ASIAN ACADEMY OF MANAGEMENT JOURNAL

EARLY VIEW

Manuscript title: Factors affecting the choice of core earnings management tool

Author: Manish Bansal

Accepted date: 6 January 2023

To cite this article: Bansal, M. (2024). Factors affecting the choice of core earnings management tool. *Asian Academy of Management Journal* (early view).

FACTORS AFFECTING THE CHOICE OF CORE EARNINGS MANAGEMENT TOOL

Manish Bansal

Finance and Accounting, Indian Institute of Management Ranchi
Ranchi, Jharkhand, India

Email: manish.bansal@iimranchi.ac.in

ABSTRACT

Prior studies document that managers manipulate core earnings through different methods to favorably influence the perception of stakeholders towards the operating performance of the firm. However, it is of interest to examine which particular core earnings manipulation method is preferred by firms because each method needs a different set of opportunities and incentives. The current study explores the methods of core earnings manipulation, namely expense misclassification and revenue misclassification in terms of opportunities and incentives. Results show that the choice of method largely depends on the size and age of the firm. In particular, results exhibit that large and old firms prefer revenue misclassification over expense misclassification for managing core earnings. This effect is found to be more pronounced among large older firms. Our subsequent tests suggest that Big four auditors have a constraining effect on expense misclassification, however, they are unable to mitigate the corporate misfeasance of revenue misclassification, implying the partial effectiveness of Big four auditors in curbing classification shifting. These results are robust to the alternative measurement of misclassification practices and endogeneity issues. The findings have important implications for auditors, analysts, and accounting standard-setters.

Keywords: big four auditors, core earnings management, expense misclassification, India, revenue misclassification

INTRODUCTION

After the collapse of big giants such as Enron, WorldCom, Satyam, etc., the quality of financial reporting has become a major concern for investors and other many important stakeholders. In the wake of a competitive environment and higher litigation risks, firms are found to be engaged in novel forms of earnings manipulations that even the Big four auditors find difficult to detect. The big four auditors include Deloitte, Ernst & Young, KPMG, and PricewaterhouseCoopers and their associate auditing firms. One such novel manipulation form of earnings manipulation is classification shifting, under which managers vertically move the income statement line items with the intent to report inflated core earnings of the firm. This tool is less likely to be detected by auditors because shifting items in the income statement merely inflate the top-line profitability (core earnings) without altering the bottom-line profitability (net profit).

Two forms of classification shifting have been documented in the earnings management literature, namely expense misclassification and revenue misclassification. Under expense misclassification, managers misclassify the selling, general and administrative expenses (operating expenses) as income-decreasing special items or discontinued operations (non-operating expenses) to report inflated core earnings. Under revenue misclassification, managers misclassify the rental or dividend income (non-operating revenue) as revenue from operations (operating revenue) to report inflated sales and core earnings. Numerous studies have investigated the issue of expense misclassification and revenue misclassification (for instance, Bansal, 2022a; Bansal et al., 2021; Fan et al., 2010; Haw et al., 2011, Malikov et al., 2018; McVay, 2006; Nagar et al., 2021), however, the best of our knowledge, there has been no study till date that have explored these practices from the lens of perceived opportunities and perceived incentives required for implementing these forms. Fraud Triangle Theory (Cressey, 1950) states that firms need sufficient opportunities and significant incentives for any kind of manipulation. The shifting of expense and revenue items within the income statement needs a sufficient magnitude of non-operating items and significant incentives for reporting inflated sales and core earnings (Malikov et al., 2018; McVay, 2006). These incentives and opportunities are likely to vary among firms depending on their cross-sectional features. Hence, firms are likely to prefer one form of misclassification over another depending on the ease and need of each shifting tool.

The current study explores two main cross-sectional features, namely firm size and firm age because these two factors are found to be important determinants of earnings management. Prior studies (for instance, Gul et al., 2009; Kim et al., 2003; Lobo & Zhou, 2006) document the size and age of the firm as important determinants of a firm's accrual and real earnings management. The current study examines these factors in the context of expense and revenue misclassification because incentives and opportunities for misclassification are likely to vary across the size and age of the firm. For instance, large and old firms are relatively diversified and have a greater magnitude of non-operating revenue (Swamidas & Kotha, 1998), which in turn, is likely to provide them greater ease in misclassifying the revenue items in the income statement. Besides, large and old firms are under greater capital market pressure to meet or beat analysts' sales forecasts (Bhushan, 1989), which incentivises them to resort to revenue misclassification because the misclassification of expenses does not inflate the sales figure of the firm.

The shifting practices are found to be lesser among firms having higher audit quality (Mulchandani & Mulchandani, 2022; Nagar et al., 2021). These studies document that firms audited by Big four auditors have a lesser magnitude of expense misclassification. These studies have ignored revenue misclassification while examining the impact of audit quality on shifting practices. The issue of role of big four auditors in mitigating revenue shifting is important because firms are found to prefer revenue misclassification over expense misclassification due to its dual advantage in terms of reporting inflated sales and core earnings (Bansal et al., 2021). For instance, the misclassification of non-operating revenue as operating revenue results in an increase in operating revenue as well as operating profit. The issue of association between firm size and age and revenue misclassification in India is more important because Indian firms have greater scope for revenue misclassification due to aggregated format of recording revenue in the income statement (Indian Companies Act, 2013). It is important to examine whether Big four auditors constrain revenue misclassification or not. Therefore, unlike prior studies (Mulchandani & Mulchandani, 2022; Nagar et al., 2021), the current study examines the moderating role of Big four auditors on both the forms of shifting practices.[1]

Based on a sample of Bombay Stock Exchange-listed firms spanning over 20 years from March 2000 to March 2019, we find a significant negative association between non-operating revenue and unexpected operating revenue among large and old firms, implying that large and old firms are engaged in revenue misclassification for reporting inflated operating performance. Further, we find that this effect is more pronounced among large older firms. These findings are consistent with the notion that firms choose the shifting tool based on the ease and need of each tool. Our subsequent tests suggest the magnitude of expense misclassification is less pronounced among firms audited by big four auditors, however, big four auditors have a lesser constraining effect on revenue misclassification practices of firms, indicating the partial effectiveness of big four auditors in curbing the corporate misfeasance of classification shifting practices. Our results are robust to the problem of endogeneity and alternative measurements of misclassification practices.

The study contributes to the literature mainly in two ways. First, the study extends the literature on earnings management, particularly classification shifting. This is among the earlier attempts to jointly investigate both forms of misclassification by taking a uniform sample of firm years and providing compelling evidence that firm-specific variables (firm size and firm age) incentivise firms to prefer one form of misclassification over another. There is a substitution relationship between shifting forms. Second, the study contributes to the corporate governance literature by undertaking a comprehensive approach to ascertain the impact of audit quality on classification shifting by studying both shifting forms (expense misclassification and revenue misclassification). Prior studies have documented the constraining effect of big four auditors on accrual-based earnings management (AEM), real earnings management (REM), and expense misclassification (Alhadab & Clacher, 2018; Khanh et al., 2018; Nagar et al., 2021). This study is among the pioneering attempts to examine the mitigating effect of big four auditors on revenue misclassification, and find that big four auditors are unable to constrain the firms' revenue misclassification practices, hence suggesting the authorities issue separate forensic auditing standards for the auditors while examining the financial statement of their clients.

LITERATURE REVIEW AND PROPOSITION DEVELOPMENT

The literature documents three main forms of earnings management, namely AEM, REM, and classification shifting. The first two tools have been extensively investigated by researchers (Kothari et al., 2005), however, research on classification shifting is relatively scarce. Under classification shifting, managers vertically move the income statement line items to report inflated core earnings. This tool is more popular due to its low-cost element (McVay, 2006) because misclassification of items neither results in the reversal of accruals like AEM nor foregone any future benefits like REM. The main theoretical motivation behind classification shifting is the investor's perception of the line items. Investors accord higher weight to operating profit than net profit due to its persistent nature (Lougee & Marquardt, 2004). Managers' compensation and debt contracts are largely dependent on firms' core earnings (Dyreng et al., 2017). Hence firms have significant incentives to report inflated core earnings through classification-shifting practices.

McVay (2006) was the first to provide evidence on classification shifting, where U.S. firms are found to be engaged in misclassifying operating expenses as income-decreasing special items to report inflated operating profits. This finding is further supported by Fan et al. (2010) by using quarterly special items. Further studies document that firms shift operating expenses to extraordinary items (Barnea et al., 1976); income-decreasing discontinued operations (Barua et al., 2010), and amongst segments within a firm (Lail et al., 2014). Besides expense misclassification, firms are found to be engaged in misclassifying non-operating revenue as operating revenue to report inflated operating revenue and operating profits (for instance, Bansal et al., 2021; Malikov et al., 2018). Consistent with the fraud triangle theory (Cressey, 1950), firms need a sufficient magnitude of non-operating items to camouflage misclassified items (McVay, 2006). Besides, firms must have significant incentives to report inflated core earnings for expense misclassification (McVay, 2006) and inflated operating revenue for revenue misclassification (Malikov et al., 2018). Firms are likely to prefer one form of misclassification over another depending on available opportunities and incentives. The current study investigates the two well-documented determinants of AEM and REM in the context of classification shifting, namely firm size and firm age because the incentives and opportunities are likely to vary across the size and age of the firm.

Earnings management practices of firms are found to be largely dependent upon the size of the firm (for instance, Kim et al., 2003; Lobo & Zhou, 2006). Relative to small firms, large firms are more likely to be engaged in AEM and REM due to their complex business structure and longer operating cycles and their strong incentive to meet or beat the benchmark numbers (Kim et al., 2003). Under classification shifting, large firms are likely to prefer revenue shifting for managing core earnings due to the following reasons. First, large firms have relatively diversified, hence they have a greater magnitude of non-operating revenue along with their core revenues (Swamidas & Kotha,1998). Their greater magnitude of non-operating revenue is likely to provide them greater leeway for revenue misclassification as firms need non-recurring items to camouflage the misclassified items (McVay, 2006). Second, large firms have greater external monitoring or analyst following (Bhushan, 1989). They are under greater capital market pressure of meeting analysts' sales forecasts (Das et al., 1998), hence they are likely to resort to revenue misclassification because the misclassification of revenues from non-operating to operating category enables them to report sales at a favorable amount. Third, relative to small firms, large firms have higher transitory gains, and firms with transitory gains are found to record these gains as part of their core operations (Curtis et al., 2014) with an intent to show their stakeholders that reported profitability is derived from the firm's core operations only.

The literature also documents the age of the firm as an important determinant of earnings management (Gul et al., 2009). Young firms are largely dependent on external sources of finance due to their lower profit margin. Hence, they are highly incentivised to positively influence the perception of capital providers toward their financial performance by manipulating numbers. Young firms are mostly introductory firms; hence they have a greater magnitude of non-operating items, which they are required to incur to set up their business. Their greater magnitude of non-recurring expense items is likely to provide them greater leeway for expense misclassification. Young firms are usually initial public offering (IPO) firms and IPO firms manage core earnings (Marquardt & Weidman, 2004) because potential investors are found to form their decision based on the firm's reported core earnings as the price-earnings ratio is not available for IPO firms. Earnings management practices are higher in newly listed firms (Nguyen & Duong, 2021). Analysts also produce revenue forecasts for younger firms (Bilinski & Eames, 2019). Hence, it incentivises young firms to report inflated revenues. Based on these arguments, it is likely that the larger and older the firm, the greater will be the magnitude of revenue misclassification and the lesser will be the magnitude of expense misclassification. Contrary to existing literature, where the firm size and firm age have been investigated from the AEM and REM perspective, we test these determinants in the context of classification shifting given that firm size and firm age is likely to impact their choice of one shifting form over another. Hence, our first two hypotheses are as follows:

H1: There is a positive association between firm-specific factors (firm size and age) and the degree of revenue misclassification.

H2: There is a negative association between firm-specific factors (firm size and age) and the degree of expense misclassification.

The strong corporate board plays an important role in limiting managerial discretions, hence reducing the earnings management practices of managers. It protects shareholders' interests and provides them with more reliable financial statements. One such strong corporate governance mechanism is to avail the auditing services from the big four auditors (Joo & Chamberlain, 2017). Research indicates that big four auditors typically provide superior audit quality than non-big four auditors (Kim et al., 2003) as they are more stringent enforcers of earnings quality. They are incentivised to protect their brand name and reputation by providing a true and fair view of the company's financial health (Francis & Krishnan, 2002). Additionally, Big four accounting firms are international organisations with global operations and, therefore, have incentives to develop and maintain a uniform reputation globally (Simunic & Stein, 1987). Therefore, they have more to lose than peer auditors by overlooking the wrong financial statements. Big four auditors are found to be negatively associated with earnings management (for instance, Francis & Yu, 2009; Gerayli et al., 2011).

Although auditors find it difficult to challenge management's classification of items due to permissive accounting and auditing standards (Zalata & Roberts, 2016), however, few studies have found the significant role of auditors in curbing classification shifting (for instance, Haw et al., 2011; Joo & Chamberlain, 2017). Under Indian institutional settings, Nagar et al. (2021)

examined whether big four auditors reduce classification shifting. They find that big four auditors are associated with significantly lower levels of classification shifting. Mulchandani and Mulchandani (2022) also documented that magnitude of expense misclassification is less among the big four audit firms. These prior studies (Mulchandani & Mulchandani, 2022; Nagar et al., 2021; Zalata & Roberts, 2016) have ignored revenue shifting while investigating the impact of the big four on classification shifting. The issue of investigating the role of the big four on revenue shifting is important because revenue shifting is found to be a preferred way among firms for managing core earnings due to its dual advantage (Bansal, 2022b). Hence, the detection of revenue shifting by auditors is important to ensure the quality of information disclosed in the financial statements. The issue is more significant for Indian firms because Indian firms are required to disclose the revenue under two heads only, namely revenue from operations and other income, and that too under aggregated format (no mandatory disclosure requirement for revenue under the Companies Act, 2013), which in turn, likely to provide Indian firms greater leeway for revenue shifting. Therefore, given that firms have greater scope and greater incentive for revenue shifting, it is of interest to examine whether the big four auditors constrain the same or not. Based on the previous findings that the big four auditors have a constraining effect on AEM and REM, we posit that the big four auditors moderates the association between firm-specific factors and classification shifting. Accordingly, our next hypotheses are as follows:

H3: BigN auditors moderates the association between firm-specific factors (firm size and age) and the degree of revenue misclassification.

H4: BigN auditors moderates the association between firm-specific factors (firm size and age) and the degree of expense misclassification.

RESEARCH METHODS

Measurement of Revenue Misclassification

The misclassification of non-operating revenue as operating revenue results in higher unexpected operating revenue (*UE_OR*). *UE_OR* is measured as the residuals from the following Malikov et al.'s (2018) operating revenue expectation model:

$$\frac{OR_{i,t}}{AT_{i,t-1}} = \alpha_0 + \beta_1 \frac{1}{AT_{i,t-1}} + \beta_2 \frac{OR_{i,t-1}}{AT_{i,t-2}} + \beta_3 MTB_{i,t-1} + \beta_4 \frac{AR_{i,t-1}}{AT_{i,t-2}} + \beta_5 \frac{AR_{i,t}}{AT_{i,t-1}} + \varepsilon_{i,t} \qquad \dots (1)$$

where OR is operating revenue (revenue from operations). *AT* is a total asset. *MTB* is the market-to-book ratio. *AR* is accounts receivable. All the variables are scaled by lagged total assets. We estimate model (1) cross-sectionally for each industry year having at least fifteen observations. We use the two-digit Standard Industrial Classification (SIC) code to identify the industries. Residuals ($\varepsilon_{i,t}$) measures *UE_OR*. We regress *UE_OR* on non-operating revenue (*NOR*) to investigate revenue misclassification.

Measurement of Expense Misclassification

The misclassification of operating expense as a non-operating expense results in higher unexpected core earnings (*UE_CE*). *UE_CE* is measured as the residuals from the following McVay's (2006) core earnings expectation model:

$$\frac{CE_{i,t}}{Sales_{i,t-1}} = \alpha_0 + \beta_1 \frac{1}{Sales_{i,t-1}} + \beta_2 \frac{CE_{i,t-1}}{Sales_{i,t-2}} + \beta_3 ATO_{i,t-1} + \beta_4 \frac{ACC_{i,t-1}}{Sales_{i,t-2}} + \beta_5 \frac{ACC_{i,t}}{Sales_{i,t-1}} + \beta_6 \Delta Sales_{i,t} + \beta_7 NEG\_\Delta Sales_{,t} + \varepsilon_{i,t} \quad \ldots (2)$$

where CE is core earnings measured as sales minus cost of goods sold and other operating expenses. *ATO* is the assets turnover ratio. *ACC* is accruals. $\Delta\ Sales$ is the percentage change in sales. $NEG\_\Delta Sales$ is a percentage change in sales if $\Delta\ Sales$ is negative, and zero otherwise. All variables are scaled by lagged total sales. Model (2) is also estimated cross-sectionally for each industry year. Residual ($\varepsilon_{i,t}$) measures *UE_CE*. We regress *UE_CE* on non-operating expenses (*NOE*) to examine expense misclassification.

Regression Model

Our first hypothesis states that firm size and firm age are positively associated with revenue misclassification, whereas the second hypothesis states that firm size and age are negatively associated with expense misclassification. We employed the following model (3) and (4) to test the assertions under the first and second hypotheses, respectively.

$$UE\_OR_{i,t} = \alpha_0 + \alpha_1 NOR_{i,t} + \alpha_2 Size_{i,t} + \alpha_3 Age_{i,t} + \alpha_4 Size * Age_{i,t} + \alpha_5 NOR * Size_{i,t} + \alpha_6 NOR * Age_{i.t} + \alpha_7 NOR * Size * Age_{it} + Controls + Fixed\ effects + \varepsilon_{it} \quad \ldots (3)$$

Where *UE_OR* is unexpected operating revenue measured as residuals from the model (1). *NOR* is non-operating revenue. The coefficient of *NOR* is expected to be negative if firms are engaged in revenue misclassification, implying a decrease in *NOR* with an increase in *UE_OR* due to the misclassification of *NOR* as operating revenue. *Size* is a dummy variable that takes a value equal to one for large firms, and zero for small firms. Following Doan and Nguyen (2018), firms are classified as "*large*" in fiscal year *t* if their beginning-of-year value of total assets is in the top quartile of all firms with data available in that year. "*Small*" firms are in the bottom quartile. *Age* is a dummy variable that takes value equal to one for old firms and zero for young firms, where firms are classified as "*old*" in fiscal year *t* if their age is in the top quartile of all firms with data available in that year. "*Young*" firms are in the bottom quartile. We include the interaction variable - *Size*Age* to understand the joint impact of firm size and age on revenue misclassification. Our main variables of interest are *NOR*Size*, *NOR*Age*, and *NOR*Size*Age*, whose coefficients are expected to be negative if large firms, old firms, and large older firms are engaged in revenue misclassification, respectively.

We include two sets of control variables in the model (3) to isolate the impact of firm size and age on revenue misclassification. In the first set of control variables, we control for AEM and REM because firms are found to be engaged in multiple tools for managing earnings (Abernathy et al., 2014; Fan & Liu, 2017). Hence, to ensure that our results are due to revenue misclassification, we control for AEM and REM. Following many prior studies (for instance, Ali & Bansal, 2021; Bansal, 2022c, Bansal & Ali, 2022, Bashir et al., 2021; Hu, 2021), we use discretionary accruals as a proxy of AEM. In the second set of control variables, we control for certain cross-sectional characteristics and corporate governance variables.[2] The first such variable is the degree of financial leverage because levered firms engaged in misclassification practices to avoid violation of EBITDA-based covenants (Fan et al., 2019). Second, we control for growth opportunities because high-growth firms are more likely to be engaged in misclassification practices to meet analysts' forecasts (McVay, 2006). Third, we control for audit fees because firms having higher audit fees are less likely to be engaged in earnings management, hence have higher earnings quality (Antle et al., 2006). Fourth, we control Chief Executive Officer (CEO) duality because the dual role of EO is found to affect earnings management (Zandi & Abdullah, 2019). We have included industry and time-fixed effects to control for unobserved cross-sectional heterogeneity across industries, and years respectively.

$$UE\_CE_{i,t} = \beta_0 + \beta_1 NOE_{i,t} + \beta_2 Size_{i,t} + \beta_3 Age_{i,t} + \beta_4 Size * Age_{i,t} + \beta_5 NOE * Size_{i,t} + \beta_6 NOE * Age_{i.t} + \beta_7 NOE * Size * Age_{it} + Controls + Fixed\ effects + \varepsilon_{it} \quad \ldots (4)$$

Where *UE_CE* is unexpected core earnings measured as residuals from the model (2). *NOE* is the non-operating expense. The coefficient of *NOE* is expected to be positive if firms are engaged in expense misclassification, implying an increase in *NOE* with an increase in *UE_CE* due to the misclassification of operating expenses as *NOE*. *Size* and *Age* have the same meaning as assigned previously. Our main variables of interest are *NOE*Size*, *NOE*Age*, and *NOE*Size*Age*, whose coefficients are expected to be positive if large firms, old firms, and large older firms are engaged in expense misclassification, respectively. We have used the same sets of control variables as used in the model (3).

Our third (fourth) hypothesis states that Big four auditors moderates the association between firm size and age and revenue (expense) misclassification. We employ the following model (5) and (6) to test these assertions.

$$UE\_OR_{i,t} = \alpha_0 + \alpha_1 NOR_{i,t} + \alpha_2 Size_{i,t} + \alpha_3 Age_{i,t} + \alpha_4 Size * Age_{i,t} + \alpha_5 NOR * Size_{i,t} + \alpha_6 NOR * Age_{i.t} + \alpha_7 NOR * Size * Age_{it} + \alpha_8 BigN_{i,t} + \alpha_9 Size * BigN_{i,t} + \alpha_{10} Age * BigN_{i,t} + \alpha_{11} Size * Age * BigN_{i,t} + \alpha_{12} NOR * BigN_{i,t} + \alpha_{13} NOR * Size * BigN_{i,t} + \alpha_{14} NOR * Age * BigN_{i.t} + \alpha_{15} NOR * Size * Age * BigN_{it} + Fixed\ effects + Controls + \varepsilon_{it} \quad \ldots (5)$$

Where *UE_OR* is unexpected operating revenue measured as residuals from the model (1). *NOR*, *Size*, and *Age* have the same meaning as assigned previously. *BigN* is an indicator variable taking a value of 1 if the firm's auditor is an affiliate member of a Big four international audit firm and 0 if otherwise. Our main variables of interest are *NOR*BigN*, *NOR*Size*BigN*, *NOR*Age*BigN*, and *NOR*Size*Age*Big N*, whose coefficients are expected to be insignificant if big four auditors constraints the revenue misclassification.

$$UE\_CE_{i,t} = \beta_0 + \beta_1 NOE_{i,t} + \beta_2 Size_{i,t} + \beta_3 Age_{i,t} + \beta_4 Size * Age_{i,t} + \beta_5 NOE * Size_{i,t} + \beta_6 NOE * Age_{i.t} + \beta_7 NOE * Size * Age_{it} + \beta_8 BigN_{i,t} + \beta_9 Size * BigN_{i,t} + \beta_{10} Age * BigN_{i,t} + \beta_{11} Size * Age * BigN_{i,t} + \beta_{12} NOE * BigN_{i,t} + \beta_{13} NOE * Size * BigN_{i,t} + \beta_{14} NOE * Age * BigN_{i.t} + \beta_{15} NOE * Size * Age * BigN_{it} + Fixed\ effects + Controls + \varepsilon_{it} \quad \ldots (6)$$

Where *UE_CE* is unexpected core earnings measured as residuals from the model (2). *NOE*, *Size*, *Age*, and *BigN* have the same meaning as assigned previously. *NOE*BigN*, *NOE*Size*BigN*, *NOE*Age*BigN*, and *NOE*Size*Age*Big N* are our main variables of interest, whose coefficients are expected to be insignificant if big four auditors constraints the expense misclassification.

Data collection and sample selection

Our sample comprises Bombay Stock Exchange (BSE) listed firms spanning over twenty years from the year ending March 2000 to March 2019. We have extracted the accounting and financial data for all the BSE-listed firms (4,945 firms) along with their two-digit Standard Industrial Classification (SIC) code from the prowess database, maintained by the Centre for Monitoring Indian Economy Private limited (CMIE). Following Malikov et al. (2018), we have excluded financial and utility firms (1,044 firms) due to their different financial reporting framework. Firms with missing observations for measuring misclassification practices and control variables were also excluded. Finally, we are left with a sample of 35,480 and 31,960 firm years for testing revenue misclassification and expense misclassification, respectively. All the continuous variables are winsorised at 1% and 99% percentiles to remove the effect of outliers. Table 1 shows the process of finalising the sample. Table 2 covers the definition and measurement of the main variables.

Table 1
Sample selection

Particulars	Firms	Firm-years
Initial sample of firms with non-missing “SIC” code (2000–2019)	4,945	98,900
Less: Financial and utilities firms (SIC codes between 60 and 64)	1,044	20,880
Less: Firms with negative assets or sales	32	640
Less: Firms with industry-year observations less than fifteen	86	1,720
Less: Firms with missing values for measuring revenue misclassification	1,355	27,100
Less: Firms with missing values for measuring control variables	654	13,080
Final sample of firms for testing revenue misclassification	1,774	35,480
Less: Firms missing values for measuring expense misclassification	176	3,520
Final sample of firms for testing expense misclassification	1,598	31,960

Table 2
Variable definition

Variables	Definition and measurement
UE_OR	Unexpected operating revenue, measured as residuals from the model (1).
NOR	Non-operating revenue includes foreign exchange gains, rental income, dividend income, plus any other income from investing and financing activities of firms.
UE_CE	Unexpected core earnings, measured as residuals from the model (2).
NOE	Non-operating expenses are computed as core earnings plus non-operating income minus net profit (Zalata & Roberts, 2016).
Size	A dummy variable that takes value equals one for large firms and zero for small firms.
Age	A dummy variable that takes value equals one for old firms and zero for young firms.
BigN	An indicator variable takes a value of 1 if the firm's auditor is an affiliate member of a Big 4 international audit firm and 0 if otherwise.
A_PROD	Abnormal levels of production costs, measured as residuals from following Roychowdhury (2006) model: $\frac{PROD_{i,t}}{AT_{i,t-1}} = \alpha_0 + \beta_1 \frac{1}{AT_{i,t-1}} + \beta_2 \frac{S_{i,t}}{AT_{i,t-1}} + \beta_3 \frac{\Delta S_{i,t}}{AT_{i,t-1}} + \beta_4 \frac{\Delta S_{i,t-1}}{AT_{i,t-1}} + \varepsilon_{i,t}$ Where, *PROD* is production cost measured as sum of COGS and change in stock. We estimate the model cross-sectionally for each industry year to control for macroeconomic shocks.
A_DISX	Abnormal levels of discretionary expenses, measured as residuals from following Roychowdhury (2006) model: $\frac{DISX_{i,t}}{AT_{i,t-1}} = \alpha_0 + \beta_1 \frac{1}{AT_{i,t-1}} + \beta_2 \frac{S_{i,t-1}}{AT_{i,t-1}} + \varepsilon_{i,t}$ Where, *DISX* is discretionary expenses, calculated as the sum SG&A and R&D expenses.
A_ACC	Abnormal levels of accruals, measured as residuals from following performance-adjusted modified Jones model (Kothari et al., 2005): $\frac{ACC_{i,t}}{AT_{i,t-1}} = \emptyset_1 \left(\frac{1}{AT_{i,t-1}}\right) + \emptyset_2 \frac{(\Delta Sales - \Delta Rec)_{i,t}}{AT_{i,t-1}} + \emptyset_3 \frac{PPE_{i,t}}{AT_{i,t-1}} + \emptyset_4 ROA_{i,t} + \varepsilon_{i,t}$ Where, *ACC* is accruals. *AT* is total assets. ΔRec is change in account receivable. *PPE* is gross value of plant, property, and equipment. *ROA* is return on assets measured as the ratio of profit after tax to total assets.
Lev	Proportion of total outside liabilities to total assets.
Growth	Sales growth, is measured as the percentage change in sales.
Audit fees	Natural logarithm of audit fees paid by firm to auditors.
Duality	A binary variable that takes value equal one for firms having CEO duality, and zero otherwise.

RESEARCH RESULTS

Descriptive Statistics and Correlation Analysis

Table 3, Panel A presents the descriptive statistics for the full sample. The mean (median) of *UE_OR* is 0.005 (-0.026) and the mean (median) of *UE_CE* is 0.004 (0.037), implying that firms record operating revenue and core earnings greater than their expected values. The mean of *NOE* and *NOR* is 0.294 and 0.067, indicating that *NOE* accounts for 29% of sales and *NOR* accounts for 7% of assets. The mean of REM metrics, namely *A_DISX* and *A_PROD* is zero as these are residuals from regression. The mean of the AEM metric (*A_ACC*) is 0.043, indicating the existence of income-increasing discretionary accruals. The average proportion of debt in the capital (*Lev*) is 79.6%, whereas the average sales growth (*Growth*) is 24.3%. The average natural logarithm of audit fees is 13.452. Further, we find that only 12.3 percent of firm-year observations are audited by Big four auditors' affiliates, which is significantly lower than these auditors' presence in the United States, the UK, Malaysia, and Singapore. This estimate is consistent with prior studies on the Indian capital market (Houqe et al., 2017).

Panel B presents group-wise descriptive statistics. Large firms have significantly larger mean *UE_OR* than their smaller counterparts (0.063 vs. 0.011), providing us initial evidence of the revenue misclassification among the former. In the same vein, old firms are found to have significantly larger mean *UE_OR* than their young counterparts (0.079 vs. 0.013), providing us initial evidence of the revenue misclassification among the former. No such higher magnitude of *UE_CE* is found among small and young firms. The average of *UE_OR* and *UE_CE* is not found to be significantly different among Big four and non-Big four audit firms.

Panel C displays correlation coefficients. A negative association (–0.043) is found between *UE_OR* and *NOR*, implying an increase in *UE_OR* with a decrease in *NOR*. A positive association (0.093) is found between *UE_CE* and *NOE*, implying an increase in *UE_CE* with an increase in *NOE*. Both coefficients are directed toward the existence of revenue and expense misclassification among sample firms. REM metrics (*A_PROD* and *A_DISX*) and AEM metric (*A_ACC*) are found to be negatively associated, indicating the substitutive relationship between earnings management tools, which is in line with the finding of prior studies (Adhikari et al., 2021; Bansal & Kumar, 2021) that firms prefer one form of earnings management tool over another depending on the ease and need of each tool. The variance inflation factor (VIF) value for the variables is lesser than 10, hence our data does not have a multicollinearity problem.

Table 3

Descriptive Statistics

Panel A: Descriptive statistics of the full sample

Variables	Mean	SD	P25	Min.	Median	P75	Max.	N
UE_OR	0.005	0.433	–0.193	–0.003	–0.026	0.184	0.252	35,480
NOR	0.067	0.186	0.034	0.002	0.073	0.100	0.156	35,480
UE_CE	0.004	1.943	–0.143	–0.093	0.037	0.150	0.312	31,960
NOE	0.294	0.880	0.140	0.064	0.183	0.321	0.483	31,960
A_DISX	0.000	0.663	–0.001	–0.003	–0.006	0.013	0.032	31,960
A_PROD	0.000	1.431	–0.003	–0.023	0.002	0.073	0.080	31,960
A_ACC	0.043	0.543	0.005	–0.002	–0.073	0.961	0.163	31,960
Lev	0.796	0.884	0.362	0.184	0.596	0.713	0.866	31,960
Growth	0.243	0.550	0.037	0.013	0.143	0.243	0.356	31,960
Audit fees	13.452	1.553	8.153	6.663	12.452	16.452	21.040	31,960
Duality	0.123	0.642	0.050	0.024	0.063	0.123	0.150	31,960

Panel B: Descriptive statistics for firms

Variables	Large firms (7,990)			Small firms (7,990)			Difference in	
	Mean	Median	SD	Mean	Median	SD	Means (t-test)	Medians (Wilcoxon test)
UE_OR	0.063	0.004	0.596	0.011	–0.143	0.703	**	***
UE_CE	0.143	0.043	0.943	0.230	0.173	1.006	***	**
	Old firms (7,990)			Young firms (7,990)				
UE_OR	0.079	0.005	0.596	0.013	–0.106	0.643	**	**
UE_CE	0.119	0.063	0.344	0.184	0.136	0.894	*	*
	BigN audit firms (3,836)			Non-BigN audit firms (29,124)				
UE_OR	0.057	0.004	0.364	0.049	–0.116	0.496	–	–
UE_CE	0.106	0.070	0.293	0.083	0.167	1.443	–	–

Panel C: Correlation matrix

Variables	*UE_CE*	*UE_OR*	*NOE*	*NOR*	*A_DISX*	*A_PROD*	*A_ACC*	*Lev*	*Growth*	*Audit fees*	*VIF*
UE_OR	0.150*										1.336
NOE	0.093**	0.164									1.452
NOR	–0.127*	–0.043	0.227**								2.163
A_DISX	–0.027	0.154**	–0.031**	0.019							3.140
A_PROD	–0.083**	–0.056**	0.096**	0.026**	–0.197**						1.845
A_ACC	–0.094**	0.196**	–0.063	–0.073**	0.163**	–0.037					2.156
Lev	0.113	–0.096	0.273**	0.073**	–0.096	0.071**	0.043**				1.884
Growth	–0.031**	0.183**	0.160**	–0.060**	0.033*	–0.016**	0.190**	0.010			2.643
Audit fees	–0.152*	–0.190*	0.073	0.123	0.034	0.043	0.067	0.182	0.177		2.116
Duality	0.016*	0.073**	–0.053	0.163	0.107	0.006	0.054	0.023	0.024	0.073	1.845

Notes: Table shows the descriptive statistics and correlation coefficients among variables. Panel A shows descriptive statistics of variables for the full sample. Panel B shows the descriptive statistics for large and small firms, old and young firms, and BigN and non-BigN audit firms. We test for a significant difference between the mean (median) of variables through a t-test (Wilcoxon test). Panel C shows Karl Pearson's correlation coefficients. VIF stands for variance inflation factor. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Multivariate Regression Analysis

Table 4 presents the regression results of models (3) and (4) used to examine the impact of firm size and firm age on revenue and expense misclassification, respectively. The coefficient of *NOR* on *UE_CE* is positive (0.072, $p < 0.05$), implying that firms are not engaged in revenue misclassification. However, the coefficient of *NOR*Size* on *UE_OR* is negative and significant at a 5% level of significance (–0.053 $p < 0.05$), implying an increase in *UE_OR* with a decrease in *NOR* among large firms. In a similar vein, the coefficient of *NOR*Age* on *UE_OR* is negatively significant (–0.037, $p < 0.05$), implying an increase in *UE_OR* with a decrease in *NOR* among old firms. These results indicate the existence of revenue misclassification among large and old firms. Further, we find that the coefficient of the triple interaction variable - *NOR*Size*Age* on *UE_OR* is negative and significant at a 1% level of significance (–0.160, $p < 0.00$), suggesting that large older firms are more likely to be engaged in revenue misclassification. These results are in line with our prediction under H1 that firm size and age positively impact revenue misclassification.

Column (2) shows that the coefficient of *NOE* on *UE_CE* is positive and significant at a 5% level of significance (0.053, $p < 0.05$), implying an increase in unexpected core earnings with an increase in non-operating expenses. It indicates the existence of expense misclassification among sample firms. However, the coefficient of *NOE*Size* on *UE_CE* (0.019, $p > 0.10$) and *NOE*Age* on *UE_CE* (0.073, $p > 0.10$) are insignificant, indicating that firm size and firm age do not impact the expense misclassification practices of firms. In other words, large and old firms are not engaged in expense misclassification. The coefficient of the interaction variable - *NOE*Size*Age* on *UE_CE* is found to be insignificant positive (0.084, $p > 0.10$). Reading together the results under columns (1) and (2), it has been found that firm size and firm age are significantly associated with revenue misclassification but not with expense misclassification. Hence, the results support our hypotheses (H1 and H2). Overall, our results exhibit that large and old firms prefer revenue misclassification over expense misclassification for reporting inflated operating performance. It can be attributed to the fact that firms choose the misclassification strategy based on the available opportunities and incentives to manipulate earnings metrics. These are consistent with the Fraud Triangle Theory and ease-need-advantage-based shifting framework of shifting practices.

Table 5 presents the regression results of models (5) and (6) used to investigate the moderating role of Big four auditors on the association between firm characteristics (firm size and firm age) and revenue and expense misclassification, respectively. Consistent with our previous findings, the coefficient of *NOR* on *UE_CR* is found to be positive (0.042, $p < 0.05$), and the coefficients of *NOR*Size* (–0.067, $p < 0.05$), *NOR*Age* (–0.070, $p < 0.10$) and *NOR*Size*Age* (–0.128, $p < 0.00$) on *UE_OR* are significantly negative, indicating that large, old and large older firms are engaged in revenue misclassification. The coefficient of *NOR*BigN* on *UE_OR* is negative, however insignificant (–0.093, $p > 0.10$), implying that firms audited by Big four auditors are engaged in revenue misclassification. The coefficient of interaction variables - *NOR*Size*BigN* (–0.070, $p < 0.05$), *NOR*Age*BigN* (–0.028, $p < 0.10$), and

*NOR*Size*Age*BigN* (–0.061, $p < 0.05$) are significantly negative, implying that Big four auditors have no constraining effect on revenue misclassification practices of large, old and large older firms.

Table 4
Test results of misclassification practices

	UE_OR (Model 3) (1)		*UE_CE* (Model 4) (2)
NOR ($\boldsymbol{\alpha_1}$)	0.072**	***NOE*** ($\boldsymbol{\beta_1}$)	0.053**
t-statistics	(2.032)		(2.219)
Standard error	0.035		0.023
Size ($\boldsymbol{\alpha_2}$)	0.106	***Size*** ($\boldsymbol{\beta_3}$)	0.037
t-statistics	(0.996)		(0.336)
Standard error	0.106		0.110
Age ($\boldsymbol{\alpha_3}$)	0.114**	***Age*** ($\boldsymbol{\beta_4}$)	0.160**
t-statistics	(2.349)		(2.009)
Standard error	0.048		0.079
Size*Age ($\boldsymbol{\alpha_4}$)	0.162**	***Size*Age*** ($\boldsymbol{\beta_5}$)	0.180*
t-statistics	(1.984)		(1.922)
Standard error	0.082		0.093
NOR*Size ($\boldsymbol{\alpha_5}$)	–0.053**	***NOE*Size*** ($\boldsymbol{\beta_6}$)	0.019
t-statistics	(–2.006)		(1.440)
Standard error	0.026		0.013
NOR*Age ($\boldsymbol{\alpha_6}$)	–0.037**	***NOE*Age*** ($\boldsymbol{\beta_7}$)	0.073
t-statistics	(–2.180)		(1.443)
Standard error	0.016		0.050
NOR*Size*Age ($\boldsymbol{\alpha_7}$)	–0.160***	***NOE*Size*Age*** ($\boldsymbol{\beta_8}$)	0.084
t-statistics	(5.163)		(1.496)
Standard error			0.056
A_DISX	0.069**	***A_DISX***	–0.743***
t-statistics	(–2.009)		(5.113)
Standard error	0.079		0.1453
A_PROD	0.096	***A_PROD***	0.050
t-statistics	(1.557)		(1.096)
Standard error	0.062		0.045
A_ACC	–0.194***	***A_ACC***	–0.019
t-statistics	(–3.163)		(0.443)
Standard error	0.061		0.043
Lev	0.094*	***Lev***	–0.032
t-statistics	(1.773)		(0.993)
Standard error	0.053		0.032
Growth	–0.069	***Growth***	0.079*
t-statistics	(1.332)		(1.833)
Standard error	0.051		0.043
Audit fees	–1.532**	***Audit fees***	–0.964**
t-statistics	(–2.336)		(–2.003)
Standard error	0.655		0.482
Duality	0.096*	***Duality***	0.064
t-statistics	(1.920)		(1.843)
Standard error	0.050		0.035

Intercept (α_0)	0.119***	Intercept (β_0)	0.149**
t-statistics	(3.169)		(2.220)
Standard error	0.037		0.067
Fixed effects	Yes	Fixed effects	Yes
Adjusted R-square	0.293	Adjusted R-square	0.362
P-value	0.000	P-value	0.000
Observations	35,480	Observations	31,960

Note: Table shows the regression results of model 3 and model 4 used to examine the impact of firm size and firm age on revenue and expense misclassification, respectively. Amounts reported are regression coefficients with robust t-statistics in parentheses. We have also reported standard errors for the coefficients. ***, **, * indicate significance at 1%, 5%, and 10% levels, respectively (P-values).[3]

Column (2) shows that the coefficient of *NOE* on *UE_CE* is significantly positive, (0.061, $p < 0.10$), which is in line with our previous findings that sample firms are engaged in expense misclassification. The coefficient of *NOE*BigN* on *UE_CE* is insignificant positive (0.116, $p > 0.10$), implying weaker evidence of expense misclassification among Big four audit firms. The coefficient of interaction variables - *NOE*Size*BigN* (0.093, $p > 0.10$), *NOE*Age*BigN* (0.043, $p > 0.10$), and *NOE*Size*Age*BigN* (–0.079, $p > 0.10$) are insignificant positive or negative, implying that Big four auditors have constraining effect on firm's expense misclassification. These results are consistent with Nagar et al. (2021) that firms audited by Big four auditors have a lesser likelihood of expense misclassification. Reading together columns (1) and (2) of Table 5 implies that the Big four has a limiting effect on expense misclassification but not on revenue misclassification. It means higher audit quality can mitigate the misclassification of expenses but not revenues. Overall, our results do not support the prediction under H3 but support the H4. It exhibits the partial effectiveness of Big four auditors in curbing the corporate misfeasance of misclassification practices.

Table 5

Test results of the impact of BigN on misclassification practices

	UE_OR (Model 5) (1)		*UE_CE* (Model 6) (2)
NOR (α_1)	0.042**	***NOE*** (β_1)	0.061**
t-statistics	(1.983)		(1.983)
Standard error	0.021		0.031
Size (α_2)	0.093	***Size*** (β_3)	0.092
t-statistics	(1.442)		(1.552)
Standard error	0.064		0.059
Age (α_3)	0.143**	***Age*** (β_4)	0.361**
t-statistics	(2.332)		(2.264)
Standard error	0.061		0.159
Size*Age (α_4)	0.084*	***Size*Age*** (β_5)	0.184*
t-statistics	(1.902)		(1.733)
Standard error	0.044		0.106
NOR*Size (α_5)	–0.067**	***NOE*Size*** (β_6)	0.015
t-statistics	(–2.442)		(1.100)
Standard error	0.027		0.013
NOR*Age (α_6)	–0.070*	***NOE*Age*** (β_7)	0.083
t-statistics	(1.883)		(1.540)

Standard error	0.037		0.054
NOR*Size*Age ($\boldsymbol{\alpha_7}$)	–0.128***	***NOE*Size*Age*** ($\boldsymbol{\beta_8}$)	0.063
t-statistics	(6.112)		(1.103)
Standard error	0.021		0.057
BigN ($\boldsymbol{\alpha_8}$)	0.063	***BigN*** ($\boldsymbol{\beta_9}$)	–0.103*
t-statistics	(1.513)		(1.645)
Standard error	0.042		0.062
Size*BigN ($\boldsymbol{\alpha_9}$)	0.109	***Size*BigN*** ($\boldsymbol{\beta_{10}}$)	0.549**
t-statistics	(1.109)		(2.187)
Standard error	0.098		0.251
Age*BigN ($\boldsymbol{\alpha_{10}}$)	0.087**	***Age*BigN*** ($\boldsymbol{\beta_{11}}$)	0.673**
t-statistics	(2.003)		(2.331)
Standard error	0.043		0.288
Size*Age*BigN ($\boldsymbol{\alpha_{11}}$)	0.153	***Size*Age*BigN*** ($\boldsymbol{\beta_{12}}$)	0.191*
t-statistics	(1.276)		(1.830)
Standard error	0.119		0.104
NOR*BigN ($\boldsymbol{\alpha_{12}}$)	0.093	***NOE*BigN*** ($\boldsymbol{\beta_{13}}$)	0.116
t-statistics	(0.547)		(1.233)
Standard error	0.170		0.094
NOR*Size*BigN ($\boldsymbol{\alpha_{13}}$)	–0.070**	***NOE*Size*BigN*** ($\boldsymbol{\beta_{14}}$)	0.093
t-statistics	(–2.110)		(1.630)
Standard error	0.033		0.057
NOR*Age*BigN ($\boldsymbol{\alpha_{14}}$)	–0.028*	***NOE*Age*BigN*** ($\boldsymbol{\beta_{15}}$)	0.043
t-statistics	(1.883)		(1.345)
Standard error	0.014		0.032
NOR*Size*Age*BigN ($\boldsymbol{\alpha_{15}}$)	–0.061**	***NOE*Size*Age*BigN*** ($\boldsymbol{\beta_{16}}$)	–0.079
t-statistics	(–2.116)		(0.884)
Standard error	0.028		0.089
Intercept (α_0)	0.139***	Intercept (β_0)	0.230***
t-statistics	(11.885)		(3.163)
Standard error	0.012		0.072
Controls and fixed effects	Yes	Controls and fixed effects	Yes
Adjusted R-square	0.329	Adjusted R-square	0.430
P-value	0.000	P-value	0.000
Observations	35,480	Observations	31,960

Note: Table shows the regression results of model 5 and model 6 used to examine the moderating role of BigN auditors on revenue misclassification, and expense misclassification, respectively. Amounts reported are regression coefficients with robust t-statistics in parentheses. We have also reported standard errors for the coefficients. ***, **, * indicate significance at 1%, 5%, and 10% levels, respectively (P-values).

Robustness Tests

An alternative measurement of UE_OR and UE_CE

Following Malikov et al. (2018), we have used two alternative specifications for estimating *UE_OR*. In the first specification, we exclude accounts receivables from the model (1) because they may contain receivables from non-operating revenues. In the second specification, we replace account receivables with the cost of goods sold to strike the balance between cost and selling per unit. In the same vein, following Alfonso et al. (2015), we have used two alternative specifications for measuring *UE_CE*. In the first specification, we exclude current-year accruals because they may include non-cash special items. In the second alternative, we replace accruals with working capital accruals to control the impact of non-cash items. We re-run our models by using these alternative specifications of *UE_OR* and *UE_CE* and find (untabulated) [4] that large and old firms prefer revenue misclassification over expense misclassification for managing earnings, and Big four auditors have a constraining effect on expense misclassification but not on revenue misclassification.

Propensity score matching technique

Since the categorization of firms under large and old firms is not entirely random, hence we use Propensity-Score Matched (PSM) model to ensure that our results are free from the endogeneity problem and self-selection bias. We construct a sample out of our main category of interest that is more comparable to our counterparts. We follow two steps while implementing PSM. First, we estimate propensity scores using a first-stage probit model for firms of interest by regressing on a set of firm characteristic variables. We use a firm's growth, leverage, return on assets, and quick ratio as the factors that affect a firm's likelihood of falling under the treatment group.[5] The model is as follows:

$$Firm_{i,t} = \alpha_0 + \beta_1 Lev_{i,t} + \beta_2 Quick\ ratio_{i,t} + \beta_3 Growth_{i,t} + \beta_4 ROA_{i,t} + \varepsilon_{it} \quad \ldots (7)$$

Where *Firm* is a binary variable that takes value equal to one for treatment firms (large and old firms) and zero for control firms (small and young firms). Table 6, Panel A shows the results of the first-stage regression model. The reported results suggest that all explanatory variables are significantly correlated with the probability of being a treatment firm.

Second, we use the obtained scores and match each treatment firm to the control firms through the nearest-neighbor matching technique. We require the difference in the predicted probabilities to be less than 0.05*standard deviation of the propensity scores. It provides treatment and control groups that are identical in terms of observable characteristics. The firm year under our initial sample is 35,480 (31,960) for revenue (expense) shifting, however, the PSM procedure produces a matched sample of 17,740 (15,980) firm years. To check the validity of the matched sample, we check the significance of the difference in the variables means under the initial and PSM sample and find that none of the differences under the matched sample is significant, hence, confirming the validity of the matched sample.

Table 6, panel B shows the results of models (5) and (6) under the PSM sample.[6] We find that the coefficient of *NOR*Size*, *NOR*Age*, and *NOR*Size*Age* under column (1) are significantly negative, whereas *NOE*Size*, *NOE*Age*, and *NOE*Size*Age* under column (2) are positive, implying that large and old firms prefer revenue misclassification over expense misclassification for managing earnings. Besides, consistent with our previous findings we find that BigN constraints the firm's expense misclassification, but not revenue misclassification. The direction and magnitude of the coefficient in the PSM sample are found to be the same as previous findings with the exception that the coefficient of *NOR*Size*Age*BigN* turns significant at a 10% level of significance only.

Table 6
Results of Propensity-Score-Matched Sample

Panel A: First Stage Logit Model

Dependent variable: *Firm* (Model 7)	Coefficient	z values	Standard error
Lev	-0.123***	(-4.550)	0.027
Quick ratio	0.109***	(9.942)	0.011
Growth	0.793***	(11.720)	0.067
ROA	0.551***	(9.665)	0.057
Intercept	0.196***	(5.702)	0.034
N		31,960	
Pseudo-R Square		0.220	

Panel B: Regression results using PSM sample

	UE_OR (Model 5) (1)		*UE_CE* (Model 6) (2)
NOR ($\boldsymbol{\alpha_1}$)	0.060*	***NOE*** ($\boldsymbol{\beta_1}$)	0.083**
t-statistics	(1.688)		(2.003)
Standard error	0.035		0.041
Size ($\boldsymbol{\alpha_2}$)	0.031	***Size*** ($\boldsymbol{\beta_3}$)	0.040
t-statistics	(1.550)		(1.442)
Standard error	0.020		0.028
Age ($\boldsymbol{\alpha_3}$)	0.170**	***Age*** ($\boldsymbol{\beta_4}$)	0.163**
t-statistics	(2.114)		(2.316)
Standard error	0.080		0.070
Size*Age ($\boldsymbol{\alpha_4}$)	0.091*	***Size*Age*** ($\boldsymbol{\beta_5}$)	0.190*
t-statistics	(1.887)		(1.894)
Standard error	0.048		0.100
NOR*Size ($\boldsymbol{\alpha_5}$)	–0.093**	***NOE*Size*** ($\boldsymbol{\beta_6}$)	0.012
t-statistics	(–2.403)		(1.083)
Standard error	0.038		0.011
NOR*Age ($\boldsymbol{\alpha_6}$)	–0.030*	***NOE*Age*** ($\boldsymbol{\beta_7}$)	0.073
t-statistics	(1.691)		(1.493)
Standard error	0.017		0.048
NOR*Size*Age ($\boldsymbol{\alpha_7}$)	–0.194***	***NOE*Size*Age*** ($\boldsymbol{\beta_8}$)	0.080
t-statistics	(8.153)		(1.092)
Standard error	0.023		0.073
BigN ($\boldsymbol{\alpha_8}$)	0.090	***BigN*** ($\boldsymbol{\beta_9}$)	–0.113*
t-statistics	(1.631)		(1.685)
Standard error	0.055		0.067
Size*BigN ($\boldsymbol{\alpha_9}$)	0.083	***Size*BigN*** ($\boldsymbol{\beta_{10}}$)	0.493**
t-statistics	(1.063)		(2.019)
Standard error	0.078		0.244
Age*BigN ($\boldsymbol{\alpha_{10}}$)	0.077**	***Age*BigN*** ($\boldsymbol{\beta_{11}}$)	0.552*
t-statistics	(2.336)		(1.884)
Standard error	0.032		0.293
Size*Age*BigN ($\boldsymbol{\alpha_{11}}$)	0.097	***Size*Age*BigN*** ($\boldsymbol{\beta_{12}}$)	0.167
t-statistics	(1.447)		(1.093)
Standard error	0.067		0.152
NOR*BigN ($\boldsymbol{\alpha_{12}}$)	0.070	***NOE*BigN*** ($\boldsymbol{\beta_{13}}$)	0.097
t-statistics	(0.334)		(1.027)
Standard error	0.209		0.094
NOR*Size*BigN ($\boldsymbol{\alpha_{13}}$)	–0.073***	***NOE*Size*BigN*** ($\boldsymbol{\beta_{14}}$)	0.064

t-statistics	(–2.631)		(1.617)
Standard error	0.028		0.039
NOR*Age*BigN ($\boldsymbol{\alpha_{14}}$)	–0.027**	***NOE*Age*BigN*** ($\boldsymbol{\beta_{15}}$)	0.037
t-statistics	(1.993)		(1.073)
Standard error	0.013		0.034
NOR*Size*Age*BigN ($\boldsymbol{\alpha_{15}}$)	–0.080*	***NOE*Size*Age*BigN*** ($\boldsymbol{\beta_{16}}$)	–0.083
t-statistics	(–1.807))		(1.500)
Standard error	0.045		0.055
Intercept (α_0)	0.450***	Intercept (β_0)	0.216***
t-statistics	(7.553)		(12.772)
Standard error	0.059		0.017
Controls and fixed effects	Yes	Controls and fixed effects	Yes
Adjusted R-square	0.442	Adjusted R-square	0.490
P-value	0.000	P-value	0.000
Observations	17,740	Observations	15,980

Note: Table shows the results for the propensity-score-matched (PSM) sample, where Panel A shows the results of the logit model (7) and Panel B presents the results of models 5 and 6 using the PSM sample as the control group. Amounts reported are regression coefficients with robust t-statistics in parentheses. We have also reported standard errors for the coefficients. ***, **, * indicate significance at 1%, 5%, and 10% levels, respectively (P-values).

DISCUSSION

Due to weaker corporate governance mechanisms in emerging nations, the issue of earnings management has gained greater attention from the academicians and researcher fraternity (Adhikari et al., 2021). Numerous studies have identified firms' characteristics that impact their earnings management practices (for instance, Kim et al., 2003; Kothari et al., 2005; Lobo & Zhou, 2006; McVay, 2006). Two such dominating characteristics, namely firm size and firm age have been documented in the literature. However, both features have been explored only in the context of accrual and real earnings management. The investigation of these factors in the terms of classification shifting practices has not been made to date. This issue is important because firms are likely to prefer one form of classification shifting over another based-on incentives and opportunities, and these incentives and opportunities are likely to vary across the size and age of the firm. The issue is also important because recent studies on classification shifting document that firms are preferring classification shifting over accrual and real earnings management due to its low-cost element as it neither results in reversal of accruals like accrual earnings management nor foregone future benefits like real earnings management (for instance, Fan et al., 2019; Malikov et al., 2018; Nagar et al., 2021). Hence, the issue of classification shifting is vital for many stakeholders.

Consistent with the conjectures, this study documents that a firm's shifting practices are largely dependent on the size and age of the firms as large and old firms are found to choose revenue shifting over expense shifting due to its ease of implementation, and greater advantage in terms of reporting favorable operating performance numbers. These findings are consistent with the Fraud Triangle Theory (Cressey, 1950), and the ease-need-advantage-based shifting framework proposed in this study, where firms are found to choose the earnings management tool based on three factors, namely ease-based shifting (higher magnitude of non-recurring items), need-based shifting (purpose of reporting sales and core earnings at inflated amount) and advantage-based shifting (firms stimulate profitability ratios more through expense shifting). Overall, our finding of choosing the shifting form based on size and age complements the findings of Abernathy et al. (2014) that firms substitute earnings management tools for their private gains.

This finding has several implications for different stakeholders. For instance, as investors are found to consider large and small-cap firms before investing, hence our findings suggest investing in small firms as they have a lower magnitude of shifting practices. Lenders are mostly found to use operating profit as a base metric before making a lending decision, hence they must be aware of the shifting practices employed by borrowing firms to favorably influence the perception of capital providers towards their core profitability. In addition, the findings aware auditors about the suspected firms (large and old firms), hence auditors should study the nature of the firm before assessing the financial statements of their clients.

The issue of classification shifting is important to minimize through superior audit quality (Nagar et al., 2021). Few prior studies attempted to analyze the impact of big four auditors on the classification-shifting practices of firms (for instance, Mulchandani & Mulchandani, 2022; Nagar et al., 2021). However, these studies have considered only expense shifting and ignored revenue shifting while examining the impact of audit quality on classification-shifting practices. Hence, to overcome the limitation of the prior studies, the current study re-examines the impact of audit quality on classification shifting by taking into account both forms of shifting practices (expense shifting and revenue shifting). Our findings contrast the findings of Nagar et al. (2021) and Mulchandani and Mulchandani (2022) that big four auditors mitigate classification shifting because we find that big four auditors are only able to mitigate the expense shifting and are unable to mitigate the revenue shifting practices of firms. It implies two things. First, auditors are unaware of the revenue misclassification tactics employed by firms to report inflated core earnings. Second, the accounting standards themselves provide greater leeway for recording revenue items in the books of account. These findings aware auditors of the firm’s revenue shifting practices and suggest critically evaluating the revenue component items of their client firms. The findings strongly recommend authorities make separate forensic accounting standards for auditors to curb the corporate misfeasance of revenue shifting.

CONCLUSION

The study examines the factors affecting the choice of core earnings management tools. Firms engaged in either misclassification of expenses or misclassification of revenue or both for reporting inflated core earnings. It is of interest to examine what incentivizes firms to prefer one tool over another. Hence, the current explores both forms of misclassification by exploring the available opportunities and significant incentives for each of the tools. The study posits that firms choose the tool based on their size and age. Results show that large and old firms prefer revenue misclassification over expense misclassification for managing earnings, consistent with the ease and need-based shifting framework. The study further examines the moderating role of Big four auditors in mitigating classification shifting forms and finds that BigN auditors have a constraining effect on expense misclassification but not on revenue misclassification, implying that partial effectiveness of audit quality in curbing the corporate misfeasance of classification shifting.

The study is among the earlier attempts to jointly investigate both forms of misclassification and provide compelling evidence that firm-specific variables (firm size and firm age) incentivize firms to prefer one form of misclassification over another. The study also contributes to the literature by undertaking a comprehensive approach to ascertain the impact of audit quality on classification shifting by studying both forms (expense and revenue misclassification). The study has a few limitations. First, the current study has explored only two firm features (size and age). Future research should identify more such firm-specific factors that incentivise or pressurise firms to engage in a particular form of misclassification. The reported results do not hold under the firm-fixed effect model[7], hence it shows that exploring the firm-specific domain in the classification shifting practices is pivotal. Second, the study did not consider industry-wise classification shifting practices, hence future studies can be conducted to examine the issue of whether shifting practices vary across industries. Manufacturing industry firms are more likely to prefer expense misclassification due to their vast categories of expenses than other counterparts in other industries. Third, the study used panel data regression models which do not control for the exogenous shocks, hence future research can be conducted by using the 'difference-in-difference' technique that enables researchers to isolate the impact of concurrent economic shocks on the earnings management practices of large and old firms.

NOTES

[1] Revenue (expense) misclassification and revenue (expense) shifting are used interchangeably in the study.

[2] We thank an anonymous reviewer for suggesting us to control these variables in our models.

[3] We have also calculated the class interval for each of the reported coefficients. To avoid making the paper bulkier, we have not reported the upper and lower values in each of the class intervals. These values are made available from authors upon the reader's request.

[4] All the untabulated results are made available from authors.

[5] We conducted weak instrument test and over-identification test to verify the suitability of instrumental variables.

[6] We use model 5 and model 6 under PSM analysis because these models are complete in terms of testing each of our hypotheses (H1-H4).

[7] The significance level of coefficients of our main variables of interest has been reduced from 1% to 10% level of significance when firm-fixed effect is included in the models. It provides useful insights to researchers working in the area od earnings management to understand the relationship more critically between cross-sectional features and firm's shifting practices. Future research can be conducted to identify more firm-specific factors that are likely to incentivise firms to prefer one form of misclassification over another because firm-fixed effect influence the firm's shifting practices.

REFERENCES

Abernathy, J. L., Beyer, B., & Rapley, E. T. (2014). Earnings management constraints and classification shifting. *Journal of Business Finance & Accounting*, *41*(5–6), 600–626. https://doi.org/10.1111/jbfa.12076

Adhikari, A., Bansal, M., & Kumar, A. (2021). IFRS convergence and accounting quality: India a case study. *Journal of International Accounting, Auditing, and Taxation*, *45*, 100430. https://doi.org/10.1016/j.intaccaudtax.2021.100430

Alfonso, E., Cheng, C. A., & Pan, S. (2015). Income classification shifting and mispricing of core earnings. *Journal of Accounting, Auditing & Finance*, 1–32. https://doi.org/10.1177/0148558X15571738

Alhadab, M., & Clacher, I. (2018). The impact of audit quality on real and accrual earnings management around IPOs. *The British Accounting Review*, *50*(4), 442–461. https://doi.org/10.1016/j.bar.2017.12.003

Ali, A., & Bansal, M. (2021). Impact of upward and downward earnings management on stock returns. *South Asian Journal of Business Studies*. https://doi.org/10.1108/SAJBS-12-2020-0417

Antle, R., Gordon, E., Narayanamoorthy, G., & Zhou, L. (2006). The joint determination of audit fees, non-audit fees, and abnormal accruals. *Review of Quantitative Finance and Accounting*, *27*(3), 235–266. https://doi.org/10.1007/s11156-006-9430-y

Bansal, M. (2022a). Impact of corporate life cycle on misclassification practices: evidence from IFRS adoption in India. *Journal of Applied Accounting Research*, 23(3), 628–649.

Bansal, M. (2022b). Do shifting practices vary across the firm life cycle? *Australian Journal of Management*, 03128962221131353.

Bansal, M. (2022c). Earnings management contagion: evidence from institutional equivalence. *Asian Journal of Accounting Research*.

Bansal, M., & Ali, A. (2022). Betting against real earnings management. *Asian Review of Accounting*, *30*(2), 233–257.

Bansal, M., & Kumar, V. (2021). Forcing responsibility? Examining earnings management induced by mandatory corporate social responsibility: evidence from India. *Review of Accounting and Finance*, *20*(2), 194–216.

Bansal, M., Kumar, A., & Badhani, K. N. (2021). Do Indian firms engage in classification shifting to report inflated core earnings? *Managerial Finance*. *47*(4), 1533–1552.

Barnea, A., Ronen, J., & Sadan, S., (1976). Classificatory smoothing of income with extraordinary items. *The Accounting Review*, *51*(1), 110–122.

Barua, A., Lin, S., & Sbaraglia, A. M. (2010). Earnings management using discontinued operations. *The Accounting Review*, *85*(5), 1485–1509.

Bashir, H. A., Bansal, M., & Kumar, D. (2021). Predictive view of the value relevance of earnings in India. *Journal of Financial Reporting and Accounting*.

Bhushan, R. (1989). Firm characteristics and analyst following. *Journal of accounting and economics*, *11*(2–3), 255–274.

Bilinski, P., & Eames, M., (2019). Analyst revenue forecast reporting and the quality of revenues and expenses. *Journal of Business Finance & Accounting*, 46(1–2), 136–158.

Cressey, D. R., (1950). The criminal violation of financial trust. *American Sociological Review*, *15*(6), 738–743.

Curtis, A. B., McVay, S. E., & Whipple, B. C. (2014). The disclosure of non-GAAP earnings information in the presence of transitory gains. *The Accounting Review*, *89*(3), 933–958.

Das, S., Levine, C. B., & Sivaramakrishnan, K. (1998). Earnings predictability and bias in analysts' earnings forecasts. *Accounting Review*, 277–294.

Doan, T., & Nguyen, N. Q. (2018). Boards of directors and firm leverage: Evidence from real estate investment trusts. *Journal of Corporate Finance*, *51*, 109–124.

Dyreng, S. D., Vashishtha, R., & Weber, J. (2017). Direct evidence on the informational properties of earnings in loan contracts. *Journal of Accounting Research*, *55*(2), 371–406.

Fan, Y., & Liu, X. (2017). Misclassifying core expenses as special items: Cost of goods sold or selling, general, and administrative expenses? *Contemporary Accounting Research*, *34*(1), 400–426.
Fan, Y., Barua, A., Cready, W. M., & Thomas, W. B. (2010). Managing earnings using classification shifting: Evidence from quarterly special items. *The Accounting Review*, *85*(4), 1303–1323.
Fan, Y., Thomas, W. B., & Yu, X. (2019). The impact of financial covenants in private loan contracts on classification shifting. *Management Science*, *65*(8), 3637–3653.
Francis, J. R., & Krishnan, J. (2002). Evidence on auditor risk-management strategies before and after the Private Securities Litigation Reform Act of 1995. *Asia-Pacific Journal of Accounting & Economics*, *9*(2), 135–157.
Francis, J. R., & Yu, M. D. (2009). Big 4 office size and audit quality. Accounting Review, *84*(5), 1521–1552.
Gerayli, M. S., Yaanosari, A. M., & Maatoofi, A. R. (2011). Impact of audit quality on earnings management: Evidence from Iran. *International Research Journal of Finance and Economics*, *66*(1), 77–84
Gul, F. A., Fung, S. Y. K., & Jaggi, B. (2009). Earnings quality: Some evidence on the role of auditor tenure and auditors' industry expertise. *Journal of Accounting and Economics*, *47*(3), 265–287.
Haw, I. M., Ho, S. S., & Li, A. Y. (2011). Corporate governance and earnings management by classification shifting. *Contemporary Accounting Research*, *28*(2), 517–553.
Houqe, M. N., Ahmed, K., & Van Zijl, T. (2017). Audit quality, earnings management, and cost of equity capital: evidence from India. *International Journal of Auditing*, *21*(2), 177–189.
Hu, J. (2021). Do facilitation payments affect earnings management? Evidence from China. *Journal of Corporate Finance*, *68*, 101936.
Joo, J. H., & Chamberlain, S. L. (2017). The effects of governance on classification shifting and compensation shielding. *Contemporary Accounting Research*, *34*(4), 1779–1811.
Khanh, H. T. M., & Nguyen, V. K. (2018). Audit quality, firm characteristics and real earnings management: The case of listed Vietnamese firms. *International Journal of Economics and Financial Issues*, *8*(4), 243.
Kim, Y., Liu, C., & Rhee, S. G. (2003). The relation of earnings management to firm size. *Journal of Management Research*, *4*, 81–88.
Kothari, S. P., Leone, A. J., & Wasley, C. E. (2005). Performance-matched discretionary accrual measures. *Journal of accounting and economics*, *39*(1), 163–197.
Lail, B. E., Thomas, W. B., & Winterbotham, G. J. (2014). Classification shifting using the "corporate/other" segment. *Accounting Horizons*, *28*(3), 455–477.
Lobo, G. J., & Zhou, J. (2006). Did conservatism in financial reporting increase after the Sarbanes-Oxley Act? Initial evidence. *Accounting Horizons*, *20*(1), 57–73.
Lougee, B. A., & Marquardt, C. A. (2004). Earnings informativeness and strategic disclosure: An empirical examination of "pro forma" earnings. *The Accounting Review*, *79*(3), 769–795.
Malikov, K., Manson, S., & Coakley, J. (2018). Earnings management using classification shifting of revenues. *British Accounting Review*, *50*(3), 291–305.
Marquardt, C. A., & Wiedman, C. I. (2004). How are earnings managed? An examination of specific accruals. *Contemporary Accounting Research*, *21*(2), 461–491.
McVay, S. E. (2006). Earnings management using classification shifting: An examination of core earnings and special items. *The Accounting Review*, *81*(3), 501–531.
Mulchandani, K., & Mulchandani, K. (2022). Do independent directors and big-4 audit firms limit classification shifting: Evidence from Indian firms. *Managerial Finance*, (ahead-of-print).
Nagar, N., Desai, N., & Jacob, J. (2021). Do Big 4 auditors limit classification shifting? Evidence from India. *Journal of International Accounting, Auditing, and Taxation*, *42*, 100376.
Nguyen, A. H., & Duong, C. T. (2021). Earnings management and new listings: Evidence from Vietnam. *Asian Academy of Management Journal*, *26*(2), 27–51.
Roychowdhury, S. (2006). Earnings management through real activities manipulation. *Journal of Accounting and Economics*, *42*(3), 335–370.
Simunic, D. A., & Stein, M. T. (1987). *Product differentiation in auditing: Auditor choice in the market for unseasoned new issues* (Vol. 13). Canadian Certified General Accountants' Research Foundation.

Swamidas, P. M. and Kotha, S., (1998). Explaining manufacturing technology used, firm size, and performance using multidimensional view of technology. *Journal of Operations Management*, 17, 23–37. https://doi.org/10.1016/S0272-6963(98)00016-3

Zalata, A., & Roberts, C. (2016). Internal corporate governance and classification shifting practices: An analysis of UK corporate behavior. *Journal of Accounting, Auditing & Finance*, *31*(1), 51–78. https://doi.org/10.1177/0148558X15571736

Zandi, G., & Abdullah, N. A. (2019). Financial statements timeliness: The case of Malaysian listed industrial product companies. *Asian Academy of Management Journal*, *24*, 127–141. https://doi.org/10.21315/aamj2019.24.s2.9