Analyst Revenue Forecast Reporting and the Quality of Revenues and Expenses

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Abstract: We decompose earnings quality into revenue and expense quality and examine their associations with analyst propensity to supplement their earnings forecasts with revenue forecasts. Analysts report more revenue forecasts to I/B/E/S when expense quality is low to compensate for the low accuracy of their earnings estimates, which has a positive association with expense quality. Expense quality is unassociated with revenue forecast accuracy, thus revenue forecasts become increasingly useful for valuing firms when expense quality is low. Analysts report fewer revenue forecasts when revenue quality is low because both earnings and revenue forecast accuracy decline as revenue quality deteriorates. To control for endogeneity, we use firm-fixed effects to control for unobserved time-invariant heterogeneity across firms, instrumental variables regressions and regression in changes.

Keywords: joint earnings and revenue forecast issues, quality of earnings components, earnings and revenue forecast accuracy, price reaction

JEL Classification: M41; N20

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1. INTRODUCTION

Analysts routinely report their earnings-per-share (EPS) forecasts to I/B/E/S, but complement only some of these with revenue forecasts.[1] This study considers the associations of revenue and expense quality with analysts' propensity to report revenue forecasts with their EPS forecasts to I/B/E/S. Our intuition is that low revenue and expense quality increase earnings forecasting difficulties and reduce the accuracy and value relevance of analysts' EPS forecasts (Bradshaw et al., 2001; Hughes et al., 2008). This in turn increases investors' reliance on and demand for complementary information.[2] We argue that low quality expenses increase the investor demand for complementary information in the form of revenue forecasts and analysts respond by reporting more revenue forecasts. We also argue that low quality revenues will reduce the reporting of revenue forecasts as a result of both a decrease in demand and analysts' reluctance to report low quality forecasts.

To examine the associations of revenue and expense quality with analysts' decisions to report a revenue forecast with an earnings forecast, we consider I/B/E/S reported annual EPS and revenue forecasts over the fiscal years 2000–2013. We focus on I/B/E/S reported forecasts, rather than on the revenue forecasts in analysts' investment reports, as only the voluntary nature of reporting to I/B/E/S allows us to examine when and how analysts respond to investor demand for revenue forecasts. Specifically, investment reports routinely include revenue forecasts as part of the forecasted income statements. With a standard research report setup, analysts will include revenue forecasts in their investment reports even if (1) there is no demand for the forecast because the EPS estimate is already of high quality (e.g. when revenue and expense quality are high) and (2) the revenue forecast is of such low quality that investors

[1] To illustrate, in our sample of the 853,789 individual analyst earnings forecasts from I/B/E/S over the period 2000–2013, over 55.1% are supplemented by revenue estimates.

[2] Revenue forecasts are useful as they permit investors to supplement earnings based valuations with revenue based assessments and achieve greater accuracy (Beatty et al., 1999 and Yoo, 2006). Furthermore, revenue forecasts provide an ex-ante check on the quality of EPS forecasts. Specifically, revenue forecasts enable investors to decompose EPS forecasts into forecasts of revenues and expenses and pay particular attention to the contribution of the former, more persistent component of the earnings forecast (Ertimur et al., 2003).

would ignore it. I/B/E/S does not require analysts to report revenue forecasts, hence voluntary revenue reporting to I/B/E/S is more likely to capture (1) investor demand for the forecast and (2) analyst inclination to report a useful revenue forecast.

I/B/E/S is an important medium for analysts to disseminate their forecasts and investors pay close attention to the type and quality of forecasts supplied to I/B/E/S. Ivkovic and Jegadeesh (2004, p.434) emphasize that "investors pay millions of dollars every year to purchase forecast and recommendation data from vendors such as First Call, I/B/E/S, and Zacks.". Furthermore, analysts issue their full reports much less frequently than they issue forecasts to I/B/E/S.[3] Ertimur et al. (2011) point out that access to I/B/E/S forecasts reduces information search and processing costs for investors by standardizing the forecast measures across analysts. I/B/E/S also gives analysts exposure to vast investor groups, including important institutional investors such as pension and mutual funds. Ertimur et al. (2011) highlight that analyst ranking services such as StarMine use I/B/E/S to rate analysts and that analyst rankings matter for analyst career prospects and compensation (Hong et al., 2000; Hong and Kubik, 2003; Leone and Wu, 2007).

We document that analysts are more likely to report revenue forecasts in association with low earnings quality and high quality revenues and the effects are economically non-trivial. A one standard deviation reduction in the log of expense quality leads to a 13.9% increase in the likelihood of issuing a joint EPS and revenue forecast. A one standard deviation reduction in the log of revenue quality reduces the likelihood of reporting a revenue forecast with an earnings forecast by 10.3%. To address the concern that our results reflect endogeneity, we perform three tests. First, we use firm-fixed effects in our regressions to control for unobserved firm characteristics that may correlate with the analyst revenue reporting decision and revenue and

[3] To illustrate, Huang et al. (2014) report that "[O]n average, an analyst issues 10.5 reports for our sample firms in 1998, and that number increases gradually to 33 by 2008." For comparison, in our I/B/E/S sample, analysts reported on average 38 EPS forecasts for the firms they covered in 1998 and close to 50 forecasts in 2013. Bradshaw (2011) mentions that I/B/E/S aggregates information from, among others, analysts' reports and morning broker notes.

expense quality. Second, we estimate the regression model with changes in revenue and expense quality as, "changes regressions are less susceptible to correlated omitted variables problems," (Skinner, 1996, p397). Third, we use instrumental variables regressions to address analyst endogenous coverage choices. Fourth, we repeat the analysis for the decile of largest Compustat stocks where analyst coverage choices are constrained.[4] As a corroborating test, we also examined the association of analyst initiation of revenue forecast reporting with the subsequent quality of revenue and expenses. If analyst revenue forecast reporting and revenue and expense quality jointly respond to external factors, we expect revenue and expense quality to change after analysts start reporting revenue forecasts, but find no evidence to support this claim. Tests that address endogeneity produce evidence supporting our predictions.

To build confidence in the validity of our conclusions, we subject the results to a battery of robustness tests. Sensitivity tests show that our conclusions are not driven by an increase in institutional investor demand for revenue forecasts or by management revenue guidance. Further, the results remain unchanged when we employ an alternative revenue quality measure and remove joint issuances of earnings and cash flow forecasts from the sample. Finally, we confirm the positive association of revenue forecast accuracy with revenue quality, but not with expense quality. Earnings forecast accuracy shows a positive association with both revenue and expense quality.

We recognize that standard valuation textbooks recommend that investors consider cash flows when earnings are of low quality (Penman, 2003), thus one might expect investors to demand cash flow forecasts and analysts to supply these forecasts when revenue and expense quality are low. However, Givoly et al. (2009) and Bilinski (2014) document that analyst cash flow forecasts are especially inaccurate, particularly in comparison with their contemporaneous EPS forecasts, when earnings quality is low. To corroborate this result, we relate revenue and

[4] Brokers routinely cover large stocks because sell-side research is compensated out of trade commissions, which increase with the size of the covered firm (Irvine 2004).

expense quality to analyst propensity to report cash flow forecasts with EPS estimates to I/B/E/S and find significantly positive associations. This result is consistent with Bilinski (2014), who finds that analysts refrain from producing cash flow forecasts when earnings quality is low due to the low accuracy of the cash flow forecasts.

This study contributes to the literature in three major ways. First, our results highlight how analysts use revenue forecasts to increase the overall informativeness of their outputs when the usefulness of their earnings forecasts is low. A large body of research reports a negative association between low earnings quality and EPS forecast accuracy (Bradshaw et al., 2001; Drake and Myers, 2011; Hughes et al., 2008; Dichev and Tang, 2009). However, these studies do not focus on complementary forecasts and a reader could mistakenly conclude that analysts passively accept low accuracy and informativeness of their research for low earnings quality firms. Our study highlights how complementary forecasts, such as revenue, help analysts mitigate the low informativeness of EPS forecasts in these settings and raise the value of their research for investors. The study is particularly interesting from the point that a low quality component of earnings (i.e. expenses) can be associated with an increase in the supply of forecasts for another component of earnings (i.e. revenue).

Second, we add to the nascent literature that examines the analyst choice to complement an I/B/E/S reported earnings forecast with a revenue forecast. To date, only Ertimur et al. (2011) and Marks (2008) have examined the determinants of reporting a revenue forecast with an earnings forecast to I/B/E/S. Both studies find that lower reputation analysts are more likely to report revenue forecasts with their EPS forecasts to I/B/E/S. Our research differs from these preceding studies by emphasizing both the demand and supply side explanations for revenue forecast reporting, i.e. how variations in expense and revenue quality impact the demand for and supply of revenue forecasts. Further, we report that controlling for the fact that more reputable analysts tend to follow firms with higher revenue and expense quality, more reputable analysts do not seem more likely to report more revenue forecasts. This result suggests caution in interpreting Ertimur et al. (2011) and Marks (2008) conclusions.

Third, our findings help explain the results in Ertimur et al. (2003) and Keung (2010) that jointly issued earnings and revenue forecasts have a greater price impact than stand-alone earnings forecasts. This finding is not surprising for our results suggest that analysts rationally respond to investor demand and more readily report revenue forecasts to I/B/E/S when these complementary forecasts are most useful to investors, i.e. when low expense quality reduces the usefulness of EPS forecasts and makes revenue forecasts comparatively more useful.

Fourth, our study responds to Bradshaw's (2011, 24–25) point that "our understanding of what analysts do and why they do it requires consideration of their portfolio of activities," and that the easiest means for gaining additional understanding of what analysts do is to examine their outputs beyond earnings forecasts. Further, our findings add valuable new insights regarding the capital market effects of firm earnings quality (Healy and Palepu, 2001; Dechow et al., 2010), the dynamic interaction between earnings quality components and information production by analysts (Barth et al., 2001a; Francis et al., 2002; Frankel et al., 2006; Beyer et al., 2010), and the role of financial analysts as information producers in capital markets (Ivkovic and Jegadeesh, 2004; Asquith et al., 2005; Ramnath et al., 2008; Chen et al., 2010).

2. PREVIOUS LITERATURE AND HYPOTHESIS DEVELOPMENT

Earnings is generally considered to be a better indicator of firm performance than other accounting measures, such as revenue (Hopwood and McKeown, 1985; Hoskin et al., 1986; Easton et al., 1992; Beyer et al., 2010; Dechow et al., 2010). Standard valuation models focus on earnings (Ohlson, 1995; Ohlson and Juettner-Nauroth, 2005) and "horse-race" tests show that earnings-based valuation multiples outperform revenue- and cash flow-based multiples (Liu et al. 2002). However, low earnings quality can reduce the reliability and usefulness of analyst earnings forecasts. Biggs (1984) identifies the income statement as the primary source of information used by financial analysts in earnings forecasting and previous studies document a negative association between earnings quality and EPS forecast accuracy. Bradshaw et al. (2001), Drake and Myers (2011), Hughes et al. (2008), and Lobo et al. (2012) employ accruals based measures of earnings quality and observe an inverse association between earnings quality and analyst earnings forecast errors. Bradshaw et al. (2001, 46) conclude that "sell-side analysts lack the necessary sophistication to understand the future implications of high levels of accruals," consistent with analysts finding it more challenging to forecast earnings when their quality is low.[5] Gu and Wang (2005) report that firms with high intangible intensity have lower forecast accuracy. Consistent with the prediction that earnings volatility reduces earnings predictability, Dichev and Tang (2009, 179) document that analysts fail to, "fully understand the implication of earnings volatility for earnings predictability," and produce less accurate forecasts for firms with more volatile earnings.

Studies considering the value-relevance of revenue are limited and typically consider its value-relevance simultaneously with that of earnings.[6] The overall tone of these studies is that revenue is particularly important in instances where earnings is less reliable. Kama (2009) argues that revenue should be particularly important in environments where earnings precision is low. Consistent with this prediction, he reports that in high R&D intensity companies the market reaction to annual earnings surprises (revenue surprises) is lower (higher) than in low R&D intensity companies. He finds similar results for the fourth fiscal quarter, which tends to have greater earnings management (Cohen et al., 2008) and significantly greater discretionary write-offs (Elliott and Shaw, 1988; Elliott and Hanna, 1996). Ghosh et al. (2005) find that investors

[5] The term earnings quality has been broadly used to reflect investors' abilities to assess the sources of and probability of recurrence of net income (see Securities and Exchange Commission Accounting Series Release No.159).

[6] Accounting research has a long history of studies on the value relevance of earnings (see Kothari, 2001; Holthausen et al., 2001; Barth et al., 2001b for reviews of this literature). This research generally finds a positive association between the value relevance of earnings and earnings quality (Bao and Bao, 2004; Cahan et al., 2009; Ecker et al., 2006).

rely more on growth in revenue than earnings when valuing firms that exhibit continuous increases in both earnings and revenue. Ertimur et al. (2003) document that investors react more strongly to revenue surprises of growth than of value firms, and attribute this result to less informative and more noisy earnings numbers for growth than value stocks. Further, they show that revenue surprises aid investors in identifying cases of earnings management as firms that barely meet analyst earnings forecasts, but have a negative revenue surprise, experience negative market reactions. Finally, Chandra and Rao (2008) report that the value relevance of revenue increases and that of earnings declines for extreme quarterly earnings surprises. They attribute this result to a lower informativeness of earnings for extreme earnings surprises.

Our study joins a stream of literature that examines how financial reporting quality affects analyst information production. Lobo et al. (2012) find a positive association between low earnings quality and analyst coverage. DeFond and Hung (2003) and Bilinski (2014) report a significant association between earnings quality and analyst propensity to issue cash flow forecasts jointly with EPS forecasts to I/B/E/S. Only two studies have considered factors contributing to sell-side analysts reporting a revenue forecast with their EPS forecast to I/B/E/S. Marks (2008) and Ertimur et al. (2011) focus on the role of analyst reputation and find that low reputation analysts are more likely than high reputation analysts to report revenue forecasts. They contend that low reputation analysts report revenue forecasts to build their reputations, and that high reputation analysts refrain from reporting revenue forecasts in order to protect their reputations, since joint revenue and earnings forecasts can reveal the sources of inaccuracies in analysts' earnings forecasts.

While previous studies have approached the analyst revenue forecast reporting issue from the standpoint of analysts' reputation, we focus on the impacts of revenue and expense quality. We propose that low quality expenses negatively impact analysts' earnings, but not revenue, forecast accuracy and value-relevance, and thus increase investor demand for revenue forecasts. Analysts respond to higher investor demand by reporting more revenue forecasts to I/B/E/S. This leads to our first research hypothesis:

H1: *Analysts are more likely to report revenue forecasts with their earnings forecasts to I/B/E/S when the quality of reported expenses is low.*

Because low revenue quality is associated with low revenue forecast accuracy, we anticipate that low quality revenues will reduce analysts' reporting of revenue forecasts. This follows from analysts being less inclined to report relatively inaccurate forecasts to investors. Low revenue forecast accuracy should also moderate any increase in investor demand for revenue forecasts stemming from low revenue quality. Thus, our second research hypothesis is:

H2: *Analysts are less likely to report revenue forecasts with their earnings forecasts to I/B/E/S when the quality of reported revenue is low.*

3. DATA

We collected annual one-year-ahead EPS and revenue forecasts for non-financial firms issued for fiscal years 2000–2013, together with their actual values from the I/B/E/S detail files.[7] We collected financial statement information from Compustat, and stock price information from CRSP. Our sample includes 853,789 EPS forecasts and 470,345 complementary revenue forecasts, by 8,941 analysts and 701 brokerage houses for 3,300 firms. Panel A of Table 1 presents sample counts of stand-alone earnings forecasts and joint earnings and revenue forecasts by fiscal year.

[Insert Table 1 around here]

The number of EPS forecasts increases from 45,788 in fiscal year 2000 to 64,882 in 2013. The number of joint EPS and revenue forecasts increases almost ten-fold, from 3,391 in 2000 to

[7] We remove financial firms from the sample because the measures of revenue and expense quality that we use are based on accruals and not well defined for financial firms.

48,239 in 2013; in percentage, 7.4% of EPS forecasts are accompanied by an I/B/E/S reported revenue forecast in 2000 and 74.3% in 2013, with a sample period average of 55.1%. While we note that revenue reporting now appears to be rather common, even in the latter years at least 24% of the time analysts chose to not report a revenue forecast with their earnings forecast.

Panel B of Table 1 presents the relative frequencies of stand-alone and revenue-accompanied EPS forecasts across 10 industries based on 2-digit I/B/E/S SIG codes.[8] Stand-alone EPS forecasts are most common in the energy and public utilities industries. These are industries with mature business models where earnings are easier to forecast and more likely to accurately reflect firm performance. Revenue forecasts are most common in the technology and healthcare industries. Disaggregating earnings for these rapidly growing industries into revenues and expenses increases the transparency and interpretability of earnings. This evidence is consistent with Bowen et al. (2002), who argue that investors rely on revenue rather than earnings in valuing technology firms.

4. REVENUE AND EXPENSE QUALITY MEASURES

(i) Revenue Quality

We use the receivables accrual model in Stubben (2010) to obtain a measure of the firm's discretionary receivables, our proxy for revenue quality. Stubben (2010) models the change in accounts receivable (ΔAR_{it}) as a function of the change in revenue (ΔR_{it}). To control for the impact of firm credit policies on accounts receivable, he includes the interaction terms of revenue change with the firm's financial strength, the firm's stage in the business cycle, and operational performance relative to industry competitors. The log of firm total assets ($\ln Assets_{it}$) proxies for the firm's financial strength. The firm's age, measured as the number of years since the firm's first appearance on CRSP, reflects the firm's stage in the business cycle. The industry

[8] The I/B/E/S SIG code is a six-digit code, representing the sector (2-digits), the industry (2-digits), and the firm's operating group (2-digits).

median-adjusted growth rate in revenue (GRR_P_{it} if positive and GRR_N_{it} if negative) and industry median-adjusted gross margin (GRM_{it}) capture the firm's operational performance relative to industry competitors. The receivables model then takes the form:

$$\begin{aligned}\Delta AR_{it} &= \alpha + \alpha_1 \Delta R_{it} + \alpha_2 \Delta R_{it} \times \ln Assets_{it} + \alpha_3 \Delta R_{it} \times \ln Age_{it} + \alpha_4 \Delta R_{it} \times Age_{it}^2 \\ &+ \alpha_5 \Delta R_{it} \times GRR\_P_{it} + \alpha_6 \Delta R_{it} \times GRR\_N_{it} + \alpha_7 \Delta R_{it} \times GRM_{it} + \alpha_8 \Delta R_{it} \times GRM_{it}^2 + \nu_{it}\end{aligned} \quad (1)$$

where Age_{it}^2 and GRM_{it}^2 control for the non-linear associations of age and gross margin with credit policies. The change in revenue and accounts receivable are scaled by average total assets. The model's residuals, ν_{it}, measure discretionary receivables. We estimate equation (1) annually for each 2-digit SIC industry with a minimum of 20 firms. We measure revenue quality (*RevQ*) as the standard deviation of the firm's discretionary receivables for years t−3 to t.

(ii) Expense Quality

We calculate expense quality by first subtracting the change in accounts receivable from current accruals so that the accruals focus on expense-related accruals. We then regress the expense-related accruals on operating cash flows and the gross value of property plant, and equipment (an approach similar to McNichols 2002), and calculate regression residuals, which measure discretionary expense-related accruals. The model takes the form:

$$CEA_{it} = \beta_0 + \beta_1 CFO_{it-1} + \beta_2 CFO_{it} + \beta_3 CFO_{it+1} + \beta_4 PPE_{it} + u_{it} \quad (2)$$

where CEA_{it} stands for current expense-related accruals for firm i in year t, defined as the change in current assets, less change in cash, less change in current liabilities, less the change in accounts receivable plus the change in debt in current liabilities, *CFO* is cash flow from operations, and *PPE* is the gross value of property plant, and equipment. CEA_{it}, the three *CFO* variables, and *PPE* are scaled by the average of total assets for the current and previous fiscal year. We estimate equation (2) annually for each 2-digit SIC industry with a minimum of 20 firms. We then measure the firm's current quality of expenses (*ExpQ*) as the standard deviation of the discretionary expense-related accruals, u_{it}, for the years $t-3$ to t.

5. REVENUE AND EXPENSE QUALITY AND JOINT EPS AND REVENUE FORECAST REPORTING

(i) The Model

We estimate the following logit model to examine the associations of revenue and expense quality with the likelihood that an analyst reports a revenue forecast with the EPS forecast.[9]

$$
\begin{aligned}
&Pr\left(DREV_{ijt}\right) = \\
&\qquad \beta_0 + \beta_1 \ln RevQ_{it-1} + \beta_2 \ln ExpQ_{it-1} + \beta_3 Star_{ijt} + \beta_4 \ln(1 + Horizon_{ijt}) \\
&\quad + \beta_5 \ln \# Firm\ followed_{ijt} + \beta_6 \ln MV_{it-1} + \beta_7 \ln Analyst\ following_{it} \\
&\quad + \beta_8 COV_{it-1} + \beta_9 B/M_{it-1} + \beta_{10} \ln Age_{it-1} + \beta_{11} ROA_{it-1} + \beta_{12} Dloss_{it-1} \\
&\quad + \beta_{13} Margin_{it-1} + \beta_{14} LEV_{it-1} + \mathrm{B}_1 Firm\ effect + \mathrm{B}_2 Year\ effects + e_{ijt}.
\end{aligned} \tag{3}
$$

where *DREV* equals 1 if an earnings forecast by analyst *j* issued for firm *i* at time *t* is accompanied by a revenue forecast and 0 otherwise. The coefficients β_1 and β_2 capture the associations of revenue and expense quality with the likelihood the EPS forecast is supplemented by a revenue estimate.

Marks (2008) and Ertimur et al. (2011) argue that low reputation analysts report more revenue forecasts to build their personal reputations, while high reputation analysts refrain from reporting revenue forecasts to protect their reputations. Following Marks (2008) and Ertimur et al. (2011), we anticipate that analysts on *Institutional Investor* magazine's All-America Research Team (*Star*) will report fewer revenue forecasts to protect their reputations. We identify *Star*

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[9] As we examine the analyst decision to complement an earnings forecast with a revenue forecast, it is necessary to conduct the analysis using individual forecasts. This differs from Ertimur et al. (2011, 39), who identify the presence of revenue forecasts with an indicator variable equal to 1, "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". Our approach recognizes that revenue forecasts that infrequently complement EPS estimates likely offer limited value to investors. To illustrate, a revenue forecast issued early in a fiscal year provides little information on the quality of analysts' consecutive EPS forecast revisions during the fiscal year.

status on the basis of inclusion on the All-American Research Team in the October issue preceding the forecast date.[10]

We include *Horizon* to control for additional investor demand for revenue forecasts early in the fiscal year. We measure *Horizon* as the number of days between the EPS forecast announcement and the respective fiscal year-end. For forecast horizon, we use log of 1 plus the variable to account for zero values.[11] We expect joint EPS and revenue forecasts to be relatively more common early in the fiscal year. The number of firms an analyst follows (*#Firm followed*) proxies for task complexity. We include the number of firms an analyst follows because actively following and producing research reports on many companies is likely to discourage an analyst from devoting the time necessary to report complementary revenue forecasts.

We use market capitalization (*MV*) and the number of analysts following a company over the 12 months preceding the forecast date (*Analyst following*) to capture the quality of the firm's information environment. Higher quality information environments should reduce the cost of producing revenue forecasts and can increase the likelihood of reporting a complementary revenue forecast. We include the coefficient of stock price variation (*COV*), which measures the daily stock price volatility in the last 90 days of the previous fiscal year, because a more challenging forecasting environment can reduce the analyst propensity to report a complementary revenue forecast. However, while high price volatility can discourage analysts from reporting revenue forecasts, it can also increase investor demand for revenue forecasts.

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[10] Ertimur et al. (2011) set their low reputation control indicator variable, *LoREP*, equal to 1 for analysts on the All-America Team in the prior year or who worked for a brokerage with a Carter-Manaster rank of 9 (Carter and Manaster, 1990). Hong and Kubik (2003) note the high correlations among brokerage size, Institutional Investor brokerage ranking, and the Carter-Manaster rankings. The disadvantage of Carter-Manaster ranks is that they are time invariant and are based on broker "tombstone" positions in stock offering announcements for offerings made between 1985 and 1991, which ignores a wave of mergers in the investment banking industry in the 1990's (Ljungqvist et al., 2006). Analyst rankings based on the All-America Team ranking do not suffer from this disadvantage.

[11] We employ log transformations to ensure more normal distributions of the variables. This particularly applies to measures of revenue and expense quality, which by construction can take only positive values. Further, log transformations account for the possibility of a diminishing impact on the dependent variable. To illustrate, we expect that the increase in firm size by $1 million will have a higher impact on analyst revenue reporting for the bottom than the top firm size decile.

We include the book-to-market ratio (*B/M*) because we expect investors to exhibit higher demand for revenue forecasts for growth firms as revenue forecasts are more useful for valuing these firms (Ghosh et al. 2005; Ertimur et al. 2003). Firm age (*Age*) reflects that analysts should be more likely to produce revenue forecasts for younger firms that are hard to value on the basis of earnings alone due to their short time-series of financial information (Li et al. 2009; Ertimur et al. 2011). Further, investor demand for revenue forecasts can vary on the basis of firm losses (*Dloss*) and profitability (*ROA*) as losses and low profitability can be non-reflective of firm value (Burgstahler and Dichev, 1997; Collins et al., 1997). We expect increased investor demand for analyst revenue forecasts for firms with high net margin (*Margin*) for this increases the impact of revenue on income. We control for solvency and firm distress risk using firm financial leverage equal to the ratio of long-term debt to total assets (*Lev*). We include firm and year dummy variables to control for firm- and year-fixed effects. We include firm-fixed effects because the significant associations between *RevQ* and *ExpQ* and the propensity to report revenue forecasts can reflect correlations between unobserved time-invariant firm characteristics and revenue and expense quality. Year dummies are based on the calendar year of the EPS forecast announcement date. All firm characteristics, except analyst following, are measured at the end of the previous fiscal year. *Analyst following* is measured at the EPS forecast issue date. All continuous variables are winsorized at the 1% level. We cluster regression standard errors by analyst to control for the serial dependence of observations. We do not cluster by firm because Cameron and Miller (2015) emphasize that it is erroneous to cluster standard errors by a group for which fixed effects are included in the model. Appendix I provides detailed definitions of our variables.

Table 2 presents descriptive statistics for the variables in equation (3). Panel A shows that over half of all EPS forecasts are accompanied by a revenue forecast (*DREV*=55.09%).

Mean *RevQ* is 0.023 and mean *ExpQ* is 0.053.[12] Panel B shows that *Star* analysts account for a relatively small portion of I/B/E/S forecasts, the average analyst follows 16 firms, and the average EPS forecast is issued in mid fiscal year. Panel C reports descriptive statistics for the firm-related characteristics. The average firm has a market capitalization of $4.5 billion, and is followed by 10.5 analysts. The mean coefficient of stock price variation is 0.094, the mean book-to-market ratio is 0.542, the mean financial leverage is 18.1%, and the average firm age is 21 years.[13] Median ROA is 4%, and the median margin is 4.1%. Panel D reports Pearson correlations for the variables in equation (3). All correlations are of the expected sign and much smaller in magnitude than 0.8, which is the rule-of-thumb for a potential multicollinearity problem (Judge et al., 1982; Hill et al., 2012).

[Insert Table 2 around here]

(ii) Multivariate Regression Results

Table 3 presents estimation results for equation (3). Column *Estimation of model* (3) presents estimation results for the full logit model with the inclusion of firm-fixed effects. The results strongly suggest that low expense quality and high revenue quality are positively associated with analysts' propensity to report revenue forecasts with their EPS forecasts, consistent with our predictions. Column *ME* reports the economic magnitudes. A one standard deviation reduction in the log of expense quality leads to a 13.9% higher likelihood of reporting joint EPS and revenue forecasts compared to the mean level. A one standard deviation reduction in the log of revenue quality reduces the likelihood of a revenue forecast by 10.3%. This suggests that the effects of revenue and expense quality on revenue forecast reporting are economically non-

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12 That expenses quality is lower than revenue quality is unsurprising given the higher persistence of revenue than expense components, e.g. Ertimur et al. (2003) highlight that "[S]ales changes are generally more persistent than changes in expenses" and that, "[A]ccounting manipulations of expenses may be easier to implement and more difficult to detect than manipulations of sales." Other studies, e.g. Swaminathan and Weintrop (1991), also document higher persistence of revenue than expenses as the latter includes different expense types and charges.

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

trivial. Substituting industry-fixed effects for the firm fixed effects in estimating equation (3) does not change our conclusions (column *Industry effects*). The final columns in Table 3 (*Changes*) consider changes in revenue and expense quality in explaining analyst propensity to report revenue forecasts. Changes regressions are less susceptible to correlated omitted variables problems (Skinner, 1996), which helps build confidence in the validity of our results. We find that an increase in revenue quality and a decrease in expense quality are significantly associated with the issuance of a revenue forecast to accompany an earnings forecast. This result is consistent with our main findings for equation (3).[14]

[Insert Table 3 around here]

6. SENSITIVITY ANALYSES AND FURTHER TESTS

In the following sections, we show that our fundamental results are unchanged under a variety of sensitivity tests and controls. Specifically, we consider a role for endogeneity, tests involving our revenue and expense quality measures individually in separate regressions, tests incorporating no logarithmic transformations of our revenue and expense quality measures, an additional proxy for revenue quality, and controls for the number of institutional investors, their percentage ownership, and management revenue guidance. Further, we repeat the analysis removing cases when analysts report a cash flow forecast jointly with the EPS forecast to ensure our results do not reflect cash flow forecast reporting in response to low quality earnings. Finally, we control

[14] Lobo et al. (2012) find a positive association between low quality earnings and analysts' coverage and argue that analysts respond to investor demand for information when earnings quality is low. We find a positive association between low expense quality and revenue forecasting. We can expect that low quality expenses substantially contribute to low earnings quality for revenue persistence is generally greater than the persistence of expenses. For example, Ertimur et al. (2003, 188), highlight that "[S]ales changes are generally more persistent than changes in expenses," and that "[A]ccounting manipulations of expenses may be easier to implement and more difficult to detect than manipulations of sales." Other studies, e.g. Swaminathan and Weintrop (1991), also document higher persistence of revenue than expenses as the latter include different expense types and charges. In our tests, the marginal impact of low expense quality on analyst revenue forecast reporting is greater than the impact of low revenue quality on revenue reporting, which supports the prediction that analysts are more responsive in their revenue reporting to low expense quality. Thus, our conclusions are in line with Lobo et al. (2012).

for the impact of correlated errors as a result of including multiple forecasts by a single analyst for a specific firm and year. These sensitivity tests provide support for our main conclusion.

(i) Endogeneity in Revenue and Expense Quality

To build confidence that the associations we document do not reflect endogeneity in revenue and expense quality, we use instrumental variables regression. The main concern is that firms manage revenue and expense quality to affect analyst revenue reporting, which could then spuriously indicate correlation between the revenue/expense quality and analyst revenue reporting. As instruments, we use industry average *RevQ* and *ExpQ* measured in the previous fiscal year. Past industry averages are not affected by endogenous choices at the firm level in the current fiscal year, which makes them valid instruments in our setting. However, we expect the instruments to correlate with our revenue and expense quality measures as firm-level revenue and expense quality are shaped by industry trends (Dechow and Dichev, 2002). Further, past industry averages should be uncorrelated with the analyst revenue reporting decision since we control for industry trends in analyst revenue reporting using firm-fixed effects. Column *2SLS* in Table 4 shows that the instrumental variables regression yields results consistent with our initial conclusions.[15]

[Insert Table 4 around here]

There may be a concern that our results reflect analyst stock coverage decisions that correlate with the quality of revenue and expenses. To address this concern, we re-estimate equation (3) for the decile of largest Compustat stocks where analyst coverage choices are

[15] In untabulated results, we also included the entrenchment index from Bebchuk et al. (2009) as an instrument. Lower entrenchment means managers have less of an influence on firm reporting and accounting choices, e.g. to opportunistically manage earnings, which suggests a correlation between the instrument and revenue and expense quality. However, controlling for reporting quality, we do not see a reason to expect a correlation between managerial entrenchment and revenue forecast reporting. In other words, revenue forecasts do not tell whether managers are able to use the firm's resources to further their personal interests at the expense of shareholders. Because the entrenchment index is available only till 2006 and for a limited number of firms, the number of observations in our sample reduces to 177,539. Regression results for this sample produce conclusions similar to our main results.

constrained. The intuition for this test is that brokers routinely cover large stocks because sell-side research is compensated out of trade commissions and these increase with the size of the covered firm (Irvine, 2004). Consistent with this prediction, we find that 99% of stocks in the largest Compustat decile are covered by analysts as opposed to 13% coverage for stocks in the lowest decile. Column *Largest stocks* in Table 4 reports regression results for equation (3) estimated for this subsample and the conclusions are qualitatively similar to our main findings.

In unreported results, we performed three further tests. First, we re-estimated equation (3) excluding the last fiscal quarter since fourth quarters tend to have greater earnings management (Cohen et al., 2008) and discretionary write-offs (Elliott and Shaw, 1988; Elliott and Hanna, 1996). Conclusions from this subsample are similar to our main results. Second, we examined the association of analyst revenue forecast reporting with the subsequent quality of revenue and expenses. If analyst revenue reporting and revenue and expense quality jointly respond to external factors, we would expect revenue and expense quality to change when analysts start reporting revenue forecasts, but we find no evidence to support this claim. Third, there may be a concern that selectivity in earnings forecast issuance, in addition to analyst coverage choices, could correlate with earnings quality and the revenue reporting decision. However, coverage and EPS forecast issuance are mechanically correlated as a higher number of earnings forecasts will depend on analyst coverage. Thus, by addressing the analyst coverage decision, we also, at least partially, address the issue of EPS forecast issuance. Further, 85% of revenue forecasts are issued jointly with an EPS estimate. Thus, it is unlikely that selectivity in the analyst decision to report EPS forecasts affects our conclusions. However, to build confidence that omitting revenue forecasts without an EPS estimate from the analysis does not affect our findings, we also redo the analysis for the sample that includes joint EPS and revenue forecasts as well as revenue forecasts issued without an EPS estimate. Our conclusions from this sample are unchanged (result untabulated).

To conclude, the results from Table 3 that report regressions with firm-fixed effects and with changes in revenue and expense quality and the tests in this section suggest that the observed associations of revenue and expense quality with analyst revenue forecast reporting are not driven by an endogenous association between analyst forecasting behavior and revenue and expense quality.

(ii) Including the Revenue and Expense Quality Measures Individually

Collinearity between revenue and expense quality could lead to coefficients with opposing signs for the two variables. Though the Pearson correlation between the two variables is not large (0.361), we repeat the analysis by including each measure separately in equation (3). Columns *only revenue quality* and *only expense quality* in Table 5 report the abbreviated regression results and the conclusions are similar to our main findings.

[Insert Table 5 around here]

(iii) No Logarithmic Transformations

Column *no logs* in Table 5 estimates equation (3) when we use the revenue and expense quality proxies without log transformations. We find the coefficient estimates for the untransformed *RevQ* and *ExpQ* measures to be significant and consistent with our prior results.

(iv) An alternative Revenue Quality Measure

The receivables model in equation (1) considers firm size, age, industry-median-adjusted growth rate in revenues, and gross margin as means for capturing firm credit policy, firm financial strength, operational performance relative to industry competitors, and stage in the business cycle. However, errors in measurement of these variables can reduce the power of the model to measure revenue quality. Stubben (2010) argues that splitting revenue into revenue generated early and late in the fiscal year reflects that sales made later in the year are more likely to remain on account at year-end. A simpler model of receivables considers the change in receivables as a function of the change in revenue in the first three quarters and in the fourth quarter. We use the standard deviation of residuals from this simpler model for years $t-3$ to t as an alternative measure of revenue quality, *RevQ2*. As before, we estimate the receivables model annually for each 2-digit SIC industry with a minimum of 20 firms. Column *Alternative revenue quality measure* in Table 5 reports results for model (3) when we include *RevQ2* instead of *RevQ*. The coefficient estimates on ln *RevQ2* and ln *ExpQ* are again significant and consistent with our initial findings.

In calculating *ExpQ*, we do not include changes in sales so that the measure focuses on capturing expense quality. However, in unreported results, we also recalculated the expense quality measure controlling for change in sales and found consistent results.

(v) Additional Control Variables

Analysts can increase their revenue reporting to cater to institutional investor demand (Frankel et al., 2006; Ljungqvist et al., 2006). If institutional holdings are correlated with the quality of revenue and expenses, then our results in Table 3 could simply reflect institutional demand for analyst revenue forecasts. To test this prediction, we include percentage institutional holdings (*% Ins. Investors*) and the number of institutional investors in a firm (*# Ins. Investors*) as control variables in equation (3). We expect a positive association between higher institutional holdings and the analyst supply of revenue forecasts. Column *Institutional holdings* in Table 6 shows that the number of institutional shareholders and their fractional ownership are positively associated with revenue forecast reporting, however, controlling for institutional ownership does not change our main conclusions regarding the associations of revenue and earnings quality with revenue forecast reporting.

[Insert Table 6 around here]

Management's revenue guidance reduces the cost of producing revenue forecasts and can stimulate analysts to report more revenue forecasts to I/B/E/S. To control for the possibility that revenue guidance is impacting our results, we estimate equation (3) with the inclusion of this guidance variable. We create a management guidance dummy (*Guidance*) equal to 1 if the firm issued revenue guidance in the 14-day period preceding the analyst's EPS forecast and the guidance is for the current fiscal period, otherwise *Guidance* is 0.[16] We collect management guidance from First Call. The *Guidance* columns in Table 6 show that the coefficient on the management guidance dummy is positive and significant, consistent with analysts being more likely to report a revenue forecast with an EPS forecast when the firm provides revenue guidance. Including *Guidance* in equation (3) leaves our conclusions regarding revenue and expense quality unchanged.

(vi) Revenue and Operating Cash Flow Forecasts

The accounting literature advocates the use of operating cash flow to help interpret the information contained in low quality earnings (Ali, 1994; Dechow, 1994; DeFond and Hung, 2003; Penman 2003). This reflects the argument that managers will typically have less discretionary power over cash flows than accruals, and thus cash flow can be a more reliable performance and valuation measure than earnings. Our results thus far could be driven by analysts being more likely to report a revenue forecast when they report a cash flow forecast in response to low quality earnings. To control for this possibility, in the *No cash flow forecasts* column in Table 6 we report results for equation (3) after removing joint cash flow and revenue forecasts from our sample. For this sample, we continue to find that low quality expenses and

[16] We use a 14-day window between management revenue guidance and the analyst EPS forecast issuance because guidance should have a stronger effect on analyst decisions to jointly issue EPS and revenue forecasts shortly after release. Consequently, a two-week window will have more power than longer windows to isolate the effect of management revenue guidance on the analyst revenue forecast reporting decision.

high quality revenue increase the likelihood of analysts accompanying their EPS forecasts with revenue forecasts.

As a corroborating test for the prediction that analysts care about forecast quality and prefer not to issue low quality estimates that are of little use to investors, we use the specification of equation (3) to predict analysts' choice to report a cash flow forecast with the EPS estimate. Cash flow forecasts are particularly useful when revenue and expense quality are low, thus we might expect increased investor demand for cash flow forecasts in this environment. However, Givoly et al. (2009) and Bilinski (2014) document that analyst cash flow forecasts are especially inaccurate, particularly in comparison with their contemporaneous EPS forecasts, when earnings quality is low. This result reflects that analysts often appear to arrive at their cash flow forecasts by simply adjusting their EPS estimates for depreciation (Givoly et al., 2009; Eames et al. 2015). Thus, concerns regarding the quality of their forecasts may reduce analyst propensity to report cash flow forecasts when revenue and expense quality are low.

Column *P(cash flow forecasts)* in Table 6 reports results for equation (3) where the dependent variable is an indicator variable that equals 1 if the analyst issued a cash flow forecast to complement the earnings forecast, and is 0 otherwise. We find that analysts are less likely to report joint earnings and cash flow forecasts when expense or revenue quality are low. This result is consistent with Bilinski (2014) and suggests that analysts refrain from issuing low quality cash flow forecasts that are of little use to investors, even in instances where demand for the forecasts is likely to be high.

(vii) Random Sample Selection and Other Tests

The dataset used for our analyses includes instances of multiple forecasts by a single analyst for a particular firm and year. Thus, correlated errors can influence the validity of the reported results. We control for correlated errors using clustering at the analyst level, but do not cluster by firm because Cameron and Miller (2015) emphasize that it is erroneous to cluster standard errors by a group for which fixed effects are included in the model. To test if our conclusions are sensitive to this control for serial dependence in error terms, we perform two tests. First, we estimate model (3) for a random sample of unique firm-analyst-year observations. Specifically, we randomly choose a single forecast for each analyst-firm pair, replicate the analysis in Table 3 for this sample, and continue to find that the likelihood of reporting a joint revenue and EPS forecast increases when expense quality is low and revenue quality is high (results untabulated). Second, we repeat the logit regression with dual-clustering of standard errors by analyst and firm (results untabulated). The conclusions from this regression are the same as for the main analysis.

Reviewing the results of our sensitivity analyses, we find consistency and essentially no differences with the conclusions drawn from Table 3 regarding the association of revenue reporting with revenue and expense quality measures.

7. THE ASSOCIATIONS OF REVENUE AND EXPENSE QUALITY WITH EARNINGS AND REVENUE FORECAST ERRORS

We argue that analysts report more revenue forecasts to I/B/E/S when expense quality is low to compensate for the low accuracy of their earnings estimates. Expense quality, by construction, is unassociated with revenue forecast accuracy, thus revenue forecasts become increasingly useful for valuing firms when expense quality is low. Analysts report fewer revenue forecasts when revenue quality is low because both earnings and revenue forecast accuracy fall as revenue quality deteriorates. As a simple illustration of the associations of revenue and expense quality with the EPS and revenue forecast accuracy, Figure 1 plots mean EPS and revenue forecast errors across quintile portfolios of our revenue and expense quality measures, *RevQ* and *ExpQ*. The current fiscal year's absolute EPS forecast error, |*EPS FE*|, is computed as the absolute difference between the forecasted and actual EPS, scaled by the stock price at the end of the previous fiscal year. The corresponding revenue forecast error, $|REV\ FE|$, is computed as the absolute difference between the forecasted and actual revenue, scaled by the product of the end-of-month number of shares outstanding and the stock price at the end of the prior fiscal year. Figure 1.a shows that the mean absolute EPS and revenue forecast errors increase as revenue quality declines. Figure 1.b replicates the analysis for expense quality quintiles. Here we find an increase in absolute earnings forecast errors, but no increase in absolute revenue forecast errors, as expense quality declines. These results are consistent with our predictions.

[Insert Figure 1 around here]

Next, to formalize Figure 1 results, we estimate the following accuracy regression:

$$\begin{aligned} Forecast\ error_{ijt} &= \varphi_0 + \varphi_1 \ln RevQ_{it-1} + \varphi_2 \ln ExpQ_{it-1} + \varphi_3 Star_{ijt} + \varphi_4 \ln(1 + Horizon_{ijt}) \\ &+ \varphi_5 \ln \#\ Firm\ followed_{ijt} + \varphi_6 \ln MV_{it-1} + \varphi_7 \ln Analyst\ following_{it} + \varphi_8 COV_{it-1} \\ &+ \varphi_9 \ln B/M_{it-1} + \varphi_{10} \ln Age_{it-1} + \varphi_{11} ROA_{it-1} + \varphi_{12} Dloss_{it-1} + \varphi_{13} Margin_{it-1} \\ &+ \varphi_{14} LEV_{it-1} + \mathrm{B}_1 Firm\ effect + \mathrm{B}_2 Year\ effects + \varepsilon_{ijt} \end{aligned} \tag{4}$$

where $Forecast\ error_{ijt}$ is either the absolute EPS or the revenue forecast error. The coefficients φ_1 and φ_2 capture the associations of revenue and expense quality with earnings and revenue forecast errors. The set of controls in equation (4) is similar to those in equation (3) for the same factors that induce analysts to report revenue forecasts should contribute to analyst difficulties in forecasting earnings and revenue. To illustrate, we include *Horizon* in equation (3) to control for investor demand for revenue forecasts early in the fiscal year and in equation (4) since it is more difficult for analysts to accurately forecast earnings early in a fiscal year (Sinha et al. 1997).

We expect Star analysts and analysts following fewer firms to produce more accurate forecasts (Stickel, 1992; Leone and Wu, 2007; Clement, 1999). Higher quality information environments reduce information acquisition costs and should result in more accurate EPS and revenue forecasts. Thus we include market capitalization and the number of analysts following a company. We include the coefficient of stock price variation as high share price volatility suggests a more challenging forecasting environment and should negatively correlate with EPS and revenue forecast accuracy. We use the book-to-market ratio to proxy for firm growth opportunities, which can make forecasting more difficult. We include firm age as analysts can find forecasting earnings and revenue easier for firms with longer time-series of financial information (Li et al., 2009; Ertimur et al., 2011). We include return on assets and a loss indicator to capture firm profitability and loss-making. We expect analysts to produce more accurate forecasts for more profitable and non-loss-making firms. Analysts may devote more effort to producing accurate revenue forecasts for firms with high net margin as revenue will have a higher effect on the bottom line net income. To control for firm solvency and distress risk, we include a measure of firm financial leverage. High distress risk can increase analyst forecasting difficulty and, consequently, revenue and EPS forecast errors. The model also includes year- and firm-fixed effects. We cluster standard errors at the analyst level.

Panel A of Table 7 reports that the mean absolute EPS and revenue forecast errors are 1.70% and 5.92% of the stock price, respectively.[17] Panel B reports results from regressing absolute EPS and revenue forecast errors on our proxies for the revenue and expense quality. To ensure comparability of results, we focus on the sample of joint EPS and revenue forecast observations. The results in Table 8 are consistent with greater absolute EPS forecast errors when revenue and expense quality decline. Further, we find a significant increase in absolute revenue forecast errors when revenue quality falls, but no significant association of absolute revenue forecast errors with the quality of expenses. Table 8 results provide an explanation for why revenue forecast reporting increases as expense quality declines and revenue quality increases.

[Insert Table 7 around here]

8. CONCLUSIONS

[17] Higher average revenue than earnings forecast errors reflect that on average price-scaled revenue-per-share is 15 times larger in magnitude than price-scaled earnings. This means that a one percent error in a revenue estimate will be on average larger in magnitude than a one percent error in an earnings forecast. In this study we focus on examining *relative* accuracy of revenue compared to earnings forecasts and on the *relative* value-relevance of revenue forecasts compared to earnings estimates with respect to earnings quality.

This study decomposes earnings quality into revenue and expense quality to examine their associations with the analyst propensity to supplement their earnings forecasts with revenue forecasts when reporting to I/B/E/S. We document that low revenue and expense quality increase earnings forecasting difficulties and reduce the accuracy and value relevance of analyst EPS forecasts, which in turn increases investors' reliance on and demand for revenue information. Analysts respond to investor demand for revenue forecasts by issuing relatively more revenue forecasts when expense quality is low as revenue forecast accuracy does not vary with expense quality. Revenue forecast accuracy falls when revenue quality declines, which reduces analysts incentives to report revenue forecasts.

Appendix I.

Variable definitions

Variable	*Definition*
1. Dependent variables	
DREV	Revenue forecast dummy, which is an indicator variable that equals one if the analyst issued a revenue forecast to complement the earnings forecast, and is zero otherwise. Revenue forecast is the I/B/E/S one-year-ahead revenue estimate. Thomson Reuters Estimates Glossary (2008) for I/B/E/S defines revenue forecasts on I/B/E/S as "a corporation's net revenue, generally derived from core business activities."
|EPS FE|	Analyst one-year-ahead earnings-per-share 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.
|REV FE|	Analyst one-year-ahead revenue forecast error, computed as the absolute difference between the forecasted and the actual revenue, both scaled by the end-of-month number of shares outstanding, divided by the stock price at the end of the previous fiscal year.
2. Revenue and expense quality measures	
RevQ	Revenue quality, which is the variation in discretionary receivables for the previous four fiscal years measured at the end of the previous fiscal year. Discretionary receivables are measured from Stubben's (2010) receivables accrual model described in equation (1). Higher values of *RevQ* associate with lower revenue quality.
ExpQ	Expense quality, which is the variation in discretionary expense-related accruals for the previous four fiscal years measured at the end of the previous fiscal year. We describe how we calculate discretionary expense-related accruals in equation (2). Higher values of *ExpQ* associate with lower expense quality.
RevQ2	An alternative revenue quality measure, which is the variation in discretionary receivables for the previous four fiscal years. Discretionary receivables are measured by regressing changes in accounts receivables on changes in revenue generated in the first three quarters of the year and revenue in the fourth quarter. We measure *RevQ2* at the end of the previous fiscal year.
3. Independent variables: analyst and firm characteristics	
Star	An indicator variable for analysts selected to the All-America Research Team by the Institutional Investor magazine in the previous year. We use the Institutional Investor magazine ranking from the October issue of year *t* to identify forecasts issued by star analysts over the subsequent 12-months.
Horizon	Forecast horizon, which is the number of days between the earnings forecast announcement date and the fiscal year-end.
#Firm followed	Analyst firm following, which is the number of companies for which an analyst issued at least one earnings forecast over the previous 12 months.
MV	Firm size computed as the firm market capitalization at the end of the previous fiscal year in $ millions.
Analyst Following	Intensity of analyst coverage calculated as the number of analysts issuing at least one earnings forecast for a company over the previous 12 months.
COV	Price volatility measured as the coefficient of variation of stock price over the 90-days prior to the end of the previous fiscal year.
B/M	Book-to-market ratio measured as the ratio of total common equity over firm market capitalization at the end of the previous fiscal year.
Age	Firm age, which is the number of years between the previous fiscal year-end and the firm's first appearance on CRSP.
ROA	Return on assets calculated as net income scaled by firm assets. *ROA* is measured for the previous fiscal year.
Margin	The net margin, which is the ratio of net income over the firm's revenue. *Margin* is measured for the previous fiscal year.
LEV	Firm financial leverage is defined as the ratio of total long-term debt over total assets. *LEV* is measured for the previous fiscal year.

(The appendix is continued on the next page.)

Appendix I (Continued)

% Ins. Investors	Percentage ownership by institutional investors.
# Ins. Investors	Number of institutional investors holding the stock.
Guidance	Revenue guidance, which is an indicator variable that takes a value of 1 if the firm issued revenue guidance in the 14-day period preceding the analyst's EPS forecast, and is zero otherwise
Firm effect	Firm dummies
Year effect	Year dummies based on the calendar year of the earnings forecast issue.

Note:
The table shows definitions of the dependent and independent variables used in the study. We divide the variables into four categories: (1) dependent variables, (2) revenue and expense quality measures, (3) independent variables: analyst and firm characteristics.

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Figure 1

Analyst Earnings and Revenue Mean Absolute Forecast Errors
by Revenue and Expense Quality Quintiles

Figure 1a. Mean EPS and revenue absolute forecast errors by *RevQ* quintiles

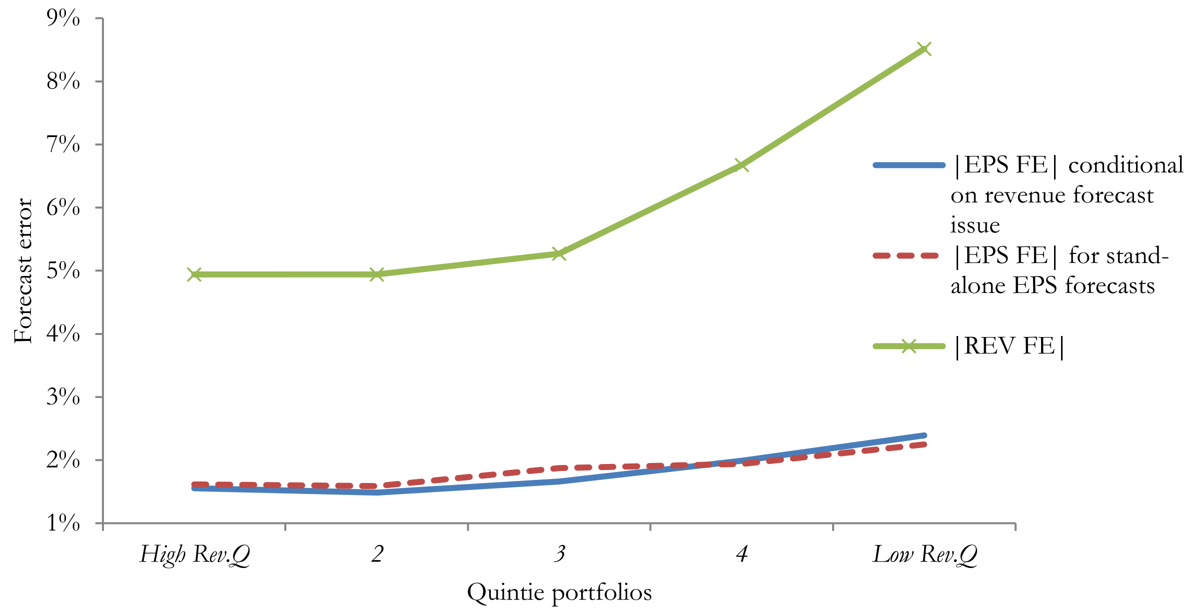
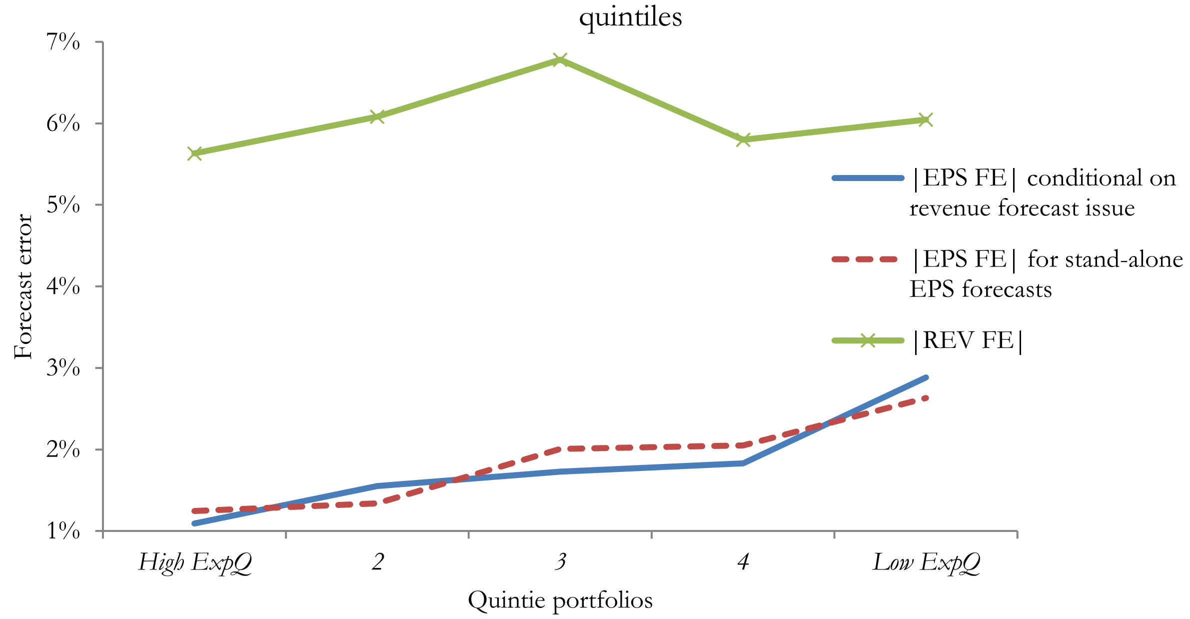


Figure 1b. Mean EPS and revenue absolute forecast errors by *ExpQ* quintiles



Note:

This figure shows the mean earnings and revenue forecast errors for quintiles based on the revenue quality measure *RevQ*, Figure 1.a, and on the expense quality measure *ExpQ*, Figure 1.b. Portfolio *High RevQ* contains stocks with the highest quality revenue and portfolio *Low RevQ* includes stocks with the lowest revenue quality. Portfolio *High ExpQ* contains stocks with the highest expense quality and portfolio *Low ExpQ* includes stocks with the lowest expense quality. |*EPS FE*| *conditional on revenue forecast issue* denotes earnings-per-share (*EPS*) forecast error for earnings estimates supplemented by revenue forecasts. |*EPS FE*| *for stand-alone EPS forecasts* denotes *EPS* forecast error for stand-alone earnings estimates. |*REV FE*| stands for revenue forecast error.

Table 1

Earnings and Revenue Forecasts, Analysts, Brokers and Firms by Fiscal Year

Panel A: Counts by Fiscal Year

	Total #EPS	*EPS w/o REV*	*EPS with REV*	*% EPS with REV*	*#Analysts*	*#Brokers*	*#Firms*
2000	45,788	42,397	3,391	7.4%	2,635	233	1,484
2001	44,462	39,390	5,072	11.4%	2,650	237	1,467
2002	47,573	40,905	6,668	14.0%	2,661	218	1,315
2003	50,002	35,194	14,808	29.6%	2,888	221	1,398
2004	56,105	30,643	25,462	45.4%	2,778	267	1,545
2005	63,941	27,610	36,331	56.8%	2,789	293	1,641
2006	66,220	25,610	40,610	61.3%	2,815	295	1,658
2007	68,338	23,999	44,339	64.9%	2,863	272	1,662
2008	65,897	22,369	43,528	66.1%	2,733	259	1,615
2009	70,557	22,261	48,296	68.4%	2,638	258	1,551
2010	67,739	20,117	47,622	70.3%	2,503	277	1,530
2011	69,505	18,322	51,183	73.6%	2,658	279	1,482
2012	72,780	17,984	54,796	75.3%	2,797	266	1,491
2013	64,882	16,643	48,239	74.3%	2,541	246	1,272
Total	853,789	383,444	470,345	55.1%	8,941	701	3,300

Panel B: Counts by Industry

	EPS w/o REV	*EPS with REV*
Health care	33.1%	66.9%
Consumer non-durables	47.5%	52.5%
Consumer services	44.9%	55.1%
Consumer durables	48.1%	51.9%
Energy	66.8%	33.2%
Transportation	52.0%	48.0%
Technology	30.3%	69.7%
Basic industries	56.5%	43.5%
Capital goods	43.2%	56.8%
Public utilities	60.5%	39.5%
N	383,444	470,345

Note:
The table shows the total number of earnings forecasts, *Total #EPS*, the number of stand-alone earnings forecasts, *EPS w/o REV*, and the number of earnings forecasts complemented by a revenue forecast, *EPS with REV*. Column *% EPS with REV* reports the percentage of earnings forecasts complemented by a revenue forecast. Column *#Analysts* shows the number of unique analysts, *#Brokers* the number of unique brokerage houses, and *#Firms* the number of unique firms. Row *Total* reports the number of unique observations in each category. Panel B shows the distributions of earnings forecasts with and without accompanying revenue forecasts across 10 industry groups based on a 2-digit I/B/E/S SIG code.

Table 2

Descriptive Statistics

Panel A: An Indicator Variable for Joint Revenue and Earnings Forecast Issues and Revenue and Expense Quality Measures (*N*= 853,789)				
Variable	Mean	Median	STD	p
DREV	55.09%	100.00%	49.74%	0.000
RevQ	0.023	0.016	0.022	0.000
ExpQ	0.053	0.036	0.051	0.000
Panel B: Analyst and Forecast Characteristics				
Variable	Mean	Median	STD	p
Star	0.30%	0.00%	5.47%	0.000
Horizon	179.926	167.000	96.194	0.000
#Firm followed	16.262	15.000	7.935	0.000
Panel C: Firm-Related Explanatory Variables (*N*=20,981 firm-years)				
Variable	Mean	Median	STD	p
MV	4581.4	636.3	16250.7	0.000
Analyst Following	10.472	8.000	9.017	0.000
COV	0.094	0.075	0.069	0.000
B/M	0.542	0.451	0.484	0.000
Age	21.369	15.085	17.044	0.000
ROA	0.20%	4.08%	17.84%	0.105
Dloss	20.9%	0.0%	40.7%	0.000
Margin	−0.182	0.041	1.280	0.000
LEV	18.1%	14.3%	18.8%	0.000

(The table is continued on the next page.)

Table 2, continued

	DREV	*RevQ*	*ExpQ*	*Star*	*Horizon*	*#Firm followed*	*MV*	*Analyst Following*	*COV*
Panel D: Pearson correlations									
DREV	1								
RevQ	−0.008	1							
ExpQ	0.122	0.361	1						
Star	−0.024	−0.010	−0.015	1					
Horizon	−0.004	0.000	0.009	−0.049	1				
#Firm followed	−0.054	−0.051	−0.082	0.033	−0.001	1			
MV	−0.023	−0.114	−0.116	0.004	0.022	−0.024	1		
Analyst Following	0.010	−0.136	−0.091	0.005	0.018	0.021	0.465	1	
COV	−0.023	0.193	0.250	−0.006	−0.003	−0.035	−0.165	−0.117	1
B/M	−0.043	−0.015	−0.121	0.003	−0.010	0.051	−0.161	−0.165	0.138
Age	−0.111	−0.140	−0.266	0.010	0.004	0.055	0.355	0.142	−0.224
ROA	−0.036	−0.098	−0.292	0.005	0.005	0.011	0.175	0.166	−0.251
Dloss	0.021	0.130	0.286	−0.005	0.001	−0.032	−0.136	−0.162	0.267
Margin	−0.025	−0.033	−0.272	0.003	0.005	0.014	0.072	0.083	−0.122
LEV	−0.100	−0.173	−0.154	0.010	−0.019	0.059	−0.127	−0.063	0.017

	B/M	*Age*	*ROA*	*Dloss*	*Margin*	*LEV*
DREV						
RevQ						
ExpQ						
Star						
Horizon						
#Firm followed						
MV						
Analyst Following						
COV						
B/M	1					
Age	−0.003	1				
ROA	−0.121	0.126	1			
Dloss	0.131	−0.148	−0.460	1		
Margin	0.043	0.094	0.592	−0.340	1	
LEV	−0.015	0.035	−0.193	0.099	−0.079	1

Note:
The table reports descriptive statistics for the variables in equation (3). Variables definitions are in Appendix I. *N* is the number of observations.

Table 3
Revenue Forecast Reporting and the Quality of Revenues and Expenses

	Estimation of model (3)			*Industry effects*		*Changes*	
	Estimate	*ME*	*p*	*Estimate*	*p*	*Estimate*	*p*
Intercept	−9.134		0.000	−0.171	0.382	1.182	0.000
ln *RevQ*	−0.068	−10.3%	0.000	−0.082	0.000		
ln *ExpQ*	0.092	13.9%	0.000	0.118	0.000		
Δ *RevQ*						−0.004	0.048
Δ *ExpQ*						0.012	0.000
Star	−0.472	−5.1%	0.009	−0.491	0.007	−0.343	0.000
ln 1+*Horizon*	−0.010	−1.4%	0.049	0.004	0.436	0.031	0.000
ln #*Firm followed*	−0.022	−3.2%	0.638	−0.008	0.848	0.000	0.976
ln *MV*	0.188	58.5%	0.000	−0.086	0.000	0.098	0.000
ln *Analyst Following*	0.054	6.5%	0.122	0.277	0.000	0.174	0.000
COV	1.331	14.5%	0.000	1.663	0.000	0.613	0.000
B/M	0.273	18.6%	0.000	0.001	0.976	−0.011	0.472
ln *Age*	1.757	240.1%	0.000	−0.100	0.000	−0.597	0.000
ROA	−0.406	−9.6%	0.000	−0.309	0.001	−0.176	0.000
Dloss	−0.079	−4.8%	0.001	−0.071	0.061	−0.080	0.000
Margin	0.018	3.0%	0.061	0.055	0.000	0.003	0.701
LEV	0.148	4.5%	0.000	−0.464	0.000	−0.036	0.369
Firm fixed effects	Yes			No		Yes	
Industry effects	No			Yes		No	
Year effect	Yes			Yes		Yes	
N	853,789			853,789		853,789	
$p(\chi^2)$	0.000			0.000		0.000	
R^2	26.94%			17.87%		23.12%	

Note:
The table reports results from logistic regressions predicting that an analyst will issue a revenue forecast to complement the earnings estimate. The column heading *ME* denotes the economic magnitude of the associations of the independent variables by providing the impact of a one standard deviation reduction in the independent variable on the likelihood of reporting a revenue forecast. Variables definitions are in Appendix I. ln is the logarithm, *p* are *p*-values for regression coefficients based on analyst-clustered standard errors. *N* is the number of observations, $p(\chi^2)$ is the p-value for the Wald χ^2-test for model specification. *pseudo* R^2 is the pseudo *R*-squared.

Table 4
Tests addressing endogeneity

	2SLS		*large stocks*	
	Estimate	*p*	*Estimate*	*p*
Intercept	0.473	0.040	−9.931	0.000
ln *RevQ*	−0.299	0.000	−0.056	0.006
ln *ExpQ*	0.370	0.000	0.081	0.000
Star	−0.086	0.000	−0.246	0.142
ln 1+*Horizon*	0.000	0.789	−0.006	0.419
ln #*Firm followed*	0.001	0.801	−0.130	0.046
ln *MV*	0.016	0.182	0.225	0.000
ln *Analyst Following*	0.036	0.006	−0.332	0.000
COV	0.023	0.736	0.967	0.000
B/M	0.021	0.292	0.747	0.000
ln *Age*	−0.030	0.508	2.312	0.000
ROA	−0.043	0.291	−0.789	0.000
Dloss	−0.004	0.757	−0.074	0.204
Margin	0.019	0.016	0.049	0.050
LEV	−0.043	0.436	0.192	0.192
Firm fixed effects	Yes		Yes	
Year effect	Yes		Yes	
N	778,908		85,337	
$p(\chi^2)$	0.000		0.000	
R^2			26.89%	

Note:
The table reports results from logistic regressions predicting that an analyst will issue a revenue forecast to complement the earnings estimate. Column *2SLS* reports results from instrumental variables regressions where the instruments are past industry average *RevQ* and *ExpQ*. Column *large stocks* reports regression results for the decile of largest Compustat stocks.

Table 5
Additional Tests

	only revenue quality		*only expense quality*		*no logs*		*Alternative revenue quality measure*	
	Estimate	*p*	*Estimate*	*p*	*Estimate*	*p*	*Estimate*	*p*
Intercept	−9.160	0.000	−8.790	0.000	−9.007	0.000	−9.009	0.000
ln *RevQ*	−0.055	0.000						
ln *ExpQ*			0.082	0.000				
RevQ					−1.938	0.000		
ExpQ					1.447	0.000		
ln *RevQ2*							−0.065	0.000
ln *ExpQ*							0.100	0.000
Controls	Yes		Yes		Yes		Yes	
Firm fixed effects	Yes		Yes		Yes		Yes	
Year effect	Yes		Yes		Yes		Yes	
N	853,789		853,789		853,789		844,457	
$p(\chi^2)$	0.000		0.000		0.000		0.000	
R^2	26.92%		26.93%		26.93%		26.73%	

Note:
Columns *only revenue quality* and *only expense quality* report logistic regressions predicting that an analyst will issue a revenue forecast to complement the earnings estimate when we include only revenue or expense quality measures. Column *no logs* reports results for equation (3) where we use revenue and expense quality measures without logarithmic transformations. Column *Alternative revenue quality measure* reports results for equation (3) when we use an alternative measure of revenue quality, *RevQ2*. *Controls* are the control variables from equation (3).

Table 6
Sensitivity Analysis

	Institutional holdings		*Guidance*		*No cash flow forecasts*		*P(cash flow forecasts)*	
	Estimate	*p*	*Estimate*	*p*	*Estimate*	*p*	*Estimate*	*p*
Intercept	−9.842	0.000	−8.944	0.000	−8.963	0.000	−10.106	0.000
ln *RevQ*	−0.062	0.000	−0.067	0.000	−0.069	0.000	−0.026	0.001
ln *ExpQ*	0.102	0.000	0.092	0.000	0.093	0.000	−0.019	0.023
% *Ins.Investors*	0.300	0.000						
# *Ins. Investors*	0.272	0.000						
Guidance			0.152	0.000				
Controls	Yes		Yes		Yes		Yes	
Firm fixes effects	Yes		Yes		Yes		Yes	
Year effect	Yes		Yes		Yes		Yes	
N	853,789		853,789		787,128		853,789	
$p(\chi^2)$	0.000		0.000		0.000		0.000	
R^2	27.89%		26.95%		29.63%		20.81%	

Note:
Column *Institutional holdings* reports results for equation (3) when we control for the percentage institutional holdings (*% Ins. Investors*) and the number of institutional investors (*# Ins. Investors*). We divide *# Ins. Investors* by 100 to avoid reporting very small coefficient estimates. Column *Guidance* reports results for equation (3) when we include an indicator variable *Guidance* that takes a value of 1 if the firm issued revenue guidance in the 14-day period preceding the analyst's EPS forecast, and is zero otherwise. Column *No cash flow forecasts* shows results when we remove joint issues of revenue and cash flow forecasts from the sample. Column *P(cash flow forecasts)* reports results from a logistic regression predicting that an analyst will issue a cash flow forecast to complement the earnings estimate. *Controls* are the control variables from equation (3).

Table 7

Earnings and Revenue Forecast Errors and Accuracy Regressions

Variable	Mean	Median	STD	p
Panel A: The EPS and Revenue Absolute Forecast Errors				
|EPS FE|	1.70%	0.41%	4.67%	0.000
|REV FE|	5.92%	1.41%	15.12%	0.000

	EPS forecast error		*Revenue forecast error*	
	Estimate	*p*	*Estimate*	*p*
Panel B: Accuracy Regressions				
Intercept	0.071	0.000	−0.003	0.539
ln *RevQ*	0.003	0.000	0.024	0.019
ln *ExpQ*	0.004	0.000	0.001	0.820
Star	−0.025	0.007	0.003	0.209
ln 1+*Horizon*	0.071	0.000	0.026	0.000
ln #*Firm followed*	−0.003	0.000	0.000	0.644
ln *MV*	−0.095	0.000	−0.023	0.000
ln *Analyst Following*	0.045	0.000	0.007	0.000
COV	0.376	0.000	0.078	0.000
ln *B/M*	0.049	0.000	0.038	0.000
ln *Age*	0.117	0.000	0.016	0.000
ROA	−0.229	0.000	−0.041	0.000
Dloss	0.073	0.000	0.006	0.000
Margin	0.012	0.000	0.002	0.000
LEV	0.071	0.000	0.011	0.000
Firm effect	Yes		Yes	
Year effect	Yes		Yes	
N	454,401		454,401	
p(F)	0.000		0.000	
R^2	13.25%		9.60%	

Note:

Panel A reports descriptive statistics for the EPS and revenue absolute forecast errors. Panel B reports regression results for equation (4) where the dependent variable is the absolute earnings-per-share (EPS) or revenue forecast error.