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Predictors of revenue shifting and expense shifting: Evidence from an emerging economy

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Prior literature established that managers engage in Revenue Shifting (RS) and Expense Shifting (ES) with an intent to report favourable operating performance; our paper extends such research in a new direction by investigating both forms based on the need, ease, and advantage of each form of shifting strategy. The study identifies firm-specific factors that incentivize firms to prefer RS over ES and vice-versa. We undertake a longitudinal study (2001–2019) using a sample size of 39,634 firm-years, enlisted in the Bombay Stock Exchange (BSE). Our results show that peer-performance, size, financial leverage, growth opportunities, accounting flexibility, and age of the firm are important determinants of RS and ES. Specifically, our results exhibit that large, levered, old, and high-growth firms are engaged in RS, whereas small, young, firms with lesser accounting flexibility, and firms operating below peer-performance are involved in ES. These results are robust to controlling for accruals earnings management, real earnings management, endogeneity, self-selection bias, and alternative measures of RS and ES. Our findings are helpful to auditors and investors in improving awareness of forms of classification shifting.

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1. Introduction

Corporate scandals such as of Enron Corporation in the United States and Satyam Computer Services in India led to an increased academic interest in accounting manipulations, euphemistically known as "earnings management." The research in this area has significantly increased since 2003, after the collapse of Enron. The extant literature helped in identifying three primary tools of earnings management, namely accrual-based earnings management (hereafter, AEM), real earnings management (hereafter, REM), and classification shifting (hereafter, CS). Under AEM, managers push (bring) current (future) earnings to future (current) earnings to deflate (inflate) current period earnings through the use of accruals. Under REM, managers deviate from the normal course of business operations to manage earnings. Under CS, managers misclassify income-statement line items with an intent to report favorable operating performance of firms. For example, managers misclassify operating expenses such as selling, general, and administrative (SG&A) expenses as non-operating expenses such as

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restructuring costs. Abernathy et al. (2014) and Zang (2012) documented that managers make trade-off decisions among AEM, REM, and CS based on the costs, constraints, and timing of each earnings management tool.[1]

The literature reveals that considereable research has been conducted on AEM (for instance, Schipper, 1989; Healy and Wahlen, 1999; Dechow et al., 2012) and REM (Roychowdhury, 2006; Xu et al., 2007). However, studies on CS are relatively scarce and the available literature indicates a growing trend of disclosing operating profits separately in the financial statements (Zalata and Roberts, 2016). Investors' perception of income statement line items is the main motivation behind CS. Investors assign higher weights to permanent line items than transient line items due to their persistent nature (Fairfield et al., 1996), greater predictive ability (Doyle et al., 2003), and higher valuation relevance (Lougee and Marquardt, 2004). Operating profit, being a top-line item, excludes the impact of non-recurring items, hence it is likely to gauge the true operational efficiency of firms (Davis, 2002). It incentivizes investors to accord more weight to operating profit than net profit while making investment decisions (Bartov and Mohanram, 2014; Bhattacharya et al., 2007; Brown et al., 2012; Wieland et al., 2013).

Besides investors, analysts and lenders are found to base their decisions on a firm's reported operating profit. Analysts use operating profit as the benchmark for prediction due to its greater predictive ability (Philbrick and Ricks, 1991; Bradshaw and Sloan, 2002). It improves the accuracy of their prediction. Lenders impose operating profit-based covenants such as earnings before interest, taxes, depreciation, and amortization (EBITDA)-based covenants in loan contracts (Demerjian and Owens, 2016). Hence, any misreporting of operating profit affects the decision-making of many stakeholders. Managers'compensation and debt contracts are also found to be largely dependent on firms' operating profit (Bentley et al., 2018; Cain et al., 2020), which in turn increases the likelihood of a firm's engagement in shifting practices.

The existing literature suggests that managers engage in two different approaches to report inflated operating profits: first, in shifting operating expenses to non-operating expenses (for instance, Barua et al., 2010; Fan et al., 2010; McVay, 2006; Lail et al., 2014)[2] and, second, in shifting non-operating revenue to operating revenue (Malikov et al., 2018; 2019; Noh et al., 2017). Several anecdotal pieces of evidence are available on the firm's shifting practices.[3] Collectively, these forms are referred to as income shifting (Alfonso et al., 2015; Pan et al., 2019), because shifting of expense and revenue items results in inflated operating income. However, in this study, we refer to the first form of shifting as "expense shifting" (hereafter, ES) and the second form as "revenue shifting" (hereafter, RS), because we aim to identify firm-specific factors that incentivize managers to prefer RS over ES, and vice-versa.

Based on the above discussion, we infer two things. First, firms can report inflated operating profits either by shifting expenses or revenues or both. Second, the shifting of revenues has a dual advantage as it enables firms to record both operating revenues and operating profits at an inflated amount as an effect of misclassification. Accordingly, firms are likely to prefer one form of shifting over another for reporting inflated operating profits. The choice of the shifting tool is likely to be dependent on opportunities available for misclassifying the expense and revenue items and the incentives for reporting the sales and operating profits at an inflated amount. Therefore, the current study aims at identifying those firm-specific factors that incentivize or provide opportunities for managers to prefer one form of shifting over another. We explored the well-documented determinants of earnings management in the context of CS. In particular, we explored seven determinants, namely, peer-performance, size, degree of financial leverage, accounting flexibility, growth opportunities, management compensation contracts, and age of the firm.

The novelty of our study is that it identifies firm-specific factors that incentivize managers to prefer one form of shifting over another. In other words, we explore the relationship between shifting tools depending on the ease,[4] need,[5] and relative advantage[6] of each tool. We identified the factors that impact the firm's preference for a particular shifting tool (ease-based, need-based, and advantage-based shifting). We studied the relationship among the forms of CS, whereas prior studies examined one form of CS at a time. For instance, McVay (2006), Fan et al. (2010), Barua et al. (2010), Haw et al. (2011), and Fan et al. (2019) investigated ES, whereas Malikov et al. (2018), Malikov et al. (2019), and Noh et al. (2017) investigated RS at a time. Moreover, existing studies on CS are undertaken in different institutional settings at different periods. We examined both forms of CS using the same set of firms during the same period. We investigated the issue under the Indian institutional settings, because the

[1] Zang (2012), while studying the relationship between AEM and REM, found that firms prefer REM over AEM when they face greater scrutiny from auditors and regulators, and have limited accounting flexibility, whereas AEM is preferred over REM when they have higher financial distress and institutional investors. Abernathy et al. (2014) studied the relationship between AEM, REM and CS and found that firms prefer CS over REM when they have lower industry market share and prefer CS over AEM to meet analyst forecasts.

[2] Firms are engaged in shifting of operating expenses to income-decreasing special items (McVay, 2006; Fan et al., 2010). Further studies report that firms not only shift to special items, but also are engaged in shifting of operating expenses to extraordinary items (Barnea et al., 1976), income-decreasing discontinued operations (Barua et al., 2010), non-recurring items (Athanasakou et al., 2009), and amongst segments within a firm (Lail et al., 2014). Other studies (for instance, Alfonso et al., 2015; Fan et al., 2019; Haw et al., 2011; Zalata and Roberts, 2016) have also found the evidence of ES.

[3] The U.S. Securities Exchange Commission (SEC) has detected several firms that engaged in CS practices. For example, SEC charged SafeNet, Inc. and Symbol Technologies, Inc. for misclassifying operating expenses as restructuring charges, a non-operating expense (Accounting and Auditing Enforcement releases - AAER # 3068, 3124). Similar evidence was found in Dell, Inc. (AAER # 3209). SEC also charged global electrical company ABB for wrongly classifying their continual revenues from the sale of fixed assets (non-operating revenue) as operating revenues (Jones, 2011).

[4] In case of ease based shifting, firms with a greater magnitude of non-operating revenue (non-recurring expenses) are more likely to prefer RS (ES) due to an ease in misclassifying the revenue (expense) items.

[5] Need-based shifting will be considered if firms want to inflate sales to meet analyst's sales forecast, then these firms resort to revenue shifting only.

[6] Revenue shifting has a dual advantage as it helps the firms to inflate sales as well as operating profit through a shift of revenues only. On the other side, the relative advantage of ES is more than RS in terms of stimulating profitability ratio. Refer to Table A.2. in Appendix Afor the illustration.

scope of RS and ES is relatively more in India due to the aggregated format of recording revenue and expense items in the income statement. In addition, the mandatory adoption of International Financial Reporting Standards (IFRS) converged standards in India is likely to provide greater leeway for misclassifying the items.

We used the core earnings expectation model (McVay, 2006), and the operating revenue expectation model (Malikov et al., 2018) to measure ES and RS, respectively. We undertook a longitudinal study (2001 to 2019) using 39,634 firm-years. Our results report a significant negative association between non-operating revenue and unexpected operating revenue in large, levered, old, high-growth, sales-based target firms, implying that these firms are engaged in RS for reporting inflated operating revenue and operating profit. Results also show a significant positive association between non-operating expenses and unexpected operating profits among small, young firms with limited accounting flexibility and firms operating below the industry-average profitability, implying that these firms are engaged in ES. It is consistent with our prediction that firms are likely to choose the tool that can be implemented with greater ease and have a greater relative advantage.We further found that RS stocks have higher excess returns, implying that investors perceive RS firms as growth firms, hence valuing these firms higher than ES firms. Our subsequent tests exhibited that firms engage in shifting practices to meet or beat benchmarks and to avoid violation of debt covenants. These results are robust to alternative measurements of shifting forms, endogeneity, and self-selection bias.

Our study contributes to the literature mainly in three ways. First, it extends the existing literature by investigating both forms of CS, namely RS and ES based on the need, ease, and advantage of each form of shifting strategy, while prior studies investigated the relationship between AEM and REM (Cohen et al., 2008; Enomoto et al., 2015; Zang, 2012), between AEM and CS (Fan et al., 2010), and among AEM, REM and CS (Abernathy et al., 2014), with no single research investigating the relationship between the forms of CS. We examined both forms of shifting by taking a uniform sample of firms over the same period to examine the relationship between RS and ES.

Second, the study extends the literature on the determinants of earnings management. Prior studies documented that peer performance, size, leverage, age, growth opportunities, accounting flexibility, and management compensation contracts affect AEM and REM. We extend this literature by documenting that these factors affect the firm's choices between RS and ES too. Our results provide compelling evidence that these firm-specific variables incentivize firms to prefer RS over ES, and vice-versa, depending on ease, need, and relative advantage of the shifting tool.

Third, our study extends the CS literature considering an emerging economy context, India, and responds to the call for research in emerging nations to identify the specific expense and revenue accounts that managers use to manipulate the accounts (Healy and Wahlen, 1999).

This study proceeds as follows. Section 2 reviews the related literature and develops hypotheses. Section 3 describes the research design for testing the hypotheses. Section 4 discusses empirical results. Section 5 covers robustness tests and section 6 concludes the paper with the discussion and practical implications of the findings.

2. Literature review and hypotheses development

2.1. Earnings management through CS

The Accounting literature documents that investors and financial analysts value income-statement line items differently depending on their placement (Bradshaw and Sloan, 2002). Hence, managers report operating profits at a favorable amount. The degree of information asymmetry between managers and shareholders provides sufficient opportunities for managers to manipulate accounting numbers. The amount of latitude in accounting provisions under accounting standards further adds to these opportunities. Besides opportunities, managers have sufficient incentives to manipulate earnings. These incentives can be explained by the positive accounting theory (PAT) developed by Watts and Zimmerman (1978). PAT provided three hypotheses, namely, the bonus plan hypothesis (manipulate earnings to increase bonus), debt hypothesis (manipulate earnings to avoid violation of debt covenants), and political cost hypothesis (manipulate earnings to avoid political intervention). The capital market pressure is also found to incentivize managers to engage in earnings manipulation (Kasznik and McNichols, 2002). Investors rely on simple heuristics such as a meeting or beating analysts' forecasts while evaluating the firm's performance, consistent with Prospect theory (Kahneman and Tversky, 1979). Burgstahler and Dichev (1997) found that managers manipulate earnings to meet benchmarks. Firms meeting the benchmarks are found to be rewarded by the market in the form of higher valuation (Cheng and Warfield, 2005; McVay et al., 2006). Hence, firms have sufficient opportunities and significant incentives to manipulate earnings.

Firms manipulate sales and profit through different tools, namely, AEM, REM, and CS. They choose the tool based on the costs and constraints associated with each tool (for instance, Abernathy et al., 2014; Zang 2012). Among the three, CS is found to be the most preferred tool of earnings management. There are several reasons for this preference. First, CS neither results in reversal of accruals in subsequent years like AEM nor does it forego, like REM, any future benefits due to sub-optimal business decisions. Second, CS merely overstates operating profits, keeping the remains of net income unchanged. Therefore, it is less likely to be detected by external auditors and has lesser litigation risk (Alfonso et al., 2015; Athanasakou et al., 2009). Third, there is considerable subjectivity in the classification of items, which, in turn, makes CS well-suitable for earnings management. Firms have multiple tools under CS to hit a particular target. For instance, to inflate operating profit, firms can either shift expense or revenue or both. Engaging in multiple tools is likely to reduce the possibility of being caught by auditors. Also, RS has a dual advantage in terms of reporting both sales and operating profit at inflated amounts.

Like AEM and REM, CS also needs significant incentives and sufficient opportunities. Consistent with the fraud triangle theory (Cressey, 1950), firms must have perceived incentives, perceived opportunities, and rationalization behind any misrepresentation. In terms of CS opportunities, firms must have a sufficient magnitude of non-operating expense (non-operating revenue) for ES (RS), because they need non-recurring items to camouflage misclassified items (McVay, 2006). In terms of CS incentives, firms must have significant incentives to inflate sales for RS because sales cannot be inflated through ES. The current study explored the determinants of shifting practices by exploring the different sets of incentives and opportunities with firms. Most CS studies are conducted under different institutional settings at different periods.[7] The current study explores both forms of shifting by taking a uniform sample of firms over the same period.

We investigated this issue under the Indian institutional settings due to the following reasons. First, the scope of misclassifying the items in the income statement is relatively more in India due to aggregated format of recording revenue and expense items. Firms are required to disclose revenue under two heads only, namely, "revenue from operations" and "other income" and that too in the aggregated form, which, in turn, is likely to increase the likelihood of a firm's engagement in shifting practices. Second, unlike other countries (for instance, Australia, Canada, France, Germany, or other member states of the European Union), India has adopted the path of convergence rather than the big-bang adoption of IFRS, and convergence itself implies allowable differences in the presentation, recognition, and disclosure of expense and revenue items. The magnitude of earnings management is found to be increased after the adoption of IFRS-converged standards in India (Adhikari et al., 2021; Bansal et al., 2021). Third, Indian firms have a higher magnitude of shifting as compared to firms in developed countries due to their weaker corporate governance mechanism and lower investor protection rights in India (Nagar and Sen, 2016; Narayanaswamy et al., 2012). Shifting practics are found to be higher in countries with similar features (Behn et al., 2013). Fourth, Dögl et al. (2012) found that Indian managers are incentivized to operate above industry numbers because their remuneration is based on relative performance evaluation (RPE). Analysts in India issue forecasts based on the industry-average (DeFond and Hung, 2003). Sales growth and firm profitability metrics are important determinants of Indian CEO compensation (Gupta and Otwani, 2016; Jaiswall and Raman, 2021; Jaiswall and Bhattacharyya, 2016; Narayanan and Dubey, 2015). Hence, Indian managers have a significant incentive to engage in shifting practices. Fifth, India is a rapidly growing economy, currently estimated to be the fifth largest in the world and is projected to become the world's third largest by 2027 (Bellman, 2018). The country has become an attractive investment hub for foreign investors. Therefore, the issue of shifting practices is important not only for Indian investors, but it affects foreign investors, too.

2.2. Hypotheses development

Earnings management literature has documented various determinants of AEM and REM. In this study, we have explored these determinants in the context of CS. These determinants include the industry-average profitability, size, degree of financial leverage, accounting flexibility, growth opportunities, age, and management compensation contracts of the firm. The following section presents the discussion of these determinants and develops hypotheses.

2.2.1. Earnings management and industry-average profitability

Prior studies document that firms engage in CS to meet the prior period's profit margins (Poonawala and Nagar, 2019) and analysts' forecasts (Fan and Liu, 2017). However, these benchmarks are not affected directly by other firms. Firms frequently scrutinize the activities of their rivals. Hence, managers are likely to set industry profitability as their target benchmark. Hence, we have explored the industry-average profitability as the motivation behind ES and RS.

Managers are incentivized for reporting operating profit margin in comparison to industry numbers, consistent with the theory of RPE (Holmstrom, 1982). The RPE has gained much popularity due to its fair performance valuation (Parrino, 1997). Hence, managers are incentivized to achieve industry-average profitability, and this incentive is relatively stronger in India because firms missing industry numbers are found to lose competitive advantage and Indian firms are afraid of losing the same (Dögl et al., 2012). Stock market analysts in India are found to use the industry-average EBITDA margin as a benchmark for forecasting (Lin et al., 2020).

The above discussion highlights the importance of recording the operating profit ratio (OPR) comparable to the corresponding industry number. Accordingly, we posit that firms operating below industry-average OPR at period t-1 are more likely to be engaged in ES or RS or both for stimulating OPR at period t. The relative advantage of ES is more than RS in terms of stimulating OPR (refer to the hypothetical example in Table A.2 in Appendix A) and, therefore, we posit that firms engage in ES for stimulating OPR, consistent with advantage-based shifting. Accordingly, our first hypothesis is as follows:

[7] McVay, 2006 (US, 1988–2003); Athanasakou et al., 2009 (UK, 1994–2003); Haw et al., 2011 (East Asian economies such as Hong Kong, South Korea, Thailand, Taiwan, Singapore, Malaysia, Indonesia, and Philippines, 2001–2004); Alfonso et al., 2015 (US, 1988–2010); Nagar and Sen, 2017 (India, 1990–2011); Malikov et al., 2018 (UK, 1995–2014); Noh et al., 2017 (Korea, 2011–2012).

H1: Other things being equal, firms operating below the industry average OPR are more likely to engage in ES rather than RS.

2.2.2. Earnings management and firm size

Prior studies (for instance, Kim et al., 2003; Lobo and Zhou, 2006) documented that large firms engage in earnings management because they have more opportunities owing to their complex business structures and longer operating cycles. Besides opportunities, they are highly incentivized to engage in earnings management as they have greater capital market pressure of meeting analysts' forecasts (Kim et al., 2003).

CS needs a sufficient magnitude of non-operating revenue (NOR) and non-operating expenses (NOE). Large and small firms are expected to have a different magnitude of non-operating items due to their scale of business. Large firms are relatively diversified in nature (Swamidass and Kotha, 1998) and have sufficient magnitude of revenue from non-operating activities along with core operations, which in turn is expected to provide them greater leeway for RS. Besides, large firms have higher analysts' coverage (Das et al., 1998) and are pressurized to meet analysts' sales forecasts (Bhushan, 1989). In India, the pressure to meet earnings targets and analysts' forecasts is the driving force for earnings management (Nagar and Sen, 2016).

Large firms have higher transitory gains and firms merge these gains with operating income to show the investors that reported profitability is from the firm's operating activities (Kinney and Trezevant, 1997). Thus, based on the ease-based shifting (large magnitude of NOR) and need-based shifting (greater capital market of meeting analyst's sales forecasts), we posit that large firms are more likely to be engaged in RS rather than ES. Accordingly, our second hypothesis is as follows:

H2: Other things being equal, large firms are more likely to be engaged in RS rather than ES.

2.2.3. Earnings management and financial leverage

The degree of financial leverage affects a firm's earnings management practices. Prior studies (for instance, DeFond and Jiambalvo, 1994; Ghosh and Moon, 2010) reported a significant positive association between financial leverage and earnings management. These studies showed that levered firms engage in AEM and REM to avoid violation of debt covenants.

In the context of CS, levered firms are found to be engaged in ES to meet operating profit benchmarks (Nagar and Sen, 2016) because the rewards for beating the benchmarks are higher for levered firms (Bartov et al., 2002). Firms engage in ES (Fan et al., 2019) and RS (Malikov et al., 2019) to avoid violation of EBITDA-based covenants. However, the mechanism of RS help levered firms to strive for multiple objectives. It enables levered firms to meet sales as well as operating profit forecasts. Hence, based on advantage-based shifting, we posit that levered firms prefer RS over ES due to its dual advantage in terms of inflating sales and operating profit as an effect of misclassification, leading to our third hypothesis as follows:

H3: Other things being equal, levered firms are more likely to be engaged in RS than ES.

2.2.4. Earnings management and accounting flexibility

Earnings management practices are affected by the flexibility in the firm's accounting system (Zang, 2012). Firms with constrained accounting systems, i.e., excessive use of accruals in one particular year, reduce their flexibility to use accruals in the subsequent year. Chen et al. (2012) found a positive relationship between accounting flexibility and AEM. They suggested that higher accounting flexibility leads to higher AEM. Sarkar et al. (2008) found that accounting flexibility does not have any significant impact on current year earnings manipulation. The constrained firms tend to focus on those manipulation practices that are lying outside the accounting system (Abernathy et al., 2014).

Unlike AEM and REM, CS is merely an accounting manipulation that neither entails any real business transactions nor results in reversal of accruals in the subsequent years. Hence, firms with lesser accounting flexibility are likely to resort to CS practices. Thus, based on the need-based shifting, we posit that firms constrained by AEM, and REM are likely to be engaged in RS or ES or both. Accordingly, we propose our next hypothesis as follows:

H4: Other things being equal, firms with lower flexibility in their accounting system engage in RS or ES or both.

2.2.5. Earnings management and growth opportunities

Sales growth is inevitable for any firm. Accounting literature reports a positive association between sales growth and earnings management, indicating that growing firms engage in upward earnings management to report a constant stream of earnings and sales, and downward earnings management to avoid the political cost and political risks (Lee et al., 2006; Sarkar et al., 2008). Ertimur et al. (2003) show that investors value the revenues of growth firms more than value firms. Analysts issue sales forecasts for firms with higher growth opportunities (Ertimur and Stubben, 2005). Hence, it is likely that high growth firms engage in RS rather than ES due to its dual benefit of meeting operating profit and revenue forecasts.

Accordingly, based on need and advantage-based shifting, we posit that high-growth firms engage in RS rather than ES. Our next hypothesis is as follows:

H5: Other things being equal, high-growth firms are more likely to engage in RS rather than ES.

2.2.6. Earnings management and firm-age

Firm-age is an important determinant of earnings management. Prior studies (for instance, Ahmad-Zaluki et al., 2011; Gul et al., 2009) show that young firms engaged in earnings management positively influence the perception of capital providers toward their operating performance. Relative to old firms, young firms are required to spend numerous non-recurring items to set up their business (start-up costs) such as accountant fees, registration charges, legal fees,employee training, etc., which, in turn, are likely to make ES easier for young firms to employ. Besides, analysts are also found to provide revenue forecasts for younger firms (Bilinski and Eames, 2019). Therefore, young firms also have a significant incentive to engage in RS. Accordingly, based on ease (greater magnitude of non-recurring items) and need (meet analyst's sales forecast), we formulate our next hypothesis as follows:

H6: Other things being equal, young firms are more likely to be engaged in RS and ES.

2.2.7. Earnings management and management compensation contracts

The bonus plan hypothesis under PAT states that managers manipulate earnings to increase their remuneration (Watts and Zimmerman, 1986). Firms are found to align the manager's objective with the firm's objectives to maximize shareholder wealth (Govindaraj and Ramakrishnan, 2001). Firms tied managers' compensation to reported sales (Jaiswall and Raman, 2021) and reported core earnings (Baber et al., 1998). Among profitability metrics, earnings before interest and tax (EBIT) and earnings before interest, tax, depreciation, and amortization (EBITDA) are found to be the frequently used metrics for incentive contracts, because they exclude the impact of non-recurring items and truly reflect the operational efficiency achieved through managers' efforts.

In India, annual sales growth rate and firm profitability metrics are the strongest factors affecting CEO compensation (Jaiswall and Raman, 2021; Jaiswall and Bhattacharyya, 2016; Narayanan and Dubey, 2015; Gupta and Otwani, 2016). Hence, managers are likely to attempt to increase sales and core earnings through CS. Firms whose manager's remuneration is tied to sales are likely to engage in RS. Hence, based on need-based shifting, we posit that sales-based target firms engage in RS.

H7: Other things being equal, sales-based target firms are more likely to be engaged in RS rather than ES.

3. Research methodology

3.1. Data collection and sample selection

The data for the study was sourced from the Prowess database maintained by the Centre for Monitoring Indian Economy (CMIE). Our sample comprised Bombay Stock Exchange (BSE) listed firms spanning over financial years from the year ended March 1999 to March 2019. Two years have been excluded due to the requirement of two years' lagged values of variables. Following many prior studies, we excluded the financial and utility firms because the former has a different financial reporting environment, and the latter has more predictable earnings growth. We excluded firms with missing observations for measuring RS, ES, and control variables. All continuous variables are winsorized at 1 % on both sides to remove the effect of outliers. After all exclusions, we were left with a balanced panel data sample of 2,086 firms or 39,634 firm-years for testing our hypotheses. Table 1 explains in detail the process of sample selection. Table A.1 in Appendix A explains the definition and measurement of all the variables used in the study.

3.2. Measurement of ES

The shifting of operating expenses to non-operating expenses results in positive unexpected core earnings. We use the following McVay's core earnings expectation model (2006) to determine the unexpected level of core earnings:

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

where *CE* is core earnings. *ATO* is the assets turnover ratio. *ACC* is accruals. $\Delta Sales$ is the percentage change in sales. $NEG\_\Delta Sales$ is a dummy variable that takes the value one if $\Delta Sales$ is negative, and zero otherwise. All the variables are scaled by lagged total sales. We estimates model (1) cross-sectionally for each industry-year to control for industry differences. We require at least ten observations per industry to make sure that we have sufficient data for the estimation of expected core earnings. Residual ($\varepsilon_{i,t}$) measures unexpected core earnings (*UE_CE*).

To check the existence of ES, we regress *UE_CE* on non-operating expenses (*NOE*) and unexpected operating expenses (*UE_OE*), as shown in the following model (2):

Table 1
Sample selection.

Particulars	Firms	Firm-years
Initial sample from Prowess database (March 2001–March 2019)	4,586	87,134
Less: Financial and utility firms	898	17,062
Less: Firms with missing observations for measuring ES and RS	957	18,183
Less: Firms with missing observation for measuring control variables	645	12,255
Final sample of firms for testing our hypotheses	2,086	39,634

$$UE\_CE_{i,t} = \alpha_0 + \beta_1 NOE_{i,t} + \beta_2 UE\_OE_{i,t} + Controls + Fixedeffects + \varepsilon_{i,t} \tag{2}$$

where *UE_CE* is unexpected core earnings measured as residuals from model (1). *NOE* is a non-operating expense. A positive coefficient of *NOE* indicates an increase in *UE_CE* with an increase in *NOE,* suggesting that firms misclassify operating expenses as non-operating expenses to inflate core earnings. Following Poonawala and Nagar (2019), we include unexpected operating expenses (*UE_OE*) in our model (2) to understand the relationship between *UE_CE* and *UE_OE*. The shifting of operating expense results in negative unexpected operating expenses, i.e., actual (reported) operating expenses is less than the expected level. A negative coefficient of *UE_OE* indicates an increase in *UE_CE* with a decrease in *UE_OE*. Following Gunny (2010), we measure *UE_OE* as the residuals from the following model (3):

$$OE_{i,t} = \alpha_0 + \beta_1 OE_{i,t-1} + \beta_2 MV_{i,t} + \beta_3 TobinQ_{i,t} + \beta_4 INT_{i,t-1} + \beta_5 \Delta Sales_{i,t} + \beta_6 NEG\_\Delta Sales_{,t} + \varepsilon_{i,t} \tag{3}$$

where *OE* is operating expenses. *MV* is the natural logarithm of the market value of equity. *Tobin Q* is the proportion of market to book value of equity. *INT* is internal funds, comprising free reserves and surpluses. Δ*Sales* and *NEG_*Δ*Sales* have the same meaning as assigned previously. All variables are scaled by lagged total assets ($AT_{i,t-1}$). Consistent with model (1), we estimate model (3) cross-sectionally for each industry-year having at least ten observations per industry. Residuals (ε_{it}) measures *UE_OE.*

Firms are classified as "expense shifters" in period *t* if an increase in *UE_CE* has been observed due to misclassification of operating expense as a non-operating expense during period *t*. However, an increase in core earnings at period *t* is the likely outcome of the firm's improved efficiency due to some non-operating expensesat period, *t*-1 or *t*. For instance, if firms write off some unproductive assets at period *t*, then it is likely to improve the firm's business operations, which in turn positively influences core earnings at *t* or *t + 1*. Therefore, to distinguish this competing explanation, we perform reversal tests, which are consistent with many prior studies (for instance, Fan and Liu, 2017; McVay, 2006).

Under "reversal tests," we model the expected change in operating expense from quarter *q* to *q* + 4 and examine the relationship between the unexpected change in operating expense and *NOE* of quarter *q*. The negative relationship between unexpected changes in operating expense from quarter *q* to quarter *q* + 4 and quarter *q NOE* indicates that firms can sustain lower levels of operating expense after incurring *NOE*. Under this finding, the efficiency gain argument is likely to hold. However, if the association is found to be positive, then it suggests that at least a portion of previously understated operating expenses reappears four quarters later, consistent with the reversal of reported operating expenses following ES. We use the following model (4) to determine the unexpected change in operating expense from quarter *q* to quarter *q* + 4:

$$\begin{aligned}\Delta OE_{i,q} = {} & \beta_0 + \beta_1 OE_{i,q-4} + \beta_2 \Delta OE_{i,q-4} + \beta_3 MV_{i,q} + \beta_4 MV_{i,q-4} + \beta_5 TobinQ_{i,q} + \beta_6 TobinQ_{i,q-4} + \beta_7 INT_{i,q} \\ & + \beta_8 INT_{i,q-1} + \beta_9 \Delta Sales_{i,q} + \beta_{10} NEG\_\Delta Sales_{i,q} + \varepsilon_{i,t}\end{aligned} \tag{4}$$

where Δ*OE* is a change in operating expense. For the expected change in operating expenses, we include both operating expenses four quarters ago ($OE_{i,q-4}$) and the change in *OE* from quarter *q*-8 to *q*-4 ($\Delta OE_{i,q-4}$) to control for possible mean reversion based on the prior year's reported *OE*. This approach is consistent with McVay (2006). *MV*, *TobinQ, INT*, Δ*Sales*, and *NEG_*Δ*Sales* have the same meaning as assigned previously. Model (4) is estimated by industry-year quarter and its residuals serve as the proxy for the unexpected change in operating expense ($UE\_\Delta OE_{i,q+4}$).

To check whether the inflated core earnings are the result of misclassification or efficiency improvement, we regress the unexpected change in *OE* four quarters later with *NOE* at the beginning of quarter *q*, as shown below in model (5):

$$UE\_\Delta OE_{i,q+4} = \beta_0 + \beta_1 NOE_{i,q} + Controls + \varepsilon_{i,t} \tag{5}$$

where $UE\_\Delta OE_{i,q+4}$ is an unexpected change in *OE* four quarters later. *NOE* is a non-operating expense, scaled by total assets at the beginning of quarter *q*. We expect the coefficient of *NOE* to be positively associated with $UE\_\Delta OE_{i,q+4}$ to rule the notion of efficiency improvement.

3.3. Measurement of RS

The shifting of non-operating revenue to operating revenue results in positive unexpected operating revenue. We employ the following operating revenue expectation model developed by Malikov et al. (2018) to determine an unexpected level of operating revenue.

$$OR_{i,t} = \alpha_0 + \beta_1 OR_{i,t-1} + \beta_2 MTB_{i,t} + \beta_3 AR_{i,t} + \beta_4 AR_{i,t-1} + \varepsilon_{i,t} \tag{6}$$

where *OR* is operating revenue. *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 (6) cross-sectionally for each industry-year with a minimum of ten observations per industry. Residual ($\varepsilon_{i,t}$) measures an unexpected operating revenue (*UE_OR*). To test the existence of RS, we regress *UE_OR* on non-operating revenue (*NOR*) as shown in the following Eq. (7):

$$UE\_OR_{i,t} = \alpha_0 + \beta_1 NOR_{i,t} + Controls + Fixedeffects + \varepsilon_{i,t} \tag{7}$$

where *UE_OR* is unexpected operating revenue measured as residuals from model (6). *NOR* is non-operating revenue. A negative coefficient of *NOR* implies a decrease in *NOR* with an increase in *UE_OR*. It indicates the existence of RS as firms are misclassifying *NOR* as *OR* to artificially report operating revenue at an inflated amount.

To isolate the impact of *NOE* and *UE_OE* on *UE_CE* in model (2) and that of *NOR* on *UE_OR* in the model (7), we include two sets of control variables. In the first set, we control the effect of other tools of earnings management, namely REM and AEM. We also control the impact of RS in model (2) while testing for ES and again the impact of ES in model (7) while testing for RS. There are two main reasons behind controlling the impact of other tools. First, prior studies (for instance, Abernathy et al., 2014; Fan and Liu, 2017) found that firms engage in multiple tools for manipulating earnings. Hence, we must control other tools to ensure that our results are due to shifting strategies. Second, our dependent variables (*UE_CE* and *UE_OR*) can also be inflated by REM through sales acceleration as a result of offering heavy price discounts or AEM through the use of discretionary accruals.

Following Zang (2012), we use abnormal production costs (*A_PROD*) and abnormal discretionary expenditure (*A_DISX*) to measure REM. Following Bansal and Kumar (2021), we use abnormal accruals (*A_ACC*) to measure AEM. See Table A.1 in Appendix A for measurement of *A_PROD*, *A_DISX*, and *A_ACC*. We include a variable – *RS* in model (2) that takes a value equal to one for firms with positive *UE_OR* and positive *NOR* or zero otherwise, where *UE_OR is* measured as residuals from the model (6). We include a variable - *ES* in model (7), where *ES* takes a value equal to one for firms with positive *UE_CE* and positive *NOE*, and zero otherwise, where *UE_CE* is measured as residuals from model (1).

In the second set of control variables, we control for certain cross-sectional characteristics that are likely to affect the level of operating profit and operating revenue. These control variables include size (*Size*), degree of financial leverage (*Lev*), growth opportunities (*Growth*), and age (*Age*) of the firm. We include industry and time-fixed effects in our models to control for unobserved cross-sectional heterogeneity across industries, and years, respectively.

3.4. Empirical model

Our first hypothesis states that firms operating below the industry-average OPR at period *t*-1 are more likely to be engaged in ES rather than RS at period *t*. To test this assertion, we test both forms of shifting at period *t* for both categories of firms, namely firms operating below and above the industry-average OPR during period *t*-1. For testing ES among these groups, we extend our model (2) as follows:

$$\begin{aligned} UE\_CE_{i,t} = {} & \alpha_0 + \beta_1 NOE_{i,t} * Above_{i,t-1} + \beta_2 NOE_{i,t} * Below_{i,t-1} + \beta_3 UE\_OE_{i,t} * Above_{i,t-1} + \beta_4 UE\_OE_{i,t} * Below_{i,t-1} \\ & + Controls + Fixed\ effects + \varepsilon_{it} \end{aligned} \tag{8}$$

where *UE_CE* is unexpected core earnings measured as residuals from model (1). *NOE* is a non-operating expense. *UE_OE* is an unexpected operating expense measured as residuals from model (3). Our main variables of interest are interaction variables, namely *NOE**Above* and *NOE**Below*, where *Above* (*Below*) takes a value equal to one in year *t* for firms operating above (below) industry-average OPR in year *t*-1. We have considered the previous year's industry-operating profit ratio as the benchmark. We argue that firms that were operating below the industry-average in the period *t*-1 are likely to manipulate operating profit in year *t* to meet the previous year's industry-average. Hence, the previous year's industry-average is the benchmark, and the firms that missed this benchmark in the previous year are suspect. The interaction of *NOE* with the *Above* and the *Below* shows the effect of firms operating above and below the industry average OPR on ES, respectively. Our hypothesis predicts a positive coefficient on $NOE * Below$.

To test RS among both groups of firms, we extend model (7) as shown in model (9).

$$UE\_OR_{i,t} = \alpha_0 + \beta_1 NOR_{i,t} * Above_{i,t-1} + \beta_2 NOR_{i,t} * Below_{i,t-1} + Controls + Fixedeffects + \varepsilon_{it} \tag{9}$$

where *UE_OR* is the unexpected operating revenue measured as residuals from Eq. (6). *NOR* is the non-operating revenue. The interaction of *NOR* with the *Above* and the *Below* shows the effect of firms operating above and below the industry average OPR on RS, respectively. The coefficient of $NOR * Below$ is expected to be negative if firms operating below the industry-average at period *t*-1 engage in RS at time *t*.

In the same vein, for testing our other hypotheses (H2–H7), we run models (7) and (9) for different categories of firms. We test both forms of shifting under each category of firms to examine the relationship between shifting forms and a firm's characteristics. For testing H2, following Doan and Nguyen (2018), we divide our sample into two categories, namely large and small firms. 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. We use quartile to overcome the issue of self-selection bias because firms in the top and bottom quartile are relatively more comparable in terms of size. Under H2, one of our arguments is that a larger magnitude of non-operating items incentivizes firms to engage in shifting practices as firms need non-recurring items to camouflage misclassified items (McVay, 2006). Hence, we test ES and RS among firms depending upon their magnitude of non-operating expense and non-operating revenue. We classify firms as firms with higher *NOE* and *NOR*, and firms with lower *NOE* and *NOR*. We use the industry-median value for classification.

For testing H3, we divide our sample into high and low levered firms and use an indicator, *Hlev* (High levered) that equals one if the firm's leverage is on the top quartile of the sample, and *Llev* (low levered) that equals the value of one for firms that are in the bottom quartile. We use the quartile measure because firms in the top and bottom quartiles are more comparable in investigating the impact of leverage on shifting practices. For testing our fourth hypothesis (H4), we use an indicator variable - *High (Low)* that equals one when the beginning of the year net operating assets (*NOA*) is greater (smaller) than the industry-median, consistent with Abernathy et al. (2014). Firms are found to refrain from blocking their funds in operating assets for long and maintain *NOA* figures comparable to the industry-median (Abernathy et al., 2014). The magnitude of *NOA* is also found to be largely dependent on the moves of peers in the same industry (Fan et al., 2010). Hence, we have used the industry-median to classify the firms for testing H4.

For testing H5, we use sales growth, where sales growth is measured as the percentage change in sales from period *t*-1 to *t*. We divide our sample based on industry-median sales growth because firms are found to beat industry-median sales growth under relative performance evaluation (Boni and Womack, 2006). For testing H6, following Liu (2017), we classify firms as older firms and younger firms based on firm experience, where the firm experience was measured by firm-age. The age of older firms is greater or equal to the medium age of the whole sample, and that of younger firms is smaller than the median age.

To test our last hypothesis (H7), we divide our sample into two categories, namely, firms with and without emphasis on sales for compensation purposes, i.e., sales and non-sales target firms. Following Lancee (2010), we use the sensitivity of different accounting numbers to assess the weight placed on sales and other earning numbers. We regress incentive compensation on sales and *EBIT* as shown below:

$$IncentiveCompensation_{i,t} = \alpha_0 + \beta_1 Sales_{i,t} + \beta_2 EBIT_{i,t} \tag{10}$$

where *Incentive Compensation* is the manager's bonus retrieved from the prowess database. We exclude base salary because it is usually unrelated to firm performance. The variables, namely, *Sales* and *EBIT* have the same definition as assigned previously. If the coefficient of Sales (*EBIT*) is significantly larger than the coefficient of *EBIT* (*Sales*), indicating that there is a stronger relationship between incentive compensation and *sales* (*EBIT*). When this proposition holds, compensation is more associated with *Sales* (*EBIT*) than *EBIT* (*Sales*): the weight on *Sales* (*EBIT*) is higher. Managers then have the incentive to increase sales more than *EBIT*, since this would increase their compensation. We classify firms into two categories, namely, STF (sales-target firms) and NSTF (non-sales target firms), where *STF* takes value equal to one for firms having β_1 greater than β_2.

3.5. Descriptive statistics and correlation analysis

Table 2 presents descriptive statistics and a correlation matrix. Panel A shows descriptive statistics for the full sample. The median of unexpected core earnings (*UE_CE*) is positive (0.019), implying that firms record core earnings greater than the expected values. The median of unexpected operating revenue (*UE_OR*) is negative (−0.016), implying that firms record operating revenue as lesser than the expected values. Panel B shows the correlation matrix. The values in the lower (upper) diagonal display Pearson (Spearman) correlation coefficients for the main variables. The *UE_OR* and *NOR* are found to be negatively associated (−0.010), implying a decrease in non-operating revenue with an increase in unexpected operating revenue, and vice-versa. Both coefficients are statistically significant at the 1 % level. A negative correlation coefficient is found between *UE_CE* and *NOE*, implying an increase in unexpected core earnings with a decrease in non-operating expenses, and vice-versa. *A_DISX* is positively correlated with the *A_ACC,* which implies that managers use both REM and AEM to manipulate earning measures. The value of the variance inflation factor (*VIF*) is<10, which implies that the data does not have a multicollinearity problem.

4. Empirical results

This section discusses the regression results under the initial as well as propensity score matched (PSM) sample.

4.1. Propensity score matching

It is important to specify the regression model properly to obtain unbiased coefficients. If the relationship is misspecified, then it generates a "functional form misspecification" and can produce biased estimates. In the current study, as the categorization of firms under each of the hypotheses is not entirely random, we therefore construct a sample of firms out of treatment firms that are more comparable to counterparts (control firms). The PSM approach can alleviate the concern of misspecification by decreasing the dependency on the specification of the relationship between the variables (Rosenbaum

Table 2
Descriptive statistics.

Panel A: Descriptive statistics for full sample (N = 39,634)

Variables	Mean	SD	P25	Median	P75
UE_CE	−0.009	1.147	−0.109	0.019	0.122
UE_OR	−0.003	0.415	−0.171	−0.016	0.140
UE_OE	0.000	0.199	−0.076	−0.021	0.058
NOE	0.351	1.441	0.044	0.081	0.151
NOR	0.043	0.142	0.006	0.016	0.036
A_DISX	0.000	0.033	−0.010	−0.002	0.007
A_PROD	0.000	0.123	−0.055	0.004	0.060
A_ACC	0.189	11.156	−3.143	−0.091	2.819
RS	0.608	0.488	0.000	1.000	1.000
ES	0.430	0.495	0.000	0.000	1.000
Size	6.915	2.207	5.338	6.823	8.390
Lev	0.792	2.635	0.373	0.580	0.748
Growth	0.280	1.433	−0.054	0.089	0.259
Age	3.651	0.385	3.367	3.555	3.829

Panel B: Correlation matrix

Variables	*UE_CE*	*UE_OR*	*UE_OE*	*NOE*	*NOR*	*A_DISX*	*A_PROD*	*A_ACC*	*Size*	*LEV*	*Growth*	*Age*	*VIF*
UE_CE		−0.009	−0.157	−0.020**	−0.049**	0.022**	−0.218**	−0.198**	−0.021**	−0.032**	−0.007	−0.008	1.058
UE_OR	−0.041**		–	−0.004	−0.010	0.374**	−0.206**	0.529**	−0.038**	−0.026**	0.444**	0.006	1.602
UE_OE	−0.123	0.212		−0.019**	−0.034**	0.074**	−0.187**	−0.213**	−0.047**	−0.041**	−0.024	−0.007	1.247
NOE	−0.124**	−0.022**	−0.102**		−0.157**	−0.053**	−0.072**	0.114**	−0.050**	0.117**	0.166**	−0.107**	1.124
NOR	−0.036**	0.007	−0.012**	0.251**		0.017**	0.032**	−0.002	0.154**	−0.101**	0.004	0.193**	1.069
A_DISX	−0.003	0.319**	−0.001	−0.030**	0.008		−0.331**	0.201**	−0.024**	−0.010	0.199**	0.013*	1.291
A_PROD	−0.104**	−0.079**	−0.094**	0.018**	0.025**	−0.343**		−0.083**	0.092**	0.048**	−0.178**	0.010	1.176
A_ACC	−0.083**	0.515**	−0.113**	−0.003	−0.038**	0.177**	−0.011		−0.008	0.021**	0.620**	0.023**	1.594
Size	−0.026**	−0.030**	−0.021**	−0.138**	−0.065**	−0.031**	0.073**	−0.010*		0.072**	0.052**	0.301**	1.128
LEV	0.004	−0.009	0.007	0.214**	0.070**	−0.006	0.027**	0.072**	−0.126**		0.008	0.098**	1.043
Growth	−0.034**	0.210**	−0.004**	0.308**	0.040**	0.084**	−0.052**	0.302**	−0.072**	0.009		−0.036**	1.256
Age	−0.005	0.010*	−0.013	−0.096*	0.130**	0.021*	0.017	0.037**	0.284**	0.103**	−0.053**		1.119

Panel A shows descriptive statistics for the full sample, whereas panel B shows correlation coefficients, where the lower (upper) diagonal shows Karl Pearson (Spearman) coefficients. UE_OE and UE_OR are available for different sets of firms, hence left blank (−). VIF stands for variance inflation factor. ***, **, * indicate significance at 1%, 5%, and 10% levels in a two-tailed test, respectively. See Appendix A for the definition of variables.

and Rubin, 1983). Under PSM, observations are chosen from both the treatment group and control groups based on several criteria with an intent to construct a sample of control firms that are more comparable with the treatment firms. It involves two steps.

First, we employed a probit model under each of our seven hypotheses for firms of interest by regressing on cross-sectional characteristics to estimate the probability of being a treatment firm. We use characteristics such as a firm's age, size, degree of financial leverage, liquidity, growth, and profitability because these variables are likely to affect a firm's likelihood of falling under the treatment group.[8] The model is as follows:

$$Firm_{i,t} = \alpha_0 + \beta_1 Age_{i,t} + \beta_2 Size_{i,t} + \beta_3 Lev_{i,t} + \beta_4 QR_{i,t} + \beta_5 Growth_{i,t} + \beta_6 ROA_{i,t} + \varepsilon_{it} \tag{11}$$

where *Firm* is a binary variable that takes the value equal to one for treatment firms and zero for control firms under each of the hypotheses. For instance, under H1, the *Firm* takes a value that equals one (zero) in year *t* for firms operating above (below) industry-average OPR in year *t*-1. In the same vein, for H2 (H3), *Firm* takes a value that equals one for large (high levered) firms and zero for small (low levered) firms. For H4, H5, H6, and H7, *Firm* takes a value equal to one for high *NOA*, high growth, young, and sales-target firms, and zero for low *NOA*, low growth, old, and non-sales target firms, respectively. Table 3, Panel A shows the results of the first-stage regression model under each of the hypotheses. 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<0.05*standard deviation of the propensity scores.[9] It provides the treatment and control groups that are identical in terms of observable characteristics. The firm-year under our initial sample is 39,634; however, the PSM procedure produces a matched sample of 23,942; 27,512; 27,748; 24,992; 26,502; 31,962; and 22,820 firm-years for testing H1–H7, respectively. To check the validity of the matched sample, following Shipman et al. (2017), we present the significance of the difference in the variable means under the initial and PSM sample. Panel B of Table 3 reports that none of the differences under the matched sample is significant, hence confirming the validity of the matched sample.

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

[9] We have also used caliper at 0.03 and 0.01 standard error of propensity scores to find matched sample.

Table 3
Results of propensity score matching.

Panel A: Results of first stage regression

Dependent variable	Hypothesis 1 *Below*		Hypothesis 2 *Large*		Hypothesis 3 *Hlev*		Hypothesis 4 *High*		Hypothesis 5 *HG*		Hypothesis 6 *Young*		Hypothesis 7 *STF*	
Co-variates	Coeff.	Z-values	Coeff.	Z-values	Coeff.	Z-values	Coeff.	Z-values	Coeff.	Z-values	Coeff.	Z-values	Coeff.	Z-values
Age	0.166***	5.730	0.826***	43.450	0.063***	3.000	17.927***	17.890	−0.366***	−17.530			0.525***	27.11
Size	0.739***	80.970			−0.055***	−14.540	0.114**	2.130	−0.023***	−6.540	0.141***	42.090	0.049***	14.41
Lev	−0.769***	−14.190	−0.204***	−11.030			−0.070***	−6.980	−0.012***	−2.830	0.053***	6.560	−0.021***	−5.62
Quick ratio	0.062***	−5.770	−0.048***	−12.830	−0.239***	−43.140	−0.272***	−15.750	−0.002	−1.120	−0.015***	−8.070	0.019***	11.62
Growth	0.043***	3.940	−0.043***	−6.430	0.011**	2.040	0.232***	13.970			−0.029***	−5.760	0.031***	2.86
ROA	4.499***	33.330	1.503***	21.250	−2.872***	−44.840	−3.729***	−24.420	1.132***	19.930	0.282***	5.020	1.887***	30.33
Intercept	−7.377***	−55.270	−3.470***	−48.060	−0.332***	−4.450	−11.381***	−68.300	0.816***	11.120	−1.063***	−40.430	−2.366***	−34.22
Pseudo-R sq.	0.511		0.169		0.101		0.632		0.210		0.145		0.326	

Panel B: Mean comparison of PSM matched sample

	Hypothesis 1		Hypothesis 2		Hypothesis 3		Hypothesis 4		Hypothesis 5		Hypothesis 6		Hypothesis 7	
Co-variates	*Full Diff.*	*Matched Diff.*	*Full Diff.*	*Matched Diff.*	*Full Diff.*	*Matched Diff.*	*Full Diff.*	*Matched Diff.*	*Full Diff.*	*Matched Diff.*	*Full Diff.*	*Matched Diff.*	*Full Diff.*	*Matched Diff.*
Age	3.220***	0.221*	1.213***	0.111*	2.112***	0.091*	2.330***	0.103*	2.003***	0.083*	3.132***	0.031*	2.119***	0.412*
Size	2.512**	0.031	1.450**	0.042	1.114**	0.013	1.513**	0.073	1.493**	0.061	1.107**	0.027	2.410**	0.013
Lev	−0.043**	0.012	−0.073**	0.017*	−0.093**	0.012	−0.070**	0.019	−0.091**	0.027	−0.037**	0.016	−0.067**	0.047
Quick ratio	−1.861**	−0.070	−1.112**	−0.061	−1.137**	−0.037	−0.112**	−0.043	−0.107**	−0.067	−1.113**	−0.073	−1.731**	−0.053*
Growth	0.084***	−0.002	0.070***	−0.004	0.094***	−0.001*	0.091***	−0.009	0.093***	−0.013	0.132***	−0.007	0.094***	−0.007
ROA	−0.097**	0.003	−0.107**	0.007	−0.093**	0.020*	−0.083**	0.001	−0.067**	0.013*	−0.107**	0.070*	−0.117**	0.037
N	39,634	23,942	39,634	27,512	39,634	27,748	39,634	24,992	39,634	26,502	39,634	31,962	39,634	22,820

Panel A shows results of the first-stage regression estimated through the probit model, whereas panel B presents the difference in variable means between groups under initial and PSM matched samples. Full difference refers to the difference between variables means for the initial sample, whereas the matched difference is the difference between variables means for the PSM matched sample. ***, **, * indicate significance at 1%, 5%, and 10% levels in a two-tailed test, respectively.

4.2. Multivariate regression analysis

Before estimating regression results, we run different tests to identify appropriate panel data regression models and check the presence of heteroscedasticity and serial autocorrelation in residuals. Table A.4 in Appendix A shows the results of these tests for different hypotheses.

4.2.1. Shifting practicesat period t among firms operating below and above the industry-average OPR at period t-1

Table 4, column (1) presents the regression results of model (8) used for testing ES at period *t* among the firms that were operating below and above the industry-average OPR at period *t*-1. The coefficient of *NOE*Below* on *UE_CE* is positive and statistically significant at a 1 % level of significance (0.348, $p < 0.00$), whereas the coefficient of *NOE*Above* on *UE_CE* is positive but insignificant (0.596, $p > 0.10$). A significant positive association between *UE_CE* and *NOE* implies that firms operating below the industry-average profitability at period *t*-1 are engaged in ES to inflate core earnings at period *t*. The coefficient of *UE_OE*Below* on *UE_CE* is also found to be significantly negative (−0.011, $p < 0.00$), indicating that a decrease in operating expense is associated with an increase in core earnings. It confirms the finding that inflated core earnings are the outcome of reduced operating expenses. These results are found to be constant under the PSM sample (column 2).

We further confirm the finding that inflated core earnings are due to ES by regressing $UE\_\ \Delta\ OE_{q+4}$ on quarter *q* *NOE* (NOE_q). Results (Table A in the Internet Appendix) show that NOE_q is positively associated with both $UE\_\ \Delta\ OE_{q+4}$ (0.093, $p < 0.05$), indicating that understated operating expenses in quarter *q* reappear in quarter *q + 4*, inconsistent with the efficiency improvement argument. In the same vein, the coefficient of NOE_q**Below* on $UE\_\ \Delta\ OE_{q+4}$ is found to be significantly positive (0.183, $p < 0.00$). Hence, these results ensure that inflated core earnings are the outcome of ES.

Column (3) presents the regression results of model (9) used for testing RS at period *t* among the firms that were operating below and above the industry-average OPR at period *t*-1. The coefficient of *NOR*Below* on *UE_OR* is negative and significant at a 10 % level of significance, implying that firms operating below the industry-average are engaged in RS (−0.095, $p < 0.10$). No such evidence is found for firms operating above the industry-average OPR as the coefficient of *NOR*Above* on *UE_OR* is positive (0.486, $p < 0.00$). A significant negative association between *UE_OR* and *NOR* implies that firms operating below the industry-average profitability at period *t*-1 are engaged in RS to inflate core earnings at period *t*. PSM sample also provides the results in the same direction (column 4).

Collectively, a positive coefficient of *NOE*Below* on *UE_CE* at 1 % level of significance under column 1 and a negative coefficient of *NOR*Below* on *UE_OR* at 10 % level of significance (column 3) implies that firms operating below industry OPR at period *t*-1 are likely to prefer ES over RS at the period to meet industry-average profitability. Hence, our results support the prediction under the first hypothesis. This finding is congruent with Yamaguchi (2020) that firms engage in earnings management to meet industry-average profitability. The firm's preference for ES can be attributed to its greater relative advantage in terms of stimulating profitability ratios. For an illustration, please refer to Table A.2 in Appendix A.

4.2.2. Shifting practices among large and small firms

Column (1) of Table 5 presents the regression results of model (8) used to examine ES among large and small firms. The coefficient of *NOE*Small* on *UE_CE* is positive and statistically significant at a 1 % level (0.320, $p < 0.00$), whereas the coefficient of *NOE*Large* on *UE_CE* is negative (−0.018, $p > 0.10$), implying that small firms are more likely to be engaged in ES. PSM sample also provides a significant positive association between *NOE* and *UE_CE* among small firms (column 2, 0.423, $p < 0.00$). The coefficient of *UE_OE*Small* on *UE_CE* is found to be significantly negative for both initial (−0.101, $p < 0.05$) and PSM samples (−0.060, $p < 0.05$), implying that small firms misclassify operating expense as a non-operating expense to inflate core earnings.

Column (3) presents regression results of model (9) used for testing RS among large and small firms. The coefficient of *NOR*Large* on *UE_OR* is negative and significant at a 5 % level of significance (−0.061, $p < 0.05$), whereas no such evidence is found among small firms as the coefficient of *NOR*Small* on *UE_OR* is positive (0.107, $p > 0.10$). It implies that, relative to small firms, large firms are more likely to be engaged in RS. The negative significant coefficient of *NOR*Large* on *UE_OR* is also found under the PSM sample (column 4, −0.062, $p < 0.05$). Hence, consistent with our argument that large firms, being diversified firms, have a larger magnitude of non-operating revenue along with their core business operations, and hence have greater leeway for RS. We test this argument by dividing our sample into firms with higher and lower *NOR* and *NOE* to examine the impact of a larger amount of non-operating items (*NOR* and *NOE*) on the shifting practices. We find that (Table A.3in Appendix A) firms with more *NOR* are more likely to engage in RS (column 3, −0.103, $p < 0.00$), and firms with more *NOE* are engaged in ES (column 1, 0.949, $p < 0.00$), and these results are also found to be constant under the PSM sample (column 2 and 4).

Hence, our result is in line with the second hypothesis that large firms are more likely to be engaged in RS. It can be attributed to sufficient opportunities and significant incentives with large firms for RS. Large firms have higher NOR due to their diversified nature of business (Swamidass and Kotha, 1998) and have greater capital market pressure of meeting analysts' sales forecasts (Bhushan, 1989; Das et al., 1998), and hence, they are found to be engaged in RS. On the contrary, relative to large firms, small firms need to incur more frequent non-recurring expenses to set their business operations, and hence are likely to prefer ES over RS due to ease in ES. It is consistent with the findings of Burgstahler and Dichev (1997) and Kim et al. (2003) that large as well as small firms are engaged in earnings management.

Table 4
Results of ES and RS for first hypothesis (H1).

	UE_CE			*UE_OR*	
	(1)	(2)		(3)	(4)
*NOE*Above*	0.596	0.650	*NOR*Above*	0.486***	0.442***
	(1.387)	(1.254)		(3.813)	(3.511)
*NOE*Below*	0.348***	0.422***	*NOR*Below*	−0.095*	−0.069*
	(5.567)	(5.592)		(1.657)	(1.845)
*UE_OE*Above*	0.026*	0.027**	*A_DISX*	1.612***	1.446***
	(1.898)	(1.962)		(14.46)	(11.68)
*UE_OE*Below*	−0.011***	−0.014***	*A_PROD*	0.226***	0.104*
	(−2.692)	(−2.837)		(5.153)	(1.929)
A_DISX	−0.452***	−0.446*	*A_ACC*	0.017***	0.018***
	(−2.649)	(−1.942)		(20.29)	(13.16)
A_PROD	−0.512***	−0.449***	*ES*	0.365***	0.305***
	(−6.424)	(−5.488)		(45.54)	(36.02)
A_ACC	−0.010***	−0.012**	*Size*	−0.031***	−0.032***
	(−3.204)	(−2.256)		(−8.117)	(−7.538)
RS	0.289***	0.260***	*Lev*	−0.018**	−0.091***
	(8.12)	(6.502)		(−2.102)	(−4.382)
Size	−0.005	−0.006	*Growth*	0.004	0.007
	(−1.079)	(−0.776)		(0.956)	(1.01)
Lev	−0.045*	−0.032*	*Age*	0.009	0.008
	(−1.752)	(−1.694)		(1.152)	(1.432)
Growth	0.077**	0.049**	Intercept	0.061**	0.172***
	(2.336)	(2.367)		(2.078)	(4.236)
Age	0.058*	0.040	Industry effect	Yes	Yes
	(1.648)	(1.419)	Time effect	Yes	Yes
Intercept	−0.053	−0.0259	Adjusted R-sq.	0.65	0.685
	(−1.632)	(−1.384)	P-value	0.000	0.000
Industry effect	Yes	Yes	N	39,634	23,942
Time effect	Yes	Yes			
Adjusted R-sq.	0.465	0.491			
P-value	0.000	0.000			
N	39,634	23,942			

The table shows regression results of models (8) and (9) used for testing ES and RS, respectively, under the first hypothesis. Columns (1) and (2) show results of model (8) under initial and PSM matched sample, respectively. Columns (3) and (4) show results of model (9) under initial and PSM sample, respectively. Above (Below) is the main variable of interest that takes a value equal to one for firms operating above (below) industry's average operating profit ratio (OPR) at period t-1, and zero otherwise. ***, **, * indicate significance at 1%, 5%, and 10% levels in a two-tailed test, respectively.

4.2.3. Shifting practices among high and low levered firms

Table 6, columns (1) and (3) present results of models (8) and (9) that are used to test ES and RS, respectively, among high and low levered firms, whereas columns (2) and (4) show the results of models under the PSM sample. The coefficient of *NOE*Llev* on *UE_CE* is positive and significant at a 1 % level of significance (column 1, 0.255, $p < 0.00$), which implies that low-levered firms are engaged in ES. However, the coefficient of *NOE*Hlev* on *UE_CE* is negative (−0.396, $p < 0.00$), which implies that high levered firms are not engaged in ES. Similar signs of coefficients are found under the PSM sample (column 2).We further regress $UE\_\Delta OE_{q+4}$ on *NOE* of quarter *q* (NOE_q) and find that the coefficient of NOE_q**Llev* on $UE\_\Delta OE_{q+4}$ is significantly positive (Table A in the Internet Appendix, column 3, 0.174; $p < 0.10$), implying that evidence of inflated core earnings among low-levered firms is the outcome of ES.

The coefficient of *NOR*Hlev* on *UE_OR* is negative and significant at a 5 % level of significance (column 3, −0.122, $p < 0.05$), suggesting that high levered firms are engaged in RS. There is no such evidence found for low-levered firms as the coefficient of *NOR*Llev* on *UE_OR* is positive (column 3, 0.071, $p < 0.05$). The PSM sample also provides results in the same direction (column 4). Collectively, our results imply that high levered firms are engaged in RS, whereas low levered firms prefer to engage in ES. The results are in congruence with our third hypothesis that high-levered firms prefer RS over ES. It can be attributed to the fact that RS has the dual advantage in terms of reporting operating profit and operating revenue at an inflated amount as an effect of misclassification. It is consistent with the findings of Dichev and Skinner (2002) and Beatty and Weber (2003) that levered firms are more likely to be engaged in earnings management to avoid violation of debt covenants.

4.2.4. Shifting practices among firms with lesser accounting flexibility

Table 7 presents the results of models (8) and (9) for firms with lesser and higher accounting flexibility. Column (1) shows that the coefficient of *NOE*High* on *UE_CE* is positive (0.391, $p < 0.10$), implying that firms with higher accounting constraints are engaged in ES. On the contrary, the coefficient of *NOE*Low* on *UE_CE* is negative (−0.338, $p > 0.10$), indicating no evidence of ES among firms with lower accounting constraints. Similar signs of coefficients are found for the PSM sample under column (2). In addition, the coefficient of *UE_OE*High* on *UE_CE* is found to be negative under both the initial sample (−0.021,

Table 5
Results of ES and RS for second hypothesis (H2).

	UE_CE			*UE_OR*	
Variables	(1)	(2)	Variables	(3)	(4)
*NOE*Large*	−0.018	−0.090	*NOR*Large*	−0.061**	−0.062**
	(−0.753)	(−0.344)		(2.188)	(2.119)
*NOE*Small*	0.320***	0.423***	*NOR*Small*	0.107	0.144
	(5.148)	(5.676)		(1.599)	(1.183)
*UE_OE*Large*	0.042**	0.044**	*A_DISX*	1.608***	1.501***
	(2.329)	(2.395)		(14.43)	(12.09)
*UE_OE*Small*	−0.101**	−0.060**	*A_PROD*	0.222***	0.142**
	(−2.477)	(−2.286)		(5.082)	(2.696)
A_DISX	−0.372*	−0.440	*A_ACC*	0.017***	0.019***
	(−1.892)	(−1.430)		(20.25)	(17.47)
A_PROD	−0.604***	−0.224***	*ES*	0.389***	0.302***
	(−6.899)	(−6.081)		(43.56)	(36.84)
A_ACC	−0.006**	−0.011**	*Size*	−0.0303***	−0.028***
	(−2.488)	(−2.176)		(−7.924)	(−7.069)
RS	0.307***	0.289***	*Lev*	−0.018**	−0.062
	(8.702)	(7.357)		(−2.11)	(1.119)
Size	−0.0105	−0.009*	*Growth*	0.004	0.009
	(−1.095)	(−1.852)		(0.965)	(0.986)
Lev	−0.058	−0.048	*Age*	0.011	0.007
	(−1.46)	(−1.044)		(1.461)	(0.838)
Growth	0.086***	0.084**	Intercept	0.058**	0.097**
	(2.640)	(2.265)		(1.97)	(2.685)
Age	0.061*	0.046	Industry effect	Yes	Yes
	(1.695)	(1.552)	Time effect	Yes	Yes
Intercept	−0.022	−0.011	Adjusted R-sq.	0.659	0.680
	(−0.544)	(−0.128)	P-value	0.000	0.000
Industry effect	Yes	Yes	N	39,634	27,512
Time effect	Yes	Yes			
Adjusted R-sq.	0.461	0.475			
P-value	0.000	0.000			
N	39,634	27,512			

The table shows regression results of models (8) and (9) used for testing ES and RS, respectively, under the second hypothesis. Large (small) is the main variable of interest that takesa value equal to one for large (small) firms, and zero otherwise. ***, **, * indicate significance at 1%, 5%, and 10% levels in a two-tailed test, respectively.

p < 0.10) and the PSM sample (−0.025, p < 0.10), indicating an increase in core earnings with a decrease in operating expenses. Further, column 4 of Table A in the Internet Appendix shows that the coefficient of NOE_q*High* on $UE\_\,\Delta\,OE_{q+4}$ is significantly positive (0.112; p < 0.00), which implies that evidence of inflated core earnings among firms with more accounting constraints is the result of ES.

Column (3) presents the results of model (9). The coefficient of *NOR*Low* on *UE_OR* is negative and significant at a 5 % level of significance (−0.098, p < 0.05), suggesting that firms with lesser accounting flexibility are engaged in RS, whereas the positive coefficient of *NOR*High* on *UE_OR* (0.131, p > 0.10) indicates that firms with higher accounting constraints are not engaged in RS. Collectively, these results imply that firms with higher accounting constraints are engaged in ES, whereas firms with lower accounting constraints are found to be engaged in RS. The probable rationale behind this finding may be the reduced opportunity for ES with firms with higher accruals. This finding corroborates the findings of Zang (2012) that firms that use higher accruals at period *t*-1 are less likely to be engaged in AEM at *t* due to reduced opportunities. Hence, it is likely that firms with lesser accounting flexibility due to high expense accruals will resort to RS.

4.2.5. Shifting practices among high and low growth firms

Table 8 shows the regression results of models (8) and (9) for high and low growth firms. Column (1) shows that the coefficient of *NOE*HG* and *NOE*LG* on *UE_CE* are negative, implying that growth opportunities do not impact the ES practices of firms. It is further confirmed by the positive coefficient of *UE_OE*HG* and *UE_OE*LG* on *UE_CE*. The PSM sample also shows a negative coefficient (column 2). Also, the coefficient of NOE_q*HG* and NOE_q*HG* on $UE\_\,\Delta\,OE_{q+4}$ is found to be insignificant and positive, implying that firms do not inflate core earnings through ES. However, the coefficient of *NOR*HG* on *UE_OR* under column (3) is found to be negative and significant (−0.062, p < 0.10), suggesting that high-growth firms are engaged in RS. No similar evidence is found for low-growth firms as the coefficient of *NOR*LG* on *UE_OR* is positive (0.119, p < 0.00). The same results are found for the PSM sample (column 4). Collectively, the results presented in Table 8 imply that high-growth firms are engaged in RS, hence supporting our fifth hypothesis. It is consistent with the notion that high-growth firms are more incentivized to engage in RS due to their capital market pressure of meeting analysts' sales growth.

Table 6
Results of ES and RS for third hypothesis (H3).

	UE_CE			UE_OR	
Variables	(1)	(2)	Variables	(3)	(4)
*NOE*Hlev*	−0.396***	−0.386***	*NOR*Hlev*	−0.122**	−0.135**
	(−4.332)	(−4.303)		(−2.103)	(−2.292)
*NOE*Llev*	0.255***	0.298***	*NOR*Llev*	0.071**	0.149***
	(3.457)	(3.457)		(2.303)	(3.336)
*UE_OE*Hlev*	0.027*	0.021	*A_DISX*	1.612***	1.665***
	(1.741)	(1.637)		(14.445)	(13.060)
*UE_OE*Llev*	0.009**	0.011**	*A_PROD*	0.223***	0.245***
	(2.218)	(2.055)		(5.074)	(4.856)
A_DISX	−0.420	−0.410*	*A_ACC*	0.017***	0.018***
	(−1.535)	(−1.857)		(20.210)	(18.280)
A_PROD	−0.539***	−0.512***	*ES*	0.352***	0.353***
	(−6.809)	(−6.203)		(47.021	(43.710)
A_ACC	−0.011**	−0.011**	*Size*	−0.031***	−0.036***
	(−2.374)	(−2.244)		(−7.991)	(−7.895)
RS	0.290***	0.278	*Lev*	−0.019**	−0.022**
	(8.430)	(7.360)		(−2.110)	(−2.292)
Size	−0.004	−0.002	*Growth*	0.004	0.006
	(−1.537)	(−1.217)		(0.971)	(1.186)
Lev	−0.028	−0.014	*Age*	0.012	0.012
	(−1.471)	(−1.289)		(1.498)	(1.443)
Growth	0.077**	0.073*	Intercept	0.060**	0.094**
	(2.293)	(1.897)		(2.024)	(2.778)
Age	0.055	0.041	Industry effect	Yes	Yes
	(1.581)	(1.421)	Time effect	Yes	Yes
Intercept	−0.076	−0.081	Adjusted R-sq.	0.658	0.67
	(−1.263)	(−1.206)	P-value	0.000	0.000
Industry effect	Yes	Yes	N	39,634	27,748
Time effect	Yes	Yes			
Adjusted R-sq.	0.460	0.474			
P-value	0.000	0.000			
N	39,634	27,748			

The table shows regression results of models (8) and (9) used for testing ES and RS, respectively, under the third hypothesis. Hlev (Llev) is the main variable of interest that takes a value equal to one for high (low) levered firms. ***, **, * indicate significance at 1%, 5%, and 10% levels in a two-tailed test, respectively.

4.2.6. Shifting practices among old and young firms

Table 9 presents the results of models (8) and (9) for old and young firms. Column (1) shows that the coefficient of *NOE*Young* on *UE_CE* is statistically positive (0.458, $p < 0.00$), which implies that young firms are engaged in ES. On the contrary, results show that the coefficient of *NOE*Old* on *UE_CE* is negative (−0.257, $p < 0.00$), indicating that old firms are not engaged in ES. Consistent with this finding, only the coefficient of *UE_OE*Young* on *UE_CE* is found to be negative (−0.061, $p < 0.05$), whereas the corresponding coefficient for old firms is positive (0.031, $p < 0.10$), implying that young firms report inflated core earnings through ES. Column (2) also provides the same results for the PSM sample. Further, the coefficient of NOE_q**Young* on $UE\_\ \Delta\ OE_{q+4}$ under column (6) of Table A in the Internet Appendix is found to be significantly positive (0.123, $p < 0.00$), confirming that increase in core earnings among young firms is due to ES.

A negative association is found between *NOR* and *UE_OR* for old firms. The coefficient of *NOR*Old* on *UE_OR* is negative and statistically significant at a 5 % level of significance (−0.110, $p < 0.05$), whereas the coefficient of *NOR*Young* on *UE_OR* is insignificantly positive (0.087, $p > 0.10$). Similar results are found for the PSM sample (column 4). Overall, empirical results exhibit that young firms prefer ES, whereas old firms prefer RS for inflating core earnings. It may be due to the ease of misclassifying the items. Young firms are required to incur frequent non-recurring expenses, which, in turn, is likely to provide them with more ease in ES, whereas old firms, having higher external monitoring, are under greater capital market pressure of meeting analyst's sales forecasts, and hence they prefer RS.

4.2.7. Shifting practices among sales and non-sales target firms

Table 10, columns (1) and (2) present the results of model (8) for sales and non-sales target firms under initial and PSM samples, respectively. The coefficient of *NOE*NSTF* on *UE_CE* is statistically positive (0.361, $p < 0.00$), which implies that non-sales target firms are engaged in ES. The coefficient of *NOE*STF* on *UE_CE* is negative (−0.310, $p < 0.00$), indicating that sales-target firms are not engaged in ES. Consistent with this finding, only the coefficient of *UE_OE*NSTF* on *UE_CE* is found to be negative (−0.041, $p < 0.05$), where the corresponding coefficient for sales-target firms is positive (0.059, $p > 0.10$), implying that only EBIT-target firms are engaged in ES. Column (2) provides the results in the same direction for the PSM sample. Further, only the coefficient of NOE_q**NSTF* on $UE\_\ \Delta\ OE_{q+4}$ under column (6) of Table A in the Internet Appendix is found to be

Table 7
Results of ES and RS for fourth hypothesis (H4).

	UE_CE			UE_OR	
Variables	(1)	(2)	Variables	(3)	(4)
*NOE*High*	0.391*	0.447*	*NOR*High*	0.131	0.129
	(1.720)	(1.728)		(1.839)	(1.971)
*NOE*Low*	−0.338	−0.386**	*NOR*Low*	−0.098**	−0.026**
	(−1.316)	(−2.509)		(2.517)	(2.358)
*UE_OE*High*	−0.048	−0.051	*A_DISX*	1.609***	1.512***
	(−1.591)	(−1.493)		(14.45)	(12.45)
*UE_OE*Low*	−0.021*	−0.025*	*A_PROD*	0.222***	0.132***
	(−1.814)	(−1.772)		(5.08)	(2.592)
A_DISX	−0.434*	−0.394	*A_ACC*	0.017***	0.017***
	(−1.955)	(−1.225)		(20.29)	(15.24)
A_PROD	−0.554***	−0.488***	*ES*	0.352***	0.313***
	(−6.944)	(−5.742)		(46.35)	(41.07)
A_ACC	−0.011**	−0.012**	*Size*	−0.031***	−0.034***
	(−2.441)	(−2.243)		(−8.017)	(−7.818)
RS	0.291***	0.259***	*Lev*	−0.018**	−0.019*
	(8.451)	(6.460)		(−2.121)	(−1.838)
Size	−0.002	−0.003	*Growth*	0.004	0.009
	(−0.891)	(−0.315		(0.967)	(1.517)
Lev	−0.044	−0.046	*Age*	0.011	0.012
	(−1.107)	(−0.927)		(1.46)	(1.345)
Growth	0.087***	0.049**	Intercept	0.061**	0.124***
	(2.628)	(2.252)		(2.054)	(3.395)
Age	0.055	0.061	Industry effect	Yes	Yes
	(1.581)	(1.138)	Time effect	Yes	Yes
Intercept	−0.078	−0.031	Adjusted R-sq.	0.658	0.676
	(−1.126)	(−1.382)	P-value	0.000	0.000
Industry effect	Yes	Yes	N	39,634	24,992
Time effect	Yes	Yes			
Adj R-sq.	0.457	0.514			
P-value	0.000	0.000			
N	39,634	24,992			

The table shows regression results of models (8) and (9) used for testing ES and RS, respectively, under the fourth hypothesis. High (Low) is the main variable of interest taking a value equal to one for firms having a high (low) level of accruals. ***, **, * indicate significance at 1%, 5%, and 10% levels in a two-tailed test, respectively.

significantly positive (0.117, $p < 0.00$), confirming that increase in core earnings among non-sales target firms or EBIT-target firms is due to ES.

Columns (3) and (4) present the results of RS (model 9) for sales and non-sales target firms under the initial and PSM samples, respectively. The coefficient of *NOR*STF* on *UE_OR* is negative and statistically significant at a 1 % level of significance (−0.148, $p < 0.00$), whereas the coefficient of *NOR*NSTF* on *UE_OR* is positive (0.074, $p < 0.10$). Similar results are found for the PSM sample (column 4). It implies that sales-target firms (*STF*) are engaged in RS, which can be attributed to their strong desire to report inflated sales to increase their managerial remuneration. Overall, the results of Table 10 exhibit that sales-target firms prefer RS for inflating core earnings, hence supporting H7.

In a nutshell, our results suggest that industry-average profitability, size, financial leverage, growth opportunities, accounting flexibility, age, and management compensation contracts of firms affect their choice of shifting tool. In particular, our results exhibit that large, levered, old, high-growth, sales-based target firms prefer RS over ES, whereas small firms, young firms, firms with lesser accounting flexibility, and firms operating below peer-performance prefer ES over RS for inflating core earnings. These results are consistent with our prediction and can be attributed to the fact that firms choose the shifting tool based on the ease, need, and relative advantage of each tool.

4.2.8. Co-existence of determinants

We further investigate ES and RS by taking into account all the seven factors together through model 12 and model 13, respectively.[10] To make these models consistent with our main empirical models (models 8 and 9), we have included fourteen interaction variables to capture the impact of all the seven factors together having two dummy variables for each of the determinants.

[10] We thank an anonymous reviewer for suggesting us to conduct this line of enquiry.

Table 8
Results of ES and RS for fifth hypothesis (H5).

	UE_CE			UE_OR	
Variables	(1)	(2)	Variables	(3)	(4)
*NOE*HG*	−0.329***	−0.376***	*NOR*HG*	−0.062*	−0.109*
	(−3.941)	(−4.245)		(−1.831)	(−1.781)
*NOE*LG*	−0.342***	−0.349***	*NOR*LG*	0.119***	0.139***
	(−4.980)	(−3.651)		(3.709)	(3.948)
*UE_OE*HG*	0.091	0.080*	*A_DISX*	1.609***	1.671***
	(1.200)	(1.789)		(14.43)	(12.43)
*UE_OE*LG*	0.020*	0.017	*A_PROD*	0.222***	0.226***
	(1.697)	(1.453)		(5.062)	(4.666)
A_DISX	−0.440	−0.404**	*A_ACC*	0.017***	0.0175***
	(−1.568)	(−2.135)		(20.35)	(18.12)
A_PROD	−0.553***	−0.482***	*ES*	0.343***	0.376***
	(−6.949)	(−5.487)		(47.23)	(40.23)
A_ACC	−0.011**	−0.012**	*Size*	−0.030***	−0.03***
	(−2.323)	(−2.331)		(−8.014)	(−6.738)
RS	0.292***	0.259***	*Lev*	−0.018**	−0.024*
	(8.185)	(6.211)		(−2.063)	(−1.692)
Size	−0.003	−0.005	*Growth*	0.005	0.003
	(−1.415)	(−1.552)		(1.038)	(0.556)
Lev	−0.046	−0.048	*Age*	0.011	0.004
	(−1.161)	(−1.023)		(1.423)	(0.309)
Growth	0.085***	0.078*	Intercept	0.06**	0.036
	(2.616)	(1.927)		(2.022)	(1.082)
Age	0.054	0.034	Industry effect	Yes	Yes
	(1.557)	(1.241)	Time effect	Yes	Yes
Intercept	−0.070	−0.019	Adjusted R-sq.	0.657	0.686
	(−1.162)	(−1.278)	P-value	0.000	0.000
Industry effect	Yes	Yes	N	39,634	26,502
Time effect	Yes	Yes			
Adjusted R-sq.	0.456	0.487			
P-value	0.000	0.000			
N	39,634	26,502			

The table shows regression results of models (8) and (9) used for testing ES and RS, respectively, under the fifth hypothesis. HG(LG) is the main variable of interest taking a value equal to one for high (low) growth firms. ***, **, * indicate significance at 1%, 5%, and 10% levels in a two-tailed test, respectively.

$$\begin{aligned} UE\_CE_{i,t} = {} & \alpha_0 + \beta_1 NOE_{i,t}{*}Above_{i,t-1} + \beta_2 NOE_{i,t}{*}Below_{i,t-1} + \beta_3 NOE_{i,t}{*}\ Large_{i,t} + \beta_4 NOE_{i,t}{*}Small_{i,t} + \beta_5 NOE_{i,t}{*}Hlev_{i,t} \\ & + \beta_6 NOE_{i,t}{*}Llev_{i,t} + \beta_7 NOE_{i,t}{*}\ High_{i,t} + \beta_8 NOE_{i,t}{*}Low_{i,t} + \beta_9 NOE_{i,t}{*}HG_{i,t} + \beta_{10} NOE_{i,t}{*}LG_{i,t} \\ & + \beta_{11} NOE_{i,t}{*}\ Young_{i,t} + +\beta_{12} NOE_{i,t}{*}\ Old_{i,t} + \beta_{13} + NOE_{i,t}{*}\ STF_{i,t} + \beta_{14} NOE_{i,t}{*}\ NSTF_{i,t} + \ Controls \\ & + Fixed\ effects + \varepsilon_{it} \end{aligned} \tag{12}$$

where *UE_CE* is unexpected core earnings. *NOE* is a non-operating expense. *Above* (*Below*) takes a value equal to one in year *t* for firms operating above (below) industry profitability in year *t*-1. *Large* (*Small*) takes a value equal to one for large (small) firms. *Hlev* (*Llev*) equals one for high (low) levered firms. *High* (*Low*) equals one for firms having net operating assets greater (smaller) than the industry-median. *HG* (*LG*) equals one for high growth (low growth) firms. *Young* (*old*) takes a value equal to one for young (old) firms. *STF* (*NSTF*) takes a value equal to one for sales (non-sales) target firms. The interaction of *NOE* with these dummy variables shows the effect of a specific category of firms on ES.

$$\begin{aligned} UE\_OR_{i,t} = {} & \alpha_0 + \beta_1 NOR_{i,t} * Above_{i,t-1} + \beta_2 NOR_{i,t} * Below_{i,t-1} + \beta_3 NOR_{i,t} * \ Large_{i,t} + \beta_4 NOR_{i,t} * Small_{i,t} \\ & + \beta_5 NOR_{i,t} * Hlev_{i,t} + \beta_6 NOR_{i,t} * Llev_{i,t} + \beta_7 NOR_{i,t} * \ High_{i,t} + \beta_8 NOR_{i,t} * Low_{i,t} + \beta_9 NOR_{i,t} * HG_{i,t} \\ & + \beta_{10} NOR_{i,t} * LG_{i,t} + \beta_{11} NOR_{i,t} * \ Young_{i,t} + \beta_{12} NOR_{i,t} * \ Old_{i,t} + \beta_{13} NOR_{i,t} * \ STF_{i,t} + \beta_{14} NOR_{i,t} * \ NSTF_{i,t} \\ & + \ Controls + Fixed\,effects + \varepsilon_{it} \end{aligned} \tag{13}$$

where *UE_OR* is unexpected operating revenue. *NOR* is non-operating revenue. All dummy variables have the same meaning as assigned previously. The interaction of *NOR* with these dummy variables shows the effect of a specific category of firms on RS.

Table B in the Internet Appendix shows the results of models (12) and (13). The results are in line with our previous findings in terms of direction and magnitude of coefficients; however, the significance level of a few coefficients has been marginally decreased. For instance, the coefficient of *NOE*Below* (column 1, 0.302, $p < 0.05$), *NOE*Llev* (column 1, 0.273**,

Table 9
Results of ES and RS for sixth hypothesis (H6).

	UE_CE			*UE_OR*	
Variables	(1)	(2)	Variables	(3)	(4)
*NOE*Young*	0.458***	0.491***	*NOR*Young*	0.087	0.071
	(4.210)	(4.352)		(1.517)	(0.954)
*NOE*Old*	−0.257***	−0.290***	*NOR*Old*	−0.110**	−0.132***
	(−3.705)	(−3.275)		(−2.378)	(−3.111)
*UE_OE*Young*	−0.061**	−0.083**	*A_DISX*	1.609***	1.534***
	(−2.385)	(−2.517)		(14.44)	(13.45)
*UE_OE*Old*	0.031*	0.037*	*A_PROD*	0.223***	0.184***
	(1.910)	(1.908)		(5.084)	(4.064)
A_DISX	−0.476*	−0.449	*A_ACC*	0.017***	0.018***
	(−1.734)	(−1.513)		(20.28)	(18.78)
A_PROD	−0.550***	−0.523***	*ES*	0.353***	0.369***
	(−6.997)	(−5.309)		(49.24)	(45.32)
A_ACC	−0.010**	−0.011**	*Size*	−0.031***	−0.032***
	(−2.203)	(−2.158)		(−7.999)	(−8.288)
RS	0.293***	0.284***	*Lev*	−0.018**	−0.017*
	(8.086)	(7.131)		(−2.117)	(−1.768)
Size	−0.003	−0.004	*Growth*	0.004	0.007
	(−1.405)	(−1.089)		(0.975)	(1.002)
Lev	−0.043	−0.040	*Age*	0.011	0.008
	(−1.117)	(−0.981)		(1.295)	(0.925)
Growth	0.082**	0.077**	Intercept	0.061**	0.080***
	(2.500)	(2.212)		(2.026)	(2.612)
Age	0.093	0.084	Industry effect	Yes	Yes
	(2.201)	1.945	Time effect	Yes	Yes
Intercept	−0.071	(−0.056)	Adjusted R-sq.	0.66	0.667
	(−1.186)	(−1.091)	P-value	0.000	0.000
Industry effect	Yes	Yes	N	39,634	31,962
Time effect	Yes	Yes			
Adjusted R-sq.	0.464	0.487			
P-value	0.000	0.000			
N	39,634	31,962			

The table shows regression results of models (8) and (9) used for testing ES and RS, respectively, under the sixth hypothesis. Young (Old) is the main variable of interest taking a value equal to one for young (old) firms. ***, **, * indicate significance at 1%, 5%, and 10% levels in a two-tailed test, respectively.

$p < 0.05$), *NOE*Young* (column 1,0.443**, $p < 0.05$) and *NOR*Old* (column 2, −0.090, $p < 0.05$) is significant at 5 % level of significance only, whereas the coefficient of *NOR*Large* is significant at 10 % level of significance only (−0.073, $p < 0.10$).[11]

4.2.9. Consequences of RS and ES to the capital market

4.2.9.1. Shifting practices and stock returns. The earnings management literature documents the existence of AEM and REM anomaly, where investors are found to perceive the different forms of earnings management differently, hence demanding different risk premium for holding the stocks (for instance, Bansal and Ali, 2021; Dayanandan and Sra, 2018; Sloan, 1996; Wu et al., 2012). In this study, we have tested the pricing impact of RS and ES to know whether these forms have the same or different consequences.[12]

We followed the standard portfolio methodology to execute the same. It includes two steps. First, we calculated the monthly excess returns for stocks.[13] Second, we formed univariate sorted portfolios based on *UE_OR* and *UE_CE* loadings to understand the relationship between shifting practices (ES and RS) and excess stock returns at the portfolio level. We divided our stocks into deciles based on the descending order of *UE_OR* and *UE_CE*, where the high (low) portfolio shows the result for the stocks having the highest (lowest) magnitude of shifting practices. The H-L portfolio presents the difference (spread) of high minus low portfolios.

Table 11, panels A and B present the univariate sorted portfolio excess returns for RS and ES loadings. The portfolio returns show a positive relationship between *UE_OR* and expected stock returns. The monotonically increasing pattern of portfolio excess returns for the increasing level of *UE_OR* loadings presents one month ahead excess returns of 1.27 % for the highest decile portfolio, while the expected excess return for the lowest decile portfolio is observed as negative (−1.70 % per month).[14] These positive and negative returns for the extreme portfolios generate a high minus low (H-L) portfolio

[11] This change may be due to the overlapping of firms under the joint impact because firms operating below industry-average profitability are relatively young due to their lesser financial resources for expansion. Large firms are relatively old because firms grow over the period of time. Overall, our results remain intact under the joint investigation of determinants of RS and ES.

[12] We thank an anonymous reviewer for suggesting us to conduct this line of inquiry.

[13] Excess returns are measured as the difference between the monthly stock returns and monthly yield of 90-days Government of India treasury bills, where monthly stock returns are measured as the first difference of the natural logarithm of monthly price data.

[14] We also tested for the three-and-six-months ahead portfolio returns and found that RS stocks have higher excess returns.

Table 10
Results of ES and RS for seventh hypothesis (H7).

	UE_CE			UE_OR	
Variables	(1)	(2)	Variables	(3)	(4)
*NOE*STF*	−0.310***	−0.238***	*NOR*STF*	−0.148***	−0.141***
	(−3.719)	(−2.573)		(3.143)	(2.908)
*NOE*NSTF*	0.361***	0.291***	*NOR*NSTF*	0.074*	0.028**
	(3.365)	(2.863)		(1.677)	(2.369)
*UE_OE*STF*	0.059	0.046	*A_DISX*	1.605***	1.597***
	(1.442)	(1.523)		(14.48)	(12.38)
*UE_OE*NSTF*	−0.041**	−0.029**	*A_PROD*	0.222***	0.194***
	(−2.182)	(−2.114)		(5.068)	(3.886)
A_DISX	−0.442	−0.525*	*A_ACC*	0.017***	0.017***
	(−1.639)	(−1.715)		(20.34)	(16.43)
A_PROD	−0.556***	−0.497***	*ES*	0.363***	0.351***
	(−6.938)	(−5.894)		(48.36)	(41.32)
A_ACC	−0.011**	−0.011**	*Size*	−0.030***	−0.028***
	(−2.344)	(−2.146)		(−8.006)	(−6.624)
RS	0.296***	0.265***	*Lev*	−0.019***	−0.016***
	(8.265)	(7.054)		(−2.111)	(−1.717)
Size	−0.005	−0.009	*Growth*	0.004	0.003
	(−1.575)	(−1.045)		(0.975)	(1.547)
Lev	−0.047	−0.046	*Age*	−0.004	−0.003
	(−1.172)	(−0.941)		(−0.843)	(−0.718)
Growth	0.087***	0.058**	Intercept	0.060**	0.046
	(2.569)	(2.421)		(2.036)	(1.403)
Age	0.055	0.033**	Industry effect	Yes	Yes
	(1.590)	(2.115)	Time effect	Yes	Yes
Intercept	−0.058	−0.012	Adjusted R-sq.	0.65	0.667
	(−1.193)	(−1.075)	P-value	0.000	0.000
Industry effect	Yes	Yes	N	39,634	22,820
Time effect	Yes	Yes			
Adjusted R-sq.	0.457	0.487			
P-value	0.000	0.000			
N	39,634	22,820			

The table shows regression results of models (8) and (9) used for testing ES and RS, respectively, under the seventh hypothesis. STF (NSTF) is the main variable of interest taking a value equal to one for sales-target (non-sales target) firms. ***, **, * indicate significance at 1%, 5%, and 10% levels in a two-tailed test, respectively.

Table 11
Test results of shifting practices and stock return.

Panel A: Equal weighted one month ahead portfolio excess return (*UE_OR* sorted stocks)											
Portfolios	High	9	8	7	6	5	4	3	2	Low	H-L
UE_OR	1.01	0.35	0.17	0.05	−0.04	−0.11	−0.19	−0.27	−0.37	−0.69	1.71
Excess_Ret	1.27**	0.87	0.51	0.33	0.10	−0.19	−0.58	−1.02	−1.18*	−1.70**	2.97***
t-statistics	1.99	1.34	0.78	0.52	0.16	0.31	0.91	1.54	1.70	2.26	10.41
Panel B: Equal weighted one month ahead portfolio excess return (*UE_CE* sorted stocks)											
UE_CE	0.53	0.20	0.14	0.10	0.07	0.03	0.00	−0.05	−0.14	−0.82	1.35
Excess_ Ret	−0.27	0.05	0.03	−0.08	−0.23	−0.19	−0.26	−0.39	−0.16	0.03	−0.30
t-statistics	0.41	0.09	0.05	0.13	0.35	0.28	0.40	0.58	0.23	0.05	1.68

The table presents one month ahead portfolio excess returns for the UE_OR (Panel A) and UE_CE (Panel B) sorted portfolios.

spread of 2.97 % monthly. Unlike RS portfolios, the presented portfolio returns (panel B) do not exhibit any significant impact of ES practices on the portfolio's expected excess returns. The average excess return for the highest and lowest decile portfolio are indifferent from zero Hence, the constituted high minus low (H-L) spreads are also insignificant, implying that there is no significant impact of ES practices on stock returns.

Overall, Table 11exhibits that RS stocks have higher excess returns. It implies that investors view RS firms as growth firms due to their consistent sales growth and value them higher. As a result, their stock prices go up and generate a higher return. It is consistent with the finding of Fama and French (2021), where growth firms have higher excess returns than value firms.

4.2.9.2. Shifting practices to meet or beat benchmarks. We examine one of the arguments that firms are likely to be engaged in shifting practices to meet or beat benchmarks.[15] Following prior studies (for instance, Gunny, 2010; Roychowdhury, 2006), we construct a measure of meeting or beating earnings benchmarks (*MBE*) using return on assets (*ROA*). *MBE* is an indicator variable that takes the value of one when *ROAt* > *ROAt*-1 and (*ROAt* - *ROAt*-1) < 0.002 (one standard deviation away from mean of *ROAt*),

[15] We thank an anonymous reviewer for suggesting us to conduct this line of enquiry.

zero otherwise. It indicates that the benchmark is the previous year's performance and improvement in financial performance this year over the previous year is marginal.

We employ models (14) and (15) to examine whether firms engage in ES and RS, respectively, to meet or beat earnings benchmarks.

$$UE\_CE_{i,t} = \beta_0 + \beta_1 NOE_{i,t} + \beta_2 MBE_{i,t} + \beta_3 NOE * MBE_{i,t} + Controls + Fixed\ effects + \varepsilon_{i,t} \quad (14)$$

where *UE_CE* is unexpected core earnings. *NOE* is a non-operating expense. *MBE* is an indicator variable that has a value equal to one for MBE firms. We include the interaction of *NOE* with *MBE*, whose coefficient is expected to be positive if firms engage in ES to meet or beat the benchmarks.

$$UE\_OR_{i,t} = \beta_0 + \beta_1 NOR_{i,t} + \beta_2 MBE_{i,t} + \beta_3 NOR * MBE_{i,t} + Controls + Fixedeffects + \varepsilon_{i,t} \quad (15)$$

where *UE_OR* is unexpected operating revenue. *NOR* is a non-operating revenue. The coefficient of interaction variable (*NOR***MBE*) is expected to be negative if firms are engaged in RS to meet or beat the benchmarks.

Table 12 shows the results of models (14) and (15). Column (1) shows that the coefficient of *NOE***MBE* (0.043p < 0.05) is significantly positive, suggesting that firms are engaged in ES to meet or beat earnings benchmarks, which is consistent with the findings of many prior studies (for instance, Athanasakou et al., 2009; Haw et al., 2011; Poonawala and Nagar, 2019). In the same vein, we find that the coefficient of *NOR***MBE* (column 3, −1.210, p < 0.05) is significantly negative, suggesting that firms are engaged in RS to meet or beat earnings benchmarks. Overall, the results show that firms engage in shifting practices to meet and beat the earnings benchmark. Hence, firms that just meet or slightly beat earnings benchmarks are highly likely to engage in RS and ES. Thus, investors and analysts should be careful when evaluating such firms.

4.2.9.3. Shifting practices to avoid violation of debt covenants. We investigate another argument that firms are likely to be engaged in shifting practices to avoid the violation of debt covenants. Covenant slack is defined as the situation where a company is close to its covenant threshold value. Following Franz et al. (2014), we measure covenant slack as the proportion of actual minus threshold value of covenant slack to the threshold value of covenant slack, where Actual is the actual value of the interest coverage covenant for firm *i* in year *t* (calculated as EBITDA divided by interest expense, which is consistent with Demerjian and Owens, 2016) and *Threshold* is the threshold value of the interest coverage covenant. To overcome the problem in the measurement of slack,[16] we define the firms that have interest coverage covenant slack within the bottom tercile of the full sample as those with tight covenant slack while all other firms are defined as having loose slack. *Slack* is our test variable that is equal to one for firms with tight interest coverage covenant slack, and zero otherwise. We replace the variable *MBE* in models 14 and 15 with a variable, namely *Slack*, to investigate whether firms engage in shifting practices to avoid violation of covenants.

The median (mean) of the slack, as expected, is significantly lower for firms with tight covenant slack than their counterparts with loose covenant slack. Results show that the *NOE***Slack* coefficient (Table 12, column 2, 0.098, p < 0.10) is significantly positive for *UE_CE* and the *NOR* **Slack* coefficient (column 4, −1.312, p < 0.05) is significantly negative for *UE_OR*. This indicates that firms employ ES and RS when they have tight interest coverage covenant slack. This suggests that when borrowers are close to violating an interest coverage covenant, their managers engage to a larger extent in RS and ES.

5. Robustness tests

Although the PSM analysis confirmed our main results, we employed other robustness tests to check the validity of our results. These are as follows:

1.1. Alternative specification for measuring UE_CE

Consistent with Alfonso et al. (2015), we use two alternative specifications for model (1). First, we exclude current year accruals (*ACC*) because it includes non-cash special items that are likely to impact core earnings. Second, we replace *ACC* with working capital accruals (*WCA*)[17] to nullify the effect of depreciation and other non-recurring accrual items on core earnings. We replace *UE_CE* in our main model (7) with the residuals obtained under these alternative specifications and re-estimate. Consistent with our main findings, we find (untabulated)[18] a significant positive association between new residuals and *NOE* among small firms, young firms, firms with lesser accounting flexibility, and firms operating below the industry-average OPR.

5.2. Alternative specification for measuring UE_OR

Following Malikov et al. (2018), we use two alternative specifications for model (6). First, we exclude accounts receivable (*AR*) to exclude the impact of receivables from non-operating revenues. Second, as RS merely overstates operating revenue

[16] Some lenders may adjust GAAP numbers when they define debt covenant thresholds. Hence, the definition of interest coverage may vary across different borrowers and debt contracts.

[17] *WCA* measured as increase in accounts receivable plus increase in inventory minus decrease in accounts payable minus decrease in income taxes payable plus increase in other current assets (Cheng and Thomas, 2006).

[18] All the untabulated results are made available from authors upon the reader's request.

Table 12
Test results of shifting practices and capital market consequences.

UE_CE(model 14)				*UE_OR*(model 15)			
NOE	0.042***	*NOE*	0.056**	*NOR*	−0.093*	*NOR*	−0.631*
	(8.160)		(2.163)		(−1.840)		(−1.717)
MBE	−0.021*	*Slack*	−0.018	*MBE*	−0.069**	*Slack*	−0.034
	(−1.936)		(−0.443)		(−2.430)		(−0.666)
*NOE*MBE*	0.043**	*NOE*Slack*	0.098*	*NOR*MBE*	−1.210**	*NOR*Slack*	−1.312**
	(2.319)		(−1.880)		(−2.150)		(−2.342)
Intercept	0.073	Intercept	−0.067	Intercept	−0.203***	Intercept	0.073
	(1.963)		(−1.544)		(−3.651)		(1.562)
Controls	Yes	Controls	Yes	Controls	Yes	Controls	Yes
Industry effect	Yes	Industry effect	Yes	Industry effect	Yes	Industry effect	Yes
Time effect	Yes	Time effect	Yes	Time effect	Yes	Time effect	Yes
Adjusted R-sq.	0.210	Adjusted R-sq.	0.361	Adjusted R-sq.	0.216	Adjusted R-sq.	0.191
P-value	0.000	P-value	0.000	P-value	0.000	P-value	0.000
Observations	39,634	Observations	31,856	Observations	39,634	Observations	31,856

The table shows results of models (14) and (15) used for examining whether firms engage in RS and ES to meet or beat the benchmark or to avoid violation of debt covenants. ***, **, * indicate significance at 1%, 5%, and 10% levels in a two-tailed test, respectively.

without affecting sales volume, we use COGS to strike the balance between sales volume and cost per unit. We replace *UE_OR* in model (9) with the residuals obtained under these alternative specifications and re-estimate. We find (untabulated) a significant negative association between new residuals and *NOR* among large, levered, old, high-growth, and sales-based target firms, which is consistent with our main findings.

5.3. Testing shifting practices under two periods

To further check the validity of our results, we divided our sample (2001–2019) into two periods, namely period I (2001–2010) and period II (2011–2019). Table C in the Internet Appendix shows that the coefficient of *NOR* on *UE_OR* is significantly negative and the coefficient of *NOE* on *UE_CE* is positive under both periods, implying that the firms are engaged in RS and ES. We re-run our main models (models 8 and 9) under both periods for each of the hypotheses and find the same results under both periods. However, the magnitude of few coefficients (particularly for H2 and H6, i.e., large and old firms) are found to be reduced during period II, although the direction remains the same. The reduced coefficient can be attributed to the impact of mandatory adoption of IFRS-converged standards in India (w.e.f. 1st April 2015), where firms with a higher net worth (large and old firms) are mandated to prepare their financial statements under new accounting standards. As these standards have more detailed disclosure requirements for recording expense and revenue items in the income statement (Zalata and Roberts, 2016), it reduces the magnitude of shifting practices among the IFRS adopter firms.

Overall, our main findings are not sensitive to the alternative specifications for the expectation model and periods.

6. Conclusion

Motivated by the increasing empirical and anecdotal evidence of RS and ES, our study identifies firm-specific factors that incentivize firms to prefer one form of shifting over another. In particular, the study explored seven well-examined determinants of earnings management, namely, industry-average profitability, size, degree of financial leverage, sales growth, accounting flexibility, age, and management compensation contracts of the firm in the context of CS. Using a sample size of 39,634 firm-years enlisted in BSE (2001–2019), we find that, on average, large, levered, old, high-growth, and sales-target firms are more likely to be engaged in RS, whereas small foirms, young firms, firms with limited accounting flexibility, and firms operating below the industry-average profitability prefer to be engaged in ES for reporting inflated operating profitability metrics. It implies that firms look at the ease, need, and advantage of shifting the items within the income statement. They are likely to shift those items that can be camouflaged easily and assist them in beating or meeting different benchmarks. We further find that RS stocks have higher excess returns, implying that investors perceive RS stocks as growth stocks, hence valuing them higher. In addition, the results exhibit that firms engage in shifting practices to meet or beat benchmarks and avoid violation of debt covenants.

The study contributes to the literature on CS by providing compelling evidence that certain firm-specific factors incentivize the firms to prefer one form of shifting over another. Besides, our study is among the pioneering attempts that jointly examine both forms of shifting by taking a uniform sample of firms over the period, whereas most of the prior studies examined one form of shifting at a time. The findings are useful to accounting standards-setting bodies, auditors, and investors because the results highlight the importance of awareness about the forms of CS in addition to AEM and REM. It suggests that firms that just meet or slightly beat the industry-average profitability levels are highly likely to engage in CS. Therefore, investors and analysts should be cautious when evaluating such firms by comparing them with other firms in the same industry. The results suggest that lenders do not make lending decisions just by viewing the favorable operating performance metrics because CS is the preferred tool for reporting inflated operating performance. Our results can be handy for standard-setting authorities to introduce more mandatory disclosure requirements for recording expense and revenue items in the income statement, which would help curb the corporate misfeasance of RS and ES. The documented firm-specific factors will enable auditors to identify the suspect firms with more ease.

Future research can take up an investigation of the shifting practices industry-wise, as manufacturing firms are more likely to prefer ES over RS due to their numerous recurring and non-recurring expenses. Hence, it is of interest to examine whether a few industries prefer one to another? Have firms moved from one type of shifting to the other over time?

Declaration of Competing Interest

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

Appendix A

Internet Appendix

Table A1
Variable definition.

Variables	Definition and measurement
CE	Core earnings (operating profit) are measured as sales minus cost of goods sold (COGS) and operating expenses, where operating expenses include selling, general, and administrative (SG&A), and research and development (R&D) expenses.
ATO	Assets turnover ratio, measured as the proportion of sales to average net operating assets. Net operating assets are the difference between operating assets and operating liabilities, where operating assets are measured as total assets minus cash and cash equivalents, and operating liabilities are computed as total assets less total debt, total equity, and minority interest.
ACC	Accruals, calculated as earnings before extraordinary items and discontinued operations minus cash flows from operations, is consistent with Zalata and Roberts (2016).
ΔSales	Change in sales from the prior period (*t*-1) to the current period (*t*).
Neg_ ΔSales	Percentage change in sales if *ΔSales* is negative, and zero otherwise.
UE_CE	Unexpected core earnings, measured as residuals from the model (1).
NOE	Non-operating expenses, measured as actual core earnings plus non-operating income minus net income, is consistent with Zalata and Roberts (2016).
OE	Operating expenses, measured as the sum of SG&A and R&D expenses.
MV	Natural logarithm of the market value of equity.
INT	Internal funds, comprising free reserves and surpluses.
Tobin Q	The proportion of market value to book value of equity.
UE_OE	Unexpected operating expenses are measured as residuals from Eq. (3).
UE_ Δ OE	Unexpected change in operating expense from quarter *q*-4 to *q*. It is residual from model (4) for the expected change in operating expense estimated by the industry-year quarter.
OR	Operating revenues are defined as revenue from operations (sales).
AT	Total assets of the firm.
MTB	The proportion of market value to book value of equity.
AR	Accounts receivable of the firm.
UE_OR	Unexpected operating revenues are measured as residuals from model (6).
NOR	Non-operating revenue includes foreign exchange gains, rental income, dividend income, plus any other income from the firm's investing and financing activities.
A_PROD	Abnormal levels of *PROD*, measured as residuals from the following Roychowdhury (2006) model: $\frac{PROD_{i,t}}{AT_{i,t-1}} = \alpha_0 + \beta_1 \frac{1}{AT_{i,t-1}} + \beta_2 \frac{Sales_{i,t}}{AT_{i,t-1}} + \beta_3 \frac{\Delta Sales_{i,t}}{AT_{i,t-1}} + \beta_4 \frac{\Delta Sales_{i,t-1}}{AT_{i,t-1}} + \varepsilon_{i,t}$where *PROD* is production cost measured as the sum of the COGS and change in inventory. *AT* is total assets. The model is estimated cross-sectionally for each industry-year having at least fifteen observations.
A_DISX	Abnormal levels of *DISX*, measured as residuals from the following Roychowdhury (2006) model: $\frac{DISX_{i,t}}{AT_{i,t-1}} = \alpha_0 + \beta_1 \frac{1}{AT_{i,t-1}} + \beta_2 \frac{Sales_{i,t-1}}{AT_{i,t-1}} + \varepsilon_{i,t}$where *DISX* is discretionary expenses measured as the sum of SG&A and R&D expenses.We run this model cross-sectionally for each industry-year having at least fifteen observations to control macroeconomic and industry shocks.
A_ACC	Abnormal levels of accruals, measured as residuals from the following performance adjusted modified Jones model (Kothari et al., 2005): $\frac{ACC_{i,t}}{AT_{i,t-1}} = \varnothing_1 \left(\frac{1}{AT_{i,t-1}}\right) + \varnothing_2 \frac{(\Delta Sales - \Delta REC)_{i,t}}{AT_{i,t-1}} + \varnothing_3 \frac{PPE_{i,t}}{AT_{i,t-1}} + \varnothing_4 ROA_{i,t} + \varepsilon_{i,t}$where ACC is accruals. *ΔREC* is the change in account receivables of firm. *PPE* is gross value of plant, property, and equipment. ROA is return on assets measured as net profit divided by total assets. The model is estimated cross-sectionally for each industry-year having at least fifteen observations.
RS	A dummy variable that equals one for firms having positive *UE_OR* and positive *NOR*, and zero otherwise.
ES	A dummy variable that equals one for firms having positive *UE_CE,* and positive *NOE*, and zero otherwise.
IC	Incentive compensation, which consists of bonus, ex-gratia, and other monetary rewards given to employees.
Size	Natural logarithm of total assets.
Lev	Proportion of total outside liabilities to total assets.
Growth	Sales growth, measured as the percentage change in sales from period *t*-1 to *t.*
Age	Natural logarithm of difference between current year and year of firm's incorporation.
QR	Quick ratio, measured as ratio of quick assets to current laibilities, where quick assets are defined as current assets minus stock and prepaid expenses.

Table A2
Comparison between ES and RS.

Particulars	Base figures	ES	RS
Sales	1000	1000	**1200**
Less: Operating expenses (*OE*)	600	**400**	600
Operating profit	400	600	600
Less: Non-operating expense (*NOE*)	300	**500**	300
Add: Non-operating revenue	300	300	**100**
Profit before tax	400	400	400
Operating profit ratio (operating profit/sales)	40 %	60 %	50 %

The above hypothetical example shows that ES has a greater relative advantage than RS in terms of stimulating the operating profit ratio.

Table A3
Results of ES and RS for firms with higher and lower non-operating items.

Variables	*UE_CE*		Variables	*UE_OR*	
	(1)	(2)		(3)	(4)
*NOE*Higher*	0.342	0.412	*NOR*More*	−0.103***	−0.071***
	(1.438)	(1.386)		(4.185)	(4.950)
*NOE*Lower*	0.949***	0.979***	*NOR*Less*	0.595	0.755
	(4.896)	(5.836)		(1.529)	(0.842)
*UE_OE*Higher*	0.021*	0.024*	*A_DISX*	1.609***	1.606***
	(1.739)	(1.739)		(9.83)	(11.99)
*UE_OE*Lower*	−0.223**	−0.285***	*A_PROD*	0.223***	0.203*
	(2.110)	(2.591)		(7.61)	(4.124)
A_DISX	−0.411	−0.391	*A_ACC*	0.017***	0.018***
	(−1.459)	(−1.539)		(20.39)	(16.94)
A_PROD	−0.546***	−0.491***	*ES*	0.364***	0.360***
	(−6.829)	(−5.799)		(8.43)	(6.227)
A_ACC	−0.01***	−0.012	*Size*	−0.030***	−0.032***
	(−2.320)	(−2.325)		(−4.80)	(−7.538)
RS	0.294***	0.265***	*LEV*	−0.018**	−0.018*
	(8.255)	(6.563)		(−2.530)	(−1.864)
Size	0.0016	0.0042	*Growth*	0.004*	0.005*
	(1.231)	(0.519)		(1.893)	(1.798)
Lev	−0.046*	−0.034*	*Age*	−0.005	0.008
	(−1.965)	(−1727)		(−1.063)	(1.432)
Growth	0.085***	0.061**	Intercept	0.058***	0.056*
	(3.547)	(−0.727)		(3.705)	(1.709)
Age	0.057*	0.039**	Industry effect	Yes	Yes
	(1.948)	(2.53)	Time effect	Yes	Yes
Intercept	−0.086	−0.0646	Adjusted R-sq.	0.659	0.661
	(−1.398)	(−929)	P-value	0.000	0.000
Industry effect	Yes	Yes	N	39,634	24,024
Time effect	Yes	Yes			
Adjusted R-sq.	0.457	0.477			
P-value	0.000	0.000			
N	39,634	23,606			

The table shows regression results of models (8) and (9) used for testing ES and RS, respectively, for firms with higher and lower non-operating items. Columns (1) and (2) show results of model (8) under initial and PSM sample, respectively. Columns (3) and (4) show results of model (9) under initial and PSM sample, respectively. Higher (Lower) is the main variable of interest taking a value equal to one for firms with higher NOE (lower NOE). More (Less) is the main variable of interest taking a value equal to one for firms with more NOR (less NOR). ***, **, * indicate significance at 1%, 5%, and 10% levels in a two-tailed test, respectively.

Table A4
Results of specification tests.

	Hypothesis 1		Hypothesis 2		Hypothesis 3		Hypothesis 4		Hypothesis 5		Hypothesis 6		Hypothesis 7	
Specification tests	ES	RS	ES	RS	ES	RS	ES	RS	ES	RS	ES	RS	ES	RS
F test	10.34	4.14	10.16	4.23	9.49	4.22	10.03	4.22	10.00	4.23	10.24	4.23	10.65	4.13
LM test	8455.02	1110.77	8363.67	1622.13	7635.49	1623.26	8196.43	1609.15	8235.38	1620.23	8470.05	1622.13	8454.37	1606.45
Hausman test	570.81	1237.73	513.77	872.43	434.96	864.23	502.18	863.47	517.39	875.61	531.27	873.10	515.59	857.42
BG test	1634.43	375.38	949.04	1368.00	432.56	286.17	226.07	293.62	126.34	245.78	127.04	239.89	111.36	224.21
BP test	5254.80	4336.45	2280.90	4532.71	2123.89	4475.54	2709.19	5586.51	2169.49	4887.11	2212.85	4515.03	2197.17	4499.35

The table shows results of different tests used to identify the appropriate panel data regression models (F test, LM test, and Hausman test) and check the serial autocorrelation and heteroskedasticity problems (Breusch-Godfrey (BG) test and Breusch-Pagan (BP) test). The null hypothesis of the F-test, LM test, and Hausman test are that there are no time-fixed effects, the variance across entities is zero, and both fixed-effects and random-effects models are consistent, respectively. Results show that these null hypotheses are rejected, hence we have used a fixed-effects model for estimating results. The null hypothesis of the BP test (BG test) is that there is no heteroskedasticity (serial autocorrelation). Results show that we could not reject this null hypothesis, hence we have reported robust *t*-statistics for the coefficients.

Table A
Result of reversal tests (model 5).

UE_ Δ OE_{q+4}													
Hypothesis 1 (1)		Hypothesis 2 (2)		Hypothesis 3 (3)		Hypothesis 4 (4)		Hypothesis 5 (5)		Hypothesis 6 (6)		Hypothesis 7 (7)	
NOE_q	0.093**	NOE_q	0.114	NOE_q	0.091***	NOE_q	0.074*	NOE_q	0.124**	NOE_q	0.127***	NOE_q	0.194**
	2.541		1.452		3.102		1.990		2.084		4.475		2.475
NOE_q*Below	0.183***	NOE_q*Large	0.224	NOE_q*Hlev	0.174	NOE_q*High	0.112***	NOE_q*HG	0.234	NOE_q*Young	0.123***	NOE_q*STF	0.147
	4.423		1.234		0.452		3.109		1.421		5.412		1.234
NOE_q*Above	0.103	NOE_q*Small	0.184***	NOE_q*Llev	0.197*	NOE_q*Low	0.184	NOE_q*LG	0.183	NOE_q*Old	−0.194**	NOE_q*NSTF	0.117***
	1.475		4.423		1.647		1.234		1.234		2.124		4.423
Intercept	−0.000**	Intercept	−0.010***	Intercept	−0.012	Intercept	−0.001**	Intercept	0.045**	Intercept	−0.023**	Intercept	0.047***
	−2.110		−3.124		−1.245		−2.475		4.625		−2.095		3.123
Controls	Yes	Controls	Yes	Controls	Yes	Controls	Yes	Controls	Yes	Controls	Yes	Controls	Yes
Adj.R-sq.	0.09	Adj. R-sq.	0.07	Adj. R-sq.	0.113	Adj. R-sq.	0.08	Adj. R-sq.	0.08	Adj. R-sq.	0.127	Adj. R-sq.	0.03
p-value	0.000	p-value	0.000	p-value	0.000	p-value	0.000	p-value	0.000	p-value	0.000	p-value	0.000

The table shows regression results of model (5) used to test the impact of change in unexpected operating expense on non-operating expense.

Table B
Results of ES and RS under coexistence of seven determinants.

UE_CE (model 12)		*UE_OR* (model 13)	
	(1)		(2)
*NOE*Above*	0.440	*NOR*Above*	0.450***
	(1.401)		(4.103)
*NOE*Below*	0.302**	*NOR*Below*	−0.130*
	(2.003)		(1.677)
*NOE*Large*	−0.017	*NOR*Large*	−0.073*
	(−0.612)		(1.957)
*NOE*Small*	0.293***	*NOR*Small*	0.093
	(7.153)		(1.611)
*NOE*Hlev*	−0.364***	*NOR*Hlev*	−0.134**
	(−6.113)		(−2.003)
*NOE*Llev*	0.273**	*NOR*Llev*	0.067**
	(2.336)		(2.337)
*NOE*High*	0.370*	*NOR*High*	0.193*
	(1.813)		(1.993)
*NOE*Low*	−0.394	*NOR*Low*	−0.083**
	(−1.220)		(1.973)
*NOE*HG*	−0.373***	*NOR*HG*	−0.081*
	(−4.551)		(−1.093)
*NOE*LG*	−0.350***	*NOR*LG*	0.123***
	(−8.193)		(4.153)
*NOE*Young*	0.443**	*NOR*Young*	0.093
	(2.270)		(1.443)
*NOE*Old*	−0.243***	*NOR*Old*	−0.090**
	(−4.181)		(−1.880)
*NOE*STF*	−0.290***	*NOR*STF*	−0.130***
	(−4.113)		(−5.513)
*NOE*NSTF*	0.309***	*NOR*NSTF*	0.063*
	(5.163)		(1.794)
Intercept	−0.040*	Intercept	0.053***
	(−1.891)		(6.150)
Control variables	Yes	Control variables	Yes
Industry effect	Yes	Industry effect	Yes
Time effect	Yes	Time effect	Yes
Adjusted R-square	0.553	Adjusted R-square	0.683
P-value	0.000	P-value	0.000
N	39,634	N	39,634

The table shows regression results of models (12) and (13) used for testing ES and RS, respectively, by taking into account all the seven determinants together. ***, **, * indicate significance at 1 %, 5 %, and 10 % levels in a two-tailed test, respectively.

Table C
Test results of shifting practices during period I and period II.

UE_CE			*UE_OR*		
Variables	Period I	Period II	Variables	Period I	Period II
NOE	0.312***	0.371***	*NOR*Large*	−0.078**	−0.089**
	(3.240)	(4.123)		(2.442)	(1.993)
UE_OE	0.051*	0.073**	*A_DISX*	1.512***	1.602***
	(1.912)	(1.881)		(8.912)	(10.112)
A_DISX	−0.332**	−0.373	*A_PROD*	0.215***	0.234***
	(−1.992)	(−1.631)		(7.152)	(8.173)
A_PROD	−0.596***	−0.375***	*A_ACC*	0.022***	0.033***
	(−5.771)	(−8.421)		(4.112)	(6.153)
A_ACC	−0.004**	−0.023**	*ES*	0.239***	0.315***
	(−2.113)	(−2.023)		(29.451)	(31.774)
RS	0.293***	0.273***	*Size*	−0.051***	−0.043***
	(11.203)	(8.110)		(−5.412)	(−6.447)
Size	−0.011	−0.019*	*Lev*	−0.012**	−0.081*
	(−1.312)	(−1.902)		(−2.331)	(−1.694)
Lev	−0.013	−0.037	*Growth*	0.072	0.030
	(−1.610)	(−1.591)		(0.881)	(0.903)
Growth	0.091***	0.073**	*Age*	0.023	0.037
	(3.770)	(2.163)		(1.400)	(0.731)

Table C (*continued*)

UE_CE			*UE_OR*		
Variables	Period I	Period II	Variables	Period I	Period II
Age	0.067*	0.051*	Intercept	0.061**	0.113***
	(1.733)	(1.812)		(2.153)	(3.125)
Intercept	−0.013	−0.047	Industry effect	Yes	Yes
	(−0.843)	(−0.223)	Time effect	Yes	Yes
Industry effect	Yes	Yes	Adjusted R-sq.	0.561	0.603
Time effect	Yes	Yes	p-value	0.001	0.000
Adjusted R-sq.	0.342	0.364	N	20,860	18,774
p-value	0.000	0.001			
N	20,860	18,774			

The table shows results of models used to examine ES and RS under two time periods. ***, **, * indicate significance at 1 %, 5 %, and 10 % levels in a two-tailed test, respectively.

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