# The analyst decision to issue revenue forecasts: do firm reporting quality and analyst skill matter?

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**Abstract** This study documents that analysts are more likely to issue revenue forecasts to complement earnings-per-share (EPS) estimates when the quality of firm financial reporting is low. This is because, compared to EPS forecast accuracy, revenue forecast accuracy is less adversely affected by poor reporting quality. Consequently, investors rely more on revenue than EPS estimates in their investment decisions, when the reporting quality is low. The result is robust to using five proxies for the quality of firm financial reporting: the variation in discretionary accruals, the absolute level of discretionary accruals, earnings persistence, absolute total accruals, and earnings volatility. Further, we document that better earnings forecasters are more likely to issue revenue estimates. This is because only more skilled analysts would want their forecasts to be subject to higher market scrutiny, and because a combination of accurate revenue and EPS forecasts is a stronger signal of the analyst forecasting skill compared to an accurate stand-alone EPS estimate.

**Keywords** analyst EPS forecasts · complementary revenue forecasts · financial reporting quality · analyst forecasting skill

**JEL Classification** M41 · N20

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## 1 Introduction

Over the past decade analysts have increasingly supplemented their earnings forecasts with estimates of other accounting numbers, such as revenue.[1] Yet we know little about what determines the analyst choice to issue revenue forecasts to complement earnings-per-share (EPS) estimates. This study examines if the firm financial reporting quality[2] and analyst forecasting skill influence the analyst decision to issue a revenue forecast. We propose that an analyst will provide a revenue forecast to complement the EPS estimate when firm reporting quality is poor. This is because revenue forecast accuracy is less adversely affected by poor reporting quality, compared to EPS forecast precision. As a result, investors rely more on revenue than EPS estimates in their investment decisions when the reporting quality is low. Further, we propose that better earnings forecasters use revenue estimates to signal their forecasting skill. This is because only more skilled analysts would want their forecasts to be subject to higher market scrutiny, and because a combination of accurate revenue and EPS forecasts is a stronger signal of analyst forecasting skill compared to an accurate stand-alone EPS estimate.

To examine the two predictions, we look at all one-year-ahead EPS estimates and the accompanying revenue forecasts for US firms over the fiscal years 2000–2008. We find that of the 539,437 individual analyst EPS forecasts reported on IBES, 50.3% are supplemented by revenue estimates, and that the proportion of revenue estimates to complement EPS forecasts increases from 11.8% in 2000 to 68.7% in 2008. This confirms that revenue forecasts have become increasingly common over the past decade.

We follow previous literature (e.g. Johnson et al. 2002; Francis et al. 2005; Elliott et al. 2010) and use the variation in discretionary accruals and the absolute level of discretionary accruals as our main firm reporting quality measures. We document that compared to stand-

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[1] We document that one in two EPS forecasts in our sample includes a complementary revenue forecast.

[2] We follow the FASB Statement of Financial Accounting Concepts and define firm financial reporting quality as the ability of the firm's financial statements to provide accurate information on firm operations and cash flows that is valuable to investors in making rational investment decisions. We discuss further the concept of firm financial reporting quality in Section 2.

alone EPS forecasts, the variation in (the magnitude of) discretionary accruals is 21% (7.3%) higher when analysts issue revenue forecasts. Multivariate logistic regressions confirm that analysts' propensity to issue revenue forecasts increases with the variation in discretionary accruals and with the magnitude of absolute discretionary accruals. The result is both statistically and economically significant, and is consistent with the prediction that investors demand revenue forecasts when the quality of a firm's financial reporting is low. Our conclusions remain robust when we use alternative measures of reporting quality, namely earnings persistence, absolute value of total accruals, and earnings volatility.

Analysts who issue more accurate EPS forecasts are more likely to produce a revenue estimate, which is consistent with more skilled analysts signaling their ability through the issue of revenue estimates. The result remains unchanged when we use alternative measures of analyst forecasting skill, namely the analyst relative EPS forecast accuracy (i.e. the accuracy of an analyst's EPS forecast relative to the accuracy of EPS forecasts by other analysts following a firm), and analyst past forecast accuracy. The finding that revenue forecasts serve to signal analyst forecasting skill complements the result in Ertimur et al. (2011), who report that analysts without established reputations are more likely to produce a revenue forecast; once an analyst has established a reputation, revenue forecasts expose the analyst to additional market scrutiny and risk of reputation loss, which reduces the analyst propensity to issue revenue forecasts.

Sensitivity analysis shows that our conclusions remain robust for annual regressions, which examine if the results are not confined to a specific sub-period, and when we use the Fama–MacBeth approach and random sample selection as alternative ways to control for inflated *t*-statistics due to the cross-sectional correlation of observations (all our regressions use dual clustering on firm and analyst). To confirm that our results are not driven by the potential recursive effect that a revenue forecast issue may have on a firm propensity to manage accruals, we repeat the analysis using only initiations of revenue forecasts for a firm. This is because a revenue estimate may aid investors in identifying firms that engage in revenue management to boost firm net income, e.g. through discount sales close to the end of the fiscal year (Roychowdhury 2006). The higher cost of revenue management in the presence of revenue forecasts may incentivize managers to substitute revenue management for accruals management. This could explain why analysts are more likely to produce a revenue forecast when the reporting quality is low. We find that the firm reporting quality and analyst forecasting skill also influence the analyst decision to start issuing revenue forecasts, which corroborates our main results.

We conjecture that investors demand revenue forecasts because revenue forecast accuracy is less adversely affected by poor reporting quality, compared to EPS forecast precision. As a result, when the reporting quality is poor, Bayesian investors rely more on the estimates of earnings' components (i.e. revenue) than on earnings themselves in their investment decisions. Consistent with this prediction, we show that low reporting quality increases the EPS forecast error, but does not affect revenue forecast accuracy. Further, we document that the price reaction to EPS forecast revisions is lower for firms with poor reporting quality; however, the price reaction to revenue forecast revisions is unaffected by reporting quality. This confirms that when reporting quality is low, investors attach lower weight to EPS forecast revisions in their investment decisions, but continue to rely on revenue estimates.

This paper contributes to the literature in three ways. First, we add to the fledgling literature that examines the analyst choice to issue forecasts of other accounting measures, such as revenue, to complement EPS estimates. To date, only Ertimur et al. (2011) and Marks (2007) have examined the determinants of the analyst decision to provide revenue forecasts, with both papers investigating if analyst reputation explains the decision to produce revenue forecasts. Our results suggest that analysts rationally respond to investor demand and produce revenue forecasts, when the complementary forecast is most useful to investors, i.e. when firm reporting quality is poor. Further, we show that controlling for analyst reputation[3], analyst EPS forecasting

[3] Analyst reputation is commonly measured from analyst rankings. However, press articles and previous studies report that analyst rankings by the Institutional Investor magazine and The Wall Street Journal do not aid investors in identifying better earnings forecasts (Dorfman 1988; Kessler 2001; and Emery and Li 2009). For example, Emery

skill is a strong predictor of the decision to issue a complementary revenue estimate. The latter result is particularly valuable to investors, as it can help them identify accurate EPS forecasts issued by more skilled analysts. This in return should improve investors' capital allocation decisions.

Second, we add important evidence to studies on the capital markets effects of issuing revenue estimates to accompany EPS forecasts. Our findings explain the results in Ertimur et al. (2011) and Keung (2010) that (1) EPS forecast revisions accompanied by revenue forecasts have a greater price impact than stand-alone EPS forecast revisions, and that (2) supplemented EPS estimates are more accurate ex post. These findings are not surprising since we document that revenue forecasts are issued by analysts with higher forecasting skill, and because investors rely on (relatively more accurate) revenue than earnings estimates in their investment decisions, when the quality of firm reporting is poor. Future studies on the capital market effects of revenue forecasts need to control for the endogeneity in the analyst decision to produce this estimate.

Third, our finding that the quality of financial reporting influences the analyst decision to produce a supplementary revenue forecast adds valuable new evidence on the capital market effects of firm disclosure (Healy and Palepu 2001; Dechow et al. 2010), and on the interaction between firm disclosure and information provision by analysts (Barth et al., 2001; Francis et al. 2002; Frankel et al. 2006; Beyer et al, 2010). Further, the finding that analysts issue complementary revenue forecasts to mitigate the adverse effect that poor reporting quality has on the accuracy and value-relevance of EPS estimates, adds important evidence to the literature on the role that financial analysts play in capital markets (Ivkovic and Jegadeesh 2004; Asquith et al. 2005; Ramnath et al. 2008; Chen et al. 2010).

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and Li (2009) document that analyst EPS forecast accuracy does not predict star analyst status from the Wall Street Journal ranking, and from the Institutional Investor magazine ranking when controlling for the analyst previous year ranking. Further, Bagnoli et al. (2008) report that EPS forecast accuracy ranks among the least important factors influencing the voting for Institutional Investor star analysts. Investors seem to recognize that popular analyst rankings are poor at identifying top EPS forecasters and react equally to EPS forecast revisions by star and non-star analysts (Gleason and Lee 2003).

The rest of the paper is organized as follows. Section 2 reviews the previous literature and develops our empirical hypotheses. Section 3 presents the research design and we describe the data in Section 4. The empirical results are presented in Section 5 and robustness tests are discussed in Section 6. Section 7 examines the relation between reporting quality and the accuracy and price impact of analyst EPS and revenue forecasts. We conclude in Section 8.

## 2 Previous literature and hypotheses development

Earnings are considered a better aggregate indicator of firm periodic performance than other accounting numbers, such as revenue (Hopwood and McKeown 1985; Hoskin et al. 1986; Easton et al. 1992; Beyer et al. 2010). However, poor financial reporting quality reduces reliability and usefulness of earnings as a firm performance measure and a predictor of future earnings (Dechow et al. 2010). As a result, the quality of firm financial reporting is likely to influence investor demand for revenue forecasts to complement earnings estimates.

Revenue numbers are valuable to investors as they facilitate earnings decomposition into its two main drivers, sales revenue and (after-tax) profit margin. Consistent with this rationale, Ertimur et al. (2003) and Jegadeesh and Livnat (2006) report higher market reactions to revenue than earnings surprises, and Ghosh et al. (2005) report that investors rely more on growth in revenue than in earnings when valuing firms that exhibit continuous increases in both earnings and revenue. This is because revenue increases are more persistent than reductions in expenses.

Research on what explains analyst choice to issue revenue forecasts is limited. Ertimur et al. (2011) show that controlling for analyst ability to understand the firm's earnings generating process[4], analyst reputation explains the decision to produce revenue forecasts. They find that analysts without established reputations are more likely to produce a revenue forecast. For

[4] Ertimur et al. (2011, 39) measure analyst ability as "the extent to which forecasts from a given analyst move the outstanding consensus toward actual earnings", which may not distinguish between the analyst EPS forecasting skill and other determinants of the analyst influence on the consensus forecast. Intuitively, the reputation of the analyst's brokerage house and analyst forecasting experience are likely to be more important in moving the consensus than the analyst forecasting skill.

established analysts, revenue forecasts expose them to additional market scrutiny and risk of reputation loss, which reduces their propensity to issue revenue forecasts. Further, using a sample of less reputable analysts only, they find that analysts who issue revenue estimates are more likely to be promoted to a more prestigious broker, and that EPS forecast revisions accompanied by revenue forecasts have a stronger price reaction. Marks (2007) provide evidence consistent with Ertimur et al. (2011).

This study proposes that investors demand revenue forecasts when the quality of firm financial reporting is low. This is because revenue forecast accuracy should be less adversely affected by poor reporting quality compared to EPS forecasts precision. As a result, investors would rely more on revenue than EPS estimates in their investment decisions when the reporting quality is low. Therefore, out first hypothesis is:

**H1** Analysts are more likely to issue revenue forecasts for firms with low quality financial reporting.

Further, we propose that controlling for analyst reputation, better earnings forecasters are more likely to issue revenue forecasts. This is because only more skilled analysts would want their forecasts to be subject to higher market scrutiny, and because a combination of accurate revenue and EPS forecasts is a stronger signal of the analyst forecasting skill compared to an accurate stand-alone EPS estimate only. In other words, a precise EPS forecast that is accompanied by an inaccurate revenue forecast signals that analyst EPS accuracy is due to luck rather than innate forecasting skill. As a result, poor EPS forecasters will be unwilling to issue revenue forecasts as they risk revealing their type to investors, which can lead to reputation loss that can have a direct effect on analyst career outcomes (Hong and Kubik 2003; Leone and Wu 2007). Consequently, the issue of revenue forecasts forms a credible signal that distinguishes better earnings forecasters from competing analysts. Thus our second hypothesis is:

**H2** Better earnings forecasters are more likely to issue revenue forecasts.

## 3 Measures of firm financial reporting quality and research design

In defining the quality of firm financial reporting, we build on the FASB Statement of Financial Accounting concepts no 1., which states that the objective of financial reporting is to "provide information that is useful to present and potential investors and creditors and other users in making rational investment, credit and similar decisions", that the information needs to be "comprehensible" to investors, and that it should help "present and potential investors in assessing the amount, timing, and uncertainty of prospective cash receipts".[5]

To measure firm financial reporting quality, we use the variation in discretionary accruals and the magnitude of discretionary accruals.[6] The two proxies measure the characteristics of firm disclosure that FASB associates with reporting quality. Further, the two measures reflect that managers can use discretionary accruals either to reduce accruals volatility, improving the quality of earnings as a measure of firm current and future performance[7], or they can use discretionary accruals to manage earnings (Dechow et al. 1995; Dechow and Dichev 2002; McNichols 2002; Dechow et al. 2003), which lowers informativeness of current earnings about firm current and future performance.

We use the predicted values from the McNichols' (2002) extension of the Dechow and Dichev (2002) accruals model to capture non-discretionary (normal) accruals originating from company operations. The model's residuals represent discretionary (abnormal) accruals, which are subject to managerial discretion and capture financial reporting quality. The accruals model takes the form

[5] The recent review of earnings quality literature by Dechow et al. (2010) also uses FASB Statement of Financial Accounting concepts no 1. to define earnings quality.
[6] For an in-depth discussion of earnings quality proxies, we refer the reader to a number of comprehensive review papers including Dechow et al. (2010), Francis et al. (2006), Lo (2008), Dechow and Schrand (2004), Imhoff (2003), Penman (2003), Nelson et al. (2003), Schipper and Vincent (2003).
[7] Low variation in discretionary accruals and low magnitude of discretionary accruals means that current earnings are more informative about future cash flow, which makes current earnings more useful to investors in firm valuation and investment decisions.

$$CA_{it} = \beta_0 + \beta_1 CFO_{it-1} + \beta_2 CFO_{it} + \beta_3 CFO_{it+1} + \beta_4 \Delta SAL_{it} + \beta_5 PPE_{it} + u_{it} \quad (1)$$

where $CA_{it}$ stands for current accruals for firm *i* in year *t*, defined as the change in current assets, less change in cash, less change in current liabilities plus the change in debt in current liabilities. *CFO* is cash flow from operations and equals net income before extraordinary items less current accruals. Both $CA_{it}$ and the three *CFO* variables are scaled by average total assets for the current and previous fiscal year and on their own form the Dechow and Dichev (2002) model. McNichols' (2002) extension of the Dechow and Dichev (2002) model includes in the accruals model the gross value of property plan and equipment, *PPE*, and changes in firm sales, $\Delta SAL$, both scaled by average assets. Including *PPE* and $\Delta SAL$ decreases the measurement error and improves the model's explanatory power (McNichols 2002; Francis et al. 2005).

The model residuals, $u_{it}$, measure firm discretionary accounting accruals. The current period accruals quality is the standard deviation of firm residuals for years $t-3$ to $t$, $CAQ$=STD($u_{it}$). Large variation in discretionary accruals means poor mapping of accruals into cash flows, which suggests poor current accruals quality. We also use absolute value of discretionary accruals, $|D\ ACC|$, as an alternative measure of reporting quality. Following Francis et al. (2005), we estimate both models annually for each 2-digit SIC industry with a minimum of 20 firms.[8] Table 1 provides detailed definitions of variables in model (1) and of other variables used in the study.

Consistent with the previous literature, we use analyst individual absolute EPS forecast error ($|FE|$) to capture analyst forecasting skill (Clement 1999; Hong et al. 2000; Dechow et al. 2000; Park and Stice 2000). Accurate EPS forecasts indicate higher forecasting skill and better EPS forecasters should be more likely to issue revenue forecasts to signal their quality. In robustness tests, we also use analyst relative forecasts accuracy, i.e. accuracy of analyst EPS

[8] We also used the modified Jones model (Dechow et al. 1995) and the Dechow and Dichev (2002) model to estimate the variation in and the magnitude of firm discretionary accruals. The results are qualitatively the same using the discretionary accruals measures from these models.

estimates relative to the accuracy of all EPS forecasts issued for the firm in a fiscal year, and analyst past EPS accuracy.

## 3.1. Research design

We use a logit model to predict the analyst choice to include a revenue forecast with the EPS estimate. Our main explanatory variables are the firm financial reporting quality and the analyst forecasting skill. We split control variables into (1) analyst- and broker-related characteristic, and (2) firm characteristics.

### *3.1.1 Analyst and broker characteristics*

EPS forecasts issued early in the fiscal year are more valuable to investors (Clement and Tse 2003) but are less likely to be accurate (Sinha et al. 1997). To increase credibility of EPS estimates issued early in the fiscal year, analysts can complement them with revenue estimates. We measure forecast timeliness as the number of days between the EPS forecast announcement and the fiscal year-end (*Horizon*). We use analyst general (*Gexp*) experience and the size of the analyst's broker firm (*Bsize*), to capture analyst's reputation. Less experienced analysts and analysts from smaller brokers may want to issue revenue forecasts to differentiate themselves from the competing analysts; once an analyst has established a reputation, revenue forecasts expose the analyst to additional market scrutiny and risk of reputation loss, which reduces the analyst propensity to issue revenue forecasts (Marks 2007, Ertimur et al. 2011). The number of firms an analyst follows (*A_#Firm*) proxies for task complexity. Actively following and producing research reports on more companies is likely to discourage the analyst from devoting time to produce a complementary forecast. Forecast horizon, analyst and broker characteristics are measured at the time of the EPS forecast issue.

*3.1.2 Firm characteristics*

We include firm market capitalization (*MV*) and the number of analysts following a company (*Follow*) to capture the quality of the firm's information environment. Better quality information environment reduces the cost of producing a complementary forecast, which should increase the likelihood an analyst will issue complementary revenue forecast.

The coefficient of stock price variation (*COV*) measures stock price variability. High price volatility means that the analyst faces a more challenging task forecasting earnings, which is likely to reduce the analyst propensity to include a complementary revenue forecast. Further, analysts will face higher difficulty forecasting revenue when firm sales vary strongly across years, which is likely to reduce analyst propensity to issue revenue forecasts. However, high stock price and revenue volatility may also increase investor demand for a complementary revenue forecast that can help investors in assessing firm performance. We use the standard deviation in firm revenues for the previous four fiscal years (*STD REV*) to capture the revenue uncertainty.

We use the book-to-market ratio (*B/M*) to measure the firm growth opportunities. We include firm age (*Age*) as analysts are more likely to produce revenue estimates for younger firms (Ertimur et al. 2011). Investors are more likely to demand revenue estimates for loss making firms and for less profitable firms where firm earnings may not be representative of firm value (Burgstahler and Dichev 1997; Collins et al. 1997). We use a dummy variable (*Dloss*) to indicate loss-making firms and return on assets (*ROA*) to capture firm profitability. Further, investors are more likely to demand revenue forecasts for firms with high operating leverage. This is because a one percentage increase in revenue has a stronger effect on firm net income for firms with high compared to low ratios of fixed to variable costs. We capture operating leverage using net margin (*Margin*). To control for solvency and firm distress risk, we include a measure of firm financial leverage (*LEV*). We include a set of year dummies (*Year dummies*) and 10 industry dummies

(*Industry dummies*) based on 2-digit IBES SIG codes to control for year- and industry-effects.[9] All firm characteristics, but analyst following, are measured at the end of the previous fiscal year. Analyst following is measured at the forecast issue date.

The empirical specification of the regression model is

$$\begin{aligned} Pr\left(DREV_{ijt}\right) = {} & \varphi_0 + \varphi_1 CAQ_{it} + \varphi_2 \ln\left|FE_{ijt}\right| + \varphi_3 \ln Horizon_{ijt} + \varphi_4 \ln Gexp_{ijt} + \varphi_5 \ln A\_\#\,Firm_{ijt} \\ & + \varphi_6 \ln Bsize_{ijt} + \varphi_7 \ln MV_{it} + \varphi_8 \ln Follow_{it} + \varphi_9 COV_{it} + \varphi_{10} B/M_{it} + \varphi_{11} \ln Age_{it} \\ & + \varphi_{12} ROA_{it} + \varphi_{13} Dloss_{it} + \varphi_{14} Margin_{it} + \varphi_{15} LEV_{it} + \sum_{k=0}^{10} \varphi_{16+k} Industry\ dummies \\ & + \sum_{k=0}^{14} \varphi_{27+k} Year\ dummies + u_{ijt} \end{aligned} \qquad (2)$$

where $DREV_{ijt}$ is an indicator variable if an EPS forecast by analyst *j* for firm *i* issued at time *t* is supplemented by a revenue estimate, and zero otherwise, and ln indicates a logarithmic transformation of the variable. For analyst EPS forecast error, experience, and forecast horizon we use log of 1 plus the variable to account for zero values. A variation of model 2 uses absolute discretionary accruals, $|D\ ACC|$, in lieu of $CAQ$ as a proxy firm reporting quality.[10] The regression standard errors are clustered by analyst and by firm to control for serial dependence of observations.[11]

## 4 Data and sample

We select all one-year-ahead earnings and revenue forecasts issued over 1995–2009 together with their actual values from IBES detail files for US firms. For comparability with EPS estimates, we

[9] IBES SIG code is a six-digit code, representing the sector (2-digits), the industry (2-digits) and the group (2-digits) a firm operates in.

[10] For the regression model where we use absolute discretionary accruals, we also control for the magnitude of absolute normal (innate) accruals, $|nD\ ACC|$, as investors may incorrectly perceive high normal accruals as indicative of poor reporting quality and demand revenue estimate when firm non-discretionary accruals are high.

[11] Our regression model differs from Ertimur et al. (2011, 39), who model "if the analyst issues at least one disaggregated forecast (that is, both a revenue and earnings forecast) during both the first half and second half of the year". Ertimur et al.' model may fail to recognize that revenue forecasts that infrequently complement EPS estimates may be of little value to investors, and that revenue forecasts that complement each EPS estimate send a stronger signal of the analyst forecasting skill. Also, Ertimur et al.' regressions do not use firm- and analyst-clustered standard errors to control for cross-sectional dependence of observations.

scale revenue forecasts by the number of shares outstanding reported on IBES at the end of the forecast issue month. We discard analyst forecasts before January 2000 to ensure sufficient variation in analyst experience estimates. This is because left censoring of data on IBES does not distinguish more from less experienced analysts in the first year of available data and the early sample period may have little variation in analyst experience (Clement 1999). Financial statement information is from Compustat and stock price information is from CRSP. Estimates of accrual quality constrain fiscal periods to between 2000 and 2009. All variables are winsorized at 1%. Our final sample includes 539,437 EPS forecasts and 271,139 revenue estimates over 2000–2008.[12]

Table 2 shows the distribution of all EPS forecasts, stand-alone EPS forecasts, and revenue estimates across the fiscal years. The total number of EPS forecasts increases from 41,104 in 2000 to 68,796 in 2008. The increase in the number of revenue forecasts that accompany EPS estimates is almost ten-fold, from 4,851 in 2000 to 47,289 in 2008. Overall, one in two EPS forecasts over the sample period included a revenue forecast, and the proportion of revenue estimates to complement EPS forecasts increases from 11.8% in 2000 to 68.7% in 2008. This shows that stand-alone EPS forecasts have become increasingly rare over time. There are 6,940 analysts and 532 brokerage houses providing forecasts for 2,615 firms. Overall, results in Table 2 suggest that analysts routinely complement EPS forecasts with revenue estimates.

## 5 Empirical results

To examine the determinants of the analyst choice to issue revenue forecasts to accompany EPS estimates, we start with a non-parametric portfolio analysis followed by a multivariate regression analysis.

[12] As our empirical tests are based on IBES data rather than individual analyst reports, our two research questions are strictly (1) whether an analyst will provide a revenue forecast to complement the EPS estimate *supplied to IBES* when reporting quality is poor and (2) whether better earnings forecasters *who report their estimates to IBES* use revenue estimates to signal their forecasting skill. As both full analyst reports and IBES data are available to investors (e.g. analyst reports can be directly purchased form the broker or through Investext), it is unlikely that analysts would engage in strategic disclosure of revenue forecasts in the report but not through IBES.

5.1 Non-parametric portfolio analysis

As a simple test of the correlation between analyst propensity to issue revenue estimates and reporting quality, we plot the frequency of complementary revenue forecasts across decile sorts on the variation in discretionary accruals (*CAQ*) and the magnitude of discretionary accruals ($|D\ ACC|$). Figure 1 shows that the proportion of revenue forecasts to accompany EPS estimates increases from 39% to 65% as we move from the decile of stocks with the highest reporting quality (*High Q*) to the decile of stocks with the lowest reporting quality (*Low Q*) formed on *CAQ*. In unreported results we find that the difference in the frequency of revenue estimates between these two portfolios is significant at 1% level. The upwards trends in the frequency of revenue estimates is also present for sorts on $|D\ ACC|$. Together, Figure 1 provides the first evidence that analysts are more likely to provide revenue estimates when firm reporting quality is low.

Building on Figure 1, Panel A of Table 3 reports average *CAQ* and $|D\ ACC|$ for stand-alone EPS forecasts and for EPS estimates accompanied by a revenue forecast. Both reporting quality measures are significantly higher when an analyst issues a revenue forecast, consistent with the prediction that revenue forecasts are more common when the quality of firm accounting accruals is poor.

Panel B of Table 3 shows the distribution of stand-alone EPS forecasts and EPS forecasts supplemented by a revenue estimate across 11 industries based on the 2-digit IBES SIG code. Stand-alone EPS forecasts are most common in the energy sector and in the public utilities industry. These are mature industries with relatively simple business models where EPS forecasts are likely to accurately reflect firm performance over the fiscal year. Revenue forecasts are most common in the technology and in the health industry. Disaggregating earnings for these industries may increase the transparency and interpretability of earnings numbers. This is consistent with Bowen et al. (2002), who argue that investors rely on revenue rather than earnings in valuing technology firms. Together, the results in Table 3 confirm that revenue estimates are more common when investors face a more difficult valuation task due to poor firm financial reporting quality.

In unreported results, we find that the mean EPS forecast error is higher for stand-alone earnings forecasts than for EPS complemented by revenue estimates (1.36% vs. 1.28%). Given that revenue forecasts are issued on average for firms with lower reporting quality, the result is consistent with better able analysts being more likely to report a complementary revenue forecast.

5.2 Multivariate analysis: descriptive statistics for the explanatory variables

We start the multivariate analysis by presenting summary statistics for the dependent and explanatory variables in regression model (2). Panel A of Table 4 shows that the mean EPS forecast error is 1.32% of the stock price, and the average forecast is issued in mid fiscal year. On average, an analyst has been present in the sample for over 6 years, follows over 13 firms, and is employed by a broker house with over 56 analysts. Panel B of Table 4 shows descriptive statistics for firm-related characteristics. Mean *CAQ* is 0.059 and the absolute value of discretionary accruals is 0.048. For completeness, we also report the value of non-discretionary accruals, which is 0.048. Average firm market capitalization is close to $4 billion, and a firm is followed on average by over 10 analysts. The coefficient of stock price variation is 0.087, mean revenue variation is 0.147, and book-to-market ratio is 0.498. Average firm age is 21 years[13], and mean firm profitability is close to 2%. Around 18% of firms reported a loss in the previous fiscal year, and the median net margin is 0.045. The average firm gearing is 0.181.

[13] We use CRSP files starting in 1926 to calculate firm age, which captures a few large companies with long-time series of stock prices. This explains high mean firm age.

*5.2.1 Multivariate regressions: empirical results*

The first columns of Table 5 show results from the logit model (2) where we use *CAQ* to capture firm reporting quality. The later columns show results for model (2) when we use the absolute magnitude of discretionary accruals to capture reporting quality.[14] For both reporting quality measures, we find that low quality accounting accruals increase the likelihood an analyst will issue a revenue forecast, which supports our prediction that poor quality reporting increases analyst propensity to produce revenue estimates. Also, both models show that analysts who issue more precise EPS forecasts (our measure of analyst forecasting skill) are more likely to issue revenue forecasts. This provides support for hypothesis H2 that better earnings forecasters are more likely to issue revenue estimates to signal higher quality of their EPS estimates, and to increase visibility of their forecasts in the market. Looking at the economic effects, we find that a one standard deviation increase in ln *CAQ* (ln $|D\ ACC|$) leads to a 10.9% (5.4%) higher (lower) likelihood of issuing a revenue forecast.

For control variables, we find that analysts are more likely to issue revenue estimates early in the fiscal year, when the uncertainty about firm next year earnings is higher. Consistent with the evidence in Marks (2007) and Ertimur et al. (2011), we find that analysts with more forecasting experience are less likely to issue revenue estimates.[15] Revenue forecasts are more common among smaller, low book-to-market and younger firms, among loss making and less profitable firms, and firms with high stock price volatility. This supports the prediction that revenue forecasts dominate among firms with high value uncertainty. Higher coverage of a firm by analysts increases the likelihood of a complementary revenue forecast, which suggests that analysts may use revenue estimates to differentiate themselves from other analysts when the

[14] Non-discretionary accruals, $|nD\ ACC|$, show no association with the analyst decision to produce a revenue forecast. This confirms previous results that only the accruals component that is subject to managerial discretion is indicative of firm reporting quality (DeFond and Park 2001; Dechow and Dichev 2002; Dechow et al. 2010).

[15] Our empirical results are qualitatively the same when we use analyst firm-specific and industry-specific experience (results untabulated). The correlation coefficient between analyst general and industry-specific experience is 0.93 and 0.634 between general and firm-specific experience.

competition among analysts is high. High variation in firm revenue and low operating leverage reduce the likelihood a revenue forecast will complement the EPS estimate. The former is consistent with the prediction that high forecasting difficulty reduces analyst propensity to produce a complementary revenue forecast; the latter evidence is consistent with revenue estimates being more informative of firm performance for firms with high fixed relative to variable costs. Analysts are less likely to produce revenue estimates for highly leveraged firms, which suggests that revenue estimates are unlikely to be useful in aiding investors in interpreting firm solvency when financial distress risk is high.

The regressions' pseudo $R^2$ is 20.15% for *CAQ* and 20.09% for $|D\ ACC|$, which suggests the two models have good predictive power. Overall, results in Table 5 confirm that analysts exhibit higher propensity to issue revenue forecasts when the quality of firm financial reporting is low, and that better earnings forecasters are more likely to issue revenue estimates to signal higher quality of their EPS estimates.

## 6 Sensitivity analysis

We start the sensitivity analysis by testing if Table 5 results are not driven by our choice of the measure of the firm financial reporting quality, and of the analyst EPS forecasting skill. Subsequently, we examine sensitivity of the results to using Institutional Investors magazine analyst rankings to identify reputable analysts, and we run annual regressions to examine if the results in Table 5 are not confined to a specific sub-period. We also test if the results persist when we use Fama–MacBeth method and random sample selection as alternative ways to control for inflated *t*-statistics due to cross-sectional correlation of observations.

6.1 Alternative measures of firm financial reporting quality

Table 6 repeats the analysis from Table 5 when use three other measure of firm reporting quality. Column "*Tot. accruals*" shows results for regression model (2) when we use absolute total accruals to measure reporting quality, which is the absolute difference between net income and operating cash flow. Total accruals, as a measure of reporting quality, include managerial choices related to current and non-current accruals. The latter reflects managerial choices related to, among others, the assets' useful life, and accounting for pension liabilities, which may have more lasting effects on the informativeness of firm earnings about future firm cash flows than managerial decisions on firm current accruals. Further, total accruals are easy to compute and not subject to estimation error as discretionary accruals are. The latter effect can reduce the power of discretionary accruals to capture reporting quality (Richardson et al. 2005). We find that analyst propensity to produce revenue estimates increases for firms with high magnitude of absolute total accruals, which corroborates our main results.

In column "*Earn. persistence*", we use earnings persistence (*E.persist*)to measure reporting quality. In their review of earnings quality proxies, Dechow et al. (2010) classifies earnings persistence as an important determinant of earnings quality because persistence directly influences the usefulness of earnings in equity valuation. This is because more persistent earnings are better inputs into firm valuation models (Ohlson 1995; Barth and Hutton 2004). We measure earnings persistence as the autoregressive coefficient of the (assets-scaled) current earnings on past earnings (Dechow and Ge 2006). The coefficient on earnings persistence is significant and negative, which means that analysts are less likely to produce revenue forecasts for firm with more persistent earnings. This is consistent with our prediction that when firm earnings are more predictable, and consequently investors find it easier to value a firm based on earnings, analysts are less likely to produce revenue forecasts.

In column "*Signed curr. accruals"* we examine if the negative association between the analyst propensity to issue revenue estimates and firm financial reporting quality persists when we use the signed magnitude of discretionary accruals, *D ACC*. We use signed abnormal accruals because high positive values of discretionary accruals may indicate opportunistic upwards earnings management.[16] Opportunistic downwards accrual management to misrepresent firm net income is less common (Nelson et al. 2002, 2003). Further, downwards accrual management may reflect managerial attempts to lower accruals volatility and to smooth earnings (Buckmaster 2001), which may serve to improve quality of firm earnings. Controlling for the level of non-discretionary accruals, we find a positive coefficient on signed discretionary accruals that is over fifteen times larger in magnitude compared to the coefficient on $|D\ ACC|$ in Table 5. The difference in magnitudes of the coefficients on *D ACC* compared to $|D\ ACC|$ is significant at less than 1%. This suggests that analysts are more likely to issue revenue forecasts when they suspect that poor reporting quality is due to opportunistic upwards earnings management.

The last columns of Table 6 present results from including firm earnings volatility (*EPS STD*) together with the variation in firm discretionary accruals, *CAQ*, in the regression model (2). This is because the positive coefficient on *CAQ* in Table 5 may reflect that analysts issue revenue forecasts for difficult-to-value firms that have high earnings volatility, even if these firms have high reporting quality. Column "*Earn. STD*" shows that the coefficient on *EPS STD* is positive and significant, which reflects that analysts are more likely to issue revenue forecasts for firms with high earnings uncertainty. Controlling for earnings volatility, *CAQ*, continues to show a positive relation with the likelihood of issuing a revenue forecast, which further corroborates our main conclusions. Overall, results in Table 6 suggest our conclusions are robust to using alternative measures of firm reporting quality.

[16] Upwards earnings management may serve to avoid the negative price reaction when failing to meet analyst earnings forecast (Collins and Hribar 2002; Dechow and Skinner 2000; Brown and Caylor 2005), to increase managers' compensation (Healy 1985; Bergstresser and Philippon 2006), or to increase firm value (Sloan 1996).

## 6.2 Alternative measures of analyst forecasting skill and analyst reputation

Table 5 shows that analysts who issue more accurate EPS signal their quality through the issue of a revenue estimate. Table 7 tests sensitivity of this result to alternative definitions of analyst EPS forecasting ability.

Column "*Past EPS accuracy*" of Table 7 reports results for regression model (2) when we use analyst past EPS forecast accuracy (|*FE prev*|) to capture analyst forecasting skill. We measure analyst past EPS forecast accuracy as the average EPS forecast error of all EPS estimates issued by the analyst for a firm in the previous fiscal year. |*FE prev*| is calculated at the announcement date of previous year earnings. Using analyst past forecast accuracy, we continue to find that better earnings forecasters have higher propensity to issue revenue forecasts, which corroborates our results in Table 5.

Clement (1999) proposes to measure analyst EPS forecasting skill using the proportional mean adjusted forecast error (*PMAFE*), which is the ratio of analyst EPS forecast error to the mean EPS forecast error of all EPS forecasts issued for a firm in a fiscal year. *PMAFE* captures analyst EPS forecasting skill *relative* to that of other analysts following the firm. Column "*PMAFE*" in Table 7 shows model (2) regression results when we substitute *PMAFE* for EPS forecast error. Using the relative EPS forecast accuracy, we continue to find that better earnings forecasters are more likely to issue revenue forecast to complement EPS estimates. This means that our conclusions are immune to the choice of absolute rather than relative analyst EPS accuracy measure.

Ertimur et al. (2011) use analyst rankings from the October issue of the Institutional Investors magazine to identify analysts with higher reputation. To test sensitivity of our result to including this measure of analyst reputation, column "*Star analysts*" show results for model (2) when we include an indicator variable for analysts ranked top by the Institutional Investors magazine in the most recent annual ranking. Specifically, we use the Institutional Investors magazine ranking from the October issue of year *t* to identify forecasts issued by star analysts over the next 12-months.[17] Consistent with Ertimur et al. (2011), we find that more reputable analysts are less likely to produce revenue forecasts. Controlling for analyst ranking, the coefficient on analyst EPS forecast error remains significant and similar in magnitude to that from Table 5 (−1.973 vs. −1.978). This further corroborates our prediction that controlling for analyst reputation, analysts use revenue estimates to signal their forecasting ability.

### 6.3 Annual regressions and Fama–MacBeth approach

Our sample period spans distinct periods for the US stock market: the market downturn following the burst of the internet bubble, the subsequent recovery period, and the recent financial crisis. Further, a number of regulatory changes have been introduced over the sample period, which could influence our results. These include the introduction of the Fair Disclosure regulation, Sarbanes–Oxley act, the Global Settlement, the NASD 2711 regulation and the SEC rule 472 intended to reduce conflicts of interests in analyst research and to promote less biased sell-side equity research. To test if our results are not confined to a specific subperiod, or influenced by certain regulatory changes, we replicate the analysis from Table 5 for each fiscal year over the sample period.

Table 8 shows results from annual regressions for the regression model (2). For brevity, we report only results from the logit regression where we use variation in firm discretionary accruals to measure reporting quality. The coefficient on *CAQ* is positive and significant in predicting the analyst decision to produce a revenue forecast across all fiscal years, which means that our results are robust to the choice of the sample period. Further, the coefficient on ln

[17] To combine analyst names from IBES with Individual Investors magazine rankings, we require the IBES translation file, which is only available for 2005 IBES edition. Using the 2005 IBES translation file could potentially misclassify top ranked analysts that started reporting on IBES after 2005. We inspected the matching process but found no evidence that the matching between Individual Investors magazine rankings and IBES is poorer after 2005. More recent versions of the IBES translation file are unavailable as Thomson-Reuters suspended access to the translation file for academic research.

$|FE|$ is negative and significant across all years but 2002 and 2007, further reinforcing our conclusions that analysts use revenue forecasts to signal their quality to investors.

The last columns of Table 8 show results from Fama–MacBeth regressions, which is an alternative way to control for inflated *t*-statistics due to cross-sectional dependence. The magnitudes and the significance of the coefficients are similar to that in Table 5. Overall, we conclude that results from annual regressions and from the Fama–MacBeth approach are similar to that in Table 5.

### 6.4 Random sample selection

Using multiple analyst EPS forecasts for a firm in a fiscal year could influence our hypothesis tests if standard-errors clustered on analyst and firm fail to fully adjust for the upwards bias in the significance of coefficient test statistics. To gauge the sensitivity of our results to this problem, we randomly choose one analyst EPS forecast for a firm in a fiscal year and replicate the analysis in Table 5. Table 9 shows that while the sample size falls to 138,114 analyst–firm observations over nine fiscal years, the relations between accruals quality measures and the likelihood of issuing revenue forecasts remain unchanged. Also, analyst EPS forecast error retains the negative relation with the likelihood of issuing a revenue forecast. This confirms proper test specification in Table 5.

### 6.5 Initiations of revenue forecast issues

Our results may be affected by the recursive effect a complementary revenue forecast issue may have on firm financial reporting quality. This is because a revenue estimate may aid investors in identifying firms that engage in revenue management to boost firm net income. In particular, a revenue forecast can help investors identify firms where unexpectedly high revenue, and consequently high earnings, come from sales of fixed assets (Bartov 1993), or discount sales close to the end of the fiscal year (Roychowdhury 2006). Higher cost of revenue management in the presence of analyst revenue forecasts may incentivize managers to substitute revenue management for accruals management, which could explain higher analyst propensity to produce a revenue forecast when the quality of firm accruals is low.[18]

To test if our results are unaffected by the potential effect revenue forecasts have on the quality of firm financial reporting, we look at initiations of complementary revenue forecasts for a firm. The dependent variable is an indicator variable, which equals one for the first revenue forecast issued for a firm, and zero otherwise. We remove all EPS forecasts for a firm after the first revenue forecast has been issued. Firm financial reporting quality is measured before the analyst initiates producing revenue estimates for the firm, thus the measure is unaffected by the potential shift to accrual-based earnings management after a revenue estimate is issued.

Table 10 shows results from logit regressions predicting initiations of revenue forecasts for a firm. The independent variables are the predictors of the analyst choice to issue a complementary revenue forecast from regression model (2). Similarly to the main results, we find that analysts are more likely to initiate revenue forecasts for firms with high variation in discretionary accruals, and for firms with high magnitude of discretionary accuracy. This supports the conclusion that low quality reporting increases analyst propensity to issue a revenue forecast to supplement the EPS estimate. Further, better earnings forecasters are more likely to initiate revenue forecasts for a firm. Overall, results from Table 10 corroborate our main findings.

## 7 Why are revenue forecasts useful to investors when the quality of firm reporting is low?

We predict that a revenue forecast is a valuable measure of firm performance when firm reporting quality is poor because revenue forecast accuracy should be less adversely affected by

[18] Our prediction is consistent with the tradeoff model between accrual and real earnings manipulations in Zang (2011). She shows that managers consider real and accrual earnings management as substitutes with the choice between the two earnings management activities depending on their marginal cost.

poor reporting quality compared to EPS forecast precision. As a result, investors rely more on the (relatively more accurate) revenue than EPS estimates in their investment decisions when reporting quality is low. To confirm validity of these propositions, we perform two additional tests. First, we examine the sensitivity of EPS and revenue forecast error to the quality of firm financial reporting. Second, we test if the price reaction to the announcement of revenue and EPS forecasts varies with the quality of firm reporting. Specifically, we expect investors to attach higher weight to revenue forecasts compared to EPS estimates when the quality of firm reporting is poor.

### 7.1 The relation between EPS and revenue forecast accuracy and reporting quality

As a simple test of the relation between EPS and revenue forecast accuracy and reporting quality, Figure 2 plots the EPS and the revenue forecast error across deciles formed on the basis of the variation in discretionary accruals and the magnitude of discretionary accruals. Figure 2a shows that the EPS forecast error for standalone EPS estimates and for EPS forecasts accompanied by revenue estimates exhibits an upwards trend when moving from the decile with the highest (*High Q*) to the lowest (*Low Q*) reporting quality. This suggests that EPS forecast quality decreases as reporting quality deteriorates. The error of a revenue estimate is less affected by poor reporting quality and shows a downward trend when moving from decile 4 to 10.[19] Figure 2b replicates the analysis for decile portfolios formed on the magnitude of discretionary accruals and shows similar patterns to that in Figure 2a.

To test the significance of the relation between the quality of firm financial reporting and the accuracy of analyst EPS and revenue forecasts, we regress the error of the EPS forecast and of the revenue estimate on the two proxies for the quality of firm reporting. The two accuracy regressions control for analyst and firm characteristics from model (2) as these characteristics

[19] The downward trend when moving from decile 4 to 10 may be because analysts devote more effort to accurately forecast revenue estimates when the quality of firm reporting is poor as accurate revenue estimates can compensate for less accurate EPS estimates and are more valuable to investors when the quality of firm reporting is poor.

correlate with analyst forecasting skill and the difficulty of the forecasting task. To ensure comparability of the EPS and the revenue accuracy results, the sample of EPS forecasts includes the EPS estimates that are accompanied by revenue forecasts. Table 11 shows that the analyst EPS forecast error increases for firms with poor reporting quality, in line with the results in Figure 2.[20] For the revenue forecast accuracy regression, the coefficients on the finical reporting quality proxies are insignificant. This means that the quality of analyst revenue estimate is insensitive to the quality of firm reporting. Overall, Table 11 confirms that a revenue forecast is a valuable (complementary) measure of firm performance when reporting quality is poor because it is unaffected by poor reporting quality.

### 7.2 Price reaction to analyst EPS forecasts and revenue forecast announcements

Next, we examine if revenue estimates are more valuable to investors when the quality of firm reporting is low. We use a three-day cumulative abnormal return (*CAR*) centered on the EPS forecast revision date to measure the price reaction to analyst percentage EPS ($\Delta EPS$) and revenue forecast revisions ($\Delta REV$).[21] We expect the coefficient on $\Delta REV$ to be positive if revenue forecasts have incremental information content compared to EPS estimates. Further, we include an interaction term between the EPS forecast revision and an indicator variable for a revenue forecast ($DREV*\Delta EPS$) to capture if the complementary revenue estimate lends credibility to the EPS forecast revision (Keung 2010). This is because the revenue forecast allows investors to verify the quality of the EPS forecast by disaggregating it into the sales volume and the profit margin. To test if revenue estimates are more valuable to investors compared to EPS estimates when the reporting quality is poor, we include interaction terms between EPS and

[20] Our conclusions remain the same when we use (1) the combined sample of stand-alone EPS forecasts and EPS forecasts accompanied by revenue estimates, and for (2) stand-alone EPS estimates.

[21] We use the CRSP value-weighted index as the benchmark to measure abnormal returns. Similarly to Keung (2010), we assume that the revenue forecast revision is zero for stand-alone EPS estimates. We require that the forecasts used to calculate revisions are not further than 300 days apart and that the revisions in EPS and revenue forecasts are for the same fiscal year. The former criterion eliminates infrequently revised forecasts and the later ensures forecast revisions reflect only analyst new information for a fiscal year. These additional selection criteria reduce the sample size to 345,632 observations.

revenue forecast revisions and the variation in discretionary accruals, i.e. $\Delta EPS*CAQ$ and $\Delta REV*CAQ$. We expect that the price reaction to EPS forecast announcement decreases as the quality of firm reporting deteriorates because the credibility of analyst EPS estimates is lower. As the accuracy of revenue estimates is unaffected by the quality of firm reporting, the coefficient on $\Delta REV*CAQ$ should be indistinguishable from zero.

To control for the effect revisions in stock recommendations have on stock prices, we include three dummy variables for the direction of the recommendation revisions. *Upgrade* (*Downgrade*) is an indicator variable that equals one if the analysts revises the stock recommendation upwards (downwards) to a more (less) favorable level, and zero otherwise. *Reiteration* is an indicator variable that equals one if the analyst reiterates the recommendation for the stock. The specification of the regression model is:

$$\begin{aligned} CAR_{ijt} &= \alpha_0 + \alpha_1 \Delta EPS_{ijt} + \alpha_2 \Delta REV_{ijt} + \alpha_3 DREV_{ijt} \times \Delta EPS_{ijt} + \alpha_4 CAQ_{it} \times \Delta EPS_{ijt} \\ &+ \alpha_5 CAQ_{it} \times \Delta REV_{ijt} + \alpha_6 Upgrade_{ijt} + \alpha_7 Reiteration_{ijt} + \alpha_8 Downgrade_{ijt} + u_{ijt} \end{aligned} \tag{3}$$

where the intercept term captures EPS forecast reiterations that are unaccompanied by either a revenue forecast revision or a stock recommendation revision. Standard errors are clustered on analyst and firm.

Table 12 reports regression results for model (3).[22] Column "*Without CAQ interactions*" shows regression results for model (3) without controlling for the effect the quality of firm financial reporting has on the price reaction to EPS and revenue forecast revisions. Consistent with the previous literature (e.g. Sinha et al. 1997; Francis and Soffer 1997), we find a positive and significant coefficient on EPS forecast revisions. Revenue forecast announcements contain incremental information to EPS forecasts with a one standard deviation increase in $\Delta REV$ leading to 0.76% (0.195*0.039) abnormal price reaction compared to 1.02% (0.032*0.314) for a one standard deviation increase in $\Delta EPS$. As in Keung (2010) and Baginski et al. (2004), we find

[22] In unreported results we find that the mean CAR is −0.16%, which reflects that the mean EPS and revenue forecast revisions are negative (−3.95% and −0.13% respectively). The negative average values for CARs, and for EPS and revenue forecast revisions are largely due to the inclusion of the recent financial crisis in the sample period.

that the presence of a revenue forecast has an incremental effect on the price response coefficient to revisions in EPS estimates. A one percent revision in an EPS forecast accompanied by a revenue estimate increases abnormal returns around the announcement date by 1.6%, a 50% increase compare to a stand-alone EPS revision. The evidence that revenue forecasts contain incremental information to earnings forecasts and stock recommendations, and that the presence of a revenue forecast adds credibility to analyst EPS forecasts is not surprising. This is because we document that analysts issue revenue forecasts to compensate for inaccurate EPS estimates when the quality of firm reporting is low.

To test if revenue estimates are more valuable to investors when the quality of firm reporting deteriorates, we examine the full specification of model (3). Column "*CAQ interactions*" shows a significant negative coefficient on $\Delta$*EPS*CAQ* but not on $\Delta$*REV*CAQ*. This confirms that investors attach a lower weight to EPS forecast revisions when the quality of firm reporting is low but continue to rely on revenue estimates in their investment decisions. Together, results in Table 11 and 12 explain why investors value revenue estimates particularly high when the quality of firm reporting is low.

## 8 Conclusions

This study examines the recent trend in analysts issuing revenue forecasts to complement EPS estimates. We document that the proportion of revenue estimates to complement EPS forecasts increases from 11.8% in 2000 to 68.7% in 2008, which suggests that stand-alone EPS estimates became less common over our sample period. However, to date we know little about what determines the analyst choice to issue revenue forecasts to complement EPS estimates.

We propose that the analyst decision to produce a revenue estimate is influenced by the quality of firm financial reporting and by the analyst EPS forecasting skill. Investors demand revenue forecasts because revenue forecast accuracy is less adversely affected by poor reporting quality compared to EPS forecasts precision, and as a result, investors rely more on revenue than on EPS estimates in their investment decision when reporting quality is low. Further, more skilled analysts can use revenue estimates to signal their forecasting skill. This is because only these analysts want their forecasts to be subject to higher market scrutiny, and because accurate revenue forecasts, as inputs into EPS estimates, are credible signals that the quality of EPS forecasts is high.

Consistent with our predictions, we find that the likelihood an analyst will supplement the EPS estimate with a revenue forecast relates negatively to a number of proxies for the quality of firm reporting that include: the variation in discretionary accruals, the magnitude of absolute discretionary accruals, earnings persistence, absolute total accruals, and earnings volatility. Further, we confirm that analysts who issue more accurate EPS forecasts are more likely to issue revenue estimates. The results are robust to a battery of sensitivity tests and supported by additional tests that examine how firm reporting quality affects EPS and revenue forecast accuracy, and how investors react to revenue and EPS forecast announcements when the quality of firm reporting is low.

This study contributes to the fledgling literature on the importance of supplementary information produced by analysts, such as revenue estimates, in firm valuation, and to the literature on the interaction between the firm and analysts as information intermediaries in the market. In particular, we document that analysts use revenue forecasts to mitigate the negative effect poor reporting quality has on the accuracy of their EPS estimates, which contributes to the debate on the role of financial analysts in capital markets.

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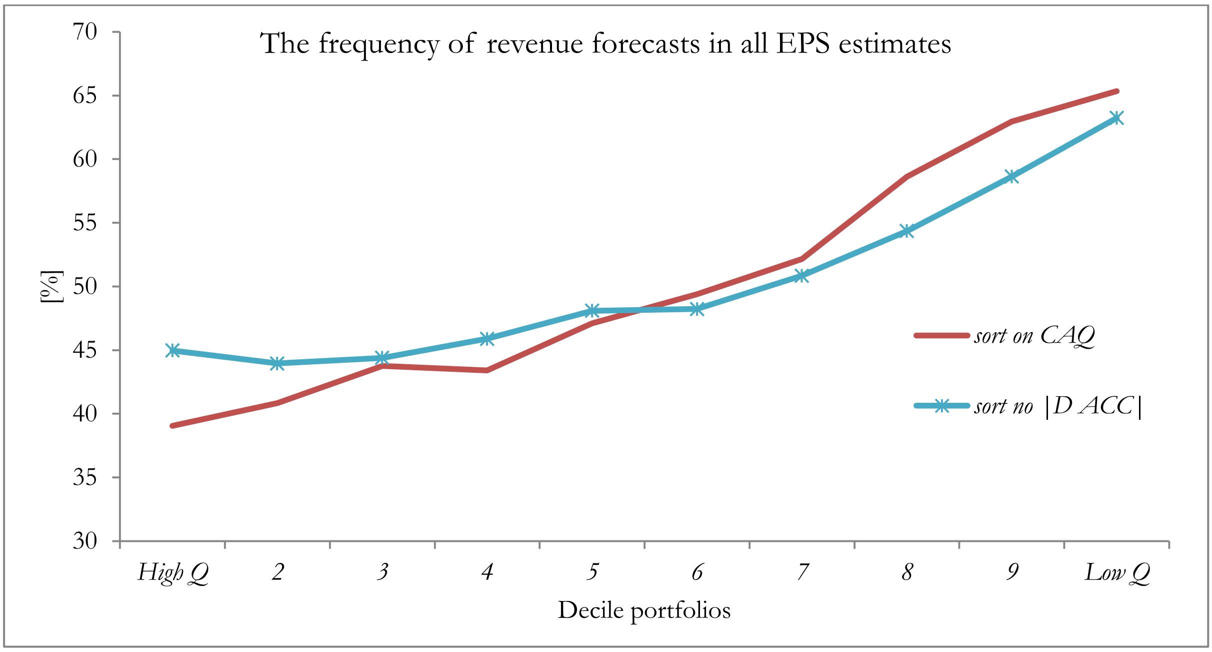
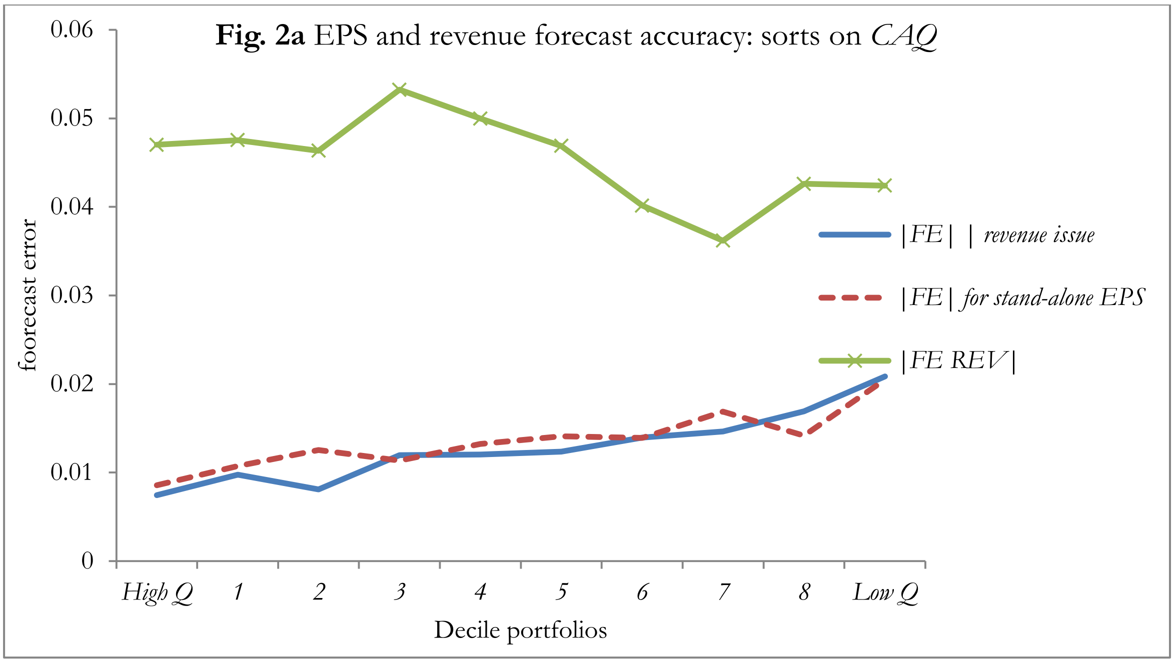



**Fig. 1** The frequency of analyst revenue forecasts in all EPS estimates

The figure shows the frequency of revenue forecasts in all EPS estimates across decile sorts on the variation in discretionary accruals (*CAQ*) and on the magnitude of discretionary accruals (|*D ACC*|). Portfolio *High Q* contains stocks with the highest quality of firm reporting and portfolio *Low Q* includes stocks with the lowest reporting quality.



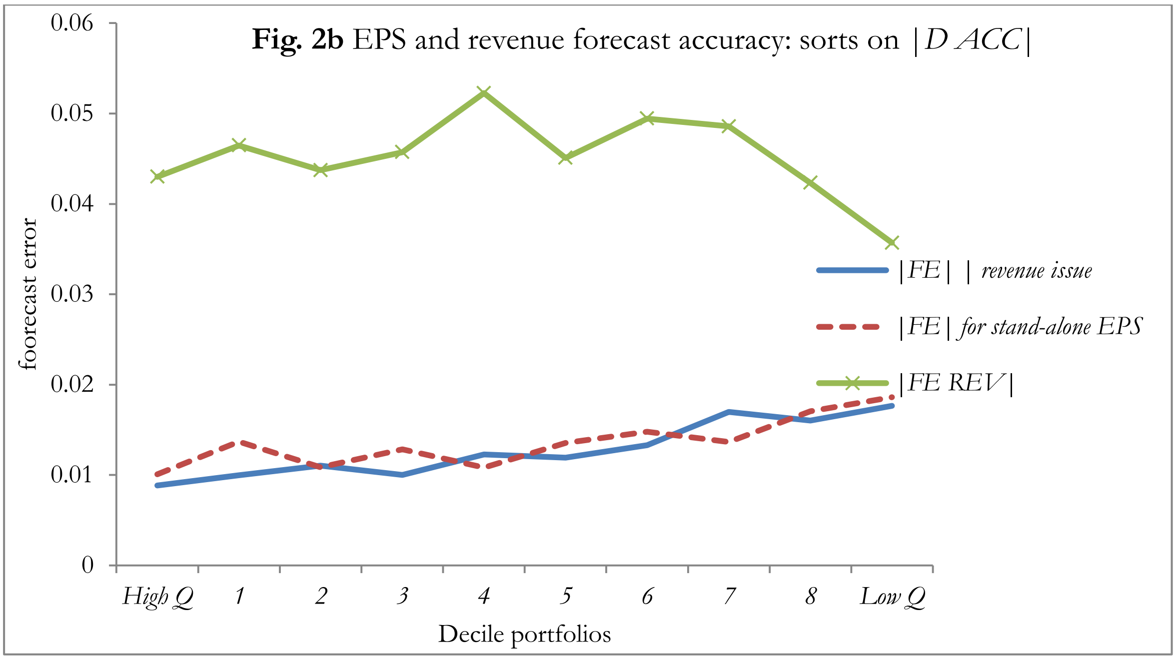




**Fig. 2** Analyst EPS and revenue forecast errors across deciles formed on the basis of firm reporting quality

The figure shows the mean EPS and revenue forecast errors for decile sorts on the variation in discretionary accruals (*CAQ*), Figure 2a, and on the magnitude of discretionary accruals (|*D ACC*|), Figure 2b. |*FE*| | *revenue issue* denotes EPS forecast error in the presence of the accompanying revenue estimate. |*FE*| *for stand-alone EPS* denotes EPS forecast error for stand-alone EPS estimates. |*FE REV*| stands for revenue forecast error. Portfolio *High Q* contains stocks with the highest quality of firm reporting and portfolio *Low Q* includes stocks with the lowest reporting quality.

**Table 1** Variable definitions

| Variable | Definition |
|---|---|
| *Analyst-level variables* | |
| *DREV* | A revenue forecast dummy, which is an indicator variable that equals one if the analyst issued a revenue estimate to complement the EPS forecast. |
| *EPS* | A one-year ahead earnings-per-share forecast. |
| *REV* | A one-year ahead revenue forecast scaled by the number of shares outstanding at the end of the forecast issue month. Thomson Reuters Estimates Glossary (2008) for IBES defines revenue forecasts on IBES as "a corporation's net revenue, generally derived from core business activities.". |
| $\lvert FE \rvert$ | Analyst EPS forecast error, computed as the absolute difference between the forecasted and the actual earnings scaled by the stock price at the end of the previous fiscal year. |
| $\lvert FE\ REV \rvert$ | Analyst revenue forecast error, computed as the absolute difference between the forecasted and the actual revenue, scaled by the end-of-month number of shares outstanding, and divided by the stock price at the end of the previous fiscal year. |
| *Horizon* | Forecast timeliness, which is measured by the number of days between the EPS forecast announcement date and the fiscal year-end. |
| *Gexp* | Analyst general experience, computed as the number of years an analyst has issued at least one EPS forecast. |
| *A_#Firm* | Analyst workload, which is measured as the number of companies for which an analyst issued at least one EPS forecast over the previous 12 months. |
| *Bsize* | Broker size, measured as the number of analysts employed by the broker that issued at least one EPS forecast in the previous 12-months. |
| $\lvert FE\ prev \rvert$ | Analyst previous forecast accuracy, measured as the mean EPS forecast error of a minimum 2 EPS forecasts issued by the analyst for a firm in the previous fiscal year. Analyst previous forecast accuracy is calculated at the announcement date of previous year earnings. |
| *PMAFE* | Analyst proportional mean-adjusted forecast error, which is the ratio of the analyst EPS forecast error to the mean EPS forecast error of all EPS forecasts issued for a given firm in a fiscal year. |
| *Firm-level variables* | |
| *CA* | Current accruals, defined as the change in current assets, less change in cash, less change in current liabilities plus the change in debt in current liabilities. *CA* are scaled by average total assets for the current and previous fiscal year. |
| *CFO* | Cash flow from operations, which is equal to income before extraordinary items less current accruals. *CFO* is scaled by average total assets for the current and previous fiscal year. |
| *PPE* | Gross value of property plan and equipment scaled by average assets. |
| *ΔSAL* | Change in firm sales reported on Compustat, current compared to previous fiscal year, scaled by average assets. |
| *CAQ* | Variation in firm discretionary accruals, which is measured by the standard deviation of firm residuals from the McNichols (2002) accruals model for the previous four fiscal years. |
| $\lvert nD\ ACC \rvert$ | The magnitude of firm non-discretionary accruals, which is measured as the predicted value from the McNichols (2002) accruals model for the firm for the previous fiscal year. |
| $\lvert D\ ACC \rvert$ | The magnitude of discretionary accruals, which is measured by the firm residual from McNichols (2002) accruals model for the previous fiscal year. |
| *MV* | Firm size, computed as the firm market capitalization at the end of the previous fiscal year in $ million. |
| *Follow* | Intensity of analyst coverage, which is calculated as the number of analysts issuing at least one EPS forecast for a company over the previous 12 months. |
| *COV* | Price volatility, measured as the coefficient of variation of stock price over 90-days prior to the end of the previous fiscal year. |

**Table 1** continued

| Variable | Definition |
|---|---|
| *STD REV* | Revenue uncertainty, computed as the standard deviation in firm revenue reported on Compustat for the previous four fiscal years. Firm revenue is scaled by total assets. |
| *LEV* | Firm financial leverage, which is defined as the ratio of total long-term debt over total assets. |
| *Age* | Firm age, which is the number of years between the previous fiscal year-end and the firm's first appearance on CRSP. |
| *NI* | Income before extraordinary items from Compustat. |
| *ROA* | Return on assets, which is *NI* scaled by firm assets. |
| *Dloss* | A loss dummy, which is an indicator variable that equals one if the firm's actual EPS on IBES is negative and zero otherwise. |
| *Marg* | Net margin, which is the ratio of *NI* over Compustat firm revenue. |
| *B/M* | Book-to-market ration, measured as the ratio of total common equity over the firm market capitalization at the end of the previous fiscal year. |
| *Other variables* | |
| *\|ACC_T\|* | Absolute total accruals, which is the absolute difference between *NI* and operating cash flow, scaled by average total assets for the current and previous fiscal year. Operating cash flow is the *NI* plus depreciation less current accruals. |
| *E.persist* | Earnings persistence, which is measured as the coefficient from Dechow and Ge's (2006) OLS regressions of the next fiscal year *NI* on current period *NI*. We scale *NI* by average total assets for the current and previous fiscal year. |
| *EPS STD* | Earnings uncertainty, measured as the standard deviation in firm *NI* for the previous four fiscal years. Firm *NI* is scaled by total assets. |
| *Star* | A star analyst indicator, which is an indicator variable that equals one if the analyst was ranked top by the Institutional Investor magazine in the most recent annual All American research ranking and zero otherwise. |
| *CAR* | Cumulative abnormal return over a three-day window centered on the EPS forecast issue date. We use the CRSP value-weighted return as the benchmark in calculating abnormal returns. |
| $\Delta$*EPS* | Earnings forecast revision, which is calculated as the percentage difference between the current and the previous analyst EPS forecast for a firm. |
| $\Delta$*REV* | Revenue forecast revision, which is calculated as the percentage difference between the current and the previous analyst revenue forecast for a firm. |
| *Upgrade* | Stock recommendation upgrade, which is an indicator variable that equals one if the analyst revises the stock recommendation upwards, and zero otherwise. |
| *Revision* | Stock recommendation revision which is an indicator variable that equals one if the analyst reiterates the stock recommendation, and zero otherwise. |
| *Downgrade* | Stock recommendation downgrade, which is an indicator variable that equals one if the analyst revises the stock recommendation downwards, and zero otherwise. |
| *Industry dummies* | 10 industry dummies based on the sector code from IBES SIG code |
| *Year dummies* | Year dummies |

The table shows definitions of the variables used in the study.

**Table 2** Distribution of earnings and revenue forecasts over the sample period

| | *Total #EPS* | *#only EPS* | *#EPS and REV* | *#Analysts* | *#Brokers* | *#Firms* |
|---|---|---|---|---|---|---|
| 2000 | 41104 | 36253 | 4851 | 2572 | 226 | 1351 |
| 2001 | 48289 | 41344 | 6945 | 2658 | 212 | 1238 |
| 2002 | 51075 | 36166 | 14909 | 2888 | 218 | 1313 |
| 2003 | 58625 | 31943 | 26682 | 2796 | 269 | 1508 |
| 2004 | 66149 | 28030 | 38119 | 2812 | 299 | 1625 |
| 2005 | 67798 | 25938 | 41860 | 2834 | 296 | 1631 |
| 2006 | 70317 | 24585 | 45732 | 2871 | 273 | 1640 |
| 2007 | 67284 | 22532 | 44752 | 2778 | 260 | 1587 |
| 2008 | 68796 | 21507 | 47289 | 2636 | 259 | 1411 |
| *Total* | 539437 | 268298 | 271139 | 6940 | 532 | 2615 |

The table shows the total number of EPS forecasts (*Total #EPS*), the number of stand-alone EPS forecasts (*#only EPS*), and the number of EPS forecasts complemented by revenue estimates (*#EPS and REV*) across fiscal years 2000–2008. Column *#Analysts* denotes the number of unique analysts, *#Brokers* the number of unique brokerage houses, and *#Firms* shows the number of unique firms. Row *Total* reports the number of unique observations in each category.

**Table 3** Univariate portfolio analysis

| | *only EPS* | | *EPS and REV* |
|---|---|---|---|
| *Panel A: Financial reporting quality measures* | | | |
| *CAQ* | 5.335% | | 6.458% |
| *p* | | 0.000 | |
| $\lvert D\ ACC \rvert$ | 4.452% | | 5.192% |
| *p* | | 0.000 | |
| *N* | 6997 | | 6307 |
| *Panel B: Industry distribution* | | | |
| Finance | 38.5% | | 61.5% |
| Health | 36.9% | | 63.1% |
| Consumer non-durables | 53.1% | | 46.9% |
| Consumer services | 50.8% | | 49.2% |
| Consumer durables | 54.4% | | 45.6% |
| Energy | 74.3% | | 25.7% |
| Transportation | 61.2% | | 38.8% |
| Technology | 32.0% | | 68.0% |
| Basic industries | 63.7% | | 36.3% |
| Capital goods | 51.0% | | 49.0% |
| Public utilities | 66.5% | | 33.5% |
| *N* | 268298 | | 271139 |

Panel A shows averages of financial reporting quality measures for stand-alone EPS forecasts (*only EPS*) and for EPS forecasts complemented by a revenue estimate (*EPS and REV*). *CAQ* is the variation in discretionary accruals, and $\lvert D\ ACC \rvert$ is the absolute level of discretionary accruals. *p* is the *p*-value for the difference in means of the financial reporting measures between the groups, and *N* is the number of observations. Panel B shows the distribution of stand-alone EPS forecasts and EPS forecasts complemented by revenue estimates across 11 industry groups based on a 2-digit IBES SIG code.

**Table 4** Descriptive statistics

| Variable | Mean | Median | STD | p |
|---|---|---|---|---|
| *Panel A: Analyst- and broker-related explanatory variables (N=539,437)* | | | | |
| *DREV* | 0.503 | 1.000 | 0.500 | 0.000 |
| IFEI | 1.32% | 0.38% | 2.98% | 0.000 |
| *Horizon* | 178.079 | 166.000 | 97.038 | 0.000 |
| *Gexp* | 6.395 | 6.000 | 3.274 | 0.000 |
| *A_#Firm* | 13.618 | 13.000 | 6.533 | 0.000 |
| *Bsize* | 56.176 | 48.000 | 41.403 | 0.000 |
| Variable | Mean | Median | STD | p |
| *Panel B: Firm-related explanatory variables (N=13,304 firm-years)* | | | | |
| *CAQ* | 0.059 | 0.038 | 0.058 | 0.000 |
| *\|D ACC\|* | 0.048 | 0.028 | 0.056 | 0.000 |
| *\|nD ACC\|* | 0.048 | 0.030 | 0.053 | 0.000 |
| *MV* | 3887 | 702 | 9811 | 0.000 |
| *Follow* | 10.547 | 8.000 | 8.958 | 0.000 |
| *COV* | 0.087 | 0.069 | 0.061 | 0.000 |
| *STD REV* | 0.147 | 0.104 | 0.137 | 0.000 |
| *B/M* | 0.498 | 0.422 | 0.396 | 0.000 |
| *Age* | 21.034 | 14.337 | 17.064 | 0.000 |
| *ROA* | 1.88% | 4.42% | 14.38% | 0.000 |
| *Dloss* | 17.91% | 0.00% | 38.35% | 0.000 |
| *Marg* | −0.111 | 0.045 | 0.900 | 0.000 |
| *LEV* | 0.181 | 0.145 | 0.184 | 0.000 |

The table shows mean and median values of the variables from the regression model (2) together with their standard deviation and p-values. Panel A shows results for analyst- and broker-related variables. Panel B shows results for firm-related explanatory variables. Variables definitions are in Table 1. *N* is the number of observations.

**Table 5** Predicting the analyst decision to issue a revenue forecast to complement EPS estimates

| | *CAQ quality measure* | | | *\|D ACC\| quality measure* | | |
|---|---|---|---|---|---|---|
| | Estimate | ME | p | Estimate | ME | p |
| *Intercept* | 1.901 | | 0.000 | 1.730 | | 0.000 |
| ln *CAQ* | 0.118 | 10.9% | 0.000 | | | |
| ln *\|D ACC\|* | | | | 0.029 | 3.9% | 0.000 |
| ln *\|nD ACC\|* | | | | 0.010 | 1.3% | 0.175 |
| ln *\|FE\|* | −1.976 | −5.4% | 0.000 | −1.978 | −5.4% | 0.000 |
| ln *Horizon* | 0.020 | 1.5% | 0.008 | 0.020 | 1.6% | 0.006 |
| ln *Gexp* | −0.146 | −7.3% | 0.015 | −0.147 | −7.4% | 0.014 |
| ln *A_#Firm* | 0.006 | 0.4% | 0.895 | 0.004 | 0.2% | 0.941 |
| ln *Bsize* | 0.035 | 3.7% | 0.234 | 0.034 | 3.6% | 0.246 |
| ln *MV* | −0.099 | −16.3% | 0.000 | −0.111 | −18.3% | 0.000 |
| ln *Follow* | 0.220 | 15.3% | 0.000 | 0.231 | 16.1% | 0.000 |
| *COV* | 1.148 | 6.3% | 0.000 | 1.281 | 7.1% | 0.000 |
| *STD REV* | −0.354 | −4.3% | 0.029 | −0.275 | −3.3% | 0.089 |
| *B/M* | −0.202 | −6.3% | 0.000 | −0.245 | −7.6% | 0.000 |
| ln *Age* | −0.165 | −12.4% | 0.000 | −0.172 | −13.0% | 0.000 |
| *ROA* | −0.509 | −5.8% | 0.000 | −0.570 | −6.5% | 0.000 |
| *Dloss* | 0.094 | 3.0% | 0.016 | 0.120 | 3.9% | 0.002 |
| *Marg* | 0.108 | 7.5% | 0.000 | 0.104 | 7.3% | 0.000 |
| *LEV* | −0.500 | −8.7% | 0.000 | −0.547 | −9.5% | 0.000 |
| *Industry effect* | Yes | | | Yes | | |
| *Year effect* | Yes | | | Yes | | |
| *N* | 539437 | | | 539437 | | |
| *Wald* $\chi^2$ | 21484.08 | | | 21531.1 | | |
| $p(\chi^2)$ | 0.000 | | | 0.000 | | |
| $R^2$ | 20.15% | | | 20.09% | | |

The table reports results (Estimate) from logistic regressions predicting that an analyst will issue a revenue forecast to complement the EPS estimate. Column *CAQ quality measure* shows results when we include the variation in discretionary accruals, *CAQ*, as the reporting quality measure. Column *|D ACC| quality measure* presents results when we use the absolute level of discretionary accruals, *|D ACC|*, to capture the quality of firm reporting. Other variables definitions are in Table 1. ME are the marginal effects, ln is the logarithm, p are p-values for regression coefficients. *N* is the number of observations, *Wald* $\chi^2$ is Wald $\chi^2$-test for model specification and $p(\chi^2)$ the corresponding *p*-value. $R^2$ is the pseudo *R*-squared.

**Table 6** Sensitivity analysis: alternative measures of reporting quality

| | *Tot. accruals* | | *Earn. persistence* | | *Signed curr. accruals* | | *Earn. STD* | |
|---|---|---|---|---|---|---|---|---|
| | Estimate | p | Estimate | p | Estimate | p | Estimate | p |
| *Intercept* | 1.545 | 0.000 | 1.594 | 0.000 | 1.595 | 0.000 | 1.762 | 0.000 |
| ln \|*ACC_T*\| | 0.354 | 0.017 | | | | | | |
| *E.persist* | | | −0.286 | 0.004 | | | | |
| ln *D ACC* | | | | | 0.461 | 0.001 | | |
| ln *nD ACC* | | | | | 0.079 | 0.457 | | |
| ln *CAQ* | | | | | | | 0.093 | 0.000 |
| *EPS STD* | | | | | | | 0.791 | 0.000 |
| ln \|*FE*\| | −1.899 | 0.000 | −1.928 | 0.000 | −1.901 | 0.000 | −2.069 | 0.000 |
| ln *Horizon* | 0.020 | 0.008 | 0.020 | 0.007 | 0.020 | 0.008 | 0.020 | 0.006 |
| ln *Gexp* | −0.147 | 0.015 | −0.147 | 0.014 | −0.147 | 0.015 | −0.145 | 0.016 |
| ln *A_#Firm* | 0.002 | 0.963 | 0.003 | 0.949 | 0.003 | 0.955 | 0.006 | 0.893 |
| ln *Bsize* | 0.034 | 0.248 | 0.034 | 0.252 | 0.034 | 0.249 | 0.035 | 0.226 |
| ln *MV* | −0.112 | 0.000 | −0.114 | 0.000 | −0.115 | 0.000 | −0.099 | 0.000 |
| ln *Follow* | 0.232 | 0.000 | 0.239 | 0.000 | 0.236 | 0.000 | 0.218 | 0.000 |
| *COV* | 1.319 | 0.000 | 1.329 | 0.000 | 1.304 | 0.000 | 1.079 | 0.000 |
| *STD REV* | −0.241 | 0.137 | −0.232 | 0.153 | −0.240 | 0.138 | −0.421 | 0.010 |
| *B/M* | −0.248 | 0.000 | −0.258 | 0.000 | −0.258 | 0.000 | −0.181 | 0.000 |
| ln *Age* | −0.173 | 0.000 | −0.176 | 0.000 | −0.174 | 0.000 | −0.163 | 0.000 |
| *ROA* | −0.558 | 0.000 | −0.443 | 0.000 | −0.698 | 0.000 | −0.381 | 0.002 |
| *Dloss* | 0.119 | 0.003 | 0.119 | 0.003 | 0.114 | 0.004 | 0.089 | 0.022 |
| *Marg* | 0.104 | 0.000 | 0.105 | 0.000 | 0.102 | 0.000 | 0.106 | 0.000 |
| *LEV* | −0.568 | 0.000 | −0.599 | 0.000 | −0.578 | 0.000 | −0.488 | 0.000 |
| *Industry effect* | Yes | | Yes | | Yes | | Yes | |
| *Year effect* | Yes | | Yes | | Yes | | Yes | |
| *N* | 539437 | | 539437 | | 539437 | | 539437 | |
| *Wald* $\chi^2$ | 21517.74 | | 21567.21 | | 21533.07 | | 21665.84 | |
| $p(\chi^2)$ | 0.000 | | 0.000 | | 0.000 | | 0.000 | |
| $R^2$ | 20.07% | | 20.07% | | 20.08% | | 20.18% | |

The table shows results (Estimate) from logistic regressions predicting that an analyst will issue a revenue forecast to complement the EPS estimate. Column *Tot. accruals* reports results for regression model (2) when we use absolute total accruals, |*ACC_T*|, to measure reporting quality, which is the absolute difference between net income and operating cash flow. Column *Earn. persistence* shows regression results when we use earnings persistence, *E.persist*, to measure reporting quality. Column *Signed curr. accruals* presents results when we use the signed magnitude of discretionary accruals, *D ACC*, , to measure reporting quality. *nD ACC* are non-discretionary accruals. Column *Earn. STD* shows results when we include earnings volatility, *STD EPS*, in the regression model (2). Other variables definitions are in Table 1. ln is the logarithm, p are p-values for regression coefficients. *N* is the number of observations, *Wald* $\chi^2$is Wald $\chi^2$-test for model specification and $p(\chi^2)$ the corresponding *p*-value. $R^2$ is the pseudo *R*-squared.

**Table 7** Sensitivity analysis: alternative measures of analyst forecasting skill

| | *Past EPS accuracy* | | *PMAFE* | | *Star analysts* | |
|---|---|---|---|---|---|---|
| | Estimate | p | Estimate | p | Estimate | p |
| *Intercept* | 1.744 | 0.000 | 1.691 | 0.000 | 1.901 | 0.000 |
| ln *CAQ* | 0.096 | 0.000 | 0.117 | 0.000 | 0.118 | 0.000 |
| ln \|*FE prev*\| | −1.928 | 0.006 | | | | |
| *PMAFE* | | | −0.121 | 0.000 | | |
| ln \|*FE*\| | | | | | −1.973 | 0.000 |
| *Star* | | | | | −0.336 | 0.088 |
| ln *Horizon* | 0.032 | 0.000 | 0.062 | 0.000 | 0.018 | 0.018 |
| ln *Gexp* | −0.158 | 0.049 | −0.148 | 0.014 | −0.145 | 0.016 |
| ln *A_#Firm* | 0.049 | 0.470 | 0.007 | 0.886 | 0.007 | 0.887 |
| ln *Bsize* | 0.036 | 0.328 | 0.034 | 0.250 | 0.036 | 0.220 |
| ln *MV* | −0.097 | 0.000 | −0.096 | 0.000 | −0.099 | 0.000 |
| ln *Follow* | 0.230 | 0.000 | 0.218 | 0.000 | 0.220 | 0.000 |
| *COV* | 1.149 | 0.000 | 1.085 | 0.000 | 1.147 | 0.000 |
| *STD REV* | −0.478 | 0.012 | −0.382 | 0.019 | −0.354 | 0.029 |
| *B/M* | −0.225 | 0.000 | −0.224 | 0.000 | −0.202 | 0.000 |
| ln *Age* | −0.169 | 0.000 | −0.169 | 0.000 | −0.165 | 0.000 |
| *ROA* | −0.611 | 0.000 | −0.471 | 0.000 | −0.509 | 0.000 |
| *Dloss* | 0.071 | 0.110 | 0.027 | 0.457 | 0.094 | 0.016 |
| *Marg* | 0.108 | 0.000 | 0.104 | 0.000 | 0.108 | 0.000 |
| *LEV* | −0.542 | 0.000 | −0.524 | 0.000 | −0.500 | 0.000 |
| *Industry effect* | Yes | | Yes | | Yes | |
| *Year effect* | Yes | | Yes | | Yes | |
| *N* | 334494 | | 539437 | | 539454 | |
| *Wald* $\chi^2$ | 11741.60 | | 22060.37 | | 21505.24 | |
| $p(\chi^2)$ | 0.000 | | 0.000 | | 0.000 | |
| $R^2$ | 17.57% | | 20.23% | | 20.16% | |

The table reports results (Estimate) from logistic regressions predicting that an analyst will issue a revenue estimate to complement the EPS forecast. Column *Past EPS accuracy* reports results for regression model (2) when we use analyst past EPS forecast accuracy (|*FE prev*|) to capture analyst forecasting skill. Column *PMAFE* shows results when we use the proportional mean adjusted forecast error (*PMAFE*) to measure analyst EPS forecasting skill. Column *Star analysts* show results for model (2) regression when we include an indicator variable for analysts ranked top by the Institutional Investor magazine in the previous year. Other variables definitions are in Table 1. ln is the logarithm, p are p-values for regression coefficients. *N* is the number of observations, *Wald* $\chi^2$is Wald $\chi^2$-test for model specification and $p(\chi^2)$ the corresponding *p*-value. $R^2$ is the pseudo *R*-squared.

**Table 8** Annual and Fama-MacBeth regressions

| | *fiscal year 2000* | | *fiscal year 2001* | | *fiscal year 2002* | | *fiscal year 2003* | | *fiscal year 2004* | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Estimate | p | Estimate | p | Estimate | p | Estimate | p | Estimate | p |
| *Intercept* | −0.373 | 0.440 | −0.698 | 0.097 | 0.626 | 0.099 | 1.533 | 0.000 | 2.091 | 0.000 |
| ln *CAQ* | 0.072 | 0.040 | 0.118 | 0.007 | 0.140 | 0.000 | 0.126 | 0.000 | 0.090 | 0.004 |
| ln \|*FE*\| | −2.535 | 0.060 | −5.037 | 0.000 | −0.656 | 0.545 | −2.396 | 0.000 | −1.929 | 0.008 |
| ln *Horizon* | −0.070 | 0.024 | −0.072 | 0.022 | −0.225 | 0.000 | −0.130 | 0.000 | −0.009 | 0.674 |
| ln *Gexp* | −0.386 | 0.017 | −0.134 | 0.209 | −0.148 | 0.090 | −0.275 | 0.002 | −0.144 | 0.115 |
| ln *A_#Firm* | −0.097 | 0.319 | 0.031 | 0.665 | 0.145 | 0.031 | 0.101 | 0.128 | −0.052 | 0.495 |
| ln *Bsize* | −0.038 | 0.440 | 0.011 | 0.758 | −0.010 | 0.760 | 0.032 | 0.363 | 0.025 | 0.536 |
| ln *MV* | −0.041 | 0.280 | −0.063 | 0.069 | −0.050 | 0.134 | −0.106 | 0.001 | −0.124 | 0.000 |
| ln *Follow* | 0.033 | 0.671 | 0.211 | 0.003 | 0.275 | 0.000 | 0.239 | 0.000 | 0.207 | 0.002 |
| *COV* | 1.633 | 0.000 | 1.512 | 0.000 | 1.250 | 0.005 | 1.019 | 0.019 | 0.491 | 0.211 |
| *STD REV* | −0.224 | 0.345 | 0.066 | 0.775 | −0.042 | 0.838 | −0.376 | 0.076 | −0.385 | 0.080 |
| *B/M* | −0.055 | 0.593 | −0.256 | 0.011 | −0.036 | 0.665 | −0.151 | 0.010 | −0.345 | 0.000 |
| ln *Age* | −0.221 | 0.000 | −0.166 | 0.000 | −0.162 | 0.000 | −0.212 | 0.000 | −0.180 | 0.000 |
| *ROA* | −0.358 | 0.296 | 0.567 | 0.077 | −0.189 | 0.468 | −0.413 | 0.046 | −0.700 | 0.007 |
| *Dloss* | 0.145 | 0.238 | 0.184 | 0.030 | −0.002 | 0.982 | 0.049 | 0.512 | 0.125 | 0.109 |
| *Marg* | 0.172 | 0.005 | 0.003 | 0.929 | 0.082 | 0.007 | 0.111 | 0.000 | 0.146 | 0.000 |
| *LEV* | 0.079 | 0.700 | −0.601 | 0.004 | −0.738 | 0.000 | −0.380 | 0.014 | −0.639 | 0.000 |
| *Industry effect* | Yes | | Yes | | Yes | | Yes | | Yes | |
| *Year effect* | Yes | | Yes | | Yes | | Yes | | Yes | |
| *N* | 41104 | | 48289 | | 51075 | | 58625 | | 66149 | |
| *Wald* $\chi^2$ | 673.52 | | 1995.08 | | 3014.47 | | 3049.10 | | 2579.31 | |
| $p(\chi^2)$ | 0.000 | | 0.000 | | 0.000 | | 0.000 | | 0.000 | |
| $R^2$ | 5.13% | | 10.63% | | 12.23% | | 11.46% | | 10.52% | |

**Table 8** continued

| | *fiscal year 2005* | | *fiscal year 2006* | | *fiscal year 2007* | | *fiscal year 2008* | | *Fama-MacBeth* | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Estimate | p | Estimate | p | Estimate | p | Estimate | p | FM estimate | p(FM) |
| *Intercept* | 1.601 | 0.000 | 1.684 | 0.000 | 1.668 | 0.000 | 0.765 | 0.066 | 0.989 | 0.017 |
| ln *CAQ* | 0.082 | 0.010 | 0.121 | 0.000 | 0.174 | 0.000 | 0.088 | 0.006 | 0.112 | 0.000 |
| ln \|*FE*\| | −2.454 | 0.000 | −1.370 | 0.043 | −1.107 | 0.116 | −1.629 | 0.034 | −2.124 | 0.001 |
| ln *Horizon* | 0.083 | 0.000 | 0.006 | 0.719 | 0.096 | 0.000 | 0.060 | 0.001 | −0.029 | 0.439 |
| ln *Gexp* | −0.138 | 0.126 | −0.150 | 0.101 | −0.119 | 0.180 | −0.023 | 0.820 | −0.169 | 0.001 |
| ln *A_#Firm* | −0.082 | 0.294 | 0.025 | 0.745 | −0.018 | 0.825 | 0.017 | 0.840 | 0.008 | 0.772 |
| ln *Bsize* | 0.010 | 0.822 | 0.029 | 0.507 | 0.055 | 0.241 | 0.140 | 0.004 | 0.028 | 0.126 |
| ln *MV* | −0.142 | 0.000 | −0.133 | 0.000 | −0.135 | 0.000 | −0.113 | 0.000 | −0.101 | 0.000 |
| ln *Follow* | 0.218 | 0.000 | 0.238 | 0.000 | 0.236 | 0.000 | 0.347 | 0.000 | 0.222 | 0.000 |
| *COV* | 0.690 | 0.192 | 1.151 | 0.023 | −0.026 | 0.959 | 0.702 | 0.090 | 0.936 | 0.001 |
| *STD REV* | −0.325 | 0.120 | −0.650 | 0.009 | −0.648 | 0.011 | −0.595 | 0.042 | −0.353 | 0.003 |
| *B/M* | −0.294 | 0.002 | −0.201 | 0.015 | −0.100 | 0.286 | −0.173 | 0.033 | −0.179 | 0.001 |
| ln *Age* | −0.152 | 0.000 | −0.103 | 0.002 | −0.128 | 0.001 | −0.177 | 0.000 | −0.167 | 0.000 |
| *ROA* | −0.614 | 0.031 | 0.003 | 0.989 | −0.392 | 0.145 | −0.566 | 0.070 | −0.296 | 0.052 |
| *Dloss* | 0.121 | 0.146 | 0.093 | 0.208 | 0.078 | 0.297 | 0.115 | 0.160 | 0.101 | 0.001 |
| *Marg* | 0.121 | 0.003 | 0.100 | 0.000 | 0.134 | 0.000 | 0.089 | 0.025 | 0.106 | 0.000 |
| *LEV* | −0.794 | 0.000 | −0.458 | 0.000 | −0.245 | 0.076 | −0.307 | 0.032 | −0.454 | 0.001 |
| *Industry effect* | Yes | | Yes | | Yes | | Yes | | Yes | |
| *Year effect* | Yes | | Yes | | Yes | | Yes | | Yes | |
| *N* | 67798 | | 70317 | | 67284 | | 68796 | | | |
| *Wald* $\chi^2$ | 2373.42 | | 1835.97 | | 1994.51 | | 1517.89 | | | |
| $p(\chi^2)$ | 0.000 | | 0.000 | | 0.000 | | 0.000 | | | |
| $R^2$ | 9.50% | | 7.59% | | 8.60% | | 7.96% | | | |

Columns *fiscal year 2000* to *fiscal year 2008* report results (Estimate) for annual logistic regressions predicting that an analyst will issue a revenue forecast to complement the EPS estimate. Column *Fama–MacBeth* shows results using Fama–MacBeth analysis. Variables definitions are in Table 1. ln is the logarithm, p are p-values for annual regressions, and p(FM) are p-values based on Fama-MacBeth *t*-test. *N* is the number of observations, *Wald* $\chi^2$ is Wald $\chi^2$-test for model specification and $p(\chi^2)$ the corresponding *p*-value. $R^2$ is the pseudo *R*-squared.

**Table 9** Random sample regression results

| | *CAQ quality measure* | | *\|D ACC\| quality measure* | |
|---|---|---|---|---|
| | Estimate | p | Estimate | p |
| *Intercept* | 2.106 | 0.000 | 1.960 | 0.000 |
| ln *CAQ* | 0.111 | 0.000 | | |
| ln \|*D ACC*\| | | | 0.025 | 0.001 |
| ln \|*nD ACC*\| | | | 0.018 | 0.011 |
| ln \|*FE*\| | −1.713 | 0.000 | −1.700 | 0.000 |
| ln *Horizon* | −0.038 | 0.000 | −0.038 | 0.000 |
| ln *Gexp* | −0.100 | 0.065 | −0.101 | 0.063 |
| ln *A_#Firm* | −0.057 | 0.185 | −0.059 | 0.167 |
| ln *Bsize* | 0.053 | 0.041 | 0.052 | 0.045 |
| ln *MV* | −0.112 | 0.000 | −0.122 | 0.000 |
| ln *Follow* | 0.235 | 0.000 | 0.244 | 0.000 |
| *COV* | 1.183 | 0.000 | 1.311 | 0.000 |
| *STD REV* | −0.190 | 0.150 | −0.125 | 0.343 |
| *B/M* | −0.208 | 0.000 | −0.243 | 0.000 |
| ln *Age* | −0.171 | 0.000 | −0.179 | 0.000 |
| *ROA* | −0.358 | 0.002 | −0.410 | 0.000 |
| *Dloss* | 0.067 | 0.100 | 0.093 | 0.022 |
| *Marg* | 0.096 | 0.000 | 0.093 | 0.000 |
| *LEV* | −0.574 | 0.000 | −0.611 | 0.000 |
| *Industry effect* | Yes | | Yes | |
| *Year effect* | Yes | | Yes | |
| *N* | 138114 | | 138114 | |
| *Wald* $\chi^2$ | 18444.99 | | 18467.45 | |
| $p(\chi^2)$ | 0.000 | | 0.000 | |
| $R^2$ | 21.01% | | 20.96% | |

The table shows results (Estimate) from logistic regressions predicting that an analyst will issues a revenue estimate to complement the EPS forecast when we randomly choose one analyst EPS forecast for a firm in a fiscal year. Column *CAQ quality measure* shows results when we include the variation in discretionary accruals, *CAQ*, as the reporting quality measure. Column |*D ACC*| *quality measure* reports results when we use the absolute level of discretionary accruals, |*D ACC*|, to capture the quality of firm reporting. Variables definitions are in Table 1. ln is the logarithm, p are p-values for regression coefficients. *N* is the number of observations, *Wald* $\chi^2$is Wald $\chi^2$-test for model specification and $p(\chi^2)$ the corresponding *p*-value. $R^2$ is the pseudo *R*-squared.

**Table 10** Revenue forecast initiations

| | *CAQ quality measure* | | *\|D ACC\| quality measure* | |
|---|---|---|---|---|
| | Estimate | p | Estimate | p |
| *Intercept* | 2.551 | 0.000 | 2.330 | 0.000 |
| ln *CAQ* | 0.132 | 0.000 | | |
| ln \|*D ACC*\| | | | 0.031 | 0.006 |
| ln \|*nD ACC*\| | | | 0.009 | 0.405 |
| ln \|*FE*\| | −1.648 | 0.003 | −1.601 | 0.004 |
| ln *Horizon* | 0.151 | 0.000 | 0.151 | 0.000 |
| ln *Gexp* | −0.594 | 0.000 | −0.594 | 0.000 |
| ln *A_#Firm* | −0.245 | 0.000 | −0.247 | 0.000 |
| ln *Bsize* | −0.012 | 0.743 | −0.013 | 0.723 |
| ln *MV* | −0.115 | 0.000 | −0.129 | 0.000 |
| ln *Follow* | 0.140 | 0.013 | 0.151 | 0.008 |
| *COV* | 1.001 | 0.001 | 1.164 | 0.000 |
| *STD REV* | −0.325 | 0.107 | −0.231 | 0.250 |
| *B/M* | −0.373 | 0.000 | −0.418 | 0.000 |
| ln *Age* | −0.361 | 0.000 | −0.369 | 0.000 |
| *ROA* | −0.875 | 0.000 | −0.928 | 0.000 |
| *Dloss* | −0.046 | 0.457 | −0.015 | 0.809 |
| *Marg* | 0.046 | 0.119 | 0.039 | 0.179 |
| *LEV* | −0.288 | 0.029 | −0.343 | 0.009 |
| *Industry effect* | Yes | | Yes | |
| *Year effect* | Yes | | Yes | |
| *N* | 173380 | | 173380 | |
| *Wald* $\chi^2$ | 6310.61 | | 6312.99 | |
| $p(\chi^2)$ | 0.000 | | 0.000 | |
| $R^2$ | 17.24% | | 17.15% | |

The table reports results (Estimate) from logistic regressions predicting initiations of revenue forecast issues for a firm. The dependent variable is an indicator variable, which equals one for the first revenue forecast issued for a firm, and zero otherwise. We remove all EPS forecasts for the firm after the first revenue forecast has been issued. Column *CAQ quality measure* shows results when we include the variation in discretionary accruals, *CAQ*, as the reporting quality measure. Column |*D ACC*| *quality measure* documents results when we use the absolute level of discretionary accruals, |*D ACC*|, to capture the quality of firm reporting. Variables definitions are in Table 1. ln is the logarithm, p are p-values for regression coefficients, *N* is the number of observations, *Wald* $\chi^2$is Wald $\chi^2$-test for model specification and $p(\chi^2)$ the corresponding *p*-value. $R^2$ is the pseudo *R*-squared.

**Table 11** EPS and revenue forecast accuracy regressions

| | EPS forecast error | | | | Revenue forecast error | | | |
|---|---|---|---|---|---|---|---|---|
| | *CAQ quality measure* | | *\|D ACC\| quality measure* | | *CAQ quality measure* | | *\|D ACC\| quality measure* | |
| | Estimate | p | Estimate | p | Estimate | p | Estimate | p |
| *Intercept* | −1.432 | 0.006 | −1.439 | 0.007 | −11.468 | 0.000 | −10.790 | 0.000 |
| ln *CAQ* | 0.136 | 0.002 | | | −0.140 | 0.443 | | |
| ln *\|D ACC\|* | | | 0.083 | 0.000 | | | 0.096 | 0.245 |
| ln *\|nD ACC\|* | | | 0.022 | 0.293 | | | 0.002 | 0.980 |
| ln *Horizon* | 0.549 | 0.000 | 0.550 | 0.000 | 2.165 | 0.000 | 2.165 | 0.000 |
| ln *Gexp* | 0.046 | 0.130 | 0.044 | 0.142 | 0.221 | 0.093 | 0.224 | 0.089 |
| ln *A_#Firm* | −0.118 | 0.000 | −0.120 | 0.000 | −0.286 | 0.063 | −0.279 | 0.073 |
| ln *Bsize* | −0.033 | 0.046 | −0.033 | 0.049 | 0.128 | 0.069 | 0.132 | 0.065 |
| ln *MV* | −0.103 | 0.007 | −0.108 | 0.003 | 0.159 | 0.301 | 0.188 | 0.210 |
| ln *Follow* | −0.095 | 0.226 | −0.088 | 0.259 | −0.934 | 0.001 | −0.973 | 0.001 |
| *COV* | 2.868 | 0.000 | 2.893 | 0.000 | 11.480 | 0.000 | 11.103 | 0.000 |
| *STD REV* | 1.244 | 0.015 | 1.293 | 0.010 | 15.458 | 0.000 | 15.181 | 0.000 |
| *B/M* | 1.216 | 0.000 | 1.204 | 0.000 | 8.374 | 0.000 | 8.485 | 0.000 |
| ln *Age* | 0.202 | 0.011 | 0.197 | 0.014 | 0.781 | 0.040 | 0.804 | 0.031 |
| *ROA* | −1.970 | 0.000 | −2.002 | 0.000 | −3.784 | 0.004 | −3.619 | 0.006 |
| *Dloss* | 2.907 | 0.000 | 2.924 | 0.000 | 2.085 | 0.000 | 2.036 | 0.000 |
| *Marg* | 0.141 | 0.166 | 0.143 | 0.158 | 0.411 | 0.010 | 0.426 | 0.008 |
| *LEV* | 1.088 | 0.000 | 1.093 | 0.000 | 4.694 | 0.000 | 4.854 | 0.000 |
| *Industry effect* | Yes | | Yes | | Yes | | Yes | |
| *Year effect* | Yes | | Yes | | Yes | | Yes | |
| *N* | 271139 | | 271139 | | 271139 | | 271139 | |
| *F-test* | 251.55 | | 243.30 | | 224.04 | | 218.45 | |
| *p(F)* | 0.000 | | 0.000 | | 0.000 | | 0.000 | |
| $R^2$ | 24.19% | | 24.23% | | 16.21% | | 16.22% | |

The table documents results (Estimate) from accuracy regressions where the dependent variable is either the EPS forecast error (EPS forecast error) or the revenue forecast error (Revenue forecast error). Column *CAQ quality measure* presents results when we include the variation in discretionary accruals, *CAQ*, as the reporting quality measure. Column *|D ACC| quality measure* show results when we use the absolute level of discretionary accruals, *|D ACC|*, to capture the quality of firm reporting. Variables definitions are in Table 1. The sample of EPS estimates includes 271,139 EPS forecasts that are accompanied by revenue estimates. ln is the logarithm, p are p-values for regression coefficients, *N* is the number of observations, *F-test* is the *F*-test for model specification and *p(F)* is the corresponding *p*-value. $R^2$ is the R-squared.

**Table 12** Price reaction to analyst EPS and revenue forecast announcements

| | *Without CAQ interaction* | | *With CAQ interaction* | |
|---|---|---|---|---|
| | Estimate | p | Estimate | p |
| *Intercept* | 0.001 | 0.035 | 0.001 | 0.030 |
| $\Delta EPS$ | 0.032 | 0.000 | 0.036 | 0.000 |
| $\Delta REV$ | 0.195 | 0.000 | 0.176 | 0.000 |
| $DREV*\Delta EPS$ | 0.016 | 0.000 | 0.018 | 0.000 |
| *Upgrade* | 0.032 | 0.000 | 0.032 | 0.000 |
| *Revision* | 0.003 | 0.123 | 0.003 | 0.122 |
| *Downgrade* | −0.052 | 0.000 | −0.052 | 0.000 |
| $CAQ*\Delta EPS$ | | | −0.068 | 0.004 |
| $CAQ*\Delta REV$ | | | 0.241 | 0.142 |
| *N* | 345632 | | 345632 | |
| *F-test* | 1425.74 | | 1067.86 | |
| *p(F)* | 0.000 | | 0.000 | |
| $R^2$ | 6.74% | | 6.77% | |

The table reports regression results (Estimate) for mode (3) that examines the price reaction to analyst EPS ($\Delta EPS$) and revenue ($\Delta REV$) forecast revisions. The dependent variable is a three-day cumulative abnormal return (*CAR*) centered on the EPS forecast announcement date. Column *Without CAQ interaction* shows regression results for model (3) without controlling for the effect quality of firm financial reporting has on the price reaction to EPS and revenue forecast revisions. Column *With CAQ interaction* shows regression results for model (3), which includes the interaction terms between EPS and revenue forecast revisions and the variation in discretionary accruals ($CAQ*\Delta EPS$ and $CAQ*\Delta REV$). Other variables definitions are in Table 1. p are p-values for regression coefficients, *N* is the number of observations, *F-test* is the *F*-test for model specification and *p(F)* is the corresponding *p*-value. $R^2$ is the R-squared.