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Analysts' revenue forecasts and discretionary revenues

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We investigate the association between analysts' revenue forecast coverage and firms' revenue manipulation. We find that coverage of revenues by financial analysts relative to earnings is positively associated with the magnitude of firms' discretionary revenues. This finding shows a pressure effect of analysts, where analysts' revenue forecasts induce incentives for managers to manipulate revenues to meet expectations. Our cross-sectional analyses show that this pressure on discretionary revenues is higher during the fourth fiscal quarter. This effect is also more pronounced for firms whose revenues are more value-relevant and when analysts exhibit greater disagreement over revenue forecasts. Further evidence related to ASC 606, a major GAAP change about revenue accounting, provides corroborating evidence for the pressure effect. Robustness checks confirm the validity of our findings and offer further insights into the role of revenue forecasts in revenue manipulation.

1. Introduction

Financial analysts are important elements of firms' information environment because they are among the most sophisticated users of financial reporting. Their reports about the firms they follow provide a reliable proxy for market expectations about the firms' performance. As a result, accounting scholars have paid close attention to analysts' earnings forecasts (Beyer et al., 2010). In addition to earnings forecasts, financial analysts also issue revenue forecasts, which are important inputs into the information environment of capital markets (Bilinski and Eames, 2019; Ertimur et al., 2011). As a line item in firms' financial reports, revenue is an important indicator of firm performance and a main component of the bottom-line earnings figure. In this study, we explore the association between analysts' revenue forecasts and firms' discretionary revenues.

The nature of the association between analysts' revenue forecasts and firms' discretionary revenues is not clear ex ante. On the one hand, the literature on the corporate governance role of financial analysts suggests that analyst forecasts have a disciplining role over firms' earnings management activities (McInnis and Collins, 2011; Yu, 2008). On the other hand, there is also evidence that analysts' forecasts might put pressure on management to meet or beat their estimates, leading to an increase in earnings management (Huang and Hairston, 2023).

Using a large sample of quarterly observations from U.S. public firms, we find that analysts' higher proportion of revenue forecast coverage relative to their earnings forecasts is associated with a higher magnitude of discretionary revenues. Taking analyst forecast information from the Thomson Reuters Institutional Brokers' Estimate System (IBES), we measure analysts' revenue forecasts as the ratio of the number of revenue forecasts over the number of total earnings forecasts for a given firm-quarter (e.g., Liu et al., 2023). Our

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results are consistent with a pressure effect, that is, analyst attention[1] on revenues increases the importance of meeting or beating revenue expectations. Our tests with signed discretionary revenues reveal that the main association is driven by positive discretionary revenues. In other words, our results provide evidence that firms with revenue-increasing discretionary activities are affected more by analysts' revenue forecasts and that their discretionary revenues are increasing in the ratio of analysts' revenue forecasts over earnings forecasts.

To provide further insight into the association between analysts' revenue forecasts and discretionary revenues, we investigate the possible moderating effect of the fourth fiscal quarter. The fourth quarter presents an interesting setting, as management might feel extra pressure to meet both quarterly and annual expectations during this period (Fan et al., 2010; Kerstein and Rai, 2007). On the other hand, fourth quarter financials might be subject to extra scrutiny through the annual audit, which could make it difficult for managers to exercise discretion over revenues (Brown and Pinello, 2007). Our tests show that the positive association between analysts' revenue forecasts and discretionary revenues is more pronounced during the fourth quarter.

The results of cross-sectional tests show that the positive association between revenue forecasts and discretionary revenues is more pronounced when analysts' revenue forecast dispersion is higher. Managers seem to exploit the disagreement among analysts and use more aggressive discretion in their revenue reporting. Moreover, we find evidence that when the value relevance of revenues is higher, the empirical association between revenue forecasts and discretionary revenues is stronger. These results provide further support for the pressure effect.

We also exploit a major update on the Generally Accepted Accounting Principles (GAAP) by the Financial Accounting Standards Board (FASB) related to revenues as an exogenous shock on the relevance of revenues and examine the association between revenue forecasts and discretionary revenues in this setting. We use Accounting Standards Codification (ASC) 606 as an event that makes revenues more transparent and thus more difficult for managers to use discretion on revenues. We find that the association between revenue forecasts and discretionary revenues becomes weaker during the post-ASC 606 period, and this result is also driven by positive discretionary revenues.

As a robustness test, we use a restricted sampling strategy in which we identify time periods before and after a firm receives an analyst's revenue forecast for the first time. After eliminating the potential confounding effects of earnings forecast coverage in this setting, we find that firms experience an increase in discretionary revenues after their revenues start being covered by IBES analysts. This result is consistent with the finding that analysts' revenue coverage puts pressure on managers. As a falsification test, we run the same analysis around the first-time initiation of analysts' cash flow forecasts, and we do not find a similar effect.

Finally, we explore the effect of revenue discretion on analysts' forecast properties in order to understand the association between these two constructs. We find that higher discretionary revenues are associated with a higher magnitude of revenue forecast errors and a higher dispersion of revenue forecasts after the earnings announcement. These results imply that discretion in reported revenues makes them less reliable in predicting future revenues.

This study contributes to the literature in two ways. First, we join the debate about the role of financial analysts in financial reporting characteristics. Yu (2008) proposes that financial analysts play a disciplining role and provides evidence that firms with higher analyst coverage have lower levels of earnings management. Subsequent studies have shown evidence consistent with this disciplining role (e.g., McInnis and Collins, 2011). However, there also is evidence suggesting that analysts' forecasts exert pressure on market participants. Prior work suggests that managers are likely to manipulate earnings to meet or beat expectations set by analysts (Burgstahler and Eames, 2006; Huang and Hairston, 2023; Matsumoto, 2002). We contribute to this debate by uncovering evidence of market pressure through the association between discretionary revenues and analysts' revenue forecasts.

Second, we highlight discretionary revenues as a tool of earnings management. As noted by Dechow et al. (2010), it is important to understand which specific tools are used for earnings management and how firms choose among them. Revenue manipulation is one of the most common tools used for earnings management (Dechow et al., 1996). Our study provides insight into the use of discretionary revenues by analyzing how it is affected by analysts' revenue forecasts.

Our paper is closely related to a recent study by Huang and Hairston (2023), which shows that the number of analysts' revenue forecasts is positively associated with revenue misstatements during that year. We complement and extend their findings in two ways. First, we use discretionary revenues to proxy for revenue manipulation, while Huang and Hairston (2023) examine restatements. Although restatements are clear indicators of manipulation, they require the joint assumption that the Securities and Exchange Commission (SEC) is able to detect all manipulations. Erickson et al. (2006) note that this assumption is likely to be too strong. Moreover, managers can manipulate revenues while staying within the boundaries of GAAP, and these will not be subject to the SEC actions and restatements. Discretionary revenues provide a tool to identify a much broader spectrum of manipulation and clerical errors affecting revenues, even without violating GAAP. We extend the context of accounting fraud to the manipulation of discretionary revenues, which is a more universal phenomenon that could be applied to the entire market (Erickson et al., 2006).

Second, while Huang and Hairston (2023) use annual data in their analysis, they call for more research on the association between analysts' revenue forecasts and revenue manipulation using quarterly data. We directly answer their call by examining this association in a quarterly setting. The use of quarterly data allows us to produce finer evidence which highlights a distinct role of the fourth quarter in the conjectured relation. While many firms are under consistent pressure to meet or beat quarterly benchmarks, quarterly financial statements generally yield lower level of assurance than annual financial statements. For instance, recent evidence shows a lower level of reporting quality in quarterly financial statements (Boyle et al., 2021). Therefore, when it comes to examining firms' discretionary

[1] We use the term "analyst attention" to refer to the relative coverage of revenues attracted from analysts as compared to that of earnings. We do not use it to mean behavioral aspects of analysts' information environment (e.g., limited attention).

reporting behavior, quarterly data offer more comprehensive insights. For example, we can capture the variation of revenue management across different quarters. As a result, we find a significant fourth quarter effect, which is new evidence to this literature.

There are several limitations related to our study. First, while the associations we identify are useful for investors and standard-setters, the nature of our tests does not allow for a causal interpretation between analysts' revenue forecasts and discretionary revenues. Second, we do not examine how management forecasts are related to analyst coverage of revenues. The combination of management forecasts and analysts' revenue forecasts and how they affect discretionary revenues could be a fruitful avenue for future research. Third, our inferences might not be applicable to certain industries and certain time periods.

The rest of the paper is organized as follows. Section 2 explains our motivation and hypothesis development. We describe our data and empirical design in Section 3 and present our empirical results in Section 4. Section 5 concludes.

2. Motivation and hypothesis development

2.1. Revenue forecasts

Revenue forecasts are one of the most prevalent products of financial analysts, but they are relatively underexplored in accounting research compared to earnings forecasts. As Ertimur et al. (2011) note, almost all analysts produce a revenue forecast in order to make an earnings forecast. In IBES, revenue forecasts were first included in the year 1995, and there has been a steady increase in the number of analysts' revenue forecasts since then.[2] The voluntary dissemination of revenue forecasts through IBES reveals additional analysts' or investors' demand for such information (Bilinski and Eames, 2019).

Ertimur et al. (2011) investigate analysts' motivations to provide revenue forecasts along with earnings forecasts and find that analysts issue revenue forecasts in order to signal their type. They show that, among less reputable analysts, those with higher ability are more likely to disseminate their revenue and expense forecasts. Similarly, Keung (2010) argues that earnings forecasts supplemented with revenue forecasts are more accurate ex post, suggesting that financial analysts provide revenue forecasts to convey their credibility.

Bilinski and Eames (2019) focus on how the quality of expenses and revenues affects the likelihood that analysts will report revenue forecasts to IBES. They show that when revenue quality is low, analysts with concerns of low revenue forecast accuracy are less likely to provide revenue forecasts. Given that low-quality expenses do not affect revenue forecast accuracy, when expense quality is low, analysts report more revenue forecasts to meet investors' demand for information. Consistent with this intermediary role of analysts, He and Lu (2018) provide evidence that analysts are more likely to issue supplementary forecasts after mandatory adoption to the International Financial Reporting Standards (IFRS), and this effect is more pronounced when the difference between IFRS and local GAAP is larger.

Studies on analysts' revenue forecasts also investigate how financial markets perceive the information provided by revenue forecasts. Ertimur et al. (2003) use revenue forecasts to measure revenue surprises and provide evidence that investors react more strongly to revenue surprises than to expense surprises. Similarly, Rees and Sivaramakrishnan (2007) investigate the value implications of analysts' revenue forecasts and show that there is a significant association between revenue forecast errors and abnormal returns around earnings announcements. They demonstrate that revenue forecasts provide incremental information to the market.

2.2. Discretionary revenues

Manipulation of revenues to attain earnings benchmarks is well-documented in the literature. Dechow et al. (1996) show that there is a greater likelihood of revenue manipulation among firms that are investigated by the SEC. Stubben (2006, 2010) investigates the role of revenues in overall earnings management and develops models to estimate discretionary revenues. Similarly, Marquardt and Wiedman (2004) develop models to identify discretion in specific accrual accounts including accounts receivables, which are related to revenue recognition.

Revenue manipulation can be achieved through accrued revenue and deferred revenue (Caylor 2010).[3] Chapman and Steenburgh (2011) demonstrate that firms boost their revenue at their fiscal year-ends by increasing marketing promotions. Another way of manipulating revenues is channel stuffing, which inflates sales figures by pushing more products through a distribution channel than would be needed to meet end-users' reasonable demand within a period (Das et al., 2012).

2.3. Hypothesis

When we consider the association between analysts' revenue forecasts and discretionary revenues, we build on two strands of the accounting literature that have documented conflicting results. On the one hand, there is a large amount of evidence that analysts' earnings forecasts in general (e.g., Yu, 2008), and analysts' disaggregated forecasts of earnings components in particular (e.g., Mauler,

[2] Stubben (2006) mentions that nearly 94% of all IBES firms received at least one revenue forecast by fiscal year 2003. However, there is still considerable time-series variation in revenue forecast coverage of IBES firms. For example, Bilinski and Eames (2019) report that more than 55.1% of their sample of IBES earnings estimates between 2000 and 2013 are supplemented by revenue forecasts.

[3] Our measure of discretionary revenues is based on accrued revenue (i.e., accounts receivable). While Caylor (2010) provides a model for discretion in annual deferred revenues, it is not straightforward to calculate it in a quarterly setting.

2019; McInnis and Collins, 2011) have a disciplining effect on firms' earnings management activities. Based on this *disciplining effect,* one can expect that revenue manipulation is constrained in firms with more revenue forecasts, as the analysts' focus on the revenue line item might make it difficult to manipulate. For example, Yu (2008) investigates how analyst following affects firms' earnings management through discretionary accruals, proposing that by engaging in private information production that detects managers' misbehavior, analysts can reduce the magnitude of accrual management. He provides supporting evidence that the number of analysts following a firm is associated with a lower magnitude of discretionary accruals. Similarly, one would expect that analysts' revenue forecast coverage would also create a disciplining effect in the specific case of the revenue line item.

On the other hand, a large body of literature in accounting examines the "meet-or-beat" phenomenon, which is the practice of earnings management to attain earnings benchmarks provided by financial analysts (Burgstahler and Eames, 2006; Matsumoto, 2002). According to this *pressure effect*, analyst benchmarks put pressure on managers to attain them, as failure to do so is typically not received well by capital markets. For example, Kasznik (1999) finds that firms make choices that lead to changes in reported earnings to meet analysts' forecasts and avoid costs associated with forecast errors. Das and Zhang (2003) provide evidence that managers manipulate earnings by rounding up the earnings per share number in financial statements to meet analysts' expectations.

One can infer that the costs associated with missing the earnings forecasts would be applicable to revenue forecasts as well. The literature consistently shows that analysts' revenue forecasts have important capital market implications. For example, Rees and Sivaramakrishnan (2007) find that meeting or beating revenue forecasts is rewarded by the market. Ertimur et al. (2003) also show that revenue surprises have valuation consequences. Moreover, Jegadeesh and Livnat (2006) provide evidence that earnings surprises accompanied by revenue surprises signal more persistent earnings growth. As a result, analysts' revenue forecast coverage is likely to pressure managers to manipulate revenues to meet or beat forecasts. Consistent with this, Huang and Hairston (2023) find evidence that the number of annual revenue forecasts and revisions is positively associated with a revenue restatement in the same year.

Consequently, the direction of the association between analysts' revenue forecasts and firms' discretionary revenues is not clear ex ante. We present our hypothesis in a null form:

H_0: The ratio of analysts' revenue forecasts over earnings forecasts is not associated with the magnitude of discretionary revenues reported by firms.

3. Data

3.1. Sample

Our main sample is drawn from the quarterly Compustat data between the years 2000 and 2023. We merge these data with IBES Summary data to identify revenue, earnings per share (EPS) and cash flow per share (CPS) forecasts.[4] Although the first revenue forecasts on IBES appear in 1995, we eliminate the years 1995–1999 from our sample because IBES just started disseminating revenue forecasts during this period, and data from those earlier years may be incomplete or not fully comprehensive. Beyond that, our main sample restriction is that all firm-quarters must have EPS and revenue forecast coverage by financial analysts. Along with the requirement for accounting control variables we use in our models, this yields a sample of 137,284 firm quarters with available data for primary analysis during our sample period.

3.2. Revenue forecast ratio

When we compare performance metrics in terms of the attention they attract from analysts and investors, revenue is only behind earnings (Rees and Sivaramakrishnan, 2007). Revenue coverage by financial analysts has important consequences for market participants. For example, Ertimur et al. (2003) use revenue forecasts to measure revenue surprises and provide evidence that investors react more strongly to revenue surprises than expense surprises. Moreover, analysts have a strong motivation to provide revenue forecasts along with their EPS forecasts, as this practice increases their accuracy and credibility (Keung, 2010). Therefore, analysts' revenue coverage of a firm reflects a demand from both investors and analysts and signals the relative importance of a firm's revenues (Liu et al., 2023). We follow the method in Liu et al. (2023) to construct the main independent variable of interest, revenue forecasts (*REV_FCST*), as the ratio of the number of analysts' quarterly revenue forecasts to the total number of analysts' quarterly EPS or revenue forecasts. Scaling with the total number of forecasts controls the effect of overall analyst following activity level and particularly highlights the impact of the revenue forecasts. To avoid selection issues that determine analyst following of EPS and revenue metrics, we limit our analysis to firm-quarters with at least one EPS and revenue forecast.

Our main test variable *REV_FCST* differs from Huang and Hairston's (2023) main test variable in two ways. First, Huang and Hairston (2023) use raw measures of analysts' revenue and earnings forecasts separately in their models, instead of taking their ratio. When we follow this design, the high correlation between revenue and earnings forecasts leads to extremely high variance inflation factors in the regression model (i.e., multicollinearity), resulting in unreliable inferences. Huang and Hairston (2023) report acceptable levels of multicollinearity in their annual sample, which indicates a difference between annual and quarterly settings. Second, Huang and Hairston (2023) combine analysts' forecasts and revisions in their measures, while we only focus on forecasts, which is a more

[4] Recent evidence on changes to the IBES database suggests that consensus estimates based on the IBES Summary file are more reliable and accurate as compared to those based on IBES Detail file (Call et al. 2021). The IBES Summary file includes the most up-to-date consensus estimates at the time of the earnings announcements, eliminating any stale or stopped estimates.

traditional measure of coverage. Huang and Hairston (2023) acknowledge that they do not run their main tests with the traditional coverage measures because the high multicollinearity between revenue and earnings forecast coverages leads to non-significant estimates.[5] We face the same multicollinearity issue when we separate the numerator and denominator of our *REV_FCST* variable in a regression. As an alternative, we measure *REV_FCST* as the ratio of revenue *forecasts and revisions* over earnings *forecasts and revisions*. Unreported results yield similar inferences to the ones with our current *REV_FCST* measure.

3.3. Discretionary revenues

In order to estimate discretionary revenues at the quarterly level, we estimate the lagged revenue model developed by Stubben (2006):[6]

$$\Delta_q AR_{iq} = \beta_0 + \beta_1 \Delta_q R_{iq} + \beta_2 \Delta_q R_{iq-1} + \beta_3 \Delta_q R_{iq-2} + \beta_4 \Delta_q R_{iq-3} + e_{iq} \tag{1}$$

where *AR* is accounts receivable as of the end of the quarter, while *R* stands for quarterly revenues. Δ_q denotes quarterly change in the relevant variable. We estimate this model in each quarter for every Fama-French 48 industry classification group, requiring at least 15 observations for each industry-quarter. We exclude utilities (SIC codes between 4900 and 4999) and financial firms (SIC codes between 6000 and 6999) while calculating discretionary revenues. The estimated error term yields discretionary revenues (*DISCREV*) from the lagged revenue model.

4. Research design and empirical results

4.1. Empirical model

We adopt the following regression model to investigate the effect of revenue forecasts on discretionary revenues:

$$\begin{aligned} DISCRETION_{it} = {} & \beta_0 + \beta_1 REV\_FCST_{it} + \beta_2 CPS\_FCST_{it} + \beta_3 LNAT_{it} + \beta_4 AGE_{it} + \beta_5 SHARES_{it} \\ & + \beta_6 LEV_{it} + \beta_7 RAISE_{it} + \beta_8 MB_{it} + \beta_9 PE_{it} + \beta_{10} PS_{it} + \beta_{11} ROA_{it} + \beta_{12} LOSS_{it} \\ & + \beta_{13} SG_{it} + \beta_{14} REVG_{it} + \beta_{15} STD\_CS_{it} + \beta_{16} STD\_CFO_{it} + \beta_{17} BIGN_{it} + \beta_{18} \Delta R_{it} \\ & + \beta_{19} \Delta R_{it-1} + \beta_{20} \Delta R_{it-2} + \beta_{21} \Delta R_{it-3} + Year - Quarter\,Fixed + Industry\,Fixed\,Effects + \varepsilon_{it} \end{aligned} \tag{2}$$

where *DISCRETION* is the signed or absolute value of discretionary revenues estimated from the lagged revenue model specified in equation (1). We construct the control variables following prior studies (e.g., Gunny, 2010; Huang and Hairston, 2023). To alleviate the concern that *REV_FCST* simply captures the influence of disaggregated forecasts, or the importance of earnings forecast coverage, we add *CPS_FCST*, the ratio of cash flow forecasts over earnings forecasts, in our model. A firm's financial strength affects its investment in accounts receivables (Petersen and Rajan, 1997); therefore, we include the logarithm of total assets (*LNAT*) in the model as a proxy for financial strength. We also include market-to-book ratio (*MB*) as another proxy for the firm's financial strength and growth options. Investor expectations and performance are controlled by including *PE*, *PS*, and *ROA*, respectively (Gunny, 2010). We control for leverage (*LEV*) in the estimation because the leverage of the firm is likely to affect firms' credit policy decisions. *AGE* and *LOSS* are included to control for the effect of revenue management (Huang and Hairston, 2023), as Callen et al. (2008) show that firms reporting losses in previous years and firms expected to report future losses are more likely to manage revenue. *SHARES* is included to address the concern that more shares outstanding require greater revenue and earnings management in order to achieve a given per-share performance target. Incentives for firms to manage revenue and earnings raised from debt and equity financing are controlled by including *RAISE* (Dechow et al., 1996). We also include sales growth (*SG*) and the change in receivables (*RECG*), given their impact on revenue manipulations (Petersen and Rajan, 1997; Stubben, 2010). Following Hribar and Nichols (2007), the standard deviations of cash sales (*STD_CS*) and operating cash flows (*STD_CFO*) are also included to control for the volatility in the operating environment of the firm. *BIGN* is included to control for auditor size (Keune and Johnstone, 2012; Lobo and Zhao, 2013). Chen et al. (2018) argue that using regression residuals as a dependent variable might lead to incorrect inferences and recommend potential solutions to this problem. We follow their suggestion and include the control variables in the discretionary revenue model (1) (from ΔR_{it} to $\Delta R_{it\text{-}4}$) in our main model (2). Time and industry fixed effects are also controlled. All variables are defined in the Appendix.

4.2. Descriptive statistics

Panel A of Table 1 presents the descriptive statistics of the variables in our main sample. We winsorize the continuous control

[5] Huang and Hairston (2023) report non-significant results with traditional coverage measures in additional tests reported in their Table 5, Panel B.

[6] Stubben (2006) develops another discretionary revenue model, the conditional revenue model, which includes other accounting variables such as size, growth rate, etc. We need to include these control variables in the main model, where discretionary revenues is the dependent variable (Chen et al., 2018). However, this leads to high multicollinearity with the other model variables as evident from the inflated variance inflation factors. Therefore, we only use Stubben's (2006) lagged model to estimate discretionary revenues.

variables at the 1 % level to remove the effect of outliers.[7] The mean of the unsigned discretionary revenues is essentially 0, which is the theoretical mean of the variable. The average absolute value of the discretionary revenues is approximately 0.02, which means the average magnitude of the discretionary revenues is approximately 2 % of the total assets. The mean of *REV_FCST* is 0.81,[8] indicating that the frequency of EPS forecasts is 25 % higher than that of revenue forecasts.

Panel B of Table 1 shows the Pearson (upper diagonal) and Spearman correlations of the variables. Unsigned discretionary revenues *DISCREV(Absolute Value)* is positively correlated with revenue forecasts *REV_FCST*. Both Pearson (0.02) and Spearman (0.02) correlations are significant, indicating a significant association between revenue forecasts and discretionary revenues. These correlations are aligned with our conjecture that revenue forecasts are related to firms' incentives to manipulate revenues in general. We also observe a non-significant correlation between discretionary revenues (*DISCREV)* and revenue forecasts, as the association between revenue forecasts and discretionary revenues might work in different directions for negative and positive discretionary revenues. In the following analysis, we present our tests separately for firms with positive and negative discretionary revenues.

4.3. Results

4.3.1. Main analysis

To understand the directional association between analysts' revenue forecasts and discretionary revenues, we examine both the signed and absolute values of the discretionary revenues. This association can manifest in opposite directions depending on disciplining and pressure explanations. Based on the disciplining explanation of analyst coverage, firms that inflate earnings through positive discretionary revenues to meet or beat earnings benchmarks will decrease this activity (McInnis and Collins, 2011), resulting in lower *DISCREV* and *DISCREV(Absolute Value)* at the same time. As for negative discretionary revenues, firms might intend to reduce their earnings for several reasons, including smoothing their earnings to sustain a long streak of earnings increases (Myers et al., 2007), negotiating favorable terms with labor unions (Bova, 2013), or attempting to obtain options with lower strike prices for managers (Coles et al., 2006). According to the disciplining effect, analysts' revenue coverage will scrutinize this activity, resulting in less negative discretionary revenues (i.e. higher *DISCREV* but lower *DISCREV(Absolute Value)*).

Conversely, under the pressure explanation, firms that use revenue-increasing accruals as an earnings management tool will intensify their manipulation activity to meet or beat expectations (Huang and Hairston, 2023), resulting in both higher *DISCREV* and *DISCREV(Absolute Value)* measures. This practice leads to future reversals in revenue accruals, which will be manifested as more negative values of discretionary revenues in certain cross-sections of the sample. The reversals will decrease *DISCREV* while increasing *DISCREV(Absolute Value)*.

In both scenarios, the magnitude of discretionary accruals captures a consistent directional effect. This warrants the use of the absolute value of the discretionary revenues in the model to address the question of how analysts' revenue forecasts affect firms' discretionary revenues, while signed values of discretionary revenues will help explain the underlying mechanism.[9] For example, McInnis and Collins (2011) investigate the effect of cash flow forecast initiations on discretionary accruals by analyzing both the signed and absolute values of accruals.

The results of the estimation of equation (2) are presented in Table 2.[10] The first two columns of Table 2 show the results when signed discretionary revenues are estimated. Column (1) reports the regression result when the negative values of discretionary revenues are the dependent variables: *REV_FCST* has a marginal effect (t-stat = −1.63) on negative discretionary revenues, indicating that analysts' revenue forecasts do not significantly affect negative discretionary revenues. Column (2) reports the regression result when the positive values of the discretionary revenues are the dependent variables, showing that analysts' revenue forecasts significantly increase positive discretionary revenues. The coefficient on *REV_FCST* is 0.003 (t-stat = 2.50). This result indicates that analysts' revenue forecasts move positive discretionary revenues further away from the natural level of zero. In other words, firms are more likely to use positive revenue discretions to adjust earnings figures (to attain certain benchmarks) when they are pressured by more analysts providing revenue forecasts. This result is in line with the pressure effect of revenue forecasts.

In Column (3), we use the absolute value of the discretionary revenues as the dependent variable of equation (3). This is applied in the literature in order to investigate the effect of a conceptual variable on the magnitude of the accrual manipulation (e.g., Bergstresser and Philippon, 2006; McInnis and Collins, 2011). The results (coefficient = 0.003 and t-stat = 2.71) are consistent with the idea that revenue forecasts increase pressure on management to manipulate revenues. We evaluate the economic magnitude of the effect by interpreting the marginal effects of our regression. A one standard deviation increase of the revenue forecast ratio in our sample is associated with an approximately 0.07 % increase in the magnitude of *DISCREV(Absolute Value)*. We may use firm size *LNAT* to show the relative significance of revenue forecasts. Firm size is an important determinant of the magnitude of discretionary revenues. Our results indicate that revenue forecasts are negatively associated with the magnitude of discretionary revenue with coefficient −0.003 (t-stat = −11.94). A one standard deviation increase in *LNAT* is associated with a 0.55 % decrease of *DISCREV(Absolute Value)*. In this context, while the effect of revenue forecasts on discretionary revenues is not as overwhelming as that of firm size (0.07 % vs. 0.55 %),

[7] We do not winsorize variables with log transformation, such as *LNAT*. Log-transformation already reduces the impact of outliers.

[8] Huang and Hairston (2023)'s discussion about their Table 5 implies that the ratio of revenue forecast coverage over earnings forecast coverage in their annual sample is 88%. This indicates a lower overlap between revenue and earnings forecast coverages at the quarterly level.

[9] We use the term "signed" to separately refer to negative and positive discretionary revenues.

[10] All t-statistics in the regression analyses are calculated based on standard errors clustered at the firm level. The levels of significance indicated in all the regressions are based on two-tailed tests.

Table 1
Panel A: Descriptive statistics.

Variable	N	Mean	Median	StdDev	25thPercentile	75thPercentile
DISCREV	137,284	0	−0.001	0.04	−0.01	0.009
DISCREV(Absolute Value)	137,284	0.018	0.01	0.036	0.004	0.021
REV_FCST	137,284	0.812	0.889	0.23	0.7	1
CPS_FCST	137,284	0.084	0	0.171	0	0.115
LNAT	137,284	6.753	6.662	1.826	5.455	7.932
AGE	137,284	20.373	15	16.35	8	28
SHARES	137,284	3.998	3.838	1.201	3.189	4.662
LEV	137,284	0.504	0.488	0.284	0.3	0.656
RAISE	137,284	0.05	0.004	0.165	0	0.026
MB	137,284	4.31	2.458	360.695	1.436	4.362
PE	137,284	58.157	54.548	5,452.51	−15.651	103.588
PS	137,284	74.315	6.294	2,023.06	2.901	13.665
ROA	137,284	−0.003	0.009	0.068	−0.008	0.022
LOSS	137,284	0.325	0	0.468	0	1
SG	137,284	0.36	0.025	69.056	−0.044	0.101
REVG	137,284	0.154	0.02	7.154	−0.071	0.126
STD_CS	137,284	0.204	0.071	7.857	0.041	0.121
STD_CFO	137,284	0.074	0.031	0.947	0.02	0.054
BIGN	137,284	0.064	0	0.244	0	0
ΔR_{t-1}	137,284	0.006	0.004	0.062	−0.008	0.019
ΔR_{t-2}	137,284	0.005	0.004	0.06	−0.008	0.019
ΔR_{t-3}	137,284	0.005	0.004	0.062	−0.008	0.019
ΔR_{t-4}	137,284	0.005	0.004	0.065	−0.008	0.018
VREV	117,270	2.979	0.392	32.377	−0.895	3.37
SFERR	132,641	2.334	0.714	131.089	0.268	1.698
SDISPERSION	116,352	0.009	0.004	0.317	0.002	0.008
DELSCOVERAGE	133,927	0.004	0	0.263	−0.04	0
SSURPRISE	136,345	−0.007	0.002	3.409	−0.003	0.008
SIZE	137,284	6.97	6.862	1.879	5.675	8.151

Panel B: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
DISCREV(1)		−0.01	0.01	−0.01	0.00	−0.01	−0.01	0.01	**0.05**	0.00	0.00	0.00	0.01	−0.01	0.00	**0.04**	**−0.10**	**−0.02**	0.00
DISCREV(Abs. Val.)(2)	−0.01		**0.02**	**−0.05**	**−0.13**	**−0.06**	**−0.10**	**0.02**	**0.07**	0.00	0.00	−0.01	0.01	**0.02**	0.00	**0.03**	**0.12**	**0.05**	−0.01
REV_FCST_CONC(3)	0.01	**0.02**		**−0.04**	**−0.19**	**−0.06**	**−0.12**	**−0.02**	**0.02**	0.00	0.00	0.01	**−0.08**	**0.13**	0.00	0.01	0.01	**0.02**	**−0.17**
CPS_FCST_CONC(4)	−0.01	**−0.05**	**−0.04**		**0.24**	**0.04**	**0.20**	**0.09**	0.01	0.00	0.00	−0.01	**0.04**	0.00	0.00	0.00	0.00	**0.03**	**−0.02**
LNAT(5)	0.00	**−0.13**	**−0.19**	**0.24**		**0.45**	**0.77**	**0.28**	**−0.05**	0.00	0.00	**−0.03**	**0.26**	**−0.30**	0.00	**−0.01**	**−0.02**	**−0.05**	**0.12**
AGE(6)	−0.01	**−0.06**	**−0.06**	**0.04**	**0.45**		**0.28**	**0.12**	**−0.06**	0.00	0.00	**−0.02**	**0.17**	**−0.24**	0.00	**−0.01**	−0.01	**−0.03**	**0.08**
SHARES(7)	−0.01	**−0.10**	**−0.12**	**0.20**	**0.77**	**0.28**		**0.19**	**−0.05**	0.00	0.00	0.00	**0.08**	**−0.10**	0.00	0.00	**−0.01**	**−0.03**	**0.08**
LEV(8)	0.01	**0.02**	**−0.02**	**0.09**	**0.28**	**0.12**	**0.19**		**0.08**	0.00	0.00	**−0.02**	**−0.11**	**0.05**	0.00	0.00	−0.01	**−0.01**	**0.04**
RAISE (9)	**0.05**	**0.07**	**0.02**	0.01	**−0.05**	**−0.06**	**−0.05**	**0.08**		0.00	0.00	**0.04**	**−0.21**	**0.09**	0.00	**0.01**	0.00	**0.01**	−0.01
MB(10)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PE(11)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.01	**−0.05**	0.00	0.00	0.00	0.00	0.00

(*continued on next page*)

Table 1 (*continued*)

Panel B: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
PS(12)	0.00	−0.01	0.01	−0.01	**−0.03**	**−0.02**	0.00	**−0.02**	**0.04**	0.00	0.00		**−0.06**	**0.05**	0.00	0.00	0.00	0.00	−0.01
ROA(13)	0.01	0.01	**−0.08**	**0.04**	**0.26**	**0.17**	**0.08**	**−0.11**	**−0.21**	0.00	0.01	**−0.06**		**−0.54**	0.00	**−0.02**	0.00	**−0.02**	**0.04**
LOSS(14)	−0.01	**0.02**	**0.13**	0.00	**−0.30**	**−0.24**	**−0.10**	**0.05**	**0.09**	0.00	**−0.05**	**0.05**	**−0.54**		0.00	**0.01**	−0.01	**0.02**	**−0.07**
SG(15)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		**0.03**	0.00	0.00	0.00
REVG(16)	**0.04**	**0.03**	0.01	0.00	**−0.01**	**−0.01**	0.00	0.00	**0.01**	0.00	0.00	0.00	**−0.02**	**0.01**	**0.03**		0.00	0.00	0.00
STD_CS(17)	**−0.10**	**0.12**	0.01	0.00	**−0.02**	−0.01	**−0.01**	−0.01	0.00	0.00	0.00	0.00	0.00	−0.01	0.00	0.00		**0.58**	0.00
STD_CFO(18)	**−0.02**	**0.05**	**0.02**	**0.03**	**−0.05**	**−0.03**	**−0.03**	**−0.01**	**0.01**	0.00	0.00	0.00	**−0.02**	**0.02**	0.00	0.00	**0.58**		−0.01
BIGN(19)	0.00	−0.01	**−0.17**	**−0.02**	**0.12**	**0.08**	**0.08**	**0.04**	−0.01	0.00	0.00	−0.01	**0.04**	**−0.07**	0.00	0.00	0.00	−0.01	

Note: Upper diagonal reports Pearson correlations. Lower diagonal reports Spearman correlations. $N = 137{,}284$. All continuous variables are winsorized at the top and bottom 1 % of their cross-sectional distributions. Correlations in bold are significant at 0.01 level (two tailed).

Table 2
Main analysis: The effect of analysts' revenue forecasts on discretionary revenues.

	(1)	(2)	(3)
	DISCREV (<0)	*DISCREV (>0)*	*DISCREV (Absolute Value)*
REV_FCST	−0.002	0.003**	0.003***
	(−1.63)	(2.50)	(2.71)
CPS_FCST	0.005***	−0.007***	−0.006***
	(3.13)	(−4.59)	(−4.12)
LNAT	0.003***	−0.003***	−0.003***
	(14.27)	(−7.64)	(−11.94)
AGE	−0.000	−0.000	0.000
	(−1.36)	(−0.93)	(0.20)
SHARES	−0.001***	0.001*	0.001***
	(−3.14)	(1.88)	(2.74)
LEV	−0.007***	0.011***	0.010***
	(−10.74)	(3.83)	(6.15)
RAISE	−0.005***	0.017***	0.012***
	(−4.29)	(7.25)	(8.14)
MB	0.000	0.000	−0.000
	(0.87)	(0.08)	(−0.82)
PE	−0.000	0.000*	0.000**
	(−1.05)	(1.88)	(2.17)
PS	0.000***	−0.000*	−0.000***
	(4.14)	(−1.69)	(−3.37)
ROA	−0.021***	0.044**	0.032***
	(−4.45)	(2.48)	(3.65)
LOSS	−0.002***	0.002***	0.002***
	(−3.90)	(2.64)	(4.33)
SG	−0.000***	−0.000**	0.000
	(−6.90)	(−2.03)	(0.13)
REVG	0.000	0.001**	0.000
	(1.40)	(2.07)	(1.09)
STD_CS	−0.001***	0.000	0.001***
	(−7.64)	(1.56)	(5.44)
STD_CFO	0.002*	0.000	−0.002*
	(1.66)	(1.25)	(−1.86)
BIGN	0.000	−0.000	−0.000
	(0.30)	(−0.70)	(−0.70)
ΔR_{t-1}	−0.034***	0.082***	0.064***
	(−3.44)	(9.66)	(11.00)
ΔR_{t-2}	−0.040***	0.041***	0.042***
	(−5.61)	(5.92)	(8.34)
ΔR_{t-3}	−0.027***	0.022*	0.025***
	(−3.47)	(1.90)	(3.94)
ΔR_{t-4}	−0.013*	0.031***	0.023***
	(−1.82)	(4.28)	(4.48)
Observations	71,317	65,967	137,284
Adj. *R*-sq	0.105	0.0898	0.0814
Qtr. and Ind. FE	Yes	Yes	Yes

Robust standard errors (clustered by firm) are calculated for *t*-statistics. Significance levels denoted by stars. (***), (**) and (*) refer to $p < 0.01$, $p < 0.05$ and $p < 0.1$, respectively. *DISCREV* is discretionary revenues calculated from the lagged revenue model (equation 1). See the Appendix for all variable definitions.

it is still a sizeable economic effect.

The majority of the coefficients of the control variables in equation (2) turn out to be significant at conventional levels. In column (3), *CPS_FCST* has a significant negative association with discretionary accruals, which is consistent with the finding of Huang and Hairston (2023) that misstatement is less likely when there are more cash flow forecasts. This negative association is also consistent with Bilinski's (2014) finding that analysts do not disclose cash flow forecasts when the quality of earnings is low. *LNAT* is negatively associated with discretionary revenues (*t*-stat = −11.94), indicating more disciplined quarterly reporting behavior from larger firms. Leverage is positively associated with discretionary revenues (*t*-stat = 6.15), as firms with debt covenants need to deliver quarterly financial results to meet covenant requirements and may manage earnings to avoid violations (Efendi et al., 2007; Franz et al., 2014; Jaggi and Lee, 2002; Jha, 2013; Sweeney, 1994). More shares outstanding (*SHARES*, *t*-stat = 2.74) and financing activities (*RAISE*, *t*-stat = 8.14) lead to a higher level of revenue manipulation as firms may require a higher level of per-share earnings target.

4.3.2. Cross-sectional tests

4.3.2.1. Fourth quarter effect. The quarterly setting allows for more granular analyses beyond the established results with annual data in the literature. Specifically, we investigate the potential difference in the association between revenue forecasts and discretionary revenues during the fourth fiscal quarter. While the effects of pressure to meet analyst expectations are relevant throughout the year, the fourth quarter presents an interesting setting as it is the time when annual financial numbers are shaping up. On the one hand, management might feel extra pressure to meet both quarterly and annual expectations during this period. For example, Jackson and Wilcox (2000) find that managers grant sales price reductions in the fourth quarter to meet annual financial reporting targets, Fan et al. (2010) show that classification shifting is more likely in the fourth quarter than in interim quarters, and Kerstein and Rai (2007) argue that firms with small cumulative losses or profits after three quarters are most likely to manage earnings upward during the fourth quarter to avoid small annual losses. On the other hand, since annual reports are subject to a full audit, the additional scrutiny might prevent managers from engaging in accrual manipulation during the fourth quarter (Brown and Pinello, 2007) and lead them to engage in alternative earnings management techniques (Fan et al., 2010). To investigate this empirical question, we augment our equation (2) by adding an interaction of an indicator variable for *Fourth Quarter* and our main variable of interest, *REV_FCST* as follows:

$$\begin{aligned} DISCRETION_{it} = {} & \beta_0 + \beta_1 REV\_FCST_{it} + \beta_2 REV\_FCST_{it} \times Fourth\ Quarter_{it} + \beta_3 CPS\_FCST_{it} + \beta_4 LNAT_{it} \\ & + \beta_5 AGE_{it} + \beta_6 SHARES_{it} + \beta_7 LEV_{it} + \beta_8 RAISE_{it} + \beta_9 MB_{it} + \beta_{10} PE_{it} + \beta_{11} PS_{it} + \beta_{12} ROA_{it} + \beta_{13} LOSS_{it} \\ & + \beta_{14} SG_{it} + \beta_{15} REVG_{it} + \beta_{16} STD\_CS_{it} + \beta_{17} STD\_CFO_{it} + \beta_{18} BIGN_{it} + \beta_{19} \Delta R_{it} \\ & + \beta_{20} \Delta R_{it-1} + \beta_{21} \Delta R_{it-2} + \beta_{22} \Delta R_{it-3} + Year - Quarter\ Fixed + Industry\ Fixed\ Effects + \varepsilon_{it} \end{aligned} \tag{3A}$$

Note that the main effect of *Fourth Quarter* is subsumed by fixed effects in the estimation, so it is omitted from the model. Table 3, Panel A presents our estimation of equation (3A). The coefficient on *REV_FCST* × *Fourth Quarter* is positive and significant (t-stat = 2.98) for the group that manipulate revenue upwards (column 2), which is consistent with the explanation that the incentive to manipulate discretionary revenues is higher during the fourth quarter. The impact of the fourth quarter is not significant (t-stat = 0.51) for the group that deflate discretionary revenues (column 1). The overall effect on the magnitude of all discretionary revenues reported in column (3) is positive and significant (t-stat = 1.86), supporting the idea that pressure from analysts' coverage of revenues on discretionary revenues is more pronounced during the fourth quarter.

4.3.2.2. Value relevance of revenues. When the value relevance of firms' revenue is higher, we expect to observe a stronger association between revenue forecasts and discretionary revenues as management may expect a stronger response from investors to firms' meeting or beating the revenue target. Therefore, we expect a positive moderating effect from the value relevance of revenue (*VREV*). We measure the value relevance of revenue on a firm-quarter basis by estimating the following regression model augmented from quarterly models of the returns-earnings association (e.g., Kothari et al., 2006; Sadka et al., 2020):

$$RET_{it} = \alpha + V_{\mathrm{Rev}\_it} \cdot \Delta REV_{it} + V_{Earn\_it} \cdot \Delta EARN_{it} + \varepsilon_{it} \tag{3B}$$

where *RET* is quarterly stock returns compounded monthly during the fiscal quarter. *ΔREV* is the seasonally adjusted change in revenue (i.e., current quarter's value minus the value of the same quarter last year) and *ΔEARN* is the seasonally adjusted change in income before extraordinary items in the fiscal quarter, both divided by the market value of common equity at the beginning of the quarter. We estimate equation (3B) for each firm-quarter using the rolling windows of 16 quarters. We require at least eight quarters of available data for each of the rolling windows. Coefficients specific to each firm-quarter, V_{Rev} and V_{Earn}, represent the value relevance of revenue and earnings, respectively. The V_{Rev} coefficient becomes our value relevance of revenue (*VREV*) measure used in subsequent analysis.[11]

Given our main result that analysts' revenue forecasts are associated with a higher magnitude of discretionary revenues, we expect this association to be exacerbated when revenues are more value relevant. Hence, we expect a positive coefficient on the interaction term *REV_FCST* × *VREV* from the following equation:

$$\begin{aligned} DISCRETION_{it} = {} & \beta_0 + \beta_1 REV\_FCST_{it} + \beta_2 VREV_{it} + \beta_3 REV\_FCST_{it} \times VREV_{it} + \beta_4 CPS\_FCST_{it} + \beta_5 LNAT_{it} \\ & + \beta_6 AGE_{it} + \beta_7 SHARES_{it} + \beta_8 LEV_{it} + \beta_9 RAISE_{it} + \beta_{10} MB_{it} + \beta_{11} PE_{it} + \beta_{12} PS_{it} + \beta_{13} ROA_{it} + \beta_{14} LOSS_{it} \\ & + \beta_{15} SG_{it} + \beta_{16} REVG_{it} + \beta_{17} STD\_CS_{it} + \beta_{18} STD\_CFO_{it} + \beta_{19} BIGN_{it} + \beta_{20} \Delta R_{it} \\ & + \beta_{21} \Delta R_{it-1} + \beta_{22} \Delta R_{it-2} + \beta_{23} \Delta R_{it-3} + Year - Quarter\ Fixed + Industry\ Fixed\ Effects + \varepsilon_{it} \end{aligned} \tag{3C}$$

Columns (1) through (3) in Table 3, Panel B present our estimation of equation (3C). The coefficient on *REV_FCST* × *VREV* is negative and significant (t-stat = −1.96) for the group that deflate discretionary revenues (column 1), while it is positive but not significant (t-stat = 1.12) for the group that manipulate revenues upwards (column 2). The overall effect on the magnitude of all discretionary revenues reported in column (3) is positive and significant (t-stat = 1.71). This is consistent with our expectation that revenue numbers with higher value relevant information are associated with a stronger magnitude of manipulation in discretionary revenues.

4.3.2.3. Dispersion of revenue forecasts. Dispersion of revenue forecasts reflects the information asymmetry among analysts about firms' future revenues. Managers may be motivated to exploit such information asymmetry and inflate earnings more aggressively. Additionally, managers may inflate their revenues even more as they feel uncertain about the revenue's target. To examine this cross-sectional prediction, we estimate the following equation and predict a positive coefficient on the interaction term *REV_FCST* × *SDISPERSION*.

[11] We scale the *VREV* measure by 100 to decrease the number of decimals in the regression coefficients.

Table 3
Cross-sectional tests.

Panel A: Effect of Fourth Fiscal Quarter on the Association between Revenue Forecasts and Discretionary Revenues

	(1)	(2)	(3)
	DISCREV (<0)	*DISCREV (>0)*	*DISCREV(Absolute Value)*
REV_FCST	−0.002	0.002	0.002**
	(−1.54)	(1.33)	(2.00)
REV_FCST x Fourth Quarter	0.001	0.005***	0.002*
	(0.51)	(2.98)	(1.86)
CPS_FCST	0.003***	−0.003***	−0.003***
	(14.29)	(−7.64)	(−11.93)
LNAT	−0.000	−0.000	0.000
	(−1.36)	(−0.93)	(0.20)
AGE	−0.001***	0.001*	0.001***
	(−3.15)	(1.88)	(2.74)
SHARES	−0.007***	0.011***	0.010***
	(−10.74)	(3.83)	(6.15)
LEV	−0.005***	0.017***	0.012***
	(−4.29)	(7.26)	(8.14)
RAISE	0.000	0.000	−0.000
	(0.88)	(0.12)	(−0.81)
MB	−0.000	0.000*	0.000**
	(−1.05)	(1.91)	(2.19)
PE	0.000***	−0.000*	−0.000***
	(4.14)	(−1.69)	(−3.36)
PS	−0.021***	0.044**	0.032***
	(−4.45)	(2.48)	(3.65)
ROA	−0.002***	0.002***	0.002***
	(−3.90)	(2.66)	(4.34)
LOSS	−0.000***	−0.000**	0.000
	(−6.90)	(−2.03)	(0.13)
SG	0.000	0.001**	0.000
	(1.40)	(2.08)	(1.09)
REVG	−0.001***	0.000	0.001***
	(−7.64)	(1.57)	(5.44)
STD_CS	0.002*	0.000	−0.002*
	(1.66)	(1.26)	(−1.86)
STD_CFO	0.000	−0.000	−0.000
	(0.31)	(−0.68)	(−0.69)
BIGN	−0.034***	0.082***	0.064***
	(−3.45)	(9.67)	(11.00)
ΔR_{t-1}	−0.040***	0.041***	0.042***
	(−5.61)	(5.92)	(8.34)
ΔR_{t-2}	−0.027***	0.023*	0.025***
	(−3.47)	(1.91)	(3.95)
ΔR_{t-3}	−0.013*	0.031***	0.023***
	(−1.82)	(4.29)	(4.49)
ΔR_{t-4}	−0.028***	0.026***	0.028***
	(−19.44)	(15.64)	(20.02)
Observations	71,317	65,967	137,284
Adj. *R*-sq	0.105	0.0899	0.0814
Qtr. and Ind. FE	Yes	Yes	Yes

Panel B: Effect of Revenue Value Relevance and Revenue Forecast Dispersion on the Association between Revenue Forecasts and Discretionary Revenues

	(1)	(2)	(3)	(4)	(5)	(6)
	DISCREV (<0)	*DISCREV (>0)*	*DISCREV (Absolute Value)*	*DISCREV (<0)*	*DISCREV (>0)*	*DISCREV (Absolute Value)*
REV_FCST	−0.002	0.002*	0.002*	−0.001	−0.001	−0.001
	(−1.27)	(1.90)	(1.95)	(−0.74)	(−0.51)	(−1.14)
VREV	0.004**	−0.003	−0.004**			
	(2.12)	(−1.39)	(−1.96)			
REV_FCST × *VREV*	−0.004*	0.003	0.004*			
	(−1.96)	(1.12)	(1.71)			
SDISPERSION				−0.154**	−0.135***	−0.158***
				(−2.19)	(−3.83)	(−6.36)
REV_FCST × *SDISPERSION*				−0.126	0.351***	0.411***
				(−1.50)	(3.86)	(6.46)
CPS_FCST	0.004**	−0.006***	−0.005***	0.005***	−0.008***	−0.007***
	(2.41)	(−3.99)	(−3.40)	(3.09)	(−4.78)	(−4.82)
LNAT	0.003***	−0.003***	−0.003***	0.002***	−0.003***	−0.003***

(*continued on next page*)

Table 3 (*continued*)

Panel B: Effect of Revenue Value Relevance and Revenue Forecast Dispersion on the Association between Revenue Forecasts and Discretionary Revenues

	(1)	(2)	(3)	(4)	(5)	(6)
	DISCREV (<0)	*DISCREV (>0)*	*DISCREV (Absolute Value)*	*DISCREV (<0)*	*DISCREV (>0)*	*DISCREV (Absolute Value)*
	(12.53)	(−10.23)	(−12.36)	(10.17)	(−5.76)	(−8.37)
AGE	−0.000	−0.000	0.000	−0.000	−0.000	−0.000
	(−0.67)	(−0.09)	(0.38)	(−0.21)	(−1.41)	(−0.81)
SHARES	−0.001***	0.000	0.001**	−0.000*	0.001**	0.001**
	(−2.92)	(1.20)	(2.25)	(−1.80)	(1.98)	(2.12)
LEV	−0.006***	0.008***	0.007***	−0.005***	0.011***	0.008***
	(−8.32)	(9.28)	(10.30)	(−7.89)	(2.96)	(4.30)
RAISE	−0.005***	0.016***	0.011***	−0.003***	0.018***	0.012***
	(−3.64)	(8.33)	(8.07)	(−2.88)	(6.80)	(7.10)
MB	−0.000	0.000	0.000	0.000	−0.000	−0.000
	(−1.02)	(0.48)	(0.84)	(0.81)	(−0.08)	(−0.68)
PE	−0.000	0.000*	0.000*	−0.000*	0.000*	0.000**
	(−0.62)	(1.75)	(1.86)	(−1.96)	(1.91)	(2.24)
PS	0.000***	−0.000***	−0.000***	0.000***	−0.000	−0.000***
	(3.31)	(−3.27)	(−3.37)	(3.86)	(−1.04)	(−2.65)
ROA	−0.019***	0.030***	0.026***	−0.020***	0.068***	0.041***
	(−3.34)	(3.45)	(4.73)	(−3.60)	(2.82)	(3.49)
LOSS	−0.002***	0.002***	0.002***	−0.002***	0.003***	0.003***
	(−4.07)	(3.03)	(4.77)	(−4.13)	(3.05)	(4.24)
SG	−0.000***	−0.000***	−0.000**	−0.000***	−0.000***	0.000
	(−6.95)	(−3.83)	(−2.40)	(−7.27)	(−3.53)	(0.17)
REVG	0.004***	0.002***	0.002***	0.000	0.001***	0.000
	(3.04)	(4.29)	(4.31)	(1.40)	(5.16)	(1.01)
STD_CS	−0.000	0.000	0.000	−0.000**	0.000	0.000
	(−0.32)	(0.65)	(0.48)	(−2.38)	(0.21)	(1.36)
STD_CFO	−0.000	0.000	0.000	−0.000	0.000	0.000
	(−0.28)	(0.25)	(0.28)	(−0.22)	(1.13)	(0.83)
BIGN	0.000	0.000	−0.000	0.001**	0.000	−0.001
	(0.06)	(0.20)	(−0.06)	(2.05)	(0.02)	(−1.25)
ΔR_{t-1}	−0.044***	0.071***	0.056***	−0.022***	0.073***	0.055***
	(−3.51)	(8.86)	(8.51)	(−3.16)	(8.08)	(9.45)
ΔR_{t-2}	−0.045***	0.030***	0.039***	−0.049***	0.033***	0.043***
	(−5.02)	(5.78)	(7.56)	(−7.07)	(4.56)	(8.40)
ΔR_{t-3}	−0.030***	0.023**	0.027***	−0.031***	0.020	0.026***
	(−3.25)	(2.37)	(4.79)	(−5.37)	(1.54)	(3.76)
ΔR_{t-4}	−0.012	0.024***	0.017***	−0.010	0.035***	0.025***
	(−1.57)	(3.65)	(3.26)	(−1.45)	(3.33)	(3.77)
Observations	60,979	56,290	117,270	60,532	55,820	116,352
Adj. *R*-sq	0.0666	0.122	0.0802	0.0789	0.106	0.0814
Qtr. and Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors (clustered by firm) are calculated for *t*-statistics. Significance levels denoted by stars. (***), (**) and (*) refer to $p < 0.01$, $p < 0.05$ and $p < 0.1$, respectively. *DISCREV* is discretionary revenues calculated from the lagged revenue model (equation 1). See the Appendix for all variable definitions.
Robust standard errors (clustered by firm) are calculated for *t*-statistics. Significance levels denoted by stars. (***), (**) and (*) refer to $p < 0.01$, $p < 0.05$ and $p < 0.1$, respectively. *DISCREV* is discretionary revenues calculated from the lagged revenue model (equation 1). See the Appendix for all variable definitions.

$$\begin{aligned} DISCRETION_{it} = {} & \beta_0 + \beta_1 REV\_FCST_{it} + \beta_2 SDISPERSION_{it} + \beta_3 REV\_FCST_{it} \times SDISPERSION_{it} + \beta_4 CPS\_FCST_{it} + \beta_5 LNAT_{it} \\ & + \beta_6 AGE_{it} + \beta_7 SHARES_{it} + \beta_8 LEV_{it} + \beta_9 RAISE_{it} + \beta_{10} MB_{it} + \beta_{11} PE_{it} + \beta_{12} PS_{it} + \beta_{13} ROA_{it} + \beta_{14} LOSS_{it} \\ & + \beta_{15} SG_{it} + \beta_{16} REVG_{it} + \beta_{17} STD\_CS_{it} + \beta_{18} STD\_CFO_{it} + \beta_{19} BIGN_{it} + \beta_{20} \Delta R_{it} \\ & + \beta_{21} \Delta R_{it-1} + \beta_{22} \Delta R_{it-2} + \beta_{23} \Delta R_{it-3} + Year - Quarter\,Fixed + Industry\,Fixed\,Effects + \varepsilon_{it} \end{aligned} \tag{3D}$$

where *SDISPERSION* is the dispersion of revenue forecasts immediately before the earnings announcement, scaled by the firm's total assets at the beginning of the quarter.

Columns (4) through (6) in Table 3 Panel B present our estimation of equation (3D). For the group of firms that inflate discretionary revenues (column (5)), the coefficient on *REV_FCST* × *SDISPERSION* is positive and significant (*t*-stat = 3.86). This result is consistent with our expectation that more disagreement among analysts over revenues leads to more manipulation of discretionary revenues. For the group of firms that deflate discretionary revenues (column (4)), the impact of revenue forecast dispersion on the association between revenue forecasts and discretionary revenues is negative, but not statistically significant (*t*-stat = −1.50) effect. Overall, as shown in column (6), dispersion of revenue forecasts exacerbates the association between revenue forecasts and discretionary revenues (*t*-stat = 6.46).

4.3.3. The effect of analysts' revenue forecasts on discretionary revenues around ASC 606

ASC 606, titled "Revenue from Contracts with Customers" mandates that public firms disaggregate revenues into categories that depict how economic factors affect revenues and cash flows (ASC 606-10-50-5). One of the primary objectives of the standard is to increase the amount of useful information in financial reports through improved disclosure requirements (FASB, 2019). These requirements had significant disclosure consequences. The literature has documented higher analyst sales forecast accuracy and lower forecast dispersion for disaggregating firms (Hinson et al., 2022), higher earnings informativeness (Chung and Chuwonganant, 2023) and liquidity (Ferreira and Jiang, 2023), as well as greater uncertainty, lower earnings predictability, and higher cost of debt (e.g., Lee et al., 2022). We identify the sub-sample period 2016–2021 for our analysis around ASC 606. We define a *POST* dummy variable which equals to one for quarters ending after December 15, 2018, the effective date of ASC 606, and zero otherwise. We estimate the following model:

Table 4
Effect of revenue forecasts around ASC 606 (2016–2021 period).

	(1)	(2)	(3)
	DISCREV (<0)	*DISCREV (>0)*	*DISCREV (Absolute Value)*
REV_FCST	0.002	0.006**	0.003
	(0.52)	(2.27)	(1.05)
POST	0.001	0.003	0.002
	(0.24)	(1.10)	(1.04)
REV_FCST × *POST*	0.001	−0.005*	−0.004*
	(0.40)	(−1.82)	(−1.87)
CPS_FCST	−0.000	−0.005*	−0.002
	(−0.12)	(−1.84)	(−0.92)
LNAT	0.003***	−0.002***	−0.003***
	(9.41)	(−6.37)	(−8.42)
AGE	−0.000**	0.000	0.000
	(−2.03)	(0.37)	(1.48)
SHARES	−0.001***	0.000	0.001**
	(−2.69)	(1.17)	(1.99)
LEV	−0.007***	0.007***	0.007***
	(−7.14)	(5.98)	(7.06)
RAISE	−0.006***	0.014***	0.012***
	(−3.28)	(6.27)	(5.32)
MB	0.000	−0.000	−0.000
	(0.76)	(−0.89)	(−1.05)
PE	−0.000	0.000***	0.000**
	(−0.87)	(2.84)	(2.35)
PS	0.000***	−0.000	−0.000***
	(4.27)	(−1.57)	(−4.42)
ROA	−0.014**	0.026***	0.019***
	(−2.41)	(2.99)	(3.32)
LOSS	−0.001*	0.000	0.001
	(−1.76)	(0.44)	(1.10)
SG	−0.001***	0.000	0.000
	(−2.76)	(0.01)	(1.07)
REVG	0.002**	0.002**	0.001**
	(2.52)	(2.57)	(2.52)
STD_CS	−0.012	0.017*	0.014
	(−1.64)	(1.72)	(1.63)
STD_CFO	−0.012	0.011	0.014*
	(−1.56)	(1.64)	(1.82)
BIGN	0.000	0.001	0.000
	(0.22)	(0.61)	(0.29)
$\Delta R_{t\text{-}1}$	−0.039***	0.051***	0.051***
	(−3.00)	(3.03)	(5.95)
$\Delta R_{t\text{-}2}$	−0.061***	0.033***	0.050***
	(−5.66)	(3.10)	(7.18)
$\Delta R_{t\text{-}3}$	−0.047***	0.035***	0.043***
	(−3.92)	(2.61)	(6.13)
$\Delta R_{t\text{-}4}$	−0.003	0.014	0.011*
	(−0.29)	(1.37)	(1.74)
Observations	16,382	14,744	31,126
Adj. *R*-sq	0.109	0.139	0.116
Qtr. and Ind. FE	Yes	Yes	Yes

Robust standard errors (clustered by firm) are calculated for *t*-statistics. Significance levels denoted by stars. (***), (**) and (*) refer to $p < 0.01$, $p < 0.05$ and $p < 0.1$, respectively. *DISCREV* is discretionary revenues calculated from the lagged revenue model (equation 1). See the Appendix for all variable definitions.

$$\begin{aligned} DISCRETION_{it} = {} & \beta_0 + \beta_1 REV\_FCST_{it} + \beta_2 POST_{it} + \beta_3 REV\_FCST_{it} \times POST_{it} + \beta_4 REV\_FCST_{it} + \beta_5 LNAT_{it} \\ & + \beta_6 AGE_{it} + \beta_7 SHARES_{it} + \beta_8 LEV_{it} + \beta_9 RAISE_{it} + \beta_{10} MB_{it} + \beta_{11} PE_{it} + \beta_{12} PS_{it} + \beta_{13} ROA_{it} + \beta_{14} LOSS_{it} \\ & + \beta_{15} SG_{it} + \beta_{16} REVG_{it} + \beta_{17} STD\_CS_{it} + \beta_{18} STD\_CFO_{it} + \beta_{19} BIGN_{it} + \beta_{20} \Delta R_{it} \\ & + \beta_{21} \Delta R_{it-1} + \beta_{22} \Delta R_{it-2} + \beta_{23} \Delta R_{it-3} + Year - Quarter\ Fixed + Industry\ Fixed\ Effects + \varepsilon_{it} \end{aligned} \tag{4}$$

We expect a negative interaction effect from *REV_FCST* × *POST* for equation (4) during this period, as ASC 606 may act as a disciplining mechanism by increasing the transparency of reported revenues.

Our analysis around the adoption of ASC 606 is presented in panel B of Table 4. We observe a negative and significant coefficient on *REV_FCST* × *POST* in column (2) (t-stat = −1.82) which is the group that actively inflated their discretionary revenues. This effect drives the decrease in overall magnitude of the discretionary revenues in column (3) (t-stat = −1.87). These results are consistent with increased transparency weakening the positive association between analysts' revenue forecasts and discretionary revenues.

4.3.4. Robustness tests

In order to understand the association between analysts' revenue forecasts and discretionary revenues at a more refined level, we perform a robustness test with a restrictive identification. Specifically, we identify cases where a firm's revenues are covered by an IBES analyst for the first time (i.e., initiation of a revenue forecast) and examine the effect of this initiation on the firm's discretionary revenues. This pre-post identification is similar to that of McInnis and Collins (2011), who examine the effect of cash flow forecast coverage on discretionary accruals.

Due to the unique characteristics of revenue forecasts on IBES, we require firms to have at least four quarters of analysts' EPS forecast coverage before the revenue forecast initiation. This is necessary to avoid the confounding effect of EPS forecast initiations. We also require firms to have a maximum of 16 quarters of data after the revenue forecast initiation in order to attain a balance between pre- and post-initiation observations. We focus on revenue forecast initiations starting in the year 2000, mainly to avoid any mechanical effect of bulk initiations of revenue forecast coverage in IBES during the late 1990 s. This sample selection results in a balanced panel of 9,715 firm-quarter observations, with roughly 50 % of these observations being in the post-revenue forecast initiation period.

Then, we estimate the following equation, with *POST_REV* defined as a dummy variable taking the value of one for the quarters after a firm's first revenue forecast coverage:

$$\begin{aligned} DISCRETION_{it} = {} & \beta_0 + \beta_1 POST\_REV_{it} + \beta_2 REV\_FCST_{it} + \beta_3 CPS\_FCST_{it} + \beta_4 LNAT_{it} \\ & + \beta_5 AGE_{it} + \beta_6 SHARES_{it} + \beta_7 LEV_{it} + \beta_8 RAISE_{it} + \beta_9 MB_{it} + \beta_{10} PE_{it} + \beta_{11} PS_{it} + \beta_{12} ROA_{it} + \beta_{13} LOSS_{it} \\ & + \beta_{14} SG_{it} + \beta_{15} REVG_{it} + \beta_{16} STD\_CS_{it} + \beta_{17} STD\_CFO_{it} + \beta_{18} BIGN_{it} + \beta_{19} \Delta R_{it} \\ & + \beta_{20} \Delta R_{it-1} + \beta_{21} \Delta R_{it-2} + \beta_{22} \Delta R_{it-3} + Year - Quarter\ Fixed + Industry\ Fixed\ Effects + \varepsilon_{it} \end{aligned} \tag{5}$$

In this equation, our main test variable is *POST_REV*; we keep the forecast coverage variables *REV_FCST* and *CPS_FCST* in the model. We also include firm fixed effects along with time fixed effects in equation (5), which effectively allows us to run a difference-in-difference estimation. While this sample identification and analysis are restrictive, they provide a more robust test with a stronger directional and causal inference on the effect of revenue forecasts on discretionary revenues.

Our results are presented in Panel A of Table 5. Column (1) and Column (2) show that the initiation of revenue forecasts, $POST\_REV_{it}$, has a non-significant effect (t-stats = −1.38 and 1.01) on discretionary revenues, while the effect signs are consistent with discretionary revenues moving away from the normal level of zero. Column (3) shows that overall, the initiation of revenue forecasts is marginally significant in increasing the magnitude of discretionary revenues (coefficient = 0.003; t-stat = 1.69). This result supports our main finding that analysts' forecasts on firms' revenues are associated with a higher magnitude of discretionary revenues. This is also consistent with Huang and Hairston's (2023) finding that analysts' revenue forecasts are associated with revenue misstatements.

We provide another robustness check through a falsification test using analysts' cash flow forecasts. Our expectation regarding the association between analysts' revenue forecasts and discretionary revenues is unique to the case of revenue forecasts, and we do not have the same expectation when it comes to analysts' cash flow forecasts. Therefore, we repeat the sample selection procedure for our estimation of equation (5), except that we collect data around the initiation of analysts' cash flow forecasts. We replace the variable $POST\_REV_{it}$ with $POST\_CFO_{it}$ and estimate equation (5). The results are presented in Panel B of Table 5. We do not observe significant coefficients on $POST\_CFO_{it}$ as we do for $POST\_REV_{it}$. This falsification test provides validity for our robustness test with revenue forecast initiations, as reported in Table 5A.

In the un-tabulated analysis, we control for quarterly discretionary accruals estimated based on Jones (1991) model in our main tests. With this additional control variable, our analysis shows incremental effects from revenue forecasts beyond their effects already reflected in quarterly discretionary accruals. The coefficients on *REV_FCST* are still significant. Our conclusion remains unchanged if we estimate discretionary accruals with several adjustments to the Jones (1991) model.

4.3.5. Consequences of discretionary revenues for analysts' revenue forecasts

Our results so far suggest a directional effect of analysts' revenue forecasts on discretionary revenues. In this section, we also explore the reverse relation and analyze the potential effects of discretionary revenues on analysts' revenue forecast characteristics. Discretionary components of reported financial numbers have been shown to be important in certain analyst forecasts, such as cash flow forecasts (DeFond and Hung, 2003). It is an empirical question whether discretionary revenues have such an effect on analysts' revenue forecasts.

We explore the effect of the magnitude of discretionary revenue on the magnitude of analysts' revenue forecast errors (i.e., inverse

Table 5
Robustness tests.

Panel A: Effect of Revenue Forecast Initiation

	(1)	(2)	(3)
	DISCREV (<0)	*DISCREV (>0)*	*DISCREV (Absolute Value)*
POST_REV	−0.002	0.003	0.003*
	(−1.38)	(1.01)	(1.69)
REV_FCST	0.003	0.001	−0.002
	(0.98)	(0.22)	(−0.75)
CPS_FCST	−0.003	−0.001	−0.000
	(−0.95)	(−0.56)	(−0.09)
LNAT	0.010***	0.000	−0.005***
	(2.76)	(0.20)	(−3.56)
AGE	0.002	0.009***	0.003*
	(1.55)	(3.47)	(2.01)
SHARES	−0.014	−0.003	0.006
	(−1.61)	(−0.89)	(1.44)
LEV	−0.008**	0.019***	0.010***
	(−2.26)	(4.77)	(3.95)
RAISE	−0.005**	0.026***	0.020***
	(−2.64)	(2.86)	(3.57)
MB	−0.000	0.000	0.000
	(−0.01)	(0.29)	(0.17)
PE	−0.000*	0.000	−0.000
	(−1.70)	(0.13)	(−0.86)
PS	0.000	−0.000	−0.000
	(0.97)	(−1.13)	(−1.54)
ROA	−0.039***	0.006	0.014
	(−5.94)	(0.47)	(1.21)
LOSS	−0.003	0.000	0.002
	(−1.43)	(0.06)	(1.02)
SG	−0.000	0.000***	0.000***
	(−1.26)	(9.98)	(17.38)
REVG	0.051***	0.000***	0.000***
	(6.08)	(2.87)	(3.02)
STD_CS	0.001	−0.003	−0.002
	(0.34)	(−0.21)	(−0.42)
STD_CFO	−0.002	0.003	0.002
	(−0.11)	(0.26)	(0.46)
BIGN	−0.003	0.002	0.003
	(−1.00)	(0.88)	(1.22)
ΔR_{t-1}	−0.080***	0.099**	0.062**
	(−4.28)	(2.41)	(2.66)
ΔR_{t-2}	−0.014	0.054***	0.036**
	(−0.99)	(2.74)	(2.48)
ΔR_{t-3}	−0.032**	0.019	0.023
	(−2.11)	(0.84)	(1.48)
ΔR_{t-4}	−0.012	0.017	0.006
	(−0.79)	(0.98)	(0.46)
Observations	4,975	4,701	9,715
Adj. *R*-sq	0.203	0.214	0.177
Time and Firm FE	Yes	Yes	Yes

Panel B: Effect of Cash Flow Forecast Initiation as a Falsification Test

	(1)	(2)	(3)
	DISCREV (<0)	*DISCREV (>0)*	*DISCREV (Absolute Value)*
POST_CFO	−0.001	−0.001	−0.000
	(−0.57)	(−0.74)	(−0.61)
REV_FCST	0.001	0.003	0.000
	(1.08)	(1.18)	(0.30)
CPS_FCST	0.002	−0.002	−0.001
	(0.53)	(−1.00)	(−0.51)
LNAT	0.004***	−0.001*	−0.002***
	(5.73)	(−1.83)	(−5.34)
AGE	0.000	0.002	0.000
	(0.38)	(1.25)	(0.13)
SHARES	−0.002*	−0.002*	0.000
	(−1.93)	(−1.85)	(0.33)
LEV	−0.003**	0.006**	0.005***

(*continued on next page*)

Table 5 (*continued*)

Panel B: Effect of Cash Flow Forecast Initiation as a Falsification Test

	(1)	(2)	(3)
	DISCREV (<0)	*DISCREV (>0)*	*DISCREV (Absolute Value)*
	(−2.30)	(2.29)	(4.11)
RAISE	−0.003**	0.019***	0.014***
	(−2.18)	(6.21)	(10.12)
MB	−0.000	−0.000***	−0.000***
	(−1.33)	(−3.69)	(−2.71)
PE	−0.000	−0.000	0.000
	(−1.20)	(−0.29)	(0.36)
PS	0.000**	−0.000	−0.000***
	(2.53)	(−0.89)	(−4.12)
ROA	−0.016	0.013	0.014**
	(−1.54)	(1.06)	(2.27)
LOSS	−0.002**	0.001	0.001
	(−2.64)	(0.87)	(1.52)
SG	−0.000***	−0.000	−0.000
	(−7.61)	(−1.27)	(−0.32)
REVG	0.001**	0.000***	0.000***
	(2.60)	(11.77)	(15.94)
STD_CS	0.000	0.000	−0.000
	(1.41)	(0.55)	(−0.69)
STD_CFO	−0.003	−0.001	0.002
	(−1.65)	(−0.38)	(1.07)
BIGN	0.000	0.000	−0.000
	(0.58)	(0.68)	(−0.62)
ΔR_{t-1}	−0.065***	0.094***	0.073***
	(−4.76)	(3.69)	(4.53)
ΔR_{t-2}	−0.041**	0.075***	0.054***
	(−2.06)	(3.26)	(3.04)
ΔR_{t-3}	−0.028**	0.054***	0.040**
	(−2.21)	(2.80)	(2.66)
ΔR_{t-4}	−0.014	0.037***	0.026**
	(−1.10)	(2.84)	(2.22)
Observations	21,110	19,729	40,857
Adj. *R*-sq	0.128	0.165	0.142
Time and Firm FE	Yes	Yes	Yes

Robust standard errors (clustered by firm) are calculated for *t*-statistics. Significance levels denoted by stars. (***), (**) and (*) refer to $p < 0.01$, $p < 0.05$ and $p < 0.1$, respectively. *DISCREV* is discretionary revenues calculated from the lagged revenue model (equation 1). See the Appendix for all variable definitions.

Robust standard errors (clustered by firm) are calculated for *t*-statistics. Significance levels denoted by stars. (***), (**) and (*) refer to $p < 0.01$, $p < 0.05$ and $p < 0.1$, respectively. *DISCREV* is discretionary revenues calculated from the lagged revenue model (equation 1). See the Appendix for all variable definitions.

of forecast accuracy) after the earnings are announced. If analysts can see through any manipulation in reported revenue numbers, they can adjust their estimates after the public announcement of these numbers and factor in reversals in accruals for the next period. This would manifest as no significant effect on the analysts' forecast errors. On the other hand, distorted financial statement numbers might lead to lower predictability of future revenues. Loss of confidence in reported revenues might cause analysts to rely more on their private information. These factors might lead to an increase in analysts' forecast errors in the next quarter. We estimate the following model to test this empirical question:

$$SFERR_{it+1} = \beta_0 + \beta_1 DISCREV(Absolute\ Value) + \beta_2 REV\_FCST_{it} + \beta_3 CPS\_FCST_{it} + \beta_4 SSURPRISE_{it} + \beta_5 MB_{it} + \beta_6 SIZE_{it} + \beta_7 ROA_{it} + \beta_8 LOSS_{it} + Year - Quarter\ Fixed + Industry\ Fixed\ Effects + \varepsilon_{it} \quad (6)$$

where $SFERR_{it+1}$ is the absolute value of the difference between reported revenues and the median analysts' revenue forecasts, scaled by total assets at the beginning of the quarter.[12] We multiply this measure by 100 to generate more meaningful regression coefficients from equation (6).

Table 6 column (1) shows the estimation results of model (6). The coefficient estimate of *DISCREV(Absolute Value)* is significantly positive (*t*-stat = 1.77), implying that analysts' revenue forecast errors are higher during the subsequent period in general when the discretion in the reported revenue numbers is higher. As discussed above, this might be interpreted as discretion in reported revenues making it harder for analysts to forecast future revenues. Moreover, this might also imply that analysts are failing to see the manipulation of the revenues.

[12] Our inferences remain similar when we use the mean of revenue forecasts to calculate the forecast error.

Table 6
Consequences of discretionary revenues for analysts' revenue forecasts.

	(1)	(2)	(3)
	$SFERR_{t+1}$	$DELSCOVERAGE_{t+1}$	$SDISPERSION_{t+1}$
DISCREV(Absolute Value)	6.581*	0.045	0.056***
	(1.77)	(1.53)	(4.83)
REV_FCST	5.675*	−0.322***	−0.003***
	(1.77)	(−44.95)	(−2.89)
CPS_FCST	0.190	0.031***	−0.005***
	(0.21)	(3.85)	(−2.71)
SSUPRISE	24.224	0.000	0.000
	(1.49)	(1.23)	(0.28)
MB	0.000	0.000**	0.000
	(0.22)	(2.16)	(1.33)
SIZE	−0.673***	−0.010***	−0.001***
	(−2.97)	(−19.81)	(−10.26)
ROA	−8.665	0.019	−0.014***
	(−1.52)	(1.44)	(−3.21)
LOSS	−1.222*	0.001	−0.001*
	(−1.77)	(0.53)	(−1.71)
Observations	147,373	153,018	129,708
Adj. *R*-sq	0.0882	0.0796	0.0719
Qtr. and Ind. FE	Yes	Yes	Yes

Robust standard errors (clustered by firm) are calculated for *t*-statistics. Significance levels denoted by stars. (***), (**) and (*) refer to $p < 0.01$, $p < 0.05$ and $p < 0.1$, respectively. *DISCREV* is discretionary revenues calculated from the lagged revenue model (equation 1). See the Appendix for all variable definitions.

Given the positive association between discretionary revenues and analysts' revenue forecast errors reported in column (1), we extend our exploration into other characteristics of analysts' revenue forecasts after the earnings announcement. We replace the dependent variable in equation (6) with the change in analysts' revenue forecast coverage from immediately before to immediately after the earnings announcement ($DELSCOVERAGE_{t+1}$) and dispersion of revenue forecasts immediately after the earnings announcement ($SDISPERSION_{t+1}$).

We report the results with these variables in columns (2) and (3) of Table 6, respectively. In column (2), we do not find a significant association between *DISCREV(Absolute Value)* and $DELSCOVERAGE_{t+1}$ (*t*-stat = 1.53). There does not seem to be any evidence that analysts' coverage decisions are affected by the magnitude in discretionary revenues. We believe this result also provides evidence against severe endogeneity stemming from a reverse causality problem in our setting. Finally, in column (3), we find a positive association between *DISCREV(Absolute Value)* and $SDISPERSION_{t+1}$ (*t*-stat = 4.83). This implies that higher discretionary revenues lead to more disagreement in analysts' revenue estimates after the earnings announcement. This is in line with the idea that high discretion in reported revenues make them less predictable, and analysts rely more on private information production to estimate the next period's revenues.

5. Conclusion

In this paper, we investigate whether there is an association between analysts' forecasts on revenues and revenue management by firms. We document evidence of a significant association between analysts' revenue forecasts and firms' discretionary revenues, especially for revenue-increasing discretionary activities. Our results show that analysts' attention on revenues increases the importance of meeting or beating revenue expectations, thereby aggravating pressure on managers to engage in revenue management to meet or beat revenue targets.

In our cross-sectional analyses, we document that the association between revenue forecasts and discretionary revenues is more pronounced during the fourth quarter, when the pressure to meet expectations is higher. We also find that the positive association between revenue forecasts and discretionary revenues is stronger when analysts' revenue forecast dispersion is greater, suggesting that managers are likely to use more aggressive discretion to attain revenue benchmarks when there is greater disagreement among analysts regarding a firm's future prospects. In addition, we find a similar positive moderation effect when the value relevance of revenues is higher, yielding consistent support for the pressure effect that managers have greater incentives to attain revenue expectations when there is a stronger market reaction towards revenue from investors.

We further study this association around a major GAAP change regarding accounting for revenues. ASC 606 introduced a more standardized approach for revenue recognition across industries, making revenues more transparent and comparable across businesses. We find that the association between revenue forecasts and discretionary revenues weakened after the adoption of ASC 606.

Overall, our findings provide consistent evidence that analysts' forecasts of firm revenues are likely to induce management to conduct more revenue manipulation to attain revenue benchmarks. We conduct several tests to confirm that this relationship is robust, including an alternative measure based on the initiation of analysts' revenue forecasts and a falsification test of analysts' cash flows forecasts. Given Huang and Hairston's (2023) evidence that this pressuring effect stems from analysts' revenue forecasts, our study complements previous work on this topic by focusing on analysts' revenue forecasts at a quarterly level and examining the variation in discretionary revenues.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix:. Variable definitions

DISCREV: Discretionary revenues calculated as the residuals from the lagged revenue model of Stubben (2006) in equation (1).

REV_FCST: The number of quarterly revenue forecasts divided by the number of quarterly earnings per share (EPS) forecasts, calculated before the earnings announcement.

CPS_FCST: The number of quarterly cash flow forecasts divided by the number of quarterly earnings per share (EPS) forecasts, calculated before the earnings announcement.

LNAT: The natural logarithm of total assets.

AGE: Firm age, measured as the number of years a firm appears in Compustat.

SHARES: Natural logarithm of the number of common shares outstanding.

LEV: Total liabilities, scaled by total assets.

RAISE: Sum of the issuance of long-term debt and the sale of common and preferred stocks, divided by lagged total assets.

MB: Market-to-book ratio of equity.

PE: Price-earnings ratio.

PS: Price-to-sales ratio.

ROA: Return on assets, calculated as net income divided by lagged total assets.

LOSS: Indicator variable taking the value of 1 if a firm reports net loss, and 0 otherwise.

SG: Sales growth rate, calculated as sales in quarter t minus sales in quarter t-1, divided by sales in quarter t-1.

REVG: Receivable in quarter t minus receivable in quarter t-1, divided by receivable in quarter t-1.

STD_CS: Standard deviation of cash sales (revenues plus the change in accounts receivable) divided by lagged total assets, between quarter t and t-35.

STD_CFO: Standard deviation of cash flows from operations divided by lagged total assets, between quarter t and t-35.

BIGN: 1 if a firm is audited by one of the Big N auditors, and 0 otherwise.

***ΔR*:** Quarterly change in total revenues scaled by average total assets.

SIZE: Firm size calculated as the natural logarithm of the market capitalization, calculated as number of shares outstanding multiplied by share price at the end of the fiscal quarter.

VREV: Value-relevance of revenue calculated on a firm-quarter basis by estimating equation 3B.

SDISPERSION: Most recent standard deviation of revenue forecast for quarter t collected in IBES summary file, scaled by total assets at the beginning of quarter t.

SFERR: Revenue forecast error magnitude, calculated as the absolute value of the difference between actual reported revenues and the median consensus estimate of analysts' revenue forecasts, scaled by lagged total assets. We multiply this measure by 100 to reduce the number of decimals in the regression coefficients.

DELSCOVERAGE: Rate of change in analysts' revenue forecast coverage from immediately before to immediately after the earnings announcement.

SSURPRISE: Revenue surprise, calculated as the difference between actual reported revenues and the median consensus estimate of analysts' revenue forecasts, scaled by lagged total assets.

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Data availability

Data will be made available on request.

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