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Earnings management strategies to maintain a string of meeting or beating analyst expectations

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ABSTRACT

Prior studies provide consistent evidence that firms use a combination of management forecast guidance, accrual earning management (AEM), and real activity earnings management (REM) to meet or beat analyst expectations (MBE). While recent evidence (e.g. Kross, Ro, & Suk, 2011) suggests that management forecast guidance is a less effective MBE strategy for firms with longer strings of MBE, less is known about the use of AEM and REM to manage MBE strings as the string lengthens. Since managements' incentives and actions taken to maintain earnings strings may differ as the string lengthens and becomes more difficult to sustain, we examine the extent to which managers use AEM and REM to MBE as the string grows longer. We find evidence that while firms with shorter MBE strings appear more likely to use income increasing AEM to sustain their MBE strings, the use of income increasing AEM decreases for longer MBE strings. Further, we document that firms with longer MBE strings use more income increasing REM to avoid breaking the MBE string. Collectively, our results suggest that researchers investigating firms' earnings management choices to sustain MBE strings should control for the length of the MBE string in their research design.

1. Introduction

Analysts' forecasts serve as an important proxy for the market's expectation of earnings and are a key benchmark for managers (Degeorge, Patel, & Zeckhauser, 1999; Graham & Harvey, 2005). The extant literature has documented significant benefits accruing to firms that meet or beat analyst expectations (hereafter “MBE”). For example, MBE firms earn higher equity return premiums (Bartov, Givoly, & Hayn, 2002; Brown & Caylor, 2005; Doyle, Lundholm, & Soliman, 2006), are perceived by investors to be less risky (Kasznik & McNichols, 2002), are more likely to receive bond rating increases and smaller initial bond yield spreads (Jiang, 2008), and have lower cost of capital (Brown, Hillegeist, & Lo, 2009; Duarte, Han, Harford, & Young, 2008).[1] Further, the prior literature suggests that the incentive to MBE is higher for firms with longer MBE strings, i.e., consecutive periods of MBE. More specifically, firms that consistently achieve analysts' forecasts have a significantly higher earnings response coefficient (Lopez & Rees, 2002) and firms with longer MBE strings experience a more negative stock price response when the MBE string is broken (e.g., Barth, Elliott, & Finn, 1999; Kasznik & McNichols, 2002; Ke, Huddart, & Petroni, 2003; Skinner & Sloan, 2002).

Prior research has found evidence consistent with firms using management forecast guidance (Bartov et al., 2002; Kross et al., 2011; Matsumoto, 2002), accrual based earnings management (AEM) (Abarbanell & Lehavy, 2003; Burgstahler & Eames, 2006; Das & Zhang, 2003; Dechow & Skinner, 2000; Matsumoto, 2002; Zang, 2012), and real activities earnings management (REM) (Gunny, 2010; Roychowdhury, 2006; Zang, 2012) to MBE. Firms often use a combination of these strategies to MBE (Burgstahler & Eames, 2006; Matsumoto, 2002; Zang, 2012), suggesting that managers likely evaluate the costs and benefits of each strategy before deciding how much of any one to use. Recently, Kross et al. (2011) provide evidence that the effectiveness of management forecast guidance to MBE decreases as the MBE string lengthens. While an understanding of the use of AEM, REM, and management forecast guidance to MBE and the limited usefulness of management forecast guidance as the MBE string grows is

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[1] Prior research has also documented that CFOs understand the importance of MBE. More specifically, in a survey of CFOs by Graham, Harvey, and Rajgopal (2005), a majority of the CFOs indicate that MBE benchmarks help “maintain or increase the stock price” and “builds credibility with capital markets” (Graham et al., 2005, p. 5).

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important, it is not clear how firms use AEM and REM to maintain their MBE strings as the string grows longer. Understanding how managers use AEM and REM in different settings is important for regulators and auditors, who are concerned with constraining earnings management in order to improve the quality of financial reports available to investors.[2] Accordingly, in this study we investigate how firms with different MBE string lengths vary their use AEM and REM to sustain their MBE strings.

We examine quarterly earnings announcements for a sample of firms for the period 2004–2014 and use I/B/E/S to classify firms based on the number of consecutive quarters they have met or beaten analyst consensus earnings forecasts prior to the current quarter. We then examine whether the length of the string explains variations in the level of AEM and REM behavior in the current quarter. We expect that firms with short MBE strings are more likely to use income increasing AEM than REM to avoid breaking the earnings string. This expectation is based on prior research, which suggests that AEM can represent a less costly form of earnings management since REM can have negative effects on firms' operating performance and cash flows (Badertscher, 2011; Cohen & Zarowin, 2010; Evans, Houston, Peters, & Pratt, 2015).[3] Consistent with our expectations, we find that firms with short MBE strings use income increasing AEM to meet or just beat analyst expectations.

However, when AEM is used over multiple periods, e.g., to maintain MBE strings, firms become increasingly constrained in their use of AEM (Abarbanell & Lehavy, 2003; Barton & Simko, 2002; Hunt, Moyer, & Shevlin, 1996). These firms, however, still have strong incentives to maintain their MBE strings and we posit that this will increase the likelihood that firms with longer MBE strings will resort to using REM more to avoid breaking their MBE strings. As such, we predict that firms with longer MBE strings use less (more) income increasing AEM (REM) to avoid breaking their string more than firms with short MBE strings or no MBE string. Consistent with our expectations, we document that as the MBE string lengthens, firms use less (more) income increasing AEM (REM) to meet or just beat analyst expectations. We further find that these associations are driven by firms with high levels of balance sheet bloat (Barton & Simko, 2002) and higher quality auditors where the ability to continue to engage in AEM is more likely to be constrained.

Our study contributes to two streams of existing research. First, it adds to the literature examining different earnings management strategies to MBE and to achieve other desired reporting objectives. Of particular importance to our study, Zang (2012) documents a tradeoff between real activities and accrual-based earnings management and shows that managers utilize REM during the year and later use AEM to fine tune the amount of earnings management to MBE. However, Zang (2012) does not examine whether this tradeoff varies as the MBE string lengthens. Although we also examine how firms use AEM and REM to MBE, we do so by examining whether this tradeoff depends on the length of the MBE string.

While not focusing on the MBE context, the extant research also shows that firms are more (less) likely to engage in REM (AEM) following the passage of SOX (Cohen, Dey, & Lys, 2008) because of the increased scrutiny of AEM. Additionally, Badertscher (2011) finds evidence that overvalued firms appear to rely more on AEM to sustain their overvaluation initially and then switch to REM as their ability to engage in AEM becomes constrained. Chan, Chen, Chen, and Yu (2014) further shows that firms reduce the use of income increasing AEM and increase their use of REM after voluntarily adopting compensation clawback provisions. We extend this literature by documenting that while firms appear to use more (less) REM (AEM) as the string grows, our findings suggest firms appear to engage in both AEM and REM to maintain their MBE string (suggesting that AEM and REM are used as complements). Documenting the changing nature of AEM and REM as the MBE string grows is also interesting because firms can engage in expectations management to achieve this particular reporting objective without actively intervening in the earnings process. Additionally, in the MBE string setting, firms should randomly miss expectations or MBE based on pre-managed earnings. As such, firms should be able to smooth earnings by building AEM cookie jar reserves when actual earnings are above expectations and then using these reserves when actual earnings are below expectations. This suggests that in the MBE string setting utilized in this study, firms may not need to switch from AEM to REM, in contrast to the Badertscher (2011) setting where firms are consistently overvalued and are therefore pressured to use income increasing earnings management over multiple consecutive periods. It also differs from the Chan et al. (2014) setting in which companies' substitution between AEM and REM is motivated by the relative cost of AEM after adoption of clawback provisions rather than by constraints in managements' ability to use AEM.

Second, our study informs the string research by specifically examining the use of earnings management to maintain a string of an important earnings based benchmark. Of particular importance to our study, our paper is similar to Kross et al. (2011) in that both papers focus on MBE string firms. However, while Kross et al. (2011) document that MBE firms use management forecasts to avoid breaking the string, our paper focuses on the decision to engage in AEM and REM. Our study thus extends the findings of Kross et al. (2011) by providing evidence that firms appear to also alter their earnings management strategies as the MBE string lengthens. Myers, Myers, and Skinner (2007) also examines string firms and finds evidence of earnings management among firms with strings of 20 consecutive seasonally adjusted quarterly earnings increases. While the findings of this study are relevant to our study, firms must rely more heavily on earnings management to continue pure earnings based strings, because they do not have the ability to engage in expectations management to beat the benchmark. Further, this study does not examine how firms with different string lengths use different earnings management strategies. Also related to our study, Chu, Dechow, Hui, and Wang (2016) find that firms with MBE strings are more likely to receive an AAER. However, they do not examine the types of earnings management (i.e. AEM or REM), and their primary analysis limits the string to just four consecutive quarters. Our study therefore extends this literature by examining the use of both AEM and REM as the MBE string lengthens.

The remainder of this study is organized as follows. Section two reviews the literature and develops the hypotheses. Section three discusses the research design. Section four presents the main results. Section five discusses additional analyses performed to strengthen the inferences once can draw from this study. Section six offers concluding remarks.

2. Prior literature and hypotheses development

Firms have an economic incentive to MBE (Bartov et al., 2002; Brown et al., 2009; Brown & Caylor, 2005; Doyle et al., 2006; Duarte et al., 2008; Jiang, 2008; Kasznik & McNichols, 2002) and this incentive increases as the MBE string lengthens (Barth et al., 1999; Kasznik & McNichols, 2002; Ke et al., 2003; Lopez & Rees, 2002; Skinner & Sloan, 2002). Lopez and Rees (2002) additionally document that the market penalty for missing analyst expectations is significantly higher than the market premium for meeting or beating analyst expectations and that the earnings response coefficient is higher for firms that meet than for

[2] Zang (2012) examines multiple settings and finds evidence that managers substitute AEM and REM based on their relatively costliness to meet or beat analyst expectations in the current period. Our study extends the Zang (2012) findings by exploring whether the substitution relation changes as the MBE string lengthens. Specifically, we find evidence that absent any string firms appear to use AEM and REM as compliments. However, as the string lengthens, our results suggest that, similar to Zang (2012), firms use of AEM and REM depends on their relative costliness.

[3] Additionally, we argue that firms with short MBE strings are able to use AEM as they are not yet constrained in their use of AEM given that AEM reversals often take more than one year to reverse (Allen et al., 2013).

firms that fail to meet analyst expectations. Related to this, Matsumoto (2002) and Burgstahler and Eames (2006) provide evidence that firms that just meet or beat typically have more income increasing than income decreasing earnings management, i.e., there is a stronger incentive to manipulate earnings to MBE if pre-managed earnings is below than when pre-managed earnings is above analysts' forecasts.

While not considering firm MBE in prior periods, Burgstahler and Eames (2006), Matsumoto (2002), and Zang (2012) together provide evidence that firms appear to use a combination of management forecast guidance,[4] AEM, and REM to MBE in any given period. In addition, Bartov et al. (2002) argue that firms are active players who try to win the "game" of MBE by either altering reported earnings or managing analyst expectations. In this study we focus on earnings management using AEM and REM to MBE and specifically how the use of AEM and REM changes as the MBE string grows.[5] AEM takes place when managers intentionally change accounting methods or intervene in the earnings process such that the amount and timing of the recognition of estimates is either accelerated or deferred. REM activities on the other hand occur when firms undertake actions that deviate from normal business practices in an effort to boost current-period earnings (Gunny, 2010; Roychowdhury, 2006).

While REM strategies can be used to boost current-period earnings, REM has been found to reduce the long term value of the firm (Badertscher, 2011; Cohen & Zarowin, 2010; Evans et al., 2015). In addition, REM must be conducted before the end of the fiscal period when actual earnings are yet finalized and analysts' forecasts are still subject to further revisions. Given the uncertainty surrounding actual earnings and analysts' forecasts, it is unlikely that firms will be able to use REM to exactly meet analyst expectations, resulting in reported earnings either falling below or exceeding expectations.[6] AEM on the other hand, generally does not directly impact cash flows and can be used to meet expectations with a higher degree of precision as AEM is conducted after the end of the fiscal period when both actual earnings (or REM manipulated earnings) and analysts' forecasts are more likely to be known.

Given the higher economic costs and timing limitations of REM relative to AEM, we expect that most firms will prefer to use AEM to MBE if possible. However, the extent to which AEM can be used to manage earnings is restricted by how much estimates can be manipulated (e.g., allowance for doubtful accounts cannot be less than zero), particularly given the increased scrutiny by auditors and regulators when discretionary accruals appear unreasonable. Additionally, firms typically cannot use AEM over an extended period of time since AEM by its nature reverses in subsequent periods (Allen, Larson, & Sloan, 2013; Bradshaw, Richardson, & Sloan, 2001; Dechow, Hutton, Kim, & Sloan, 2012). As such, firms become increasingly constrained in their continued use of AEM after multiple periods (Abarbanell & Lehavy, 2003; Barton & Simko, 2002; Hunt et al., 1996). While some REM activities also face similar limitations (e.g. SG&A cuts cannot be reduced below zero), they are generally not subject to the increased auditor and regulatory scrutiny that AEM activities are. Given that prior research suggest that AEM generally reverses within a couple years (Chu et al., 2016; Dechow et al., 2012), we conjecture that firms with shorter MBE strings are, on average, less constrained in their ability to use AEM to MBE relative to firms with longer MBE strings. Assuming that firms with short MBE strings are not yet constrained in their use of AEM and that AEM is on average less costly than REM, we predict that firms with short MBE strings will have more income increasing AEM than firms with no MBE strings. This initial prediction is based on the increasing incentive that firms face to establish an MBE string. Consistent with Badertscher (2011), we expect that firms with longer MBE strings are on average more constrained in their use of AEM, and become more (less) likely to use income increasing REM (AEM) to maintain their MBE strings. Formally, we hypothesize that:

H1a. Firms initially increase their use of income increasing AEM as the MBE string lengthens.

H1b. Firms reduce their use of income increasing AEM as the MBE string continues to lengthen.

H2a. Firms initially do not use income increasing REM.

H2b. Firms increase their use of income increasing REM as the MBE string continues to lengthen.

3. Sample and research design

3.1. Sample

Our sample comes from the intersection of the I/B/E/S summary file and the COMPUSTAT quarterly file for periods reported between January 1, 2004 and December 31, 2014. To create our measure of backward looking consecutive quarters of MBE, we require that firms have non-missing I/B/E/S data beginning January 1, 2001. Consistent with prior research, we also exclude firms in regulated industries (financial SIC 6000–7000 and utility SIC 4400–5000), which results in 2284 unique firms with 38,236 firm-quarter observations. Since the focus of our study is on the use of income increasing AEM and REM, after estimating AEM and REM we also eliminate firm-quarter observations with negative AEM or REM to arrive at our sample. This additional restriction yields a sample of 14,234 firm quarter observations to test our hypotheses. Additional details about our sample composition can be found in (Table 1).

3.2. Research design

3.2.1. AEM and REM measures

We measure our accrual based earnings management (AEM) measure using the following modified (Dechow, Sloan, & Sweeney, 1995) Jones (1991) model:

$$TACC_{i,t}/TA_{i,t-1} = \gamma_0 + \gamma_1(1/TA_{i,t-1}) + \gamma_2(GPPE_{i,t}/TA_{i,t-1}) + \gamma_3(\Delta REV_{i,t}/TA_{i,t-1}) + \gamma_4(ROA_{i,t}) + \varepsilon_{i,t} \quad (1)$$

where the following variables are defined at time t for firm i:

TACC is total accruals computed as earnings less cash flow from operations;
TA is the total assets of the firm;
GPPE is gross property, plant, and equipment; and.
ΔREV is change in revenue, and ROA is return on assets.

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[4] Management forecast guidance occurs when managers intentionally dampen analysts' earnings forecasts in order to produce (avoid) a positive (negative) earnings surprise upon the earnings release (Bartov et al., 2002). Specifically, in order to dampen analysts' earnings forecasts, managers provide pessimistic outlooks about the future in an attempt to cause analysts to revise their former earnings forecasts lower. Burgstahler and Eames (2006) provides evidence that downward forecasts revisions occur more frequently when the earnings forecast revision allows the firm to avoid a negative earnings surprise, suggesting managers' can influence analysts' earnings forecast revisions.

[5] We do not focus on earnings forecast guidance as Kross et al. (2011) find that although firms with longer MBE strings continue to engage in management forecast guidance, the efficacy of this guidance appears to decrease as analysts are less likely to incorporate the negative guidance into their forecasts. In addition, the literature suggests that the negative stock price reaction to downward guidance often trumps the positive effects of MBE (Kasznik & Lev, 1995; Rees & Twedt, 2011).

[6] Roychowdhury (2006) highlights the timing issue in his study, but concludes that managers are less likely to rely on AEM alone in order to avoid the potential risk in which the realized year-end shortfall between un-manipulated earnings and the desired threshold exceed the maximum amount of possible manipulated accruals.

Table 1
Identification of the sample.

Intersection of I/B/E/S and COMPUSTAT from 2004 to 2014 after excluding financial (SICH: 6000–6999) and utility (SICH 4400–4999) firms	81,497
Less: observations with missing data necessary to calculate variables	(22,817)
Total available observations from 2004 to 2014 (used in Model 1–3)	58,680
Less: negative AEM or negative REM	(44,446)
Total observations for our Model (4) and Model (5) estimation	14,234

The residuals from quarterly industry estimations of Model (1) represent abnormal accrual levels and represent our AEM measure. Our measure of real transactions based earnings management (REM) is the residual from the estimation of the following discretionary expenditure model developed by Roychowdhury (2006):

$$DISEXP_{i,t}/TA_{i,t-1} = \gamma_0 + \gamma_1(1/TA_{i,t-1}) + \gamma_2(\Delta REV_{i,t}/TA_{i,t-1}) + \varepsilon_{i,t} \tag{2}$$

where the following variable is defined at time t for firm i:

DISEXP is SG&A expenses plus R&D expenses.

The residuals from quarterly industry estimations of Model (2) represent abnormal discretionary expenditures and are used as our primary REM measure. Our approach to focus on DISEXP is consistent with other studies that exclude other REM proxies from their primary analysis (Greiner, Kohlbeck, & Smith, 2017; Kim & Park, 2014; Trejo-Pech, Weldon, & Gunderson, 2016). For example, Kim and Park (2014) finds support for CFO and DISEXP, but not PROD, while Gunny (2010) obtains significant results for DISEXP and PROD, but not for abnormal asset gains. Most studies additionally tend to exclude one or more potential proxies suggested by Roychowdhury (2006), e.g., Gunny (2010) and Zang (2012) exclude CFO and Trejo-Pech et al. (2016) excludes both CFO and PROD. It appears that with the exception of DISEXP, REM proxies are generally used inconsistently and have inconsistent results. The inconsistent use and results for CFO is perhaps explained by various REM activities having opposing effects on CFO, resulting in a net effect on CFO that is ambiguous (Roychowdhury, 2006; Zang, 2012). Similarly, certain REM activities related to PROD are only available to manufacturing, thereby reducing the usefulness of PROD as a REM proxy in studies like ours that include both manufacturing and non-manufacturing industries (Roychowdhury, 2006). Based on this discussion, we use DISEXP as our proxy for REM in the primary analysis. Given that a positive residual for Model (2) represents abnormal additional expenditures, we multiply the residual by negative one so that a positive REM measure represents an income increasing REM action.

3.3. Model for hypotheses testing

We test our hypotheses by examining the association between the length of the MBE string and the level of income increasing AEM (REM) in the current quarter over the 2004 to 2014 period.[7] We recognize that the decision to engage in income increasing AEM (REM) is not a random event, and therefore employ a Heckman (1979) two-stage approach similar to Zang (2012) to address the endogeneity concern created by our increasing AEM (REM) sample selection. Specifically, we first estimate a model using the full 58,680 firm quarter observations to predict whether a firm would likely engage in both income increasing AEM and income increasing REM (INC_AEM/REM), and then include the inverse Mills ratio from our first-stage model in each of our AEM and REM models. Consistent with the procedures suggested by Lennox, Francis, and Wang (2012) our income increasing AEM or REM prediction model (first stage) includes all of the independent variables used in our AEM and REM models (second stage). Additionally, we include a variable which identifies suspect firms (SUSPECT_MBE), defined as firms that meet or just beat by no more than one penny the consensus earnings expectation in the current quarter. This variable is omitted from the second stage to satisfy the exclusion restriction.

MBE string length is defined as the number of consecutive quarters that the firm has been able to meet or beat the mean analyst consensus prior to the current quarter. Given that our hypothesis predicts that the use of AEM is likely to change as the string lengthens, we use a quadratic function to estimate the predicted non-linear relation. Specifically, we expect that firms will initially increase their use of income increasing AEM as the string begins to grow (H1a suggests a positive association between AEM and MBE string length for shorter string); and then H1b predicts that this relation will become weaker as the string continues to grow and firms become more constrained in their continued use of income increasing AEM. Similarly, our second set of predictions assume that firms will only utilize the more costly REM when the string is sufficiently long. We therefore do not expect a positive association between REM and MBE string length for shorter MBE strings (H2a), and then a positive association between REM and MBE string length for longer strings (H2b). We allow for this non-linear prediction through the following models. The first model (Model 3) represents the probit model used to calculate the inverse Mills ratio (IMR), which is then included in the second model (Model 4) and third model (Model 5), which are used to test our AEM and REM hypotheses, respectively. We follow Zang (2012) in our construction of the AEM and REM models. Specifically, we exclude our AEM measure in the estimation of our REM model (Model 5) and retain the fitted value and residuals from this estimation (predicted REM and unexpected REM per Zang, 2012). We then include the predicted REM and unexpected REM in our AEM model (Model 4) to adjust for the assumed sequential nature of REM occurring prior to AEM.[8] This provides us with the following models to test our hypotheses:

$$\begin{aligned} INC\_AEM/REM = {} & \beta_0 + \beta_1(SUSPECT\_MBE_{i,t}) + \beta_2(MBE\_STRING_{i,t-1}) \\ & + \beta_3(MBE\_STRING_{i,t-1})^2 + \beta_4(SIZE_{i,t}) + \beta_5(ROE_{i,t}) \\ & + \beta_6(OCF_{i,t}) + \beta_7(MTB_{i,t}) + \beta_8(NUMEST_{i,t}) \\ & + \beta_9(LITIGATION_{i,t}) + \beta_{10}(ALTMANZ_{i,t}) \\ & + \beta_{11}(BIG4_{i,t}) + \sum \beta_i Quarter + \sum \beta_j Firm + \varepsilon \end{aligned} \tag{3}$$

$$\begin{aligned} AEM = {} & \beta_0 + \beta_1(MBE\_STRING_{i,t-1}) + \beta_2(MBE\_STRING_{i,t-1})^2 \\ & + \beta_3(Pred\_REM_{i,t}) + \beta_4(Unexp\_REM_{i,t}) + \beta_5(SIZE_{i,t}) \\ & + \beta_6(ROE_{i,t}) + \beta_7(OCF_{i,t}) + \beta_8(MTB_{i,t}) + \beta_9(NUMEST_{i,t}) \\ & + \beta_{10}(LITIGATION_{i,t}) + \beta_{11}(ALTMANZ_{i,t}) + \beta_{12}(BIG4_{i,t}) \\ & + \beta_{13}(IMR) + \sum \beta_i Quarter + \sum \beta_j Firm + \varepsilon \end{aligned} \tag{4}$$

$$\begin{aligned} REM = {} & \beta_0 + \beta_1(MBE\_STRING_{i,t}) + \beta_2(MBE\_STRING_{i,t})^2 + \beta_3(SIZE_{i,t}) \\ & + \beta_4(ROE_{i,t}) + \beta_5(OCF_{i,t}) + \beta_6(MTB_{i,t}) + \beta_7(NUMEST_{i,t}) \\ & + \beta_8(LITIGATION_{i,t}) + \beta_9(ALTMANZ_{i,t}) + \beta_{10}(BIG4_{i,t}) \\ & + \beta_{11}(IMR) + \sum \beta_i Quarter + \sum \beta_j Firm + \varepsilon \end{aligned} \tag{5}$$

where the following variables are defined at time t for firm i:

INC_AEM/REM is an indicator variable equal to one if the firm engaged in income increasing AEM (positive residual from Model 1)

[7] We use 2004 as the initial year because Cohen et al. (2008) find that firms switch from AEM to REM after the passage of the Sarbanes-Oxley Act (SOX). Thus, by using the data two years after SOX, we believe that firms' earnings management choices are less likely to be affected by SOX.

[8] The rational for this design choice is that REM activities need to occur prior to the end of the fiscal period, while AEM decisions are generally made after the end of the fiscal period. Therefore, it is likely that the REM behavior will influence AEM decisions, but not vice versa. Similar to Zang (2012), we find evidence consistent with this assumption and discuss this more in our additional analysis section.

and income increasing REM (negative residual from Model 2), or zero otherwise;
SUSPECT_MBE is an indicator variable equal to one if the firm meets or beats the mean analyst expectation by no more than one penny, or zero otherwise;
AEM is the residual obtained from the estimate of Model (1);
REM is the residual from the estimate of Model (2) multiplied by negative one so that a positive value corresponds to income increasing REM;
MBE_STRING is the number of consecutive quarters the firm has met or beaten the mean analyst consensus forecast prior to the current quarter;
Pred_REM is the fitted value from the estimation of Model (5);
Unexp_REM is the residual value from the estimation of Model (5);
SIZE is the natural log of total market value of the firm;
ROE is operating income before depreciation divided by average common equity;
OCF is net cash flow from operating activities divided by total assets;
MTB is market value of equity divided by common equity;
NUMEST is the natural log of 1 plus the number of analysts covering the firm;
LITIGATION is an indicator variable equal to one if the firm is in the following industries (SICH: 2833–2836, 3570–3577, 3600–3674, 5200–5961, 7370–7374), or zero otherwise;
ALTMANZ is the Zscore obtained from the formula used in Altman (2000);
BIG4 is an indicator variable equal to one if the firm is audited by Deloitte, EY, KPMG, or PwC in the current fiscal year, or zero otherwise; and.
IMR is the inverse Mills Ratio calculated based on the estimation of Model 3.

Our variable of interest in both Model (4) and Model (5) is β_1 and β_2, which together capture the association between the length of the MBE string and income increasing AEM (REM) for longer strings. Our control variables capture firm, analyst, and auditor characteristics that are likely to influence financial reporting quality as well as the information environment. We control for firm size (SIZE), as Kasznik and Lev (1995) find that firm size is positively associated with company's forecast disclosure. We also we include ROE, OCF, and the Altman's Zscore (Altman, 2000) in the model to control for financial health which has been found to be associated with earnings management (Zang, 2012). We also control for market-to-book (MTB), because it is commonly controlled for in analyst research as a proxy for company's potential growth (e.g. Bamber & Cheon, 1998; Verrecchia, 1983). We control for analyst following (NUMEST) because Lang and Lundholm (1993) finds that analyst coverage is positively associated with the quality of analysts' forecasts. We control for *ex ante* litigation risk by including an indicator variable (LITIGATION) to identify industries that prior research (Ali & Kallapur, 2001; Francis, Philbrick, & Schipper, 1994 and Soffer, Thiagarajan, & Walther, 2000) has identified as having high risk. Finally, we include BIG4 to control for audit quality.[9]

4. Empirical results

4.1. Descriptive statistics

Table 2, Panel A reports descriptive statistics for the variables used in our analysis. We note that 84% of our sample is audited by the BIG4, and that firms have an average string of just under 4 quarters for our observations. The average firm in our sample is financially healthy as evidenced by an average Altman Zscore above 3. Panel B of Table 2 reports the Pearson correlation matrix for our variables. We observe an insignificant correlation between AEM and MBE_STRING and a positive correlation between REM and MBE_STRING. Given that our motivation for H1a and H1b predicts that the association between MBE_STRING and AEM is non-linear, that is, positive at first (and perhaps initially even increasing in string length) and then less positive, it is not particularly surprising that we observe an insignificant correlation between AEM and MBE_STRING. The positive correlation between REM and MBE_STRING is also consistent with our motivation for H2a and H2b, as we expect no relation between REM and MBE for shorter MBE strings and a positive relation between REM and MBE for longer MBE strings. We further note that only one correlation is > 0.50 (SIZE and NUMEST = 0.718), which suggests that multicolinearity is not likely to adversely influence our model estimates.

4.2. Multivariate results

To address potential sample selection bias we first estimate Model (3) and calculate IMR based on this probit estimation. IMR is then included as an additional explanatory variable in our main regressions, i.e., Models (4) and (5). Table 3 shows the results from the estimation of Model (3). The selection model fit statistics show an area under the ROC curve of 0.643, which suggests that Model (3) explains a significant amount of the variation in the probability of a firm engaging in both income increasing AEM and income increasing REM. Further, the inclusion of IMR in Model (4) and Model (5) does not appear to introduce a multicollinearity problem. More specifically, the maximum variance inflation factors in Model (4) and Model (5) is < 3, which is below the conventional cut-off of 10 and is similar to prior research using IMR, for example, Feng et al. 2009.

We use the results from Model (4) to test our first hypothesis that predicts that firms with shorter MBE strings are likely to increase their use of AEM to build their string (H1a) and that firms with longer MBE strings are less likely to use income increasing accruals-based earnings management to continue sustaining their MBE strings (H1b). Table 4 reports the results for the estimation of Model (4) and documents a positive coefficient estimate for MBE_STRING ($p < 0.01$) and a negative coefficient estimate for MBE_STRING^2 ($p = 0.01$). These two effects together indicate an initial positive relation between string length and AEM (consistent with H1a) that is marginally decreasing and eventually turns negative as the string increases in length (consistent with H1b). The coefficient estimates for MBE_STRING and MBE_STRING^2 in Model (4) together show an initial positive slope with an inflection point of 18-quarters. This implies that firms initially increase, but at a decreasing rate, their use of income increasing AEM until approximately the 18th quarter (4.5 years) after which they reduce their use of income increasing AEM. Firms abandon income increasing AEM after 35-quarters (just under nine years).[10] However, these specific point estimates should be interpreted with caution given that only 94 firms have MBE strings that extend beyond 16-quarters.

Our second hypothesis predicts that while firms are not expected to use income increasing REM to initially build an MBE string (H2a), they are more likely to use real earnings management to sustain a long MBE string (H2b). Table 5 contains the coefficient estimates of Model (5) with REM as the dependent variable. The results show an insignificant negative coefficient on MBE_STRING ($p = 0.24$) and a significant positive coefficient estimate on MBE_STRING^2 ($p < 0.01$). The positive coefficient estimate on MBE_STRING^2 indicates an increasing positive relation between MBE string length and REM, which is consistent with

[9] To examine the potential impact of outliers on our inferences, we estimate (untabulated) all regressions after eliminating observations where the absolute value of the studentized residual is > 3. All of our hypotheses and inferences are unchanged after removing these potential outliers.

[10] When we exclude influential observations, coefficient estimates suggest that firms begin reducing their use of income increasing AEM after 10 quarters and stop using income increasing AEM after 20-quarters.

Table 2

Panel A: Descriptive statistics (N = 14,234).

Variable[a]	Mean	Median	Std. dev	Lower quartile	Upper quartile
AEM	0.1808	0.0424	0.4176	0.0156	0.1212
REM	0.0699	0.0584	0.0564	0.0236	0.1004
MBE_STRING	3.8516	1.0000	6.5397	0.0000	5.0000
SIZE	7.3110	7.2648	1.8800	6.0166	8.5281
ROE	0.0752	0.0673	0.1501	0.0363	0.1048
OCF	0.0495	0.0460	0.0860	0.0084	0.0956
MTB	2.9418	2.2287	4.0459	1.3814	3.6401
NUMEST	2.0056	2.0794	0.7752	1.3863	2.6391
LITIGATION	0.2913	0.0000	0.4544	0.0000	1.0000
ALTMANZ	3.6701	2.3257	5.4188	1.3487	3.9363
BIG4	0.8421	1.0000	0.3647	1.0000	1.0000
IMR	0.6304	0.6305	0.0504	0.5937	0.6669

Panel B: Correlation matrix

Variable[b] (*N* = 14,234)	REM	MBE_STRING	SIZE	ROE	OCF	MTB	NUMEST	LITIGATION	ALTMANZ	BIG4	IMR
AEM	**0.197**	−0.015	−0.007	−0.002	0.012	**0.026**	**−0.021**	**0.021**	−0.013	−0.009	**−0.102**
REM		**0.021**	0.013	0.000	**−0.028**	**0.038**	**−0.031**	**0.044**	**0.068**	−0.006	**−0.329**
MBE_STRING			**0.312**	**0.088**	**0.132**	**0.095**	**0.286**	**0.122**	**0.046**	**0.146**	**−0.031**
SIZE				**0.171**	**0.291**	**0.201**	**0.718**	**0.033**	**0.033**	**0.477**	**−0.402**
ROE					**0.178**	**0.436**	**0.145**	**−0.049**	**−0.020**	**0.081**	**−0.154**
OCF						**0.080**	**0.233**	0.009	**0.136**	**0.119**	**−0.317**
MTB							**0.142**	**0.086**	**0.208**	**0.035**	**0.070**
NUMEST								**0.081**	**−0.030**	**0.390**	**−0.230**
LITIGATION									**0.195**	**−0.039**	**0.302**
ALTMANZ										**−0.097**	**0.022**
BIG4											**−0.141**

[a] Where *AEM* is the residual obtained from the estimate of Model (1); *REM* is the residual from the estimate of Model (2), multiplied by negative one so that a positive value indicates income increasing REM; *MBE_STRING* is the number of consecutive quarters the firm has met or beaten the mean analyst consensus forecast prior to the current quarter; *SIZE* is the natural log of total market value of the firm; *ROE* is operating income before depreciation divided by average common equity; *OCF* is net cash flow from operating activities divided by total assets; *MTB* is market value of equity divided by common equity; *NUMEST* is the natural log of 1 plus the number of analysts covering the firm; *LITIGATION* is an indicator variable equal to one if the firm is in the following industries (SICH: 2833–2836, 3570–3577, 3600–3674, 5200–5961, 7370–7374), or zero otherwise; *ALTMANZ* is the zscore obtained from the formula used in Altman (2000); *BIG4* is an indicator variable equal to one if the firm is audited by Deloitte, EY, KPMG, or PwC in the current fiscal year, or zero otherwise; and *IMR* is the inverse Mills ratio obtained from the estimation of Model (3).

[b] Variables are defined in Table 2. Correlations in bold are significant at the 0.05 level.

H2b, suggesting that firms increase their reliance on income increasing REM as the string grows longer.

Collectively, the results reported in Tables 4 and 5 provide support for the notion that firms are more (less) likely to use income increasing REM (AEM) as the MBE string expands. Fig. 1 graphically depicts AEM and REM behavior among the firms in our sample that have strings of at least 4 years (16 quarters), and reports median AEM and REM data for the first 8 years (32 quarters) of MBE string growth. The graph provided in Fig. 1 depicts a slightly declining median AEM and an increasing median REM as the MBE string grows. These trends are consistent with our hypotheses and the notion that firms use of income increasing AEM (REM) declines (increases) as the MBE string grows.[11]

To provide additional support for our arguments that the move away from AEM is driven by increased auditor scrutiny of AEM, and the move toward REM is driven by the inability to continue using AEM to sustain the string, we consider the impact of Big 4 on our AEM model and balance sheet bloat on our REM model. Regarding auditor scrutiny, early research predicted that Big 4 auditors would likely provide higher quality audits than non-Big 4 auditors (Deangelo, 1981; Francis & Wilson, 1988). Although empirical research examining this hypothesized relation provided some mixed results (Defond, Erkens, & Zhang, 2016; Lawrence, Minutti-Meza, & Zhang, 2011), more recent research finds support for this initial prediction (Jiang, Wang, & Wang, 2018). We, therefore, use our Big 4 variable to identify observations where auditor scrutiny is likely to be elevated and re-estimate Model (4) separately for observations where the firm is audited by a Big 4 relative to those firms audited by non-Big 4 firms. We report the results from this analysis in Table 6. Consistent with increased scrutiny influencing the observed reduced likelihood of observing income increasing AEM as the MBE string grows, we are only able to find support for H1a and H1b among our Big 4 subsample. While we are careful to not draw too large of an inference from an insignificant results in the non-Big 4 subsample, we note that the sign of the coefficient estimates on our variables of interest are opposite of the H1a and H1b predictions. We further note that explained variance, as indicate by R^2, appears to be slightly higher for the non-Big 4 subsample relative to the Big 4 subsample, suggesting that the observed differences in our test variable between the two subsamples is not simply due to lack of power.[12] To the extent that restricting the use of AEM as the MBE string expands is an indicator of

[11] We acknowledge increased variability in median AEM and REM starting around the 16-quarter (4-year) long MBE string, and suggest that this is likely due to a much smaller number of observations for long MBE strings (e.g. only 94 firms have MBE strings that extend beyond 16-quarters, while 752 firms have strings of at least 4-quarters).

[12] Despite the larger R^2 for the non-Big 4 subsample estimation, it is important to note that there is a large decline in the number of observations used in that estimation. Further, there are only 3 significant coefficient estimates among the non-test variables in the non-Big 4 subsample estimation, which is less than the 4 significant coefficient estimates among the non-test variables in the Big4 subsample estimation. Consequently, the lack of significant estimates on test variables in our non-Big4 estimation should be interpreted with a degree of caution.

Table 3
Estimation of Model (3): Regression estimation to obtain inverse Mills ratio.

Variable[a]	Estimate
(N = 58,680)	
Intercept	−2.3460 (< 0.01)
SUSPECT_MBE	−0.0132 (0.38)
MBE_STRING	−0.0037* (0.07)
(MBE_STRING)^2	0.0000 (0.82)
SIZE	0.0769*** (< 0.01)
ROE	0.3636*** (< 0.01)
OCF	0.6318*** (< 0.01)
MTB	−0.0198*** (< 0.01)
NUMEST	−0.0355*** (< 0.01)
LITIGATION	−0.3326*** (< 0.01)
ALTMANZ	0.0028** (0.01)
BIG4	−0.0743*** (< 0.01)
Firm and quarter fixed effect	Included
Area under ROC	0.643

$$\begin{aligned} INC\_AEM/REM = {} & \beta_0 + \beta_1(SUSPECT\_MBE_{i,t}) + \beta_2(MBE\_STRING_{i,t-1}) \\ & + \beta_3(MBE\_STRING_{i,t-1})^2 + \beta_4(SIZE_{i,t}) + \beta_5(ROE_{i,t}) \\ & + \beta_6(OCF_{i,t}) + \beta_7(MTB_{i,t}) + \beta_8(NUMEST_{i,t}) \\ & + \beta_9(LITIGATION_{i,t}) + \beta_{10}(ALTMANZ_{i,t}) + \beta_{11}(BIG4_{i,t}) \\ & + \sum \beta_i Quarter + \sum \beta_j Firm + \varepsilon \end{aligned} \tag{3}$$

[a] *INC_AEM/REM* is an indicator variable equal to one if the firm engaged in income increasing AEM (positive residual from Model 1) and income increasing REM (negative residual from Model 2), or zero otherwise; *SUSPECT_MBE* is an indicator variable equal to one if the firm meets or beats the mean analyst expectation by no more than one penny, or zero otherwise. All other variables are defined in Table 2. ***,**,* denote significance at the 0.01, 0.05, and 0.10 based on two-tail *p*-values reported in parenthesis below the coefficient estimate.

Table 4
Estimation of Model (4): Test of H1a (positive relation between AEM and MBE string over shorter string) and H1b (negative relation between AEM and MBE string over longer string).

Variable[a]	Prediction	Estimate
(N = 14,234)		
Intercept		0.8812 (0.01)
MBE_STRING	H1a: +	0.00492*** (< 0.01)
(MBE_STRING)^2	H1b: -	−0.00014*** (0.01)
Pred_REM	?	5.45966 (0.31)
Unexp_REM	?	0.72536*** (< 0.01)
SIZE	?	−0.04749** (0.03)
ROE	+	−0.03177 (0.46)
OCF	+	0.06299 (0.24)
MTB	?	0.00379* (0.07)
NUMEST	?	0.01216 (0.46)
LITIGATION	?	−0.85412 (0.36)
ALTMANZ	?	−0.00187 (0.29)
BIG4	?	−0.00656 (0.90)
IMR	?	−0.77749 (0.13)
Firm and quarter fixed effect		Included
R^2		0.24

$$\begin{aligned} AEM = {} & \beta_0 + \beta_1(MBE\_STRING) + \beta_2(MBE\_STRING)^2 + \beta_3(Pred\_REM) \\ & + \beta_4(Unexp\_REM) + \beta_5(SIZE) + \beta_6(ROE) + \beta_7(OCF) + \beta_8(MTB) \\ & + \beta_9(NUMEST) + \beta_{10}(LITIGATION) + \beta_{11}(ALTMANZ) + \beta_{12}(BIG4) \\ & + \beta_{13}(IMR) + \sum \beta_i Quarter + \sum \beta_j Firm + \varepsilon \end{aligned} \tag{4}$$

[a] Variables are defined in Table 2. ***,**,* denote significance at the 0.01, 0.05, and 0.10 based on two-tail (one-tail where predicted) *p*-values reported in parenthesis below the coefficient estimate.

increased audit quality, this result may also provide additional support to the claim that Big 4 auditors may provide a higher level of audit quality.

Regarding the impact of balance sheet bloat, Barton and Simko (2002) argue that firms with higher levels of NOA are constrained in their ability to engage in income increasing AEM in the future. Consistent with the arguments advanced by Barton and Simko (2002), we therefore divide our REM sample into those with above median adjusted NOA (High NOA) and those with below median adjusted NOA (Low NOA). We then re-estimate Model (5) and report the results from this analysis in Table 7. Consistent with the impact of balance sheet bloat, we find that the positive association between REM and longer MBE strings (predicted H2b relation) is only observed for the High NOA subsample. This finding supports the notion that firms only increase their use of the more costly MBE tool (REM) when they are forced to do so.

5. Additional analysis

Our main analysis does not impose a minimum MBE string length restriction on our sample selection. A limitation of this sampling approach is that our treatment effect (firms with shorter/longer MBE strings) is not random. For example, there are some firms in our main sample that never have enough consecutive quarters of MBE to ever have a string of meaningful length. If the firms with longer strings are fundamentally different than firms with shorter strings, then the effects of string length on AEM and REM behavior that we are currently attributing to the length of the string could in fact be driven by firm level characteristics. In other words, it is possible that short/no string firms are fundamentally different than the firms that have MBE strings and that this difference is driving the results rather than differences in string length. We currently include firm fixed effects in all of our regressions to address this concern. To further evaluate this concern, we perform an additional analysis in which we eliminate observations that are not a part of at least a 12 quarter (3-year) string.[13] This additional restriction removes firms with short strings and no strings, and allows us to examine our hypotheses within a potentially more homogenous group of

[13] Dechow, Sloan, and Sweeney (1996) and Perols and Lougee (2011) show that the use of income increasing discretionary accruals over a three year period puts increasing pressure on management to engage in more aggressive earnings management techniques (i.e. fraud) as the discretionary accruals reverse.

Table 5
Estimation of Model (5): Test of H2a (no positive relation between REM and MBE string over shorter string) and H2b (positive relation between REM and MBE string over longer string).

Variable[a]	Prediction	Estimate
(N = 14,234)		
Intercept		−0.01047 (0.69)
MBE_STRING	H2a:?	−0.00012 (0.24)
(MBE_STRING)^2	H2b: +	0.00001*** (< 0.01)
SIZE	?	0.00443*** (< 0.01)
ROE	+	−0.0097 (0.74)
OCF	+	0.00856* (0.06)
MTB	?	0.00010 (0.45)
NUMEST	?	0.00195** (0.03)
LITIGATION	?	0.16423*** (< 0.01)
ALTMANZ	?	0.00018* (0.08)
BIG4	?	0.00787*** (< 0.01)
IMR	?	−0.03909 (0.21)
Firm and quarter fixed effect		Included
R^2		0.79

$$REM = \beta_0 + \beta_1(MBE\_STRING) + \beta_2(MBE\_STRING)^2 + \beta_3(SIZE) + \beta_4(ROE) + \beta_5(OCF) + \beta_6(MTB) + \beta_7(NUMEST) + \beta_8(LITIGATION) + \beta_9(ALTMANZ) + \beta_{10}(BIG4) + \beta_{11}(IMR) + \sum \beta_i Quarter + \sum \beta_j Firm + \varepsilon \quad (5)$$

[a] Variables are defined in Table 2. ***,**,* denote significance at the 0.01, 0.05, and 0.10 based on two-tail (one-tail where predicted) p-values reported in parenthesis below the coefficient estimate.

Table 6
Estimation of Model (4): Test of H1b conditional on the level of auditor scrutiny (Big 4 versus non-Big 4).a

Variable[a]	Prediction	Estimate	Estimate
		BIG4 = 1 (n = 11,986)	BIG4 = 0 (n = 2248)
Intercept		0.14540 (0.74)	4.44441 (0.14)
MBE_STRING	H1a: +	0.00530*** (< 0.01)	−0.01039 (0.17)
(MBE_STRING)^2	H1b: -	−0.00019*** (0.01)	0.00069 (0.16)
Pred_REM	?	9.81037* (0.09)	12.21473 (0.38)
Unexp_REM	?	0.80302*** (< 0.01)	0.43988 (0.17)
SIZE	?	−0.05517** (0.04)	0.02801 (0.67)
ROE	+	0.01933 (0.35)	−0.02267 (0.84)
OCF	+	0.07134 (0.24)	0.37805** (0.03)
MTB	?	0.00057 (0.82)	0.00662 (0.17)
NUMEST	?	−0.00863 (0.64)	0.09061** (0.04)
LITIGATION	?	−1.60619 (0.11)	−1.73293 (0.40)
ALTMANZ	?	−0.00360* (0.09)	0.00244 (0.52)
IMR	?	0.43546 (0.50)	−3.09971*** (< 0.01)
Firm and quarter fixed effect		Included	Included
R^2		0.25	0.27

$$AEM = \beta_0 + \beta_1(MBE\_STRING) + \beta_2(MBE\_STRING)^2 + \beta_3(Pred\_REM) + \beta_4(Unexp\_REM) + \beta_5(SIZE) + \beta_6(ROE) + \beta_7(OCF) + \beta_8(MTB) + \beta_9(NUMEST) + \beta_{10}(LITIGATION) + \beta_{11}(ALTMANZ) + \beta_{12}(IMR) + \sum \beta_i Quarter + \sum \beta_j Firm + \varepsilon \quad (4)$$

[a] Variables are defined in Table 2. ***,**,* denote significance at the 0.01, 0.05, and 0.10 based on two-tail (one-tail where predicted) p-values reported in parenthesis below the coefficient estimate.

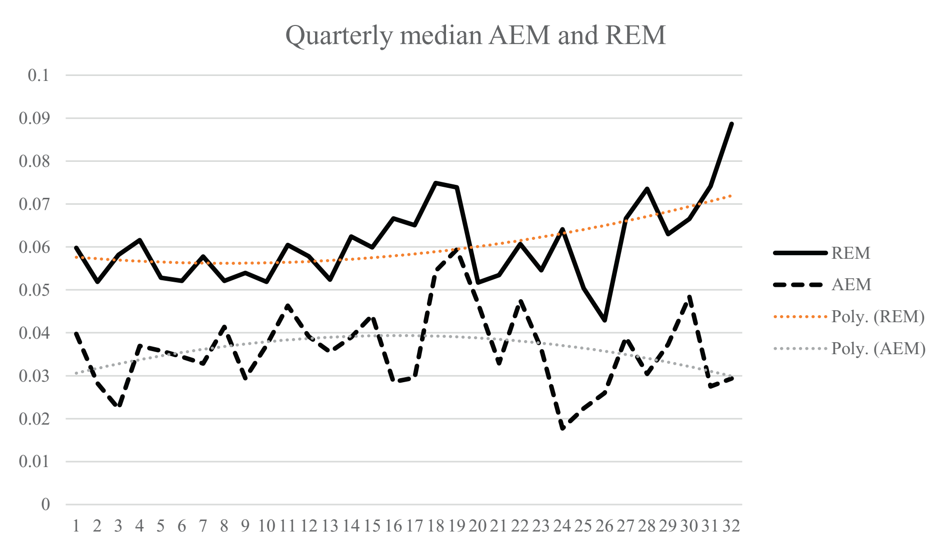

Fig. 1. This graph depicts the median AEM and REM values for our sample observations where the current quarter is part of an MBE string that extends for at least 16 quarters (4-years).

Table 7
Estimation of Model (5): Test of H2b conditional on the level of balance sheet bloat (above and below median industry adjusted NOA).

Variable[a]	Prediction	Estimate	Estimate
		HIGH NOA (n = 6832)	LOW NOA (n = 7402)
Intercept		0.59693***	−0.01179
		(< 0.01)	(0.68)
MBE_STRING	H2a:?	0.00029*	0.00021
		(0.10)	(0.18)
(MBE_STRING)^2	H2b: +	0.00001***	−0.00000
		(< 0.01)	(0.49)
SIZE	?	−0.00635***	0.00253***
		(< 0.01)	(0.01)
ROE	+	−0.05536***	0.00328***
		(< 0.01)	(0.33)
OCF	+	−0.08754***	0.01598***
		(< 0.01)	(< 0.01)
MTB	?	0.00277***	0.00004
		(< 0.01)	(0.77)
NUMEST	?	0.00711***	0.00247*
		(< 0.01)	(0.05)
LITIGATION	?	0.20810***	0.15025***
		(< 0.01)	(< 0.01)
ALTMANZ	?	−0.00023	0.00033*
		(0.16)	(0.05)
BIG4	?	0.01088***	0.00999***
		(< 0.01)	(< 0.01)
IMR	?	−0.88319***	0.00225
		(< 0.01)	(0.94)
Firm and quarter fixed effect		Included	Included
R^2		0.82	0.80

$$REM = \beta_0 + \beta_1(MBE\_STRING) + \beta_2(MBE\_STRING)^2 + \beta_3(SIZE) + \beta_4(ROE) + \beta_5(OCF) + \beta_6(MTB) + \beta_7(NUMEST) + \beta_8(LITIGATION) + \beta_9(ALTMANZ) + \beta_{10}(BIG4) + \beta_{11}(IMR) + \sum \beta_i Quarter + \sum \beta_j Firm + \varepsilon \quad (5)$$

[a] Variables are defined in Table 2. ***,**,* denote significance at the 0.01, 0.05, and 0.10 based on two-tail (one-tail where predicted) p-values reported in parenthesis below the coefficient estimate.

firms.[14]

Consistent with our full sample results, we continue to find support for our hypotheses among this restricted sample. Specifically, we estimate a positive coefficient (0.00312, *p*-value = .02) on MBE_STRING and a negative coefficient (−0.00019, p-value < .01) on MBE_STRING^2 in our AEM model estimation and a positive coefficient (0.00001, p-value = .07) on MBE_STRING^2 in our REM model estimation. These estimates together indicate that long string firms initially increase their use of income increasing AEM as they build their MBE string. After about eight quarters they begin reducing the amount income increasing AEM and switch from income increasing AEM to income decreasing AEM after approximately 16 quarters.

Second, prior REM research generally employs multiple REM proxies in their analysis (e.g., Gunny, 2010; Kim & Park, 2014; Roychowdhury, 2006). To provide additional support for our hypotheses, we therefore follow Zang (2012) and use a combination of DISEXP and PROD as the REM proxy. Consistent with our results based on only DISEXP, we continue to find support for our hypotheses when using a REM measure that combines DISEXP and PROD. More specifically, in the REM model using this alternative measure for REM we estimate a positive coefficient estimate (0.00001, *p*-value < .01) for MBE_STRING^2. We similarly continue finding support for our AEM hypotheses with a positive coefficient estimate (0.00160, p-value = .02) for MBE_STRING and a negative coefficient estimate (−0.00008, p-value < .01) for MBE_STRING^2.

Third, our MBE_string variable does not include the current quarter. This design choice was made because of the timing differences between AEM and REM. Specifically, REM activities need to be completed prior to the end of the period, while AEM activities can be engaged in after the period end. However, this design choice also adds some noise to our MBE string measure, because firms that miss expectations in the current period would be incentivized to not engage in further income increasing AEM or REM. Consequently, we create an alternative string measure where we include the current quarter. Under this specification, we increase the string length variable by one for firms that continue to meet or beat expectations in the current quarter, and set the string length to 0 if they miss in the current quarter. Not surprisingly, our results get even stronger under this specification in support of our hypotheses. Specifically, we estimate a positive coefficient (0.00421, *p*-value < .01) on MBE_STRING and a negative coefficient (−0.00010, p-value < .01) on MBE_STRING^2 in our AEM model estimation and a positive coefficient (0.00001, p-value < .01) on MBE_STRING^2 in our REM model estimation.

Finally, we suggest that because REM must occur during the fiscal period, companies are able to wait to determine the amount of AEM to engage in after the amount of REM is known. This results in REM likely affecting AEM, but not vice versa (which is tested and confirmed by Zang, 2012). We, therefore, conduct a Hausman test to test the exogeneity of REM (AEM) in the AEM (REM) equations in our sample. Similar to Zang (2012) we fail to reject the exogeneity of REM in the AEM equation (p = 0.88), but do reject the exogeneity of AEM in the REM equation (p < 0.01). Collectively, these findings are consistent with AEM being partially determined by the level of REM activities but not vice-versa, and that REM generally precedes AEM.

6. Conclusion

This study examines how firms with longer MBE strings alter their use of AEM and REM to sustain their MBE string relative to firms with shorter MBE strings. Consistent with our expectations, we find that while firms appear to engage in both AEM and REM to maintain their string, firms with short MBE strings are more likely to use income increasing AEM to MBE relative to non-MBE firms. We suggest that the short string result is due to the positive economic incentives enjoyed by firms who establish an MBE string outweighing the potential costs associated with income increasing AEM. We further find that the use of income increasing AEM weakens as the MBE string lengthens, and that firms use more income increasing REM to sustain those longer MBE strings. We also find evidence consistent with the decision to engage in more (less) REM (AEM) as the string lengthens being influenced by the inability to continue engaging in AEM (as proxied for by balance sheet bloat), and the increased scrutiny of AEM (as proxied for by Big 4 auditor) as the string lengthens.

Our study is not without its limitations. As with other earnings management studies, our inferences are limited by the ability of our AEM and REM proxies to accurately reflect the construct they are purported to represent. For example, we assume that positive coefficient estimates represent more income increasing AEM and REM. However, because of the inability to separate income increasing from income decreasing AEM and REM (especially when these measures are close to zero), we are unable to rule out the possibility that the estimate is in fact due to less income decreasing choices.

Our results inform the growing literature on how firms with longer MBE strings behave differently than other firms. Specifically, we extend Kross et al. (2011), which focused on the impact of string length on

[14] Untabulated results indicate that observations that are a part of a string that extends beyond 11 quarters are different than those that are not. More specifically, we find that all of our control variables are significantly different between the two subsamples.

management forecast guidance, by providing evidence that firms also appear to alter their use of AEM and REM as the MBE string lengthens. Our findings should be of interest to future researchers examining the relationship between earnings management and MBE by suggesting that their research methodology would likely benefit from inclusion of a measure of past MBE performance. This paper also extends research that examines how firms vary the extent of AEM and REM to achieve desired reporting objectives by examining this question in a new setting. Using the MBE strings setting, in which firms have the ability to engage in expectations management to achieve the reporting objective without actively intervening in the earnings process, we document that firms will vary their use of different earnings management tools to keep their MBE string from breaking.

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