$	0.3925*** (.0001)	0.1553*** (.0001)	0.1489*** (.0061)	0.1455*** (.0013)	0.0957*** (.0007)
$BDIND_t$	0.5215*** (.0001)	0.0659** (.0311)	0.1209** (.0411)	0.0046* (.0899)	0.0133* (.0516)
D_CAP_t	0.0266*** (.0014)	0.0374*** (.0073)	0.0194** (.0342)	0.0232** (.0258)	0.0573*** (.0001)
$DISP_t$	−0.3382*** (.0001)	−0.0787* (.0521)	−0.1388** (.0172)	0.0114 (.7549)	−0.0126 (.6782)
$BETA_t$	−0.0228 (.3749)	−0.0638*** (.0001)	−0.0451** (.0350)	−0.0640*** (.0001)	−0.0692*** (.0001)
LIT_t	−0.0189 (.6851)	0.1169*** (.0001)	−0.0166 (.6466)	0.0529** (.0200)	0.0359** (.0485)
ROA_t	0.4833*** (.0001)	0.1174*** (.1354)	0.0258 (.8192)	−0.0277 (.6958)	−0.0876 (.1347)
$SIZE_t$	−0.0111 (.3130)	0.0564*** (.0001)	−0.0388*** (.0005)	0.0266*** (.0001)	0.0166*** (.0015)
$LOSS_t$	−0.0528 (.1288)	0.0028 (.8962)	−0.1151*** (.0002)	−0.0235 (.2250)	0.0244 (.1285)
$GROWTH_t$	−0.0012*** (.0001)	−0.0001 (.2026)	0.0002 (.2065)	0.0001 (.2272)	0.0002*** (.0030)
$EARNSTD_t$	0.5621*** (.0043)	0.1857 (.1304)	−0.4598*** (.0092)	−0.1335 (.2288)	0.0471 (.6076)
$NANAL_t$	0.4238*** (.0001)	0.0612*** (.0005)	0.0763*** (.0025)	0.0246** (.0198)	0.0363*** (.0056)
$HORIZON_t$			0.0007*** (.0001)		
X_{t-1}		0.1799*** (.0077)	0.0770 (.4274)	0.0525 (.3891)	0.0304 (.5470)
X_t		0.3111*** (.0045)	−0.1438 (.3608)	0.2698*** (.0064)	0.2911*** (.0004)
X_{t3}		0.0237 (.4542)	0.0739 (.1047)	−0.0438 (.1261)	0.0693*** (.0034)
R_{t3}		0.0009 (.8844)	−0.0091 (.3246)	0.0091* (.0973)	−0.0031 (.5207)

Table 7 continued

Variable	First-stage of Heckman Full Sample (n = 13,420)	First-stage of 2SLS Restricted sample (n = 6,482)			
	Column 1 *Dep. Var.* = DF_t	Column 2 *Dep. Var.* = LNF_t	Column 3 *Dep. Var.* = $PREC_t$	Column 4 *Dep. Var.* = DQA_JOINT_t	Column 5 *Dep. Var.* = DCL_JOINT_t
Year and industry dummies	Included	Included	Included	Included	Included
Likelihood ratio score (Pr > χ^2)	2,759.47 (.0001)				
Adjusted R^2		0.2406	0.1056	0.1355	0.1407

The first-stage Heckman model is estimated using a probit regression, and the first-stage 2SLS models are estimated using OLS regressions. When estimating the coefficient standard errors, we use White's (1980) method to correct for heteroskedasticity as well as a clustering procedure that accounts for serial dependence across years for a given firm (Petersen 2009)

Two-tailed p-values are presented in the parentheses. *, **, and *** denote p-values <10, 5, and 1%, respectively. Continuous variables with values falling into the extreme top and bottom percentiles of their respective distributions are winsorized. The sample size is reduced (for the full sample from 18,253 to 13,420 observations and for the restricted sample from 7,353 to 6,482 observations) due to additional data requirements

$INST_t$ = the percentage of institutional ownership at the beginning of fiscal year t; $BDIND_t$ = the percentage of board independence at the beginning of fiscal year t; as in the prior research, independent directors refer to those who are not corporate executives and have no business relationship with the firm; D_CAP_t = 1 if the sum of debt or equity issued during the year t is greater than 5% of total assets and 0 otherwise; $DISP_t$ = analyst forecast dispersion in year t, measured as the standard deviation of 1-year-ahead EPS forecasts, scaled by the absolute mean forecast; we use the most recent consensus forecast before the end of year t; $BETA_t$ = equity beta for fiscal year t; LIT_t = 1 for firms in high litigation risk industries (SIC codes 2833-2836, 3570-3577, 7370-7374, 3600-3674, 5200-5961, 8731-8734) and 0 otherwise; ROA_t = return on assets for fiscal year t; and $HORIZON_t$ = the average forecast horizon (i.e., the number of days between the forecast dates and the fiscal period-end dates) in fiscal year t; DCL_JOINT_t = 1 if a (quarterly or annual) short-term forecast *and* a (quarterly or annual) long-term forecast are issued during fiscal year t, 0 otherwise; and all other variables as defined in Table 2, panel A

$$
\begin{aligned}
LNF_t, DQA\_JOINT_t \text{ or } DCL\_JOINT_t = {} & d_0 + d_1 INST_t + d_2 BDIND_t + d_3 D\_CAP_t \\
& + d_4 DISP_t + d_5 BETA_t + d_6 LIT_t + d_7 ROA_t + d_8 SIZE_t + d_9 LOSS_t + d_{10} GROWTH_t \\
& + d_{11} EARNSTD_t + d_{12} NANAL_t + d_{13} X_{t-1} + d_{14} X_t + d_{15} X_{t3} + d_{16} R_{t3} \\
& + Year\,Dummies + Industry\,Dummies + \varepsilon_t
\end{aligned}
\tag{9}
$$

$$
\begin{aligned}
PREC_t = {} & d_0 + d_1 INST_t + d_2 BDIND_t + d_3 D\_CAP_t + d_4 DISP_t + d_5 BETA_t \\
& + d_6 LIT_t + d_7 ROA_t + d_8 SIZE_t + d_9 LOSS_t + d_{10} GROWTH_t + d_{11} EARNSTD_t \\
& + d_{12} NANAL_t + d_{13} HORIZON_t + d_{14} X_{t-1} + d_{15} X_t + d_{16} X_{t3} + d_{17} R_{t3} \\
& + Year\,Dummies + Industry\,Dummies + \varepsilon_t
\end{aligned}
\tag{10}
$$

where for year t:

$HORIZON_t$ = the average forecast horizon (that is, the number of days between the forecast dates and the fiscal period-end dates) in fiscal year t; and all other variables are as previously defined.

For the forecast frequency (LNF_t) and precisions ($PREC_t$) models, we include all independent variables used in the Heckman first-stage model. We add average forecast horizon ($HORIZON_t$) to the precision model, following the forecast frequency and specificity models in Ajinkya et al. (2005, 356). Ajinkya et al. (2005) find that institutional ownership ($INST_t$), board independence ($BDIND_t$), or both are positively associated with management forecast frequency and precision. We also include all of the variables used in the second-stage equation as suggested by Larcker and Rusticus (2008).

The results of the first-stage estimation, provided in Table 7, are largely consistent with prior studies. Institutional ownership ($INST_t$), board independence ($BDIND_t$), and an indicator variable for external financing (D_CAP_t) are positively associated with the dependent variables in most regressions. We also find that the partial F-statistics for the instruments used in the first-stage 2SLS models are more significant than the benchmarks in Stock et al. (2002), which suggests that these models are unlikely to be subject to weak instrument problems.

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