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Earnings Management Constraints and Classification Shifting

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I. INTRODUCTION

Classification shifting is an earnings management strategy whereby managers move items within the income statement to improve core earnings (McVay, 2006). Literature has also provided evidence of accruals earnings management (hereafter AEM; Healy, 1985; McNichols and Wilson, 1988; Jones, 1991) and real earnings management (hereafter REM; Roychowdhury, 2006; Zang, 2012). Often, managers have the capacity to use all three forms of earnings management to meet earnings targets, but may make trade-off decisions among the different methods based on the costs, constraints and timing of each strategy. Extant research (e.g., Ewert and Wagenhofer, 2005; Cohen et al., 2008; Badertscher, 2011; Zang, 2012) suggests when one form of earnings management is constrained, or more costly, managers use alternative forms of earnings management to achieve reporting objectives. However, literature has not investigated the interaction of all three forms of earnings management together to consider tradeoffs between earnings management techniques based upon the constraints and timing of each method. This study examines how previously identified earnings management constraints are associated with the use of classification shifting to manage earnings.

Understanding the use of classification shifting when other earnings management strategies are constrained is important because of recent concerns regarding classification shifting. Specifically, Haw et al. (2011) suggests that earnings management through classification shifting can serve to undermine the credibility of financial statements by misleading investors about the persistence of firms' performance, which is critical to well-functioning capital markets. Toward that end, Alfonso et al. (2013) find that the market overprices core earnings reported by classification shifters. In addition, the Securities and

Exchange Commission (SEC) has explicitly indicated that the issue of classification shifting is important by stating, “The appropriate classification of amounts within the income statement is as important as the appropriate measurement or recognition of such amounts” (SEC, 2000).

Additionally, the SEC has been actively pursuing companies that engage in income classification shifting. Dell, Inc., Symbol Technologies, Inc., and SafeNet, Inc. are examples of companies that have been charged by the SEC with improper classification of ordinary operating expenses as non-recurring expenses.

Classification shifting has also received attention on an international level because firms often have greater discretion over classification of revenues and expenses under International Financial Reporting Standards (IFRS) (Shirato and Nagata, 2012).¹ For example, Haw et al. (2011) show that expense misclassification is prevalent and economically significant in East Asian countries, while Shirato and Nagata (2012) provide evidence that Japanese firms opportunistically shift revenues and expenses to increase core earnings. Further, there has been a great deal of discussion about the practice of classification shifting by United Kingdom (U.K.) firms (Athanasakou et al., 2011). For example, Athanasakou et al. (2009) provide evidence suggesting that large U.K. firms engage in classification shifting of small core expenses to other non-recurring items to meet analyst forecasts. Such international attention on classification shifting further underscores the importance and relevance of our study. Understanding the costs and constraints of REM and AEM and the corresponding effect on firms’ use of classification shifting is pertinent for both United States (U.S.) and international firms.

¹International Accounting Standards (IAS) 1, *Presentation of Financial Statements*, requires a clear distinction between core and exceptional income components, allowing firms to disclose material items of an exceptional nature separately on the income statement. This allows managers to exercise discretion in classifying non-recurring items.

Zang (2012) investigates the trade-off between REM and AEM. She provides evidence that managers use the two forms of earnings management as substitutes. We extend Zang (2012) by first examining the trade-off between classification shifting and REM constraints (i.e., higher tax rates, poorer financial condition, higher institutional ownership and lower industry market share). Specifically, we examine whether the likelihood of classification shifting is associated with effective tax rates, percentage of institutional ownership, financial condition, and market share within an industry.

We also examine the trade-off between classification shifting and AEM constraints. An unintended consequence of the increased attention given to AEM by auditors and regulators may be the increased use of classification shifting as an earnings management strategy. For example, Fan et al. (2010) provides evidence that classification shifting is more prevalent for fiscal year-end reporting than for interim reporting. A possible explanation is that managers resort to classification shifting because AEM is more constrained by the auditor at year-end than in the interim reporting periods, which are unaudited. Therefore, we investigate the constraints associated with AEM documented in prior literature (McInnis and Collins, 2011; Zang, 2012) to examine their effect on classification shifting. We extend Fan et al. (2010) by addressing constraints to AEM identified in prior literature while also including REM constraints. Specifically, we examine whether firms are more likely to use classification shifting when constrained from AEM by a Big N auditor, a long-tenured auditor, operating in the post-SOX environment, less accounting flexibility, as proxied by high levels of net operating assets and shorter operating cycles, and analyst cash flow forecasts.

Finally, we investigate the trade-off among REM, AEM, and classification shifting based on the timing of each earnings management strategy. The timing of each earnings manipulation

method is quite distinct. REM must occur during the fiscal year, while AEM occurs after the end of the accounting period but within the confines of the accounting system. Classification shifting, on the other hand, provides a flexible earnings management strategy because it is done outside of the accounting system and is likely one of the last earnings management strategies available to meet earnings targets. As a result, the timing of the strategy is an important factor in the decision made by management. That is, managers can offset overly impactful REM and AEM by using classification shifting.

We use logistic regression analysis to investigate the relations between classification shifting and both REM and AEM. We measure REM using the methodology employed by Roychowdhury (2006). Our results first show that when REM is constrained by poor financial condition, high percentage of institutional ownership, and low industry market share, managers are more likely to use classification shifting. We also document a positive association between classification shifting and constraints to AEM from low accounting system flexibility (i.e., high net operating assets) and the provision of an analyst cash flow forecast. In addition, when we reduce our sample to firms that are most likely to manipulate earnings (suspect firms); we continue to find support for constraints of both REM and AEM. Similar to Zang (2012) and Athanasakou et al. (2011), we identify firms most likely to manipulate earnings (suspect sample) as those firms that meet one of the following three criteria: 1) met analyst annual earnings per share forecast by two cents or less, 2) Institutional Brokers' Estimate System (IBES) reported positive earnings less than two cents per share, or 3) change from prior year IBES earnings was an increase of less than two cents per share. Together, the results shed light on the potential consequences of increased constraints to REM and AEM. That is, when firms are inhibited from using REM and AEM they may be more likely to use classification shifting to manage earnings.

Finally, our results provide evidence suggesting managers make trade-off decisions among the three forms of earnings management. We document a negative and significant relation between classification shifting and the level of unexpected REM and AEM. The results are consistent with managers using classification shifting as a substitute for both REM and AEM. We also document negative relations between classification shifting and the level of predicted REM and predicted AEM. Zang (2012) provides evidence of a positive relation between predicted REM and AEM which suggests managers may at times use REM and AEM jointly to manage earnings. Our results indicate managers are not likely to use classification shifting jointly to manage earnings with REM or AEM, but rather classification shifting is a substitute for *both* REM and AEM.

We contribute to the literature in several ways. First, while prior studies have investigated the relation between REM and AEM (Cohen et al., 2008; Zang, 2012) as well as AEM and classification shifting (Fan et al., 2010), there is little research that investigates the tradeoff between REM and classification shifting. Athanasakou et al. (2011) investigate REM, AEM and classification shifting by U.K. firms to meet analyst expectations. Their research highlights the importance of concurrently considering multiple strategies. Therefore, we extend prior research by investigating three manipulation strategies based upon the associated costs, constraints, and timing of each strategy. Second, our findings support a substitute relation between classification shifting and REM. Third, we provide support for a similar relation between classification shifting and AEM, while prior research documents a substitute relation between AEM and REM (Zang, 2012).

The remainder of this paper is organized as follows. Section II reviews the related research and Section III develops the hypotheses. Section IV describes the sample selection

process and details our research methodology. Section V presents our results, while Section VI concludes the paper.

II. LITERATURE REVIEW

Three main forms of earnings management have been addressed in literature: accruals earnings management (AEM), real earnings management (REM), and classification shifting. Research on earnings management has historically focused on AEM. Evidence of AEM has been documented in several contexts, using various different accruals, and in response to many managerial incentives.² AEM occurs when managers, through the use of discretionary accruals, “borrow” earnings from future periods to increase current period earnings or conversely, push earnings from the current period to future periods in order to decrease current period earnings. Therefore, the cost of AEM used to increase current earnings, in addition to the cost of detection, is a one-to-one reduction of future earnings. Future period earnings are lowered mechanically as a result of the net income that is accelerated to the current period. Management’s decision to use AEM should ensure that the benefits of using AEM to manage earnings exceed the associated costs and constraints.

Another earnings management method investigated in literature is real earnings management (REM). REM occurs when managers deviate from optimal business decisions with real activities (i.e., overproducing to lower cost of goods sold (COGS), cutting discretionary expenses such as research and development (R&D), etc.) to meet earnings targets. Initial REM research focused on the manipulation of R&D expenditures to improve current operating results (e.g., Baber et al., 1991; Dechow and Sloan, 1991; Bushee, 1998). The motivation to study REM was underscored by Graham et al.’s (2005) survey of company executives, who confirmed their willingness to engage in different forms of earning manipulation to meet earnings targets.

² See Healy and Wahlen (1999) and Dechow et al. (2010) for literature reviews of AEM and earnings quality.

Consistent with these results, Roychowdhury (2006) provides empirical support that managers avoid reporting losses or missing analyst forecasts through the manipulation of real activities. Specifically, his study provides evidence that managers manipulate sales, reduce discretionary expenditures, and overproduce inventory to decrease COGS. Other types of REM include the sale of profitable assets (Bartov, 1993; Herrmann et al., 2003), sales price reductions (Jackson and Wilcox, 2000), derivative hedging (Barton, 2001; Pincus and Rajgopal, 2002), stock repurchases (Hribar et al., 2006), securitizations (Dechow and Shakespeare, 2009), and cutting advertising expenditures (Cohen et al., 2010).

The manipulation of real activities by management can increase income, but it may not occur without cost. For example, if management cuts R&D expenditures to improve current year net income, the future firm performance may be hurt because of the lost opportunities from decreased R&D. However, the manipulation of real activities by management is not a Generally Accepted Accounting Principles (GAAP) violation, merely a questionable business decision. Therefore, the cost of detection associated with REM is lower than AEM (McVay, 2006). Cohen et al. (2008) show a decrease in AEM and an increase in REM following the passage of SOX. Their results provide support for an increase in REM when AEM is constrained or the cost of detection is more significant. However, the cost of detection is not the only cost associated with both forms of earnings management. In a recent study, Zang (2012) investigates the trade-off decision faced by managers between using AEM and REM. Her study demonstrates that firms decide between the two earnings management strategies based on the relative costs or constraints of each strategy. As a result, AEM and REM are substitutes (Zang, 2012).

A third type of earnings management addressed in literature is classification shifting. Classification shifting refers to misclassifying items within the income statement while net

income remains unchanged (McVay, 2006).³ For example, classification shifting includes shifting expenses from operating expense to non-recurring expenses in order to increase core earnings. McVay (2006) provides support for classification shifting between operating expenses and special items. While the misclassification of items on the income statement may appear innocuous because net income remains unchanged, the different income statement line items are informative to financial statement users. Permanent line items are closer to the top of the income statement which indicates a higher likelihood of persisting in the future (e.g., Lipe, 1986; Fairfield et al., 1996). Conversely, transient income statement line items; that is, line items that are less likely to continue in the future, are closer to the bottom of the income statement (e.g., Burgstahler et al., 2002). Therefore, classification shifting misrepresents the persistence of line items within the income statement and, as a result, could mislead investors regarding the future performance of the firm.

Recent research on classification shifting suggests that firms engage in classification shifting by moving operating expenses to income-decreasing discontinued operations in order to increase core earnings (Barua et al., 2010). Using a U.S. sample of firms, McVay (2006) finds classification shifting is more pervasive when it allows firms to meet or exceed analyst forecasts. Fan et al. (2010) provides support that classification shifting is more prominent in the fourth quarter and that managers are more likely to use classification shifting when they are constrained from using AEM. Further, Athanasakou et al. (2009) provide evidence that U.K. firms use classification shifting as a primary means to achieve analyst targets.

³ While classification shifting has received more attention recently in academia, earlier research also suggests that managers use classification shifting (e.g., Barnea et al., 1976; Beattie et al., 1994). Kinney and Trezevant (1997) documented that managers manipulated the presentation of the income statement (without actually misclassifying expenses) in order to influence the perception of a firm's performance.

Prior research provides evidence that firms switch from AEM to REM when their ability to engage in AEM is constrained. For example, Cohen et al. (2008) provide evidence that firms switched from AEM to REM subsequent to the passage of SOX, which placed regulatory emphasis on AEM. Similarly, Chi et al. (2011) find that firms audited by high quality auditors are more likely to engage in REM because their ability to manipulate accruals is constrained. Furthermore, Badertscher (2011) finds that overvalued firms move from AEM to REM as they run out of accruals management options in order to sustain their overvalued equity, while Cohen and Zarowin (2010) find that firms choose to engage in REM around the time of seasoned equity offerings based on the costs related to AEM. Zang (2012) provides further evidence that managers use the AEM and REM as substitutes. She finds that the trade-off decision is based on the relative costliness of each earnings management strategy. In addition, Zang (2012) suggests that managers adjust the level of AEM according to the realized level of REM. While the above studies document a trade-off between REM and AEM, to our knowledge, no other study examines the trade-off between REM and classification shifting while considering associated constraints.

In addition, earnings management research has recently begun to investigate all three forms of earnings management together. For example, Athanasakou et al. (2011) investigate the market response to meeting analyst earnings expectations associated with earnings management (AEM, REM and classification shifting) and earnings forecast guidance strategies. They find that firms that use classification shifting to meet analyst expectations receive a lower market reward than do firms that genuinely meet or beat the earnings target. Their study highlights that there are three earnings management techniques available to managers to manipulate earnings, and all three should be considered by researchers and regulators. While there has been an increase in

classification shifting research recently, prior studies have not investigated the trade-off decision faced by management among all three forms of earnings management while considering associated constraints.

III. HYPOTHESIS DEVELOPMENT

To address our research question of how the costs, constraints, and timing of REM and AEM are associated with the use of classification shifting, we first hypothesize the relation between REM constraints and classification shifting. Next, we present our hypotheses regarding the relation between AEM constraints and classification shifting. Finally, we hypothesize the association among all three forms of earnings management (i.e., REM, AEM, and classification shifting) by considering the timing of managers' trade-off decisions.

Managers have at their disposal different forms of earnings management (i.e., REM, AEM, classification shifting) that they can implement to help achieve desired goals. The associated costs and constraints of a particular earnings management strategy may cause a manager to resort to another form of earnings management. Therefore, when REM is constrained, managers may be more likely to use classification shifting to manage earnings. The relative costliness of each earnings management method is likely determined by the firm's operating and accounting environment. As a result, we investigate four constraints of REM to examine their impact on managers' decision to use classification shifting: higher effective tax rates, poorer financial condition, higher percentage of institutional ownership, and lower industry market share.

Specifically, prior research shows that REM is costly based on tax constraints (Zang, 2012). When firms increase book income by cutting discretionary expenditures or by over-producing inventory, they also increase taxable income and incur higher tax costs in the current

period. In contrast, classification shifting increases core earnings without tax consequences. Based on the greater tax costs associated with REM, firms with higher effective tax rates should be more likely to resort to classification shifting. This leads to the following prediction:

***H1a:** Other things being equal, firms with higher effective tax rates have a greater likelihood of classification shifting.*

Another constraint to REM is poor financial health. For firms in financial distress, the marginal cost of deviating from optimal business strategies is likely to be high. In this case, managers might perceive REM as relatively costly because their primary goal is to survive and improve operations. In Graham et al. (2005), Chief Financial Officers (CFOs) admit that if the company is in a “negative tailspin,” they are more concerned about performance than financial reporting. Conversely, firms in poor financial health may cut discretionary spending due to liquidity concerns, which would reduce the need to classification shift. Therefore, we present the following hypothesis in the null form:

***H1b:** Other things being equal, firms with poorer financial health are not associated with the likelihood of classification shifting.*

Prior studies suggest that institutional investors, as a monitoring mechanism, act to reduce REM. For example, Bushee (1998) finds that firms are less likely to cut R&D expenditure to avoid a decline in earnings when institutional ownership is high. Further, Roychowdhury (2006) finds a negative relation between institutional ownership and the use of REM to avoid losses. This research supports the notion that institutional investors, who are more sophisticated and informed than other investors, have a better understanding of the long-term implication of firms’ real operating activities, leading to more effort to monitor and mitigate REM. Classification shifting could potentially increase as an indirect consequence of this reduced REM. However, institutional investors may also be able to monitor and mitigate the use

of classification shifting. The institutional investors' sophisticated knowledge of the industry, the company, and the company's financial statements suggests they may be able to recognize and mitigate classification shifting. Accordingly, we present the following hypothesis in the null form:

***H1c:** Other things being equal, firms with higher institutional ownership are not associated with the likelihood of classification shifting.*

Finally, since REM is a departure from optimal operational decisions, it can be particularly costly for firms that face intense competition in the industry (Zang, 2012). Therefore, managers in firms who have a lower percentage of industry market share may perceive REM as more costly because it can further erode their status within the industry. We therefore predict the following:

***H1d:** Other things being equal, firms with lower industry market share have a greater likelihood of classification shifting.*

Our second set of hypotheses investigates the use of classification shifting when AEM is constrained. If firms are constrained from using AEM, they may resort to using classification shifting for their earnings management strategy. Fan et al. (2010) find that classification shifting increases when AEM is constrained by optimistic reporting in previous periods. We extend Fan et al. (2010) by investigating the trade-off between AEM and classification shifting after controlling for REM constraints. In addition, Zang (2012) provides evidence that the costs and constraints of each strategy lead to the trade-off between AEM and REM. We extend her study by addressing the costs and constraints of AEM on firms' propensity to use classification shifting to manage earnings. Therefore, we investigate the effect of five AEM constraints on managers' use of classification shifting to manage earnings: Big N auditor, long-tenured auditor, operating

in a post-SOX environment, less accounting flexibility, and firms with an analyst cash flow forecast.

Prior research provides evidence that Big N audit firms constrain AEM (e.g., DeFond and Jiambalvo, 1991, 1993; Becker et al., 1998; Francis et al., 1999; Cohen et al., 2008; Zang, 2012). Additionally, because audits are generally balance sheet focused, an increase in audit quality focused on the balance sheet may lead to increased management of income statement classifications, an area that is of less audit focus, to meet earnings targets (Bell et al., 1997). Increased audit effort focused on the balance sheet may constrain managers' earnings management choices which could increase the motive for managers to resort to classification shifting on the income statement. Additionally, since classification shifting does not alter the bottom line GAAP earnings it may be subject to less scrutiny by auditors (Nelson et al., 2002). However, it is also possible that Big N auditors may directly decrease classification shifting. If Big N auditors increase the overall quality of an audit, then it is likely Big N auditors would have a greater likelihood of discovering and mitigating the use of classification shifting. Accordingly, we formulate the following hypothesis in the null form:

H2a: *Other things being equal, firms audited by Big N audit firms are not associated with the likelihood of classification shifting.*

Similarly, Myers et al. (2003) document a significant and negative relation between AEM and auditor tenure after controlling for auditor type (Big 8 versus non-Big 8). They suggest that, on average, auditors place greater constraints on AEM as their relationship with the client lengthens. Based upon our previous discussion, we expect that as AEM is constrained, firms resort to more classification shifting. However, if auditors, through increased exposure to their client, become more knowledgeable about appropriate income statement classifications, then

audit tenure may also decrease classification shifting. Therefore, we present the following hypothesis in the null form:

H2b: *Other things being equal, firms with longer auditor tenure are not associated with the likelihood of classification shifting.*

Further, according to Cohen et al. (2008), AEM decreased after implementation of the Sarbanes-Oxley Act (SOX). This suggests that the increased regulation results in higher costs of AEM.⁴ Faced with these higher costs, managers may resort to alternative forms of earnings management. However, SOX also directly affected pro-forma reporting (Heflin and Hsu, 2008). Therefore, to the extent SOX increased the scrutiny of classificatory choices; the likelihood of detecting classification shifting is potentially higher post-SOX. Accordingly, we formulate the following hypothesis in the null form:

H2c: *Other things being equal, firms in the post-SOX period have no association with the likelihood of classification shifting.*

In addition to auditors and regulation, AEM is affected by accounting system flexibility (Zang, 2012). If firms have accounting systems that lack flexibility, they are less able to engage in AEM and focus on earnings management outside the confines of the accounting system. Classification shifting is implemented outside of the accounting system and therefore, may be a less costly option for managers. Therefore, our hypothesis is as follows:

H2d: *Other things being equal, firms with lower flexibility in their accounting system have a greater likelihood of classification shifting.*

The final constraint to AEM we investigate is the presence of a cash flow forecast. McInnis and Collins (2011) provide evidence that AEM declines following the provision of a cash flow forecast by analysts. The issuance of the cash flow forecast, in addition to the earnings

⁴ Regulation Fair Disclosure (Reg FD) became effective in 2000 and regulated the ability of companies to disseminate information to analysts (Gintschel and Markov, 2004). This increase in regulation in 2000, along with other regulation, could potentially confound the results of our test which focuses specifically on SOX regulation. We address this in the next section.

forecast, implicitly provides a forecast of operating accruals. According to McInnis and Collins (2011), the cash flow forecast increases the transparency and associated costs of AEM. As a result, managers may be more likely to use classification shifting to manage earnings. Therefore, we hypothesize the following:

H2e: *Other things being equal, firms with an analyst cash flow forecast have a greater likelihood of classification shifting.*

An important variation among earnings management strategies is the timing of when the different forms of manipulation are implemented by management. Bhojraj et al. (2009) and Zang (2012) highlight the importance of the timing of the earnings management strategies. The timing has an influence on which earnings management method is used by management. REM occurs within the period based on the nature of the manipulation. AEM happens after the end of the period but within the confines of the accounting system (i.e. before a company closes its books). However, classification shifting occurs after the end of the period but before the earnings announcement (McVay, 2006). Therefore, classification shifting can be used to complement REM and AEM to meet earnings targets, or to offset an overly impactful REM or AEM.

The third set of hypotheses addresses directly the effect of the timing difference on management's trade-off decision among the three forms of earnings management. As discussed previously, the timing of earnings management strategies is likely to be as follows: first, REM; second, AEM; and finally, classification shifting.⁵ Therefore, the timing of each earnings management strategy is potentially a key factor in determining its use by management. Zang (2012) provides support for the effect of the timing difference on management's trade-off decision between REM and AEM and suggests the two forms of earnings management are

⁵ The decision to use AEM or classification shifting is likely jointly determined subsequent to REM, which must be done within the accounting period.

substitutes. We extend Zang (2012) by investigating the relation between classification shifting and REM and also the relation between classification shifting and AEM.

REM occurs during the period because of the nature of the manipulation. However, the effect of REM cannot be precisely determined by management as it occurs. Therefore, if REM turns out to be unexpectedly high (low), managers may decrease (increase) the extent of both AEM and classification shifting. Therefore, we predict a negative relation between classification shifting and REM. Therefore, the hypothesis is stated as follows:

H3a: Other things being equal, the likelihood of classification shifting is negatively related to the unexpected amount of real earnings management.

REM occurs during the period and therefore is based on an estimate of the “necessary” earnings management. Both AEM and classification shifting occur after period-end when the “necessary” earnings management is more accurately known. As a result, if management chooses to use AEM to manipulate earnings, then management will be less likely to use classification shifting. Our final hypothesis is stated as follows:

H3b: Other things being equal, the likelihood of classification shifting is negatively related to the unexpected amount of accruals earnings management.

IV. SAMPLE AND RESEARCH METHODOLOGY

Data and Sample Selection

We obtain data for the years 1988 to 2011 from the annual Compustat North America Fundamental Industrial Annual File, CRSP, IBES and Thomson Reuters databases. Consistent with prior research; we exclude financial firms and utilities (Athanasakou et al., 2011). Each firm-year observation is required to have sufficient data to calculate variables in our models. Following McVay (2006) we eliminate firm-year observations from the sample for the following reasons: 1) annual sales less than \$1 million, 2) change in fiscal year-end during the year, or 3)

less than 15 observations within the industry-year. We base our industry classifications on Fama and French (1997). The full sample consists of 33,619 firm-year observations.

To further examine managers' trade-off decisions among classification shifting, REM, and AEM, we investigate a sample of earnings management suspect firms where the firms are in a setting with more incentive to manage earnings. That is, this sample focuses our tests on the trade-off decision among the three earnings management activities, rather than whether or not to engage in earnings management. Based on prior research (Roychowdhury, 2006; Zang, 2012) that assumes earnings management is likely to have occurred when reported earnings just met earnings benchmarks, we examine our hypotheses for a subsample of firms (suspect sample) that meets one of the following three criteria: 1) met analyst annual earnings per share forecast by two cents or less, 2) IBES reported positive earnings less than two cents per share, or 3) change from prior year IBES earnings was an increase of less than two cents per share. The suspect sample consists of 7,638 firm-year observations. Table 1 lists the variable definitions used in our analyses with Compustat codes.

Insert Table 1 Here

Research Methodology

We first estimate core earnings for each firm in our sample. Expected core earnings is predicted for each firm based on the McVay (2006) model.⁶ The following model is estimated for each industry-year:

$$CE_t = \beta_0 + \beta_1 CE_{t-1} + \beta_2 ATO_t + \beta_3 WCA_{t-1} + \beta_4 WCA_t + \beta_5 \Delta SALES_t + \beta_6 NEG_ \Delta SALES_t + \varepsilon_t \quad (1)$$

where CE_t is core earnings (sales minus both COGS and selling, general and administrative expenses) scaled by sales, ATO_t is asset turnover ratio, WCA is working capital accruals (change

⁶Consistent with Athanasakou et al. (2011), we replace current and prior year accruals with current and prior year working capital accruals (WCA).

in total current assets net of change in cash, minus change in current liabilities net of change in the current portion of long-term debt) scaled by total assets, $\Delta SALES_t$ is the percentage change in sales and ΔNEG_SALES_t is the percentage change in sales when the sales change is negative to allow for different slope coefficients for sales increases and decreases.

Next, unexpected core earnings ($UnCE_t$) is determined for each firm-year by subtracting the predicted core earnings from the estimation of equation (1) from the actual core earnings reported. We follow the methodology of Athanasakou et al. (2011) and classify firms as classification shifting firms ($CS = 1$) if their $UnCE$ is positive and IBES earnings per share is greater than GAAP net income per share. We follow Zang (2012) in the constraints to REM, AEM and control variables we include in the model. We use the following logit model of the probability that a firm is a classification shifting firm based on the constraints to REM and AEM, respectively:

$$\begin{aligned}
 (Prob\ CS_t=1) = & \alpha_0 + \alpha_1 TaxRate_{t-1} + \alpha_2 Zscore_{t-1} + \alpha_3 InstHoldings_{t-1} \\
 & + \alpha_4 MarketShare_{t-1} + \alpha_5 BigN_t + \alpha_6 LongTenure_t + \alpha_7 SOX_t \\
 & + \alpha_8 HighNOA_t + \alpha_9 OpCycle_{t-1} + \alpha_{10} CFO_Forecast_t \\
 & + \alpha_{11} LogAssets_{t-1} + \alpha_{12} ROA_{t-1} + \alpha_{13} MtB_t \\
 & + \alpha_{14} Inverse_Mills_t + \varepsilon_t
 \end{aligned} \tag{2}$$

The first set of hypotheses (H1a-H1d) investigates the relation between REM and classification shifting. $TaxRate_t$, our proxy for firms' effective tax rates, is calculated by dividing total taxes paid by pre-tax income.⁷ Based on H1a, we expect a positive and significant α_1 . $Zscore_t$ is the proxy used for firms' financial health and is measured as the modified version of Z-Score (Altman, 1968, 2000); lower values of $Zscore_t$ represent poorer financial health. $InstHoldings_t$ is the percent of institutional ownership, calculated as the number of shares held by institutions divided by total shares outstanding. Statistically significant coefficient estimates for

⁷ $TaxRate_t$ is constrained to be within of 0 to 100 percent of pre-tax income.

α_2 or α_3 reject the null hypotheses of H1b and H1c, respectively. Finally, $MarketShare_t$ is measured as a firm's percentage of industry sales and is calculated by dividing the firm's lagged sales total by the lagged industry (three-digit SIC code) sales total. A negative and significant coefficient on $MarketShare_t$ provides support for H1d.

The second set of hypotheses (H2a-H2e) investigates the constraints to AEM and how those constraints affect classification shifting. $BigN_t$ is an indicator variable that takes the value of one if the firm is audited by one of the Big N audit firms, and zero otherwise, while $LongTenure_t$ is an indicator variable that equals one if the firm has retained the auditor longer than the sample median of eight years, and zero otherwise (Zang 2012). We create an indicator variable (SOX_t) that takes the value of one if the fiscal year is after 2003, and zero otherwise.⁸ Statistically significant coefficient estimates for α_5 , α_6 or α_7 , reject the null hypotheses of H2a, H2b and H2c, respectively.

We include two proxies for the flexibility of a firm's accounting system, $HighNOA_t$ and $OpCycle_t$. Consistent with Zang (2012) and Fan et al. (2010), $HighNOA_t$ is an indicator variable that equals one if the net operating assets (NOA) at the beginning of the year divided by lagged sales is above the median of the corresponding industry-year, and zero otherwise.⁹ The length of a firm's operating cycle is the second proxy for accounting flexibility. $OpCycle_t$ is measured as days receivable plus the days in inventory at the beginning of the year, which is consistent with

⁸Another major regulatory change occurred in October 2000, with the introduction of Regulation Fair Disclosure (Reg FD), which prohibits firms from privately disclosing information to select audiences. We also analyze the tradeoff decision that managers face in the pre- and post-Reg FD periods. Our primary results are similar when we use Reg FD rather than SOX.

⁹Zang (2012) suggests that managers' capacity to manage accruals upward in the current period is constrained by accruals manipulation in previous periods. We use net operating assets (NOA) at the beginning of the year as a proxy for the extent of AEM in the previous periods (Barton and Simko, 2002). NOA is measured as shareholder's equity less cash and marketable securities plus total debt and minority interests (Hirshleifer et al., 2004; McVay, 2006).

Zang (2012).¹⁰ A positive (negative) and significant α_8 (α_9) is consistent with H2d. We create an indicator variable ($CFO_Forecast_t$) that takes the value of one if the firm has a cash flow forecast in IBES, and zero otherwise. Finally, we expect α_{10} to be positive and significant which is consistent with H2e.

Control variables are also included in the model. $LogAssets_{t-1}$ (calculated as the log value of lagged total assets) is included to control for relative firm size. ROA_{t-1} , computed as net income divided by total assets, provides a control for firm performance. Market-to-book ratio (MtB_t), measured as the log of market value of equity divided by book value of equity, is also included to control for firms' growth rates. Finally, the model includes both industry and year fixed effects. We estimate the model using both the full and the suspect samples. For the suspect sample, we include the inverse Mills ratio ($Inverse_Mills_t$) to control for potential sample selection bias.¹¹ We use independent variables from prior research that suggests capital market incentives dominate other incentives for meeting or beating earnings targets (Zang, 2012).

In the third set of hypotheses (H3a and H3b), we investigate the relation among the three forms of earnings management. We test the hypotheses by investigating the relation between classification shifting and unexpected REM and between classification shifting and unexpected AEM. First, we calculate the proxy for REM. Consistent with Zang (2012), our proxy for REM (REM_t) is the combined residuals from the following equations for discretionary expenses (decreases with REM) and production costs (increases with REM) (Roychowdhury, 2006):

$$DISEXP_t = \beta_0 + \beta_1(1/AT_{t-1}) + \beta_2(Sales_t/AT_{t-1}) + \varepsilon_t \quad (3)$$

$$PROD_t = \beta_0 + \beta_1(1/AT_{t-1}) + \beta_2(Sales_t/AT_{t-1}) + \beta_3(\Delta Sales_t/AT_{t-1}) + \beta_4(\Delta Sales_{t-1}/AT_{t-1}) + \varepsilon_t \quad (4)$$

¹⁰ Longer operating cycles provide firms with more flexibility in accruals because the accruals accounts are larger and the length of time for reversal of accruals is longer (Zang 2012).

¹¹ See Table 1 for the selection model.

where $DISEXP_t$ is discretionary expenditures (i.e., the sum of R&D, advertising, and SG&A expenditures) in year t , scaled by lagged assets; $Sales_t$ is net sales in year t ; and $PROD_t$ is the sum of COGS in year t plus the change in inventory from $t-1$ to t , all scaled by lagged assets. In order to create one measure of REM, the residuals from equation (3) are multiplied by negative one so that higher values indicate greater amounts of discretionary expenditure reduction by firms to increase earnings. Finally, the negative residual from equation (3) is added with the residual from equation (4) to create one proxy for REM (REM_t) (Zang, 2012).

Next, we calculate the proxy for AEM. Our proxy for accruals earnings management (AEM_t) is the estimated residuals from the following modified Jones (1991) model:

$$\begin{aligned} Accruals_t/AT_{t-1} = & \beta_0 + \beta_1(1/AT_{t-1}) + \beta_2(\Delta AdjustedSales_t/AT_{t-1}) \\ & + \beta_3(PPE_t/AT_{t-1}) + \beta_4(OpInc_t/AT_{t-1}) + \beta_5(\Delta OpCF_t/AT_{t-1}) \\ & + \beta_6Neg\Delta OpCF_t + \beta_7(\Delta OpCF_t/AT_{t-1}) * Neg\Delta OpCF_t + \varepsilon_t \end{aligned} \quad (5)$$

where $Accruals_t$ is the earnings before extraordinary items minus the cash flows from operations reported in the statement of cash flows in year t ; AT_{t-1} is the total assets in year $t-1$;

$\Delta AdjustedSales_t$ is the change in net sales from $t-1$ to t less the change in accounts receivable from $t-1$ to t ; and PPE_t is the gross property, plant and equipment at year t ; $OpInc_t$ is operating income before depreciation; $\Delta OpCF_t$ is the change in cash flows from operations reported in the statement of cash flows from year $t-1$ to t ; $Neg\Delta OpCF_t$ is an indicator variable that takes the value of one if $\Delta OpCF_t$ is less than zero.

Finally, we calculate unexpected REM ($UnREM_t$) and unexpected AEM ($UnAEM_t$) as the residuals from the following two equations, respectively:

$$\begin{aligned} REM_t = & \beta_0 + \beta_1TaxRate_{t-1} + \beta_2Zscore_{t-1} + \beta_3InstHoldings_{t-1} + \beta_4MarketShare_{t-1} \\ & + \beta_5BigN_t + \beta_6LongTenure_t + \beta_7HighNOA_t + \beta_8OpCycle_{t-1} \\ & + \beta_9CFO_Forecast_t + \beta_{10}LogAssets_{t-1} + \beta_{11}ROA_{t-1} + \beta_{12}MtB_t + \beta_{13}Earn_t \\ & + \beta_{14}Inverse_Mills_t + \varepsilon_t \end{aligned} \quad (6)$$

$$AEM_t = \beta_0 + \beta_1TaxRate_{t-1} + \beta_2Zscore_{t-1} + \beta_3InstHoldings_{t-1} + \beta_4MarketShare_{t-1}$$

$$\begin{aligned}
& + \beta_5 \text{BigN}_t + \beta_6 \text{LongTenure}_t + \beta_7 \text{HighNOA}_t + \beta_8 \text{OpCycle}_{t-1} + \beta_9 \text{CFO_Forecast}_t \\
& + \beta_{10} \text{LogAssets}_{t-1} + \beta_{11} \text{ROA}_{t-1} + \beta_{12} \text{MtB}_t + \beta_{13} \text{UnREM}_t + \beta_{14} \text{PredREM}_t \\
& + \beta_{15} \text{Inverse_Mills}_t + \varepsilon_t
\end{aligned} \tag{7}$$

Each model includes earnings management constraint variables for both REM and AEM.¹² We also include control variables: *LogAssets*_{t-1}, *ROA*_{t-1}, *MtB*_t and *Inverse_Mills*_t. Consistent with Zang (2012), in equation (6), we include pre-managed earnings (*Earn*_t) to control for the goal of managing earnings. *Earn* is measured as the earnings before extraordinary items, minus discretionary accruals and production costs, plus discretionary expenditures. In equation (7), *Earn*_t is replaced by unexpected (*UnREM*_t) and predicted (*PredREM*_t) REM, which are determined from the estimation of equation (6).

The third set of hypotheses is tested by adding the variables *UnREM*_t and *UnAEM*_t to model (2) above as follows:

$$\begin{aligned}
(\text{Prob } CS_t=1) = & \alpha_0 + \alpha_1 \text{UnREM}_t + \alpha_2 \text{UnAEM}_t + \alpha_3 \text{TaxRate}_{t-1} + \alpha_4 \text{Zscore}_{t-1} \\
& + \alpha_5 \text{InstHoldings}_{t-1} + \alpha_6 \text{MarketShare}_{t-1} + \alpha_7 \text{BigN}_t + \alpha_8 \text{LongTenure}_t \\
& + \alpha_9 \text{SOX}_t + \alpha_{10} \text{HighNOA}_t + \alpha_{11} \text{OpCycle}_{t-1} + \alpha_{12} \text{CFO_Forecast}_t \\
& + \alpha_{13} \text{LogAssets}_{t-1} + \alpha_{14} \text{ROA}_{t-1} + \alpha_{15} \text{MtB}_t + \alpha_{16} \text{PredREM}_t \\
& + \alpha_{17} \text{PredAEM}_t + \alpha_{18} \text{Inverse_Mills}_t + \varepsilon_t
\end{aligned} \tag{8}$$

A negative and significant coefficient on α_1 and α_2 provide support for H3a and H3b, respectively.

V. RESULTS

Table 2 provides descriptive statistics for the variables used in the empirical analysis. The descriptive statistics are for the full sample of firms, which includes 33,619 firm year observations from 1988-2011. Twenty-one percent of our sample firms are classified as classification shifters (*CS*= 0.210), which is the dependent variable for our primary tests tabulated on Tables 4 and 5. Eighty-eight percent of the sample was audited by *Big N* public

¹² We exclude *SOX* from both equations because the models are estimated by industry-year.

accounting firms ($BigN = 0.880$) and nearly half of the firm year observations occurred during the Post-SOX era ($SOX = 0.497$). The average length of the operating cycle ($OpCycle$) is 128.362 days. Finally, the average size ($LogAssets$) of the full sample is 6.138. The descriptive statistics for the suspect sample are similar in size and distribution to the full sample and are therefore excluded for brevity.¹³ The suspect sample includes 7,638 firm year observations that: 1) met analyst annual earnings per share forecast by two cents or less, 2) IBES reported positive earnings less than two cents per share, or 3) change from prior year IBES earnings was increase of less than two cents per share.

Insert Table 2 Here

Prior to implementing the multivariate regression analysis, we examine the Pearson correlations among the variables used in the regression analysis. The correlation matrix for the full sample is reported in Table 3; the correlation matrix for the suspect sample is quite similar and therefore not tabulated for brevity. Significant correlation coefficients are shown in **bold**. The positive and significant correlation coefficient (0.458) between $CFO_Forecast$ and SOX suggests firms are more likely to issue a cash flow forecast subsequent to SOX. The positive and significant correlation coefficient (0.405) between $LogAssets$ and $MarketShare$ is consistent with larger firms having a greater industry market share. The positive and significant correlation coefficient (0.544) between $LogAssets$ and $CFO_Forecast$ indicates larger firms are more likely to issue a cash flow forecast. Finally, the negative and significant correlation coefficient (-0.407) between $PredREM$ and MtB suggests growth firms are less likely to use REM to manage earnings. The correlation statistics indicate that the correlation coefficients are not large enough to prohibit the use of a multivariate regression analysis.

¹³ In addition, the descriptive statistics for our full sample and suspect sample are similar in size and distribution to prior research (McVay 2006; Zang, 2012).

Insert Table 3 Here

The results from our multivariate analyses used to test Hypotheses 1 and 2 are presented in Table 4. Our first set of hypotheses (H1a – H1d) examines constraints associated with the trade-off decision made by management to manipulate earnings. Column 1 of Table 4 presents the results from estimating equation (2) for the full sample of firms. The coefficient of -0.0581 on *TaxRate* is not significant at conventional levels ($z=-0.65$) which fails to provide support for H1a. However, the negative and significant coefficient of 0.010 on *Zscore* ($z=-3.38$) suggests that firms constrained from engaging in REM because of poor financial condition resort to classification shifting, which rejects the null hypothesis for H1b of no association. The coefficient of 0.422 on *InstHolding* is positive and significant ($z=6.61$), which rejects the null hypothesis of H1c and suggests that firms constrained from engaging in REM because of monitoring from institutional investors are more likely to resort to classification shifting. This also provides support for the long-term focus of sophisticated institutional investors suggesting that they are concerned with the negative future implications of REM. Finally, the coefficient on *MarketShare* is negative (-0.597) and significant ($z=-3.77$), which is consistent with our prediction for H1d. Taken together, these results provide evidence of increased classification shifting when REM is constrained for our full sample of firms. Specifically, when REM is constrained by poor financial condition, higher scrutiny from institutional shareholders, and lower industry market share, firms resort to classification shifting.

Insert Table 4 Here

Our second set of hypotheses (H2a – H2e) investigates the trade-off decision made between AEM and classification shifting. The coefficient on *BigN* is not statistically significant ($z=1.19$), which supports the null hypothesis of H2a. However, the coefficient on *LongTenure* is

negative (-0.068) and statistically significant ($z=-2.05$), which rejects the null hypothesis of H2b. These results suggest that while higher quality auditors may constrain AEM, this does not lead to an increase in the use of classification shifting. In fact, our evidence suggests that longer auditor tenure actually acts to constrain classification shifting.

We document an insignificant coefficient ($z=0.031$) on *SOX*, which suggests that increased regulation surrounding financial reporting decreased managers' capacity to use AEM had no effect on firms use of classification shifting.¹⁴ The coefficient on *HighNOA* is positive and statistically significant (coefficient=0.190; $z=5.68$). However, the coefficient on *OpCycle* is not statistically different from zero ($z=1.47$). Therefore, we provide support for H2d for the full sample of firms when *HighNOA* is used as a proxy for accounting system flexibility, but not when using *OpCycle*. Finally, the coefficient on *CFO_Forecast* is positive and significant (coefficient=0.177; $z=4.19$), which provides support for H2e. These results suggest that managers use classification shifting as a substitute for AEM. Specifically, when AEM is constrained by high NOA and the presence of a cash flow forecast, firms are more likely to use classification shifting.

Column 2 of Table 4 presents the results from our multivariate analyses when we limit the sample to firms that just met or beat an earnings benchmark (suspect sample). We test our hypotheses using the suspect sample because it provides a setting where firms have greater incentive to manage earnings and provides a more direct test of the trade-off among earnings management strategies, rather than the decision of whether to engage in earnings management. Therefore, we anticipate finding results consistent with the full sample. Consistent with results from the full sample, the coefficient on *TaxRate* is not statistically significant ($z=-0.40$). The

¹⁴ As mentioned previously, the inability to reject the null hypothesis H2c may also be a result of the confounding effects of other regulation that was effective before SOX (i.e., Reg FD).

negative and significant coefficient of 0.012 on *Zscore* ($z=-2.31$) suggests that firms constrained from engaging in REM because of poor financial condition resort to classification shifting. The coefficient of 0.325 on *InstHolding* is positive and significant ($z=2.32$), while the coefficient on *MarketShare* is negative and significant (coefficient -0.971; $z=-3.09$), which is consistent with our expectations. Taken together, for our suspect sample, when REM is constrained by poor financial condition, higher scrutiny from institutional shareholders, and lower industry market share, firms resort to classification shifting. These results are similar to and consistent with results from the full sample of firms.

Turning to our investigation into the trade-off decision made between AEM and classification shifting for suspect firms, we find no significant coefficient on *BigN* ($z=-0.83$), *LongTenure* ($z=-1.24$), or *SOX* ($z=0.24$). The results fail to reject the null hypotheses for H2a, H2b, and H2c for our suspect sample. For the results of our investigation into accounting system flexibility and classification shifting, the coefficient on *HighNOA* is positive (0.167) and statistically significant ($z=2.57$), which is consistent with our results for the full sample of firms. However, the coefficient on *OpCycle* is positive and statistically significant (coefficient=0.001; $z=2.07$), which is opposite our expectations.¹⁵ Therefore, we continue to provide support for H2d for our suspect sample when *HighNOA* is used to proxy for accounting system flexibility, but not when using *OpCycle*. Finally, the coefficient on *CFO_Forecast* is positive and significant (coefficient=0.175; $z=2.08$), which provides support for H2e for the suspect sample. Consistent with results from the full sample of firms, the results for the suspect sample suggest that managers are more likely to use classification shifting when AEM is constrained by high NOA and the presence of a cash flow forecast.

¹⁵ Long operating cycles could indicate exhausted accounting flexibility. In this case, the association between *OpCycle* and classification shifting may not be linear, which could explain this result.

Unexpected REM and AEM

Table 5 presents the results from our multivariate analyses used to test H3. Column 1 of Table 5 presents the results of equation (8) for the full sample of firms. The coefficient on *UnREM* is negative and significant (coefficient=-0.266; $z=-4.63$) suggesting that firms with unexpectedly high REM are less likely to engage in classification shifting. This result provides support for H3a. Furthermore, the negative and significant coefficient of 1.751 on *UnAEM* ($z=-8.32$) suggests that firms with unexpectedly high AEM are also less likely to resort to classification shifting, which is consistent with H3b.

Insert Table 5 Here

Limiting our sample to only suspect firms produces similar results. Specifically, Column 2 of Table 5 presents the results from Equation (8) for our suspect sample. For the suspect sample, the coefficient on *UnREM* is negative and significant (coefficient=-0.541; $z=-3.64$) and the coefficient on *UnAEM* is -1.759 ($z=-2.57$) which provides further support that firms are less likely to resort to classification shifting when REM and AEM are unexpectedly high.

In addition, the control variables *PredREM* and *PredAEM* are also included in Table 5. The coefficients for both variables are negative and significant in both columns. Zang (2012) finds a positive association between AEM and predicted REM which suggests the two forms of earnings management are often used jointly to manage earnings. Zang (2012) also documents a negative relation between unexpected REM and AEM which also suggests AEM is used by management to offset overly impactful REM. Our results suggest a substitutive association between classification shifting and the other two forms of earnings management (AEM and REM). The negative coefficients on *PredREM* and *PredAEM* suggest firms likely use classification shifting as a substitute for *both* AEM and REM. This is also supported by a

negative relation between both *UnREM* and *UnAEM*, and classification shifting. Therefore, firms are less likely to use classification shifting in conjunction with AEM and REM. This result is intuitive in that classification shifting is a GAAP violation. Therefore, if firms can meet earnings thresholds using earnings management techniques that do not violate GAAP, they will choose to do so.

Together, the analysis suggests the importance of understanding the costs and constraints of each form of earnings management. In particular, if the costs of AEM or REM are high, managers may resort to using classification shifting to manage earnings. Our results provide evidence supporting an increase in the use of classification shifting when REM is constrained by poor financial condition, higher scrutiny from institutional shareholders, and lower industry market share. The results suggest an increase in the attention placed on a firm's optimal decision making and long-term performance lead to an increase in classification shifting. These firms are less likely to use REM which may result in a decrease in future operating performance. In addition, we provide support for an increase in the use of classification shifting when AEM is constrained by high NOA and the presence of a cash flow forecast. However, audit and regulatory constraints do not appear to affect the use of classification shifting. These findings suggest auditors and regulators potentially constrain both AEM and classification shifting.

Our results also suggest a substitute relation between classification shifting and the two other forms of earnings management (AEM and REM). That is, managers that use REM and AEM to manage earnings are less likely to use classification shifting. Therefore, a potential unintended consequence of constraining REM and AEM could be an increase in the use of classification shifting.

VI. CONCLUSION

Prior literature has investigated three main forms of earnings manipulation: AEM, REM, and classification shifting. However, the literature has not investigated all three earnings management strategies simultaneously with cost and constraint considerations. An essential facet of earnings management is the trade-off decision made by management between the different strategies. It is important to understand why managers choose different earnings management strategies. Accordingly, the objective of this study is to examine the costs, constraints, and timing associated with REM and AEM and the corresponding effect on classification shifting.

In her study, Zang (2012) investigates the trade-off decision made by management between AEM and REM based on the costs and constraints of each earnings management strategy. She provides evidence that REM and AEM are substitutes for one another. However, her study does not consider earnings management through classification shifting. We extend her study by including classification shifting as an earnings management strategy. Such an investigation into classification shifting is important because classification shifting can mislead investors about firm performance and distort valuation (Alfonso et al., 2013).

Based on the relative constraints of the different earnings management strategies, we find evidence consistent with increased use of classification shifting when REM is constrained. Specifically, we show that when REM is constrained by poor financial performance, high institutional ownership, and low industry market share, managers are more likely to resort to classification shifting. Further, we hypothesize and find a positive relation between classification shifting and specific costs of AEM including accounting system flexibility and analyst issuance of cash flow forecasts. When the sample includes only firms that are most likely to manipulate earnings (suspect firms), we continue to find support for constraints of both REM and AEM (poor financial health, high institutional ownership, low accounting system flexibility, and

issuance of cash flow forecasts) leading to greater likelihood of classification shifting. Finally, we examine the effect of the timing of the different earnings management strategies on the use of classification shifting. Our results suggest firms use classification shifting as a substitute for both REM and AEM.

Our study provides multiple contributions. First, we investigate the trade-off decision managers make among earnings management strategies by investigating all three (AEM, REM, and classification shifting) earnings management methods in our analysis. Second, our results provide evidence that when managers are constrained from using REM, they are more likely to use classification shifting to increase core earnings. Third, we find that when a firm's ability to use accruals to manage earnings is constrained in certain settings, they turn to shifting items within the income statement to increase core earnings. However, all AEM constraints do not indirectly increase classification shifting; we do not find evidence of more classification shifting for AEM constraints that are most directly related to improved financial reporting quality (i.e., Big N auditors, long tenured auditors and regulation). Finally, our results provide support for a substitute relation between *both* REM and AEM, and classification shifting. The findings of this study should be of interest to accounting standards-setting bodies, auditors, and investors, because they highlight the importance of an awareness of classification issues in addition to other forms of earnings manipulation.

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TABLE 1
Variable Definitions with Corresponding Compustat Codes

Variable	Definition
<i>AEM</i>	Accruals Earnings Management, calculated as the residual from modified Jones model: $Accruals_t/AT_{t-1} = \beta_0 + \beta_1(1/AT_{t-1}) + \beta_2(\Delta AdjSALES_t/AT_{t-1}) + \beta_3(PPE/AT_{t-1}) + \beta_4(OpInc_t/AT_{t-1}) + \beta_5(\Delta OpCF_t/AT_{t-1}) + \beta_6 Neg\Delta OpCF_t + \beta_7(\Delta OpCF_t/AT_{t-1}) * Neg\Delta OpCF_t + \varepsilon_{i,t}$ <i>Accruals</i> is income before extraordinary items (IBC – (OANCF – XIDOC)); <i>AT</i> is total assets (AT); $\Delta AdjSALES$ is change in adjusted sales (SALE _t – SALE _{t-1} – RECT _t + RECT _{t-1}); <i>PPE</i> is gross property, plant and equipment (PPEGT); <i>OpInc</i> is operating income before depreciation (OIBDP); $\Delta OpCF$ is change in operating cash flows (OANCF); <i>Neg</i> $\Delta OpCF$ is indicator variable equal to one when $\Delta OpCF$ is negative.
<i>BigN</i>	Big N Auditor, which is an indicator variable equal to one when the firm is audited by a Big N audit firms and zero otherwise.
<i>CE</i>	Core Earnings (before Special Items and Depreciation), calculated as (Sales - Cost of Goods Sold - Selling, General, and Administrative Expenses) /Sales, where Cost of Goods Sold and Selling, General, and Administrative Expenses exclude Depreciation and Amortization, as determined by Compustat: (OIBDP /SALE).
<i>CFO_Forecast</i>	Cash Flow from Operations Forecast, which is an indicator variable equal to one when the firm has cash flow forecasts in IBES and zero otherwise.
<i>CS</i>	Classification Shifting firm, which is indicator variable equal to one when UnCE (from equation (1)) is positive and IBES earnings per share is greater than GAAP net income per share (Athanasakou et al. 2011) and zero otherwise.
<i>HighNOA_t</i>	High Net Operating Assets, which is an indicator variable equal to one when beginning of the year NOA is greater than the industry median; zero otherwise. NOA is shareholder's equity less cash and marketable securities plus total debt: NOA = (SEQ - CHE + DLTT + DLC) / SALE.
<i>InstHoldings</i>	Institutional Ownership, calculated as the number of shares held by institutions divided by total shares outstanding.
<i>Inverse_Mills</i>	Inverse Mills ratio calculated from the following equation (Zang 2012): $JustBeat_t = \beta_0 + \beta_1 NumberBeat_t + \beta_2 Issue_{t+1} + \beta_3 MtB_{t-1} + \beta_4 Shares_t + \beta_5 AF_t + \beta_6 ROA_{t-1} + YearIndicators + \varepsilon_t$ <i>NumberBeat</i> is number of times in the previous three years that firm met an earnings benchmark: analyst forecast consensus, non-negative EPS or prior year EPS; <i>Issue</i> is indicator variable equal to 1 if firm issues equity during fiscal year (CSHI > 0), and 0 otherwise; <i>MtB</i> is market to book ratio calculated as natural log of (market value of equity (PRCC_F * CSHO) divided by book value of equity (CEQ)); <i>Shares</i> is natural log of the number of shares outstanding (CSHO); <i>AF</i> is natural log of the number of analysts following the firm; <i>ROA</i> is return on assets calculated as net income scaled by total assets (NI / AT).
<i>LogAssets</i>	Log of Assets, calculated as log of total assets (AT).
<i>LongTenure_t</i>	Long Tenured Auditor, which is an indicator variable equal to one when audit tenure is more than eight years (sample median for audit tenure) and zero otherwise.
<i>MarketShare</i>	Firm's percentage of its industry's sales, calculated as the firm's sales total divided by the industry (three-digit SIC code) sales total.
<i>MtB</i>	Natural log of the Market to Book ratio, which is a control variable for growth and calculated as log (market value of equity (PRCC_F * CSHO) divided by book value of equity (CEQ)).
<i>OpCycle</i>	Operating Cycle, calculated as the days receivable plus days in inventory at the beginning of the year.
<i>PredAEM</i>	Predicted Accruals Earnings Management, calculated from the following equation (7) that regresses AEM on REM constraints, AEM constraints, and control variables: $AEM_t = \beta_0 + \beta_1 TaxRate_{t-1} + \beta_2 Zscore_{t-1} + \beta_3 InstHoldings_{t-1} + \beta_4 MarketShare_{t-1} + \beta_5 BigN_t + \beta_6 LongTenure_t + \beta_7 HighNOA_t + \beta_8 OpCycle_{t-1} + \beta_9 CFO_Forecast_t + \beta_{10} LogAssets_{t-1} + \beta_{11} ROA_{t-1} + \beta_{12} MtB_t + \beta_{13} UnREM_t + \beta_{14} PredREM_t + \beta_{15} Inverse_Mills_t + \varepsilon_t$

Table 1 (Continued)

<i>PredREM</i>	<p>Predicted Real Earnings Management, calculated from the following equation (6) that regresses REM on REM constraints, AEM constraints, and control variables:</p> $REM_t = \beta_0 + \beta_1 TaxRate_{t-1} + \beta_2 Zscore_{t-1} + \beta_3 InstHoldings_{t-1} + \beta_4 MarketShare_{t-1} + \beta_5 BigN_t + \beta_6 LongTenure_t + \beta_7 HighNOA_t + \beta_8 OpCycle_{t-1} + \beta_9 CFO_Forecast_t + \beta_{10} LogAssets_{t-1} + \beta_{11} ROA_{t-1} + \beta_{12} MtB_t + \beta_{13} Earn_t + \beta_{14} Inverse_Mills_t + \varepsilon_t.$
<i>REM</i>	<p>Real Earnings Management; estimated from Roychowdhury (2006) regressions for discretionary expenses and production costs. $REM_t =$ - equation (3) residual + equation (4) residual</p> $DISEXP_t = \beta_0 + \beta_1(1/AT_{t-1}) + \beta_2(Sales_t/AT_{t-1}) + \varepsilon_t \quad (3)$ $PROD_t = \beta_0 + \beta_1(1/AT_{t-1}) + \beta_2(Sales_t/AT_{t-1}) + \beta_3(\Delta Sales_t/AT_{t-1}) + \beta_4(\Delta Sales_{t-1}/AT_{t-1}) + \varepsilon_t \quad (4)$ <p>$PROD_t$ is production costs: Cost of goods sold (COGS) + change in inventory (INVT_t - INVT_{t-1}), scaled by lagged assets (AT_{t-1}); $Sales_t$ is sales total (SALE_t); $\Delta Sales_t$ is annual change in sales (SALE_t - SALE_{t-1}).</p>
<i>ROA</i>	Return on Assets, which is calculated as net income (NI) divided by total assets (AT).
<i>SOX</i>	Post-Sarbanes-Oxley Period, which is an indicator variable equal to one for fiscal years after 2003 and zero otherwise.
<i>TaxRate</i>	The firm's tax rate, calculated as total taxes paid divided by pre-tax net income (TXT/PI) and constrained to be between 0 and 100 percent.
<i>UnAEM</i>	<p>Unexpected Accruals Earnings Management, calculated as the residual from the following equation (7) that regresses AEM on REM constraints, AEM constraints, and control variables:</p> $AEM_t = \beta_0 + \beta_1 TaxRate_{t-1} + \beta_2 Zscore_{t-1} + \beta_3 InstHoldings_{t-1} + \beta_4 MarketShare_{t-1} + \beta_5 BigN_t + \beta_6 LongTenure_t + \beta_7 HighNOA_t + \beta_8 OpCycle_{t-1} + \beta_9 CFO_Forecast_t + \beta_{10} LogAssets_{t-1} + \beta_{11} ROA_{t-1} + \beta_{12} MtB_t + \beta_{13} UnREM_t + \beta_{14} PredREM_t + \beta_{15} Inverse_Mills_t + \varepsilon_t.$
<i>UnCE</i>	<p>Unexpected Core Earnings is the difference between reported and predicted Core Earnings, where the predicted value is calculated using the coefficients from model (1) estimated by fiscal year and industry as follows:</p> $CE_t = \beta_0 + \beta_1 CE_{t-1} + \beta_2 ATO_t + \beta_3 WCA_{t-1} + \beta_4 WCA_t + \beta_5 \Delta SALES_t + \beta_6 NEG_ \Delta SALES_t + \varepsilon_t.$ <p>CE is Core Earnings, calculated as (Sales - Cost of Goods Sold - Selling, General, and Administrative Expenses) / Sales (OIBDP / SALE). Note: Cost of Goods Sold and Selling, General, and Administrative Expenses exclude Depreciation and Amortization; ATO is Asset Turnover Ratio, defined as $SALE_t / ((NOA_t + NOA_{t-1}) / 2)$. Net operating assets are required to be positive. NOA is shareholder's equity less cash and marketable securities plus total debt plus minority interests. $NOA = (SEQ - CHE + DLTT + DLC + MIB)$; WCA is Working capital accruals scaled by lagged assets, calculated as (change in total current assets (ACT) net of change in cash (CHE), minus change in current liabilities (LCT) net of change in the current portion of long-term debt (DLC)) / lagged total assets (AT); $\Delta Sales$ is percent Change in Sales, calculated as $(SALE_t - SALE_{t-1}) / SALE_{t-1}$; $Neg_ \Delta Sales$ is negative percent change in sales, calculated as $\Delta SALES_t$ if $\Delta SALES_t$ is negative and zero otherwise.</p>
<i>UnREM</i>	<p>Unexpected Real Earnings Management, calculated as the residual from the following equation (6) that regresses REM on REM constraints, AEM constraints, and control variables:</p> $REM_t = \beta_0 + \beta_1 TaxRate_{t-1} + \beta_2 Zscore_{t-1} + \beta_3 InstHoldings_{t-1} + \beta_4 MarketShare_{t-1} + \beta_5 BigN_t + \beta_6 LongTenure_t + \beta_7 HighNOA_t + \beta_8 OpCycle_{t-1} + \beta_9 CFO_Forecast_t + \beta_{10} LogAssets_{t-1} + \beta_{11} ROA_{t-1} + \beta_{12} MtB_t + \beta_{13} Earn_t + \beta_{15} Inverse_Mills_t + \varepsilon_t.$
<i>Zscore</i>	<p>Altman's Z-Score, calculated as modified version of Z-score (Altman 1968, 2000).</p> $ZSCORE = 3.3 * (NI/AT) + 1.0 * (SALE/AT) + 1.4 * (RE/AT) + 1.2 * (WCAP/AT) + 0.6 * (CSHO * PRCC_F/LT).$

TABLE 2
Descriptive Statistics

Variable	N	Mean	Standard Deviation	25%	Median	75%
<i>CS_t</i>	33,619	0.210	0.408	0.000	0.000	0.000
<i>TaxRate_{t-1}</i>	33,619	0.277	0.187	0.128	0.330	0.380
<i>Zscore_{t-1}</i>	33,619	5.525	6.623	2.314	3.791	6.342
<i>InstHoldings_{t-1}</i>	33,619	0.533	0.297	0.283	0.553	0.784
<i>MarketShare_{t-1}</i>	33,619	0.063	0.135	0.001	0.008	0.051
<i>BigN_t</i>	33,619	0.880	0.325	1.000	1.000	1.000
<i>LongTenure_t</i>	33,619	0.448	0.497	0.000	0.000	1.000
<i>SOX_t</i>	33,619	0.497	0.500	0.000	0.000	1.000
<i>HighNOA_{t-1}</i>	33,619	0.495	0.500	0.000	0.000	1.000
<i>OpCycle_{t-1}</i>	33,619	128.362	80.183	72.172	113.374	164.759
<i>CFO_Forecast_t</i>	33,619	0.386	0.487	0.000	0.000	1.000
<i>LogAssets_{t-1}</i>	33,619	6.138	1.915	4.728	5.973	7.413
<i>ROA_{t-1}</i>	33,619	0.024	0.149	0.005	0.050	0.092
<i>MtB_t</i>	33,619	0.792	0.763	0.292	0.755	1.249
<i>PredREM_t</i>	33,619	0.003	0.230	-0.117	0.009	0.129
<i>PredAEM_t</i>	33,619	0.001	0.041	-0.021	0.000	0.022
<i>UnREM_t</i>	33,619	0.000	0.284	-0.135	0.004	0.143
<i>UnAEM_t</i>	33,619	0.000	0.069	-0.029	0.001	0.032
<i>CE_t</i>	33,619	0.110	0.241	0.060	0.121	0.197

Notes:

Table 2 presents the descriptive statistics for the full sample, which covers the period 1988–2011, and meets the sample selection criteria. Table 1 defines the variables.

TABLE 3
Pearson Correlation Matrix

	<i>CS_t</i>	<i>TaxRate_{t-1}</i>	<i>Zscore_{t-1}</i>	<i>InstHoldings_{t-1}</i>	<i>MarketShare_{t-1}</i>	<i>BigN_t</i>	<i>LongTenure_t</i>	<i>SOX_t</i>	<i>HighNOA_{t-1}</i>	<i>OpCycle_{t-1}</i>	<i>CFO_Forecast_t</i>	<i>LogAssets_{t-1}</i>	<i>ROA_{t-1}</i>	<i>MtB_t</i>	<i>PredREM_t</i>	<i>PredAEM_t</i>	<i>UnREM_t</i>
<i>TaxRate_{t-1}</i>	-0.017																
<i>Zscore_{t-1}</i>	-0.045	0.021															
<i>InstHoldings_{t-1}</i>	0.078	0.136	0.018														
<i>MarketShare_{t-1}</i>	0.011	0.133	-0.097	0.129													
<i>BigN_t</i>	0.053	0.087	-0.021	0.172	0.114												
<i>LongTenure_t</i>	0.023	0.080	-0.068	0.213	0.160	0.200											
<i>SOX_t</i>	0.012	-0.107	-0.087	0.315	0.035	-0.162	0.070										
<i>HighNOA_{t-1}</i>	0.064	-0.016	-0.077	0.019	-0.014	-0.002	-0.010	0.002									
<i>OpCycle_{t-1}</i>	0.013	-0.106	0.060	-0.087	-0.096	-0.031	0.007	-0.103	0.199								
<i>CFO_Forecast_t</i>	0.082	-0.002	-0.077	0.332	0.135	0.108	0.110	0.458	0.068	-0.131							
<i>LogAssets_{t-1}</i>	0.132	0.153	-0.191	0.383	0.405	0.265	0.260	0.276	0.114	-0.147	0.544						
<i>ROA_{t-1}</i>	-0.059	0.346	0.257	0.161	0.102	0.039	0.104	0.023	-0.072	-0.121	0.093	0.192					
<i>MtB_t</i>	0.024	-0.035	0.262	0.075	0.029	0.055	0.012	-0.014	-0.157	-0.003	0.078	0.033	0.060				
<i>PredREM_t</i>	-0.004	0.070	-0.206	-0.063	0.067	-0.104	-0.018	0.003	0.213	-0.145	-0.016	0.100	0.014	-0.407			
<i>PredAEM_t</i>	-0.048	-0.079	-0.015	-0.094	0.002	-0.053	0.008	-0.019	-0.015	0.101	-0.049	-0.033	-0.031	-0.051	0.040		
<i>UnREM_t</i>	-0.034	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.001	-0.002	0.004	0.211	
<i>UnAEM_t</i>	-0.044	-0.001	0.002	-0.001	0.000	-0.001	-0.001	0.000	0.002	0.000	0.000	0.000	-0.001	-0.003	0.003	0.003	0.000

Notes:

Table 1 defines the variables. Table 3 presents the Pearson correlations among regression variables for full sample (33,619 firm-year observations) during the period 1988–2011 that meet the sample selection criteria. Amounts in bold are significant at the 0.05 level.

TABLE 4
Logistic Analysis of the Probability of Classification Shifting Based on
Real and Accruals Earnings Management Constraints

<i>Variable</i>	<i>Predicted Sign</i>	<i>(1)</i> <i>Full Sample</i> <i>Coefficient</i> <i>(z-statistic)</i>	<i>(2)</i> <i>Suspect Sample</i> <i>Coefficient</i> <i>(z-statistic)</i>
<i>Intercept</i>		-3.129*** (-17.85)	-3.995*** (-4.68)
<i>TaxRate</i> _{<i>t-1</i>}	+	-0.0581 (-0.65)	-0.07 (-0.40)
<i>Zscore</i> _{<i>t-1</i>}	+/-	-0.010*** (-3.38)	-0.012** (-2.31)
<i>InstHoldings</i> _{<i>t-1</i>}	+/-	0.422*** (6.61)	0.325** (2.32)
<i>MarketShare</i> _{<i>t-1</i>}	-	-0.597*** (-3.77)	-0.971*** (-3.09)
<i>BigN</i> _{<i>t</i>}	+/-	0.0713 (1.19)	-0.090 (-0.83)
<i>LongTenure</i> _{<i>t</i>}	+/-	-0.068** (-2.05)	-0.083 (-1.24)
<i>SOX</i> _{<i>t</i>}	+/-	0.042 (0.31)	0.086 (0.24)
<i>HighNOA</i> _{<i>t-1</i>}	+	0.190*** (5.68)	0.167*** (2.57)
<i>OpCycle</i> _{<i>t-1</i>}	-	0.000 (1.47)	0.001** (2.07)
<i>CFO_Forecast</i> _{<i>t</i>}	+	0.177*** (4.19)	0.175** (2.08)
<i>LogAssets</i> _{<i>t-1</i>}		0.213*** (16.17)	0.243*** (9.30)
<i>ROA</i> _{<i>t-1</i>}		-1.241*** (-10.94)	-1.116*** (-4.84)
<i>MtB</i> _{<i>t</i>}		0.087*** (3.94)	0.191** (3.05)
<i>Inverse_Mills</i> _{<i>t</i>}			0.456 (1.09)
Industry Indicator Variables		Yes	Yes
Year Indicator Variables		Yes	Yes
Log likelihood		-16,459.82	-3,733.48
Chi-square		1105.75	387.86
p-value		<.0001	<.0001
Correctly classified		65.0%	66.8%
Number of observations		33,619	7,638

Notes: Table 4 presents the results of estimating equation (2) for the sample firms:

$$(Prob\ CS_t=1) = \alpha_0 + \alpha_{1-4}REM\ Constraints + \alpha_{5-10}AEM\ Constraints + \alpha_{11-14}Controls + \varepsilon_t$$

See Table 1 for variable definitions and calculations. *, **, and *** denote statistical significance at 10%, 5%, and 1% percent, respectively. Significance tests are one-tailed for variables with a predicted sign; and two-tailed otherwise.

TABLE 5
Logistic Analysis of the Probability of Classification Shifting Based on
Unexpected Real and Accruals Earnings Management

<i>Variable</i>	<i>Predicted Sign</i>	<i>(1)</i> <i>Full Sample</i> <i>Coefficient</i> <i>(z-statistic)</i>	<i>(2)</i> <i>Suspect Sample</i> <i>Coefficient</i> <i>(z-statistic)</i>
<i>Intercept</i>		-3.103*** (-17.50)	-4.216*** (-4.81)
<i>UnREM_t</i>	-	-0.266*** (-4.63)	-0.541*** (-3.64)
<i>UnAEM_t</i>	-	-1.751*** (-8.32)	-1.759*** (-2.57)
<i>TaxRate_{t-1}</i>	+	-0.072 (-0.81)	-0.078 (-0.44)
<i>Zscore_{t-1}</i>	+/-	-0.012*** (-3.87)	-0.014*** (-2.65)
<i>InstHoldings_{t-1}</i>	+/-	0.393*** (6.15)	0.297** (2.10)
<i>MarketShare_{t-1}</i>	-	-0.547*** (-3.57)	-0.879*** (-2.93)
<i>BigN_t</i>	+/-	0.038 (0.62)	-0.133 (-1.23)
<i>LongTenure_t</i>	+/-	-0.063* (-1.88)	-0.075 (-1.13)
<i>SOX_t</i>	+/-	0.044 (0.33)	0.070 (0.19)
<i>HighNOA_{t-1}</i>	+	0.199*** (5.79)	0.202*** (3.03)
<i>OpCycle_{t-1}</i>	-	0.000 (-1.30)	0.001* (1.74)
<i>CFO_Forecast_t</i>	+	0.167*** (3.93)	0.166** (1.96)
<i>LogAssets_{t-1}</i>		0.221*** (16.82)	0.254*** (9.60)
<i>ROA_{t-1}</i>		-1.210*** (-10.52)	-1.037*** (-4.46)
<i>MtB_t</i>		0.050** (2.05)	0.150** (2.38)
<i>PredREM_t</i>		-0.242*** (-2.78)	-0.377*** (-3.20)
<i>PredAEM_t</i>		-2.199*** (-5.76)	-2.065*** (-3.85)
<i>Inverse_Mills_t</i>			0.640 (1.49)
Industry Indicator Variables		Yes	Yes
Year Indicator Variables		Yes	Yes
Log likelihood		-16,375.10	-3,703.25
Chi-square		1232.93	428.07
p-value		<.0001	<.0001
Correctly classified		65.8%	68.0%
Number of observations		33,619	7,638

Table 5 (Continued)

Notes: Table 5 presents the results of estimating equation (8) for the sample firms:

$$(Prob\ CS_i=1) = \alpha_0 + \alpha_1 UnREM + \alpha_2 UnAEM + \alpha_{3-6} REM\ Constraints + \alpha_{7-12} AEM\ Constraints + \alpha_{13-18} Controls + \varepsilon_i$$

See Table 1 for variable definitions and calculations. *, **, and *** denote statistical significance at 10%, 5%, and 1% percent, respectively. Significance tests are one-tailed for variables with a predicted sign; and two-tailed otherwise.