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Achieving Revenue Benchmarks Conditional on Growth Properties

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Abstract: This study examines whether certain firm characteristics, specifically growth properties, are associated with the likelihood of achieving market expectations for revenues, as well as which mechanism (revenue manipulation or expectation management) growth firms utilize in order to avoid missing these expectations. The results show that growth firms are more likely to meet or exceed analyst revenue forecasts than non-growth firms. We also find that growth firms are more inclined to manipulate their reported revenues upwards, and less inclined to guide market expectations for revenues downward, in order to meet or beat expected revenues relative to non-growth firms. These findings suggest that window-dressing activities by growth firms may not be sustainable in the long-run and can misguide users of financial statements in their decision-making.

Keywords: growth; sustainability; revenue manipulation; revenue expectations management; revenue forecasts

1. Introduction

This study examines whether or not certain firm characteristics, specifically growth properties, are associated with stronger incentives in order to avoid negative revenue surprises. We define revenue surprises as the difference between the latest consensus of analyst revenue forecasts and actual firm revenues consistent with prior studies. The latest consensus (median) of analyst annual revenue forecasts reported one month before the current period earnings announcement is used as a proxy for market revenue expectations. We find that growth firms are more likely to emphasize revenue surprises than value firms to the extent that market participants place heavier weight on the revenue signals of growth firms versus value firms. We additionally focus on the use of two possible tools for growth firms to achieve favorable revenue surprises: (1) revenue manipulation, and (2) revenue expectation management. Since costs associated with both mechanisms may be different depending on the firms' growth properties, we examine which mechanism best allows growth firms to meet or beat market expectations for revenues versus value firms.

Prior literature provides evidence that the market rewards significantly higher equity premiums for firms meeting or beating both analyst earnings and revenue forecasts, and conversely penalizes firms for missing them (Jegadeesh and Livnat [1]; Rees and Sivaramakrishnan [2]; Chandra and Ro [3]). Nelson et al. [4] show that many attempts in earnings management to meet or beat market expectation involved revenue manipulation. More importantly, Ertimur et al. [5] finds that market participants react negatively to growth firms missing revenue expectations even if these firms successfully meet or beat earnings expectations. Furthermore, Kama [6] reports that the impact of revenue surprises on stock returns is higher in research and development (R&D) intensive firms. These findings suggest that the costs associated with missing revenue expectations are much greater for growth firms versus value firms. These high costs might provide stronger incentives for growth firms to closely observe revenue signals. These increased incentives may accordingly lead growth firm managers to undertake additional actions such as manipulating reported revenues upward and managing revenue expectations downward in order to generate favorable revenue surprises. For example, Stubben [7] uses univariate analysis and presents evidence that growth firms use more upward revenue manipulation to meet or beat analyst revenue forecasts than value firms. We build on this research by examining how growth firm managers avoid missing market revenue expectations.

We hypothesize that growth is positively associated with the likelihood of achieving either zero or positive revenue surprises because the importance of valuation revenue information is higher for growth firms. Using a book-to-market ratio as a growth proxy, we find that growth firms are more likely to meet or beat analyst revenue expectations versus value firms (cf. Collins et al. [8]).

Since the costs and benefits derived from earnings management and expectations management may vary by growth properties, we test which is more commonly used by growth firm managers in order to achieve either zero or positive revenue surprises. We accordingly examine the impacts of an interaction term between growth proxy and a proxy for upward revenue manipulation as well as the impact of an interaction term between growth proxy and a proxy for downward revenue expectation management on the likelihood of meeting or beating analyst revenue forecasts. We proxy for revenue manipulation by estimating discretionary revenue using the Stubben [9] model. Following Matsumoto [10] we also proxy for revenue expectation management using a measure of the revenue forecast guidance. These results suggest that revenue manipulation increases or decreases the likelihood of meeting or exceeding revenue expectations for growth firms and value firms, respectively; while expectation management decreases or increases the likelihood for growth firms and value firms, respectively. Revenue manipulation and revenue expectation management are, respectively, accordingly a more- or less-commonly used tool for growth firms in achieving favorable revenue news versus value firms. These findings imply that growth firms are more inclined to distort their reported revenue numbers in order to achieve short-term objectives relative to value firms. It may have negative impacts on a growth firm's future performance and eventually deteriorate its sustainability.

This study contributes to the literature in highlighting the importance of revenue information for certain firms. Prior research provides evidence that managers have strong incentives to focus on revenue signals because market participants may consider revenue-related information more important and value-relevant under various circumstances, such as a specific industry (e.g., internet business industry) (Bowen et al. [11]), firms having negative earnings (Hayn [12]; Callen et al. [13]), firms having a high volatility of earnings (Ertimur and Stubben [14]), and firms having high growth properties (Ertimur et al. [5]; Kama [6]). We add to this research by providing additional evidence that growth firms are more likely to meet or exceed analyst revenue expectations than value firms.

Moreover, this study also contributes to the research examining the mechanisms used to successfully reach analyst revenue expectations. Although some prior studies investigate revenue manipulation in order to achieve zero or small positive revenue surprises (Stubben [9]), there is no prior work on whether or not firms use expectations management, revenue management, or both as a tool to achieve expected revenues. This paper provides implications for future research, in that the practices used by managers in order to avoid missing an important revenue target are influenced by certain firm characteristics, as shown by the differing mechanism effectiveness for growth properties.

The remainder of this paper is organized as follows. Section 2 discusses the related literature and hypotheses. We describe the sample selection in Section 3. Section 4 explains the research design and variables. Section 5 contains descriptive statistics and empirical results. Finally, Section 6 provides the concluding remarks.

2. Related Literature and Hypotheses Development

2.1. Likelihood of Meeting or Beating Analyst Revenue Forecasts Depending on Firm Growth Properties

Previous research shows that an increasingly high proportion of public companies are either meeting or beating financial analysts' forecasts (Brown [15]; Matsumoto [10]; Burgstahler and Eames [16]; Walker [17]). Research has also examined the impact of meeting or exceeding analyst forecasts on firm value in order to identify firm incentives to focus on forecasts as an important threshold. Various studies show the existence of higher market equity premiums for firms which either meet or beat analyst earnings forecasts over firms which fail to meet them (Bartov et al. [18]; Kasznik and McNihols [19]).

Prior literature also provides evidence that the market rewards or penalizes, respectively, firms that meet or beat, or miss both analyst earnings and revenue forecasts (Jegadeesh and Livnat [1]; Rees and Sivaramakrishnan [2]; Chandra and Ro [3]). This implies that market participants consider positive earnings surprises to be more persistent in the future when accompanied by positive revenue surprises. More importantly, Ertimur et al. [5] examine whether or not the market reacts differently to earnings and revenue surprises which are conditional on firm growth perspectives. They provide empirical evidence showing that market participants react negatively to growth firms missing revenue expectations, even if those firms successfully met or beat earnings expectations. Although they report negative returns for growth firms meeting or beating the expected revenue but missing the earnings targets, these negative reactions are not statistically significant. In contrast, they find no significant market punishments for value firms missing revenue targets if these firms meet or exceed earnings expectations. These findings suggest that for growth firms, the market places a higher weight on whether firms meet or beat revenue expectations versus earnings expectations. Accordingly, market participants are more disappointed when growth firms fail to meet or beat the expected revenue targets despite positive earnings surprises. Kama [6] further extends Ertimur et al. [5] by investigating certain circumstances where the revenue signal has incremental explanatory power over the earnings signal in determining stock returns. He documents that the impact of revenue surprises on stock returns is higher in R&D intensive firms. This finding also suggests that certain firm characteristics, specifically growth properties, make revenue information more important. Dechow et al. [20] additionally document that managers meet or exceed market expectations in order to avoid the negative market reactions associated with missing expectations. This strong incentive to avoid an unfavorable market response could lead growth firm managers to closely focus on achieving revenue targets. We hypothesize:

Hypothesis 1 (*H1*). *Growth firms are more likely to meet or beat analysts' revenue forecasts than value firms*.

2.2. Revenue Manipulation versus Revenue Expectation Management

Numerous studies examine how managers avoid missing analyst forecasts. Papers on this topic are heavily concentrated on two mechanisms: (1) the manipulation of reported accounting numbers in order to meet or beat analysts' forecasts (Dechow et al. [20]; Payne and Robb [21]; Burgstahler and Eames [16]; and (2) the management of market expectations (Bartov et al. [18]; Richardson et al. [22]; Koh et al. [23]; Athanasakou et al. [24]).

Managers can utilize either of these tools in order to avoid negative revenue surprises. They can attempt to either manipulate reported revenues or manage market expectations for revenues by influencing analyst forecasts. In order to meet or beat analyst revenue forecasts, managers may manipulate reported revenues by either opportunistically accelerating revenue recognition or recognizing fictitious revenues. Dechow and Schrand [25] indicate that over 70% of the 294 Securities and Exchange Commission Accounting and Auditing Enforcement Releases they examined were involved in overstating revenues. This evidence suggests that revenue manipulation is very common. Furthermore, Bowen et al. [11] show that certain industries (e.g., the internet), have strong incentives to manipulate revenues since investors believe that information related to revenue is more important and value relevant. Stubben [9] and Zhang [26] find that growth firms are more likely to use discretion in order to manipulate revenues. These studies accordingly suggest that firms use the potential tool of revenue manipulation using discretionary revenues in order to meet or beat market expectations. It is furthermore possible that firms manage overall market expectations in order to meet or exceed expected revenues, avoiding optimistic market expectations by guiding expectations downward.

Firms which have some concerns regarding missing market expectations may actively utilize either of these tools individually or in combination in order to avoid negative surprises due to the market penalties associated with a failure to meet or exceed analyst expectations (Kasznik and McNichols [19]; Rees and Sivaramakrishnan [2]). Although both mechanisms are available, the costs and benefits for each approach are major considerations. If firms manipulate revenues in order to avoid negative revenue surprises, then they could enjoy higher equity premiums as rewards. However, this activity can elevate suspicion from auditors and/or the board of directors, increasing the likelihood of detection and subsequent public revelation. The market will severely punish a firm once its revenue manipulation is detected and reported (Wu [27]). Furthermore, the reversal of discretionary revenue during subsequent periods may prevent firms from continuous management that can raise revenue above analyst expectations in the future.

Several studies test whether firms meet or beat analyst forecasts by influencing analysts—so-called expectation management. Expectation management can also be costly, since managing analyst revenue forecasts entails the downward revision of current expectations if initial revenue forecasts are excessively optimistic (cf. Bartov et al. [18]). These downward revision activities could result in unfavorable market reactions on the forecast revision date. Continually revising revenue forecasts downward in order to sustain beatable revenue forecast levels could also result in a period of falling share prices (Rees and Sivaramakrishnan [2]). The cost of the adverse market responses associated with either downward revenue forecast revisions or the detection of revenue manipulation should therefore not exceed the cost of missing market expectations for the greatest managerial benefit. Finally, Matsumoto [10] investigates whether firms use earnings management or expectation management to avoid missing earnings expectations. She concludes that firms effectively utilize both earnings management and expectation management mechanisms to achieve the targeted levels of earnings based on analysts' earnings forecasts.

Managerial tool selection could therefore be different depending on the cost-benefit ratio in achieving the expected revenue targets. The effectiveness of both mechanisms would differ by certain firm characteristics, specifically the firm's growth properties. We hypothesize that revenue manipulation is used more extensively by growth firms in order to achieve positive revenue surprises for a couple of reasons. First, the reversal of premature or fictitious revenue accruals generated from upward revenue management is likely to be less concerning for growth firms. Growth firms are likely to sustain the higher levels of revenue growth necessary to cover the accrual reversals used to achieve positive revenue surprises during previous periods. A growth firm's ability to continually generate higher revenues could make revenue manipulation a more enticing method. Second, the costs of managing revenue forecasts downward are likely to exceed the costs of missing expected revenues for growth firms versus value firms. The negative market reactions accompanying downward forecast revisions are likely to be stronger for growth firms because market participants are more sensitive to this signal for growth versus value firms. Consequently, revenue manipulation is more likely to be used by growth firms in order to avoid negative revenue surprises. We hypothesize:

Hypothesis 2a (*H2a*). *The marginal effect of revenue manipulation on the probability of meeting or exceeding analyst revenue forecasts is greater for growth firms than value firms.*

Hypothesis 2b (*H2b*). *The marginal effect of revenue expectation management on the probability of meeting or exceeding analyst revenue forecasts is smaller for growth firms than value firms.*

3. Sample Selection

We use the consensus of analyst annual revenue forecasts obtained from the Institutional Brokers Estimate System (I/B/E/S) as a proxy for market revenue expectations (Bartov et al. [18]; Ertimur et al. [5]; Rees and Sivaramakrishnan [2]). We obtain annual analyst revenue forecasts from the I/B/E/S, which began providing revenue forecasts in a machine-readable format in 1996. Limited observations are available between 1996 and 1998, so we accordingly limit our sample to the years between 1999 and 2010. We also follow Bartov et al. [18] by requiring that each firm have at least three revenue forecasts in order to ensure that there is an initial forecast, a forecast revision, and a final forecast during the fiscal period. We also confirm that the first available revenue forecast is disclosed after the prior revenue announcement date, and that the last available forecast is released before the current announcement date. We use the fourth quarter earnings announcement date as the annual revenue announcement date. For comparability we estimate revenue surprises by comparing revenue forecasts versus actual revenue from I/B/E/S. We use annual accounting data to calculate discretionary revenues, and other variables were compiled from the COMPUSTAT database. Consistent with Matsumoto [10] we exclude financial institutions, utilities industries, and regulated industries the Standard Industrial Classification (SIC) codes between 5999 and 7000, between 4799 and 5000, and 3999 and 4500 respectively) because these firms are likely to have different earnings management incentives from other firms. The total number of firm-year observations included in the final sample is 29,520.

4. Research Design

4.1. Empirical Analysis Model for H1

We test the first hypothesis using a multivariate model with control variables as suggested in prior research as potential confounding factors on either meeting or exceeding market expectations (cf. Athanasakou et al. [24]). We perform the following logistic regression analysis to estimate the probability that a firm successfully achieves analysts' revenue forecasts on the announcement date.

$$\begin{gathered}\text{Prob (MBR} = 1 \mid \text{X)} = \text{F} (\alpha_0 + \alpha_1\text{GROWTH}_i + \alpha_2\text{LOSS}_i + \alpha_3\text{VOL\_EARNINGS}_i + \\ \alpha_4\text{LTG\_RISK}_i + \alpha_5\text{POS}\Delta\text{REV}_i + \alpha_6\text{INDPROD}_i + \alpha_7\text{SIZE}_i + \alpha_8 \mid \text{FE}_i \mid + \alpha_9\text{E\_SUR}_i + \varepsilon_i)\end{gathered} \quad (1)$$

where:

$$\text{F}\left(\alpha'\text{X}\right) = \frac{\text{e}^{\alpha'\text{X}}}{1 + \text{e}^{\alpha'\text{X}}}.$$

The dependent variable MBR is equal to 1 if the firm reports revenue greater than or equal to the latest consensus (median) of analyst revenue forecasts; and otherwise, 0. GROWTH is measured in two ways. First, after dividing the final full sample into three groups (high, medium, or low) based on the book-to-market ratio, the GROWTH variable equals 1 if a firm is included in the medium or low growth rate groups, and 0 if it is included in the high growth rate group (cf. Collins et al. [8]). Second, we simply use the book-to-market ratio. We estimate the model separately with each growth proxy. We predict that the coefficient α_1 on GROWTH is statistically and significantly negative, implying that the probability of firms meeting or beating analyst revenue forecasts increases as book-to-market ratios decrease. High growth firms are therefore more likely to have positive revenue surprises than low growth firms.

Consistent with previous studies (Matsumoto [10]; Athanasakou et al. [24]), we also include several variables in order to control for possible effects on the probability of achieving positive revenue surprises. We include losses (LOSS) and volatility of earnings (VOL_EARNINGS) in order to control loss and high earnings volatility situations where earnings information is less meaningful in equity valuations relative to revenue information (Callen et al. [13]; Zhang [26]). We code a value of 1 for LOSS if a firm reports a loss (income before extraordinary items < 0), and 0 otherwise. The earnings volatility is measured as the standard deviation of firm j's earnings for the prior three years. Consistent with Matsumoto [10], we include a variable of LTG_RISK in the model in order to control for the risk of shareholder litigation. We classify firms in the high-risk industries of biotechnology (SIC 2833–2836), computers (SIC 3570–3577 and 7370–7374), electronics (SIC 3600–3674), and retailing (SIC 5200–5961). We control for unexpected macroeconomic shocks to revenue surprises by also including the variables of revenue change (POSΔREV) and average annual growth in industrial production (INDPROD). The revenue change (POSΔREV) is a dummy variable coded with the value of 1 if the firm's annual change of revenue is positive, and 0 otherwise. Following Matsumoto [10] we include the log of the market value of equity as a proxy for firm size. Uncertainty in the forecasting environment is controlled by including an additional variable (|FE|) as the absolute value of the earliest revenue forecast errors scaled by the prior-year-end market equity value. Finally, we include earnings surprises deflated by the price per share at the end of the preceding year (E_SUR) in order to control for earnings effects. Earnings surprises are measured as the difference between the actual earnings per share and the consensus (median) of analyst earnings forecasts.

4.2. Revenue Management versus Expectation Management

We investigate whether revenue manipulation or expectations management is more likely to be actively utilized in order to avoid negative revenue surprises by examining the association between targeted revenues and proxies for either revenue manipulation or expectation management.

4.2.1. Proxy for Revenue Management

Stubben [9] develops a model measuring discretionary revenues as a proxy for revenue management. We use this model to detect revenue manipulation, since the model focuses on identifying the discretionary portion of revenues. We utilize the discretionary revenue model in order to estimate discretion in revenues on an annual level.

$$\Delta AR_{i,t}/TA_{i,(t-1)} = \beta_0[1/TA_{i,(t-1)}] + \beta_1[\Delta R1\_3_{i,t}/TA_{i,(t-1)}] + \beta_2[\Delta R4_{i,t}/TA_{i,(t-1)}] + \varepsilon_{i,t} \quad (2)$$

where: ΔAR = Annual Change of Account Receivables at the end of fiscal year; ΔR1_3 = Annual Change in Revenues of the first three quarters (1Q, 2Q, and 3Q) relative to those of the prior year's first three quarters; ΔR4 = Change in Revenue of the fourth quarter relative to that of the prior year's fourth quarter; TA = Average Total Assets at $(t-1)$.

The model parameters (β_0, β_1, β_2) are estimated for each year and industry (Fama-French 48 industries, Fama and French [28]) using the ordinary least squares (OLS) regression model. We then compute nondiscretionary revenue based on the parameters estimated in Model 2:

$$NonDR_{i,t}/Asset_{i,(t-1)} = \beta_0'[1/TA_{i,(t-1)}] + \beta_1'[\Delta R1\_3_{i,t}/TA_{i,(t-1)}] + \beta_2'[\Delta R4_{i,t}/TA_{i,(t-1)}] \quad (3)$$

where: NonDR = Nondiscretionary revenues in the event year t; β_0', β_1', β_2' = Coefficients of β_0, β_1, β_2 acquired from the Model (2) regression.

Finally, we compute discretionary revenue as the difference between the change in account receivables (ΔAR) and nondiscretionary revenues (NonDR). We consider that firms manipulated their reported revenue upward if the value of discretionary revenues is positive.

$$DR_{i,t} = \Delta AR_{i,t} - NonDR_{i,t} \quad (4)$$

where: $DR_{i,t}$ = Discretionary revenues for firm i in year t.

4.2.2. Proxy for Expectation Management

We apply a methodology suggested by prior research to estimate whether or not firms manage analyst earnings forecasts (Matsumoto [10]). By applying the Matsumoto [10] unexpected earnings forecasts model into the estimation of unexpected revenues forecasts, we compute a proxy of revenue expectation management. This model allows us to compute the expected analyst forecasts during a given period in the absence of firm expectation management. By comparing the last consensus of actual analyst forecasts with the expected model forecasts we can estimate analysts' downward forecast revisions which are likely to have been caused by firms' forecast management. We apply her model after adjusting it to revenues; the first two Equations (5) and (6) are estimated to distinguish the expected portion of forecasts from the original analyst revenue forecasts. We utilize all available information that financial analysts may employ in their revenue forecasts. Equation (5) is constructed under the assumption that actual revenue changes, deflated by the lagged market value of equity ($\Delta REV_{i,t}/MV_{i,(t-1)}$), can be explained as the previous year's revenue changes by the lagged market value of equity ($\Delta RVE_{i,(t-1)}/MV_{i,(t-2)}$) and cumulative excess returns during the current year ($CRET_{i,t}$). This variable CRET is included in order to capture extra value-relevant information for analysts during forecasting periods. We use the OLS regression method by year and Fama-French 48 industry classification codes to estimate each coefficient in Equation (5):

$$\Delta REV_{i,t}/MV_{i,(t-1)} = \lambda_{0,t} + \lambda_{1,t}(\Delta REV_{i,(t-1)}/MV_{i,(t-2)}) + \lambda_{2,t}(CRET_{i,t}) + \sigma_{i,t} \quad (5)$$

where: ΔREV = Annual Change of Revenue for firm *i* during year *t*; MV = Market Value of Equity for firm *i* at the end of year; CRET = Cumulative monthly excess (market-adjusted) returns from the month following the year $(t-1)$ revenue announcement to the month of the year *t* revenue announcement. Before running the OLS we winsorize the top and bottom 1% of all variables in order to alleviate the impact of extreme values on parameter estimation.

After obtaining all parameter estimates for the prior year from Equation (5) we use these values to determine the expected change of revenues $E(\Delta REV_{i,t})$ in Equation (6). This process ensures that all information used in estimating the expected revenue forecasts is data that is available to analysts when establishing revenue forecasts:

$$E(\Delta REV_{i,t}) = [\lambda'_{0,t} + \lambda'_{1,t}(\Delta REV_{i,(t-1)}/MV_{i,(t-2)}) + \lambda'_{2,t}(CRET_{i,t})] \times MV_{i,(t-1)} \quad (6)$$

We then add the estimated expected revenues $E(\Delta REV_{i,t})$ to the actual prior year revenues in order to calculate the expected portion of revenue forecasts for the current year ($E(F_{i,t})$):

$$E(F_{i,t}) = REV_{i,(t-1)} + E(\Delta REV_{i,t}) \quad (7)$$

Finally, the unexpected analyst revenue forecast is calculated as the difference between the latest consensus of revenue forecasts and the expected revenue forecasts:

$$UE(F_{i,t}) = REV\_AF_{i,Last} - E(F_{i,t}) \quad (8)$$

By comparing the sign of the unexpected revenue forecasts estimated from the model, we determine whether firms manage market expectations for revenues downward or upward. We consider firms to have managed expectations downward if the value of unexpected revenue forecasts is negative, and upward if it is positive.

4.2.3. Empirical Analysis Model for *H2*

We test the second hypothesis by augmenting the Matsumoto [10] model with interaction terms. The model, Equation (9), allows us to test the relation between the probability of meeting or exceeding analyst revenue forecasts and proxies for either revenue manipulation or expectation management, conditional on the firm's growth proxy. We use a logit regression with all variables of interest except the control variables as categorical terms (0 or 1). Similar to the earlier empirical model, we use the value of 1 for firms having zero or positive revenue surprises; and otherwise, 0. If firms have a positive discretionary revenue, then a variable indicating a revenue manipulation proxy (POSDR) will have a value of 1; and otherwise, 0. Furthermore, we code the variable DOWN as 1 if the firms manage analysts' expectations for revenue downward in order to meet or beat expectations, and 0 otherwise. Consistent with Matsumoto [10], we include four control variables in the model. The coefficient for the interaction term ($GROWTH_i \times POSDR_i$) provides a test of *H2a*. A significantly negative coefficient would indicate that the use of upward revenue manipulation is significantly greater for growth companies. Meanwhile, as a test of *H2b*, the coefficient for the interaction term ($GROWTH_i \times DOWN_i$) is expected to be significantly positive, because downward revenue expectation management is likely to make it challenging for growth firms to meet or exceed revenue expectations:

$$\begin{aligned} \text{Prob}(MBR = 1 \mid X) = F(&\alpha_0 + \alpha_1 POSDR_i + \alpha_2\, DOWN_i + \alpha_3 GROWTH_i + \alpha_4 GROWTH_i \times POSDR_i + \\ &\alpha_5 GROWTH_i \times DOWN_i + \alpha_6 POS\Delta REV_i + \alpha_7 INDPROD_i + \alpha_8 SIZE_i + \alpha_9 \mid FE_i \mid + \alpha_{10} E\_SUR_i + \varepsilon_i) \end{aligned} \quad (9)$$

5. Empirical Analysis Results

5.1. Analysis Model for H1

5.1.1. Descriptive Statistics

Panel A of Table 1 reports descriptive statistics for the sample. The mean of the dependent variable (MBR) indicates that approximately 57% of firm-year observations are classified as either meeting or beating the analysts' revenue forecasts. The book-to-market ratio has a mean (median) of 0.57 (0.44). On average (median), the sample firms report losses 34% (25%) of the time during the sample period. The mean for the earnings volatility and forecast error variables are 1.64 and 0.16, respectively, whereas the medians are 0.52 and 0.05. This suggests that the distribution of both variables is slightly right skewed. Approximately 33% of firm-years in the final sample are from firms in high litigation risk industries. Moreover, 72% of observations in the entire panel have positive revenue changes relative to the prior year (POSΔREV). Finally, the average (median) size of the sample firms is 6.38 (6.31).

Table 1. Descriptive Statistics.

Panel **A**: Descriptive Statistics of Dependent Variable and Proxies for Growth and Control Variables.

Variable	N	Mean	Std Dev	Median	1Q	3Q
Dependent Variable:						
MBR	29,520	0.5670	0.4960	1	0	1
Proxies for Growth:						
Book_to_Market	28,545	0.5740	0.4950	0.4440	0.2640	0.7160
Control Variables:						
LOSS	29,520	0.3360	0.3370	0.2500	0	0.5710
VOL_Earnings	27,706	1.6360	3.8550	0.5220	0.2430	1.2900
LTG_RISK	29,520	0.3340	0.4720	0	0	1
POSΔREV	29,520	0.7180	0.4500	1	0	1
INDPROD	29,520	0.3760	4.1540	2.0880	−3.1360	2.9900
SIZE	28,220	6.3780	1.7960	6.3060	5.1350	7.5220
lFEl	28,224	0.1600	0.3270	0.0510	0.0170	0.1430
E_SUR	29,341	−0.0200	0.1330	0.0003	−0.0020	0.0020

Panel **B**: *t*-Test of Mean Difference between MBR = 1 and MBR = 0.

Variables	MBR		Diff(G1-G2)	*t* Value	Pr > |t|
	0	1			
Book_to_Market	0.6446	0.5216	0.1230	20.9600	<0.0001
LOSS	0.3798	0.3020	0.0778	19.5500	<0.0001
VOL_Earnings	1.6595	1.6178	0.0416	0.8900	0.3732
LTG_RISK	0.3389	0.3302	0.0087	1.5700	0.1158
POSΔREV	0.6409	0.7765	−0.1356	−25.4600	<0.0001
INDPROD	1.2431	0.4080	−0.1260	−2.6000	0.0093
SIZE	6.0479	6.6327	−0.5848	−27.2700	<0.0001
lFEl	0.1873	0.1406	0.0466	11.4400	<0.0001
E_SUR	−0.0384	−0.0052	−0.0332	−19.6100	<0.0001

MBR is a categorical variable equal to 1 if a firm has either a zero or positive revenue surprise, and 0 otherwise. Revenue surprises are computed as the difference between actual revenues reported and the consensus of forecasted revenues reported in the I/B/E/S database (reported revenue $\geq$ latest median revenue forecasts).

Panel B presents the results from the t-test of differences in the means between the two groups (MBR = 1 and 0). Consistent with this prediction, firms either meeting or exceeding analyst revenue expectations (MBR = 1) have lower book-to-market ratios than those of firms missing the expected revenue (MBR = 0). The mean for MBR = 1 firms is 0.52, compared to 0.65 for MBR = 0 firms, and the difference between the two groups (0.12) is significantly different from zero. In contrast to our expectations, the reported losses during the sample period are significantly lower for the MBR = 1 group than the MBR = 0 group. There are no significant mean differences in the volatility of earnings and the proportion of high-litigation-industry groups. However, other variables (POSΔREV, INDPROD, SIZE, and |FE|) have significant differences in their means between MBR = 1 and MBR = 0.

Table 2 reports the Pearson and Spearman correlation matrix for all variables. Of specific interest is the correlation between the dependent variable and growth proxy (book-to-market) variable. As expected, the MBR is significantly and negatively correlated with the book-to-market ratio. While correlations between the MBR and the POSΔREV or INDPROD are significantly positive, correlations between the MBR and the LOSS or |FE| are significantly negative. However, the VOL_Earnings and LTG_Risk variables are not significantly correlated with the dependent variables. Overall, correlations between the dependent and independent variables are generally low in magnitude (<0.2).

Table 2. Pearson (above the diagonal) and Spearman (below the diagonal) Correlations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
MBR (1)	1	−0.123	−0.115	−0.005	−0.009	0.149	0.015	0.161	−0.067	0.124
		<0.0001	<0.0001	0.373	0.116	<0.0001	0.010	<0.0001	<0.0001	<0.0001
Book_to_Market (2)	−0.107	1	0.120	0.074	−0.094	−0.214	−0.101	−0.420	0.252	−0.189
	<0.0001		<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
LOSS (3)	−0.107	0.106	1	0.094	0.228	−0.168	0.017	−0.484	0.058	−0.180
	<0.0001	<0.0001		<0.0001	<0.0001	<0.0001	0.004	<0.0001	<0.0001	<0.0001
VOL_Earnings (4)	−0.002	0.156	0.373	1	−0.015	−0.051	0.003	−0.091	0.077	−0.034
	0.711	<0.0001	<0.0001		0.015	<0.0001	0.628	<0.0001	<0.0001	<0.0001
LTG_RISK (5)	−0.009	−0.151	0.200	0.002	1	0.007	0.010	−0.070	−0.084	−0.015
	0.116	<0.0001	<0.0001	0.744		0.200	0.080	<0.0001	<0.0001	0.010
POS_RC (6)	0.149	−0.211	−0.178	−0.102	0.007	1	0.269	0.180	−0.191	0.100
	<0.0001	<0.0001	<0.0001	<0.0001	0.200		<0.0001	<0.0001	<0.0001	<0.0001
INDPROD (7)	0.022	−0.113	0.005	0.023	0.002	0.223	1	0.026	−0.089	−0.002
	0	<0.0001	0.397	0	0.763	<0.0001		<0.0001	<0.0001	0.779
SIZE (8)	0.161	−0.383	−0.495	−0.214	−0.084	0.180	0.037	1	−0.191	0.212
	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001		<0.0001	<0.0001
lFEl (9)	−0.070	0.333	0.084	0.172	−0.153	−0.274	−0.046	−0.245	1	−0.133
	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001		<0.0001
E_SUR (10)	0.211	−0.025	−0.064	0.013	0.039	0.047	−0.025	0.085	−0.033	1
	<0.0001	<0.0001	<0.0001	0.026	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	

5.1.2. Results from Logistic Regression for *H1*

The results from testing *H1* are reported in Table 3. We present the estimation results by not only using book-to-market ratios in a continuous form, labeled Model (1), but also by using the indicator variable of growth based on a book-to-market ratio (high growth group versus medium or low growth group), labeled Model (2). Both results are statistically similar.

As conjectured in *H1*, the coefficients on Book_to_Market and Rank_BtM are both negative and significant, suggesting that high growth firms are more likely to either meet or beat analyst revenue forecasts versus low growth firms. Consistent with prior research, we find that firms with lower earnings value-relevance are more inclined to focus on revenue signals so that the coefficient on VOL_Earnings is significantly positive in both models. However, inconsistent with our prediction, we find that LOSS is significantly and negatively associated with the likelihood of MBR. One possible explanation could be that firms which frequently report losses do not have the economic strength necessary to satisfy analyst revenue expectations because their losses are not strategic but permanent, resulting from actual low firm performance. Additionally, the LTG_Risk variable does not have the expected positive and significant coefficient. One possible explanation is that shareholders in high litigation risk industries may consider the earnings signal to be the only critical factor in their decision-making processes versus revenue signals or other information.

Table 3. Logit Analysis of the Probability of Meeting or Beating Analyst Revenue Forecasts and Growth Proxy (Book-to-Market Ratio). Model: Prob (MBR = 1 | X) = F ($\alpha_0 + \alpha_1 GROWTH_i + \alpha_2 LOSS_i + \alpha_3 VOL\_EARNINGS_i + \alpha_4 LTG\_RISK_i + \alpha_5 POS\Delta REV_i + \alpha_6 INDPROD_i + \alpha_7 SIZE_i + \alpha_8 |FE_i| + \alpha_9 E\_SUR_i + \varepsilon_i$).

Variables	Predicted Sign	Model (1)		Model (2)	
		Coefficient (z-Stat)	Marginal Effects	Coefficient (z-Stat)	Marginal Effects
Constant		−0.628 *** (−3.45)		−0.737 *** (−4.76)	
Proxies for Growth:					
Book_to_Market	-	−0.183 ** (−2.49)	−0.079		
Rank_BtM	-			−0.107 ** (−2.07)	−0.046
Control Variables:					
LOSS	+	−0.124 ** (−2.26)	−0.053	−0.121 ** (−2.15)	−0.052
VOL_Earnings	+	0.010 *** (3.41)	0.004	0.010 *** (3.40)	0.004
LTG_Risk	+	0.001 (0.02)	0.000	0.004 (0.08)	0.002
POSΔREV	+	0.574 *** (5.32)	0.246	0.586 *** (5.59)	0.251
INDPROD	+	−0.016 (−0.62)	−0.007	−0.015 (−0.58)	−0.006
SIZE	+	0.104 *** (4.44)	0.045	0.115 *** (5.63)	0.049
lFEl	-	−0.046 (−0.50)	−0.020	−0.075 (−0.89)	−0.032
E_SUR	+	1.674 *** (9.65)	0.718	1.748 *** (10.78)	0.750
Log Likelihood		−16,800.83		−16,811.34	
Wald Chi-Square		1278.72		1257.70	
p-Value		<0.001		<0.001	
Pseudo R-Squared		0.037		0.036	
Total Observations		25,535		25,535	

Dependent variable (MBR) is equal to 1 if a firm has a zero or positive revenue surprise, and is otherwise 0. Reported z-statistics are based on firm- and year-clustered standard errors. Notations *** and ** indicate significance at the 1, 5 percent significance levels respectively.

Table 3 shows the marginal effect for each variable included in Models (1) and (2). We compute the marginal effects using a semi-elasticity basis so that the marginal effects in the logistic regression results represent the change of probability in terms of one unit change for the independent variable. Accordingly, the fact that the marginal effect of the Book_to_Market is –0.079 means that for one unit increase in the book-to-market ratio, the probability of meeting or exceeding revenue expectations declines by approximately 7.9%. In Model (2) a similar analysis suggests that moving from a high growth group (Rank_BtM = 0) to a low growth group (Rank_BtM = 1) decreases the probability of either meeting or beating analysts' revenue forecasts by approximately 4.6%. Although other variables also have impacts on the MBR, it appears that the marginal effect of the growth proxy measured as the book-to-market ratio on the MBR is larger than other variables except for POSΔREV.

5.2. Analysis Model for H2

5.2.1. Association between MBR and Two Mechanisms

Table 4 provides contingency tables illustrating the relationship between either meeting or beating analyst revenue forecasts (MBR) and two available mechanisms based on the overall firm-year observations. The first 2-by-2 table in Table 4 shows the association between the MBR and upward-revenue manipulation (POSDR). The results from this contingency table illustrate that 54% of firm-years in which firms achieve positive revenue surprises (MBR = 1) manipulate their reported revenues upward (POSDR = 1), relative to 49% of firm-years in which firms have negative revenue surprises (MBR = 0). This finding demonstrates the significant positive relation between the MBR and revenue manipulation proxy (χ^2 = 282.53, $p < 0.001$). Similarly, the second 2-by-2 table presents the relationship between the MBR and downward-expectation revenue management (DOWN). These outcomes show that 32% of either firms meeting or exceeding analyst revenue forecasts manage their revenue expectations downward versus 25% of firms missing these expectations. The Chi-square test indicates that the difference between these two groups is statistically significant. Overall, the results from the two contingency tables in Panel A suggest that both revenue manipulation and revenue expectation management are effective mechanisms managers utilize in order to either meet or exceed market expectations.

Table 4. Association between the Probability of Meeting or Beating Revenue Expectations and, (1) Revenue Manipulation or (2) Revenue Expectations Management.

	Frequency	**POSDR**		
	Percent	1	0	Total
MBR	1	8193	7009	15,202
		53.89%	46.11%	56.53%
	0	5774	5915	11,689
		49.4%	50.6%	43.47%
	Total	13,967	12,924	26,891
		51.94%	48.06%	100%
	χ^2 = 282.53		$p < 0.001$	

	Frequency	**DOWN**		
	Percent	1	0	Total
MBR	1	3767	8075	11,842
		31.81%	68.19%	58.58%
	0	2129	6245	8374
		25.42%	74.58%	41.42%
	Total	5896	14,320	20,216
		29.17%	70.83%	100%
	χ^2 = 282.53		$p < 0.001$	

Contingency Tables Organizing Firm-Year Observations Based on: Indicators of Meeting or Beating Analyst Revenue Forecasts, and (1) Indicators of Positive Discretionary Revenues (POSDR), and (2) of Unexpected Revenue Forecasts (DOWN).

We also conduct a similar contingency analysis based on differing growth levels (high, medium, or low). Table 5 demonstrates that the association between the MBR and the PODR is conditional on a firm's growth. These tables confirm that the differences between the percentage of firms achieving zero or positive revenue surprises (MBR = 1) and the percentage of firms having negative revenue surprises (MBR = 0) are gradually increasing as they move from the low to the high growth group (from 2.34% to 4.98%) among firms using positive discretionary revenues (POSDR = 1). These initial findings suggest that revenue manipulation is a more effective tool for high growth firms in either meeting or beating analyst revenue expectations relative to low growth firms. Furthermore, Panel B in Table 5 reports the association between MBR and DOWN as being conditional on a firm's growth. In contrast to revenue manipulation, these results indicate that differences between the percentage of firms achieving expected revenues (MBR = 1) and the percentage of firms missing revenue expectations (MBR = 0) monotonically decrease when shifting from the low to the high growth group (from 13.99 to 1.68) among firms using downward expectation management (DOWN = 1). These outcomes reveal that revenue expectation management is a less effective tool for high growth firms than for low growth firms in terms of accomplishing either zero or positive revenue surprises.

Table 5. Association between the Probability of Meeting or Beating Revenue Expectations and, (1) Revenue Manipulation or (2) Revenue Expectations Management Conditional on Growth Proxy (Book-to-Market Ratio).

(1). MBR and POSDR by Growth Level												
	High Growth				**Medium Growth**				**Low Growth**			
	Frequency	**PODR**			**Frequency**	**PODR**			**Frequency**	**PODR**		
	Percent	1	0	Total	**Percent**	1	0	Total	**Percent**	1	0	Total
MBR	1	3170	2197	5367	1	2747	2366	5113	1	2083	2257	4340
		59.06%	40.94%	62.02%		53.73%	46.27%	58.66%		48%	52%	50.2%
	0	1777	1509	3286	0	1790	1813	3603%	0	1966	2340	4306
		54.08%	45.92%	37.98%		49.68%	50.32%	41.34%		45.66%	54.34%	49.8%
	Total	4947	3706	8653	Total	4537	4179	8716	Total	4049	4597	8646
		57.17	42.83	100		52.05	47.95	100		46.83	53.17	100
	$\chi^2 = 20.70$		$p < 0.001$		$\chi^2 = 13.86$		$p < 0.0002$		$\chi^2 = 4.75$		$p < 0.029$	
(2). MBR and DOWN by the Level of Growth												
	High Growth				**Medium Growth**				**Low Growth**			
	Frequency	**DOWN**			**Frequency**	**DOWN**			**Frequency**	**DOWN**		
	Percent	1	0		**Percent**	1	0	Total	Percent	1	0	Total
MBR	1	885	3150	4035	1	1216	2977	4193	1	1522	1788	3310
		21.93%	78.07%	63.48%		29%	71%	60.46%		45.98%	54.02%	52.63%
	0	470	1851	2321	0	600	2142	2742	0	953	2026	2979
		20.25%	79.75%	36.52%		21.88%	78.12%	39.54%		31.99%	68.01%	47.37%
	Total	1355	5001	6356	Total	1816	5119	6935	Total	2475	3814	6289
		21.32%	78.68%	100		26.19%	73.81%	100%		39.35	60.65	100%
	$\chi^2 = 2.49$		$p < 0.11$		$\chi^2 = 43.47$		$p < 0.001$		$\chi^2 = 128.6$		$p < 0.001$	

Contingency Tables Organizing Firm-Year Observations Based on: Indicators of Meeting or Beating Analyst Revenue Forecasts, and (1) Indicators of Positive Discretionary Revenues (POSDR) and (2) of Unexpected Revenue Forecasts (DOWN) Conditional on Growth Proxy (Book-to-Market Ratio).

5.2.2. Results from Logistic Regression for *H2a* and *H2b*

Table 6 reports the results from the logistic regression analysis, Equation (9), testing the use of these two mechanisms to either meet or beat the analyst revenue forecasts conditional on firm growth. In order to establish consistency over the analysis, we show the test results using both versions of the growth proxy. In order to rule out potential alternative explanations—e.g., a possible mechanical relation between the probability of meeting or beating analyst revenue forecasts and revenue manipulation of growth firms—using the Collins et al. [8] model we rerun Equation (9). Untabulated results show no difference in statistical implication (we are indebted to one reviewer's insightful suggestion to rule out this alternative explanation using the Collins et al. model).

In these two models, the coefficients for Book_to_Market and Rank_BtM are both negative and significant, consistent with previous findings from the test of *H1*. Also as expected, the coefficients for both indicators of the positive discretionary revenues (POSDR) and the downward-expectation management for revenue (DOWN) are positively associated with the probability of achieving either zero or positive revenue surprises within these two models. These significant positive signs indicate that, overall, firms are using both mechanisms in order to avoid negative revenue surprises. For example, in Model (1), revenue manipulation and revenue expectation management both increase the probability of either meeting or beating the revenue expectations by approximately 10% and 21%, respectively. More importantly, the coefficient on the interaction term for $BtM_i \times POSDR_i$ is significantly negative in the first model, where $Rank\_BtM_i \times POSDR_i$ is negative but not significant. The negative signs on these interaction variables reveal that revenue manipulation increases the probability of either meeting or exceeding the expected revenue forecasts as firm growth increases. Specifically, in Model (1) the marginal effect of $BtM_i \times POSDR_i$ is −0.065, indicating that the revenue manipulation contributes to roughly a 7% decrease in the probability of having positive revenue surprises when the book-to-market ratio increases by one unit. Consistent with *H2a* we find that growth firms are more likely to use upward revenue manipulation versus downward revenue expectation management in order to avoid missing analyst revenue expectations. On the other hand, the interaction for growth proxy and downward expectation management $BtM_i \times DOWN_i$ ($Rank\_BtM_i \times DOWN_i$) is positively associated with the likelihood of achieving either zero or positive revenue surprises in both models. The marginal effect for this variable implies that the revenue expectation management reduces the likelihood of either meeting or exceeding analyst revenue expectations by approximately 16% as a one unit decrease in the book-to-market ratio. This result, accordingly, confirms that the expectation management for revenues is a less effective tool for growth firms attempting to avoid negative revenue surprises than it is for value firms, supporting *H2b*.

Table 6. Logit Analysis of the Effectiveness of Mechanisms to Meet or Beat Analyst Revenue Forecasts Depending on Growth Proxy (Book-to-Market Ratio). Model: $Prob(MBR = 1 | X) = F(\alpha_0 + \alpha_1 POSDR_i + \alpha_2 DOWN_i + \alpha_3 GROWTH_i + \alpha_4 GROWTH_i \times POSDR_i + \alpha_5 GROWTH_i \times DOWN_i + \alpha_6 POS\Delta REV_i + \alpha_7 INDPROD_i + \alpha_8 SIZE_i + \alpha_9 |FE_i| + \alpha_{10} E\_SUR_i + \varepsilon_i)$.

Variables	Predicted	Model (1)		Model (2)	
		Coefficient	Marginal Effects	Coefficient	Marginal Effects
Constant		−0.802 *** (−4.13)		−0.993 *** (−6.18)	
Proxies for Growth:					
Book_to_Market	-	−0.350 *** (−4.22)	−0.144		
Rank_BtM	-			−0.173 ** (−2.22)	−0.071
Proxies for Mechanisms:					
POSDR	+	0.231 *** (4.13)	0.095	0.197 *** (3.72)	0.081
DOWN	+	0.509 *** (4.99)	0.209	0.457 *** (3.92)	0.187
Interaction b/w Growth Proxy and Mechanisms:					
BtM*POSDR	-	−0.158 *** (−2.80)	−0.065		
BtM×DOWN	+	0.377 *** (3.44)	0.155		
Rank_BtM×POSDR	-			−0.069 (−0.94)	−0.028
Rank_BtM×DOWN	+			0.375 *** (3.56)	0.154
Control Variables:					
POSΔREV	+	0.672 *** (7.98)	0.276	0.692 *** (8.60)	0.284
INDPROD	+	0.017 (0.69)	0.007	0.019 (0.73)	0.008
SIZE	+	0.094 *** (3.11)	0.039	0.111 *** (4.24)	0.046
lFEl	-	−0.046 (−0.53)	−0.019	−0.085 (−1.02)	−0.035
E_SUR	+	1.465 *** (6.86)	0.601	1.550 *** (7.91)	0.636
Log Likelihood		−11,914.86		−11,933.24	
Wald Chi-Square		916.93		907.97	
p-value		<0.001		<0.001	
Pseudo R-Squared		0.0432		0.0417	
Total Observations		18,398		18,398	

Dependent variable (MBR) is equal to 1 if a firm has a zero or positive revenue surprise, and is otherwise 0. Reported z-statistics are based on firm- and year-clustered standard errors. Notations *** indicates significance at the 1 percent significance level.

6. Conclusions

This study investigates whether a firm's growth properties are associated with its likelihood of meeting or beating analyst revenue forecasts. We expect that growth firms pay closer attention to achieving zero or positive revenue surprises than value firms. This is in part because revenue information is more relevant for the market in making appropriate valuation decisions relative to earnings information. Our findings provide evidence that high growth firms are more likely to either meet or exceed analyst revenue expectations versus low growth firms.

This study also examines whether the use of two possible mechanisms (revenue manipulation and revenue expectation management) for avoiding negative revenue surprises varies conditional on a firm's growth property. We postulate that the use of these tools might differ in their growth properties, although they are both effective mechanisms for generating favorable revenue information. Our results confirm that both mechanisms increase the likelihood of achieving either zero or positive revenue surprises. However, we find that upward-revenue manipulation is more actively used by growth firms than value firms to meet or exceed analyst revenue forecasts, while downward-revenue expectation management is less utilized by growth firms. The reported existence of revenue manipulation by growth firms in order to achieve short-term goals *may* not be sustainable in the long run, and can misguide users of financial statements in their decision making. Although this study provides empirical evidence of upward-revenue manipulation used by growth firms, future research needs to investigate the role of other players in financial market—including, but not limited to, auditors, policymakers, and regulators—to minimize such opportunistic behaviors.

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