The real consequences of classification shifting: Evidence from the efficiency of corporate investment

Abstract

This study investigates the real consequences of earnings management, i.e., classification shifting, by examining its effect on corporate investment efficiency. The underlying expectation is that the ways of reporting different profit items within the income statement should accentuate information asymmetry between managers and capital providers regarding the level of core, and so more likely repeatable, firm performance. We anticipate that classification shifting will aggravate agency problems and distort managers' own perceptions of their firms' sustainable profitability, resulting in imperfect investment-related information sets for them, ultimately leading to inefficient investing. We find that classification shifting strongly and significantly decreases the responsiveness of investment to growth opportunities and is thus associated with more inefficient investing. After investigating the economic mechanisms explaining this association, our results are more pronounced when other information and agency problem-related factors that should protect against inefficient investing are weaker and also for firms whose managers show reduced signs of learning from peers, which could alleviate potential classification shifting-related distortion effects on managerial perceptions. Our study provides evidence on the adverse real consequences of classification shifting, a form of earnings management without any bottom-line performance reversing effects, with reference to a very important firm-level outcome, namely efficient investing.

Keywords: classification shifting; investment efficiency; earnings management; information asymmetry; peer information

JEL classifications: M40; M41, G10, G31

1. Introduction

Classification shifting (CS) refers to the deliberate and improper inclusion of core expenses in negative special items (Joo & Chamberlain, 2017) and represents a form of non-bottom-line profit manipulation that increases core earnings without affecting bottom-line profit (e.g., Haw et al., 2011; Joo & Chamberlain, 2017; McVay, 2006). Firms have incentives to engage in this practice because core earnings are more informative than non-core ones in predicting future earnings (e.g., Haw et al., 2011; McVay, 2006). A large body of research focuses on the determinants of CS (e.g., Kaplan et al. (2020) on tax-related incentive-triggering CS or Haw et al. (2011) on the role of effective corporate governance for mitigating this practice). Despite the pervasive use of CS, there is, however, limited research that investigates the consequences of this financial reporting practice with the exception of two papers. Liu and Wu (2021) provide evidence that the existence of CS around IPOs negatively affects one-year ahead post-IPO stock returns. Anagnostopoulou et al. (2021) further show that CS around IPOs negatively affects future IPO survival over longer time horizons. Both studies focus on the consequences of CS for future one-year or longer-term firm success within the IPO context.

In this paper, we extend limited research on the consequences of CS by departing from the IPO context and examine whether this practice is associated with firm-level investment efficiency. We directly test for the real consequences of CS—a widespread practice of misclassifying income statement line items—by focusing on all firms, rather than on firms that have recently engaged in IPOs only. We hypothesize that CS can be negatively associated with firm investment efficiency for two reasons.

First, previous empirical and theoretical research has mainly emphasized information asymmetry and agency problems between managers and the suppliers of capital as the main factors that make firms deviate from investing optimally (e.g., Benlemlih & Bitar, 2018; Biddle & Hilary, 2006; Biddle et al., 2009; García Lara et al., 2016). CS may aggravate information asymmetry by misleading capital providers about the actual core, so more persistent, performance of firms and thus obstruct the ability of capital providers to formulate valid expectations about the repeatable performance of firms in the future (Doyle et al., 2013; Ha & Thomas, 2021). The reporting of non-realistic core profits may prevent capital providers from efficiently appraising anticipated cash flows and the riskiness of their actual or potential investments, thus leading to increases in agency conflicts between managers and capital providers. Therefore, to the extent that CS increases information asymmetry and agency concerns, it can negatively affect investment efficiency.

Second, CS can affect managers' own perceptions of the permanent vs. transitory component of earnings, resulting in imperfect information sets being used by them when making investment decisions. Therefore, to the extent that CS alters managers' own perceptions about their firm's ability to perform sustainably in the future, and results in managers basing their investment decisions on unrealistic or inaccurate information, CS could be negatively associated with efficient investing by firms.

We examine our research question in relation to North American nonfinancial firms between 1990–2019 by measuring CS following Joo and Chamberlain (2017), based on the methodology established by McVay (2006). We measure investment efficiency by examining the sensitivity of a firm's investment to its growth opportunities (e.g., Asker et al., 2015; Badertscher et al., 2013; Shroff et al., 2014), where investment is defined as capital expenditures (Bae et al., 2017; Shroff, 2020) and growth opportunities are defined as growth in sales (Asker et al., 2012; Badertscher et al., 2013; Biddle et al., 2009; Kausar et al., 2016). The higher sensitivity of investment to growth opportunities indicates more efficient investing, as investment should be more responsive to growth opportunities when adjustment costs, i.e., information frictions and agency problems, are low (Hubbard, 1998; Shroff et al., 2014).

Our findings show that firm engagement in CS strongly decreases the sensitivity of investment to growth opportunities, suggesting that this practice has a negative effect on firms' investment efficiency. Our baseline result is robust to alternative methods of measuring investment opportunities and CS. It is also robust to the implementation of an extensive set of controls for the existence of potential endogeneity concerns related to omitted factors, reverse causality, and measurement errors in CS, in an effort to avoid the possibility that this potential problem could put the validity of our findings into question. This could stem, for example, from the existence of potential omitted factors that could simultaneously affect both the engagement in CS and investment efficiency or from concerns related to the direction of causality between the two concepts. The controls we implement involve the application of firm fixed effects, a two-stage least squares (2SLS) analysis, lead-lag analysis, and suspect firm analysis. We also apply a difference-in-differences (DID) analysis by making use of 2002 as the event year of an externally imposed shock on CS, attributable to the contemporaneous (at the year level) passing of both SOX and the FAS 146 regulation (Joo & Chamberlain, 2017). Our finding, namely that CS is negatively associated with investment efficiency, still holds after implementing all these analyses aimed at excluding an endogenous explanation for our findings, although it is difficult to completely rule out this possibility.

Next, we investigate the mechanisms through which CS negatively affects investment efficiency by performing two cross-sectional analyses aimed at examining whether the above-hypothesized agency and learning mechanisms hold. First, we find that our baseline result is more pronounced for firms that face larger financial constraints. This finding can be explained with reference to the fact that the adverse consequences of CS on the ability of capital providers to assess a firm's repeatable performance should be magnified for firms that already experience difficulties in securing funding. Second, we find that our baseline result is weaker for firms operating in richer external information environments. This finding can be explained by the fact that this type of peer information environment should decrease information asymmetry and can also help increase opportunities for firm management to learn from peer disclosures. Thus, a richer peer information environment should increase opportunities for managerial learning through improvement in managerial information sets, and thus alleviate any CS-caused distortion effects on managerial perceptions through improved managerial learning from peers. This is because managers can make up for imperfect information sets available to them because of CS though improved learning from peer firms. Overall, our cross-sectional analyses show that the existence of lower vs. higher levels of agency problems and/or peer information environment affect the strength of our baseline finding, suggesting that agency considerations and managerial perceptions represent mechanisms through which CS drives inefficient investment.

Finally, we perform a number of supplementary analyses. First, we decompose special items into a predicted and opportunistic component, following the methodology of Cain et al. (2020). We find that opportunistic special items are more strongly associated with investment inefficiency, compared to predicted ones. In addition, we estimate our baseline analysis for firms with higher vs. lower unexpected investment than the sample median when the former is a factor reflective of poor firm performance (Chen et al., 2017b). We observe that CS is more harmful to efficient investing particularly for firms facing stronger challenges to invest efficiently because of their poor performance. Finally, we examine the possibility that cross-sectional variation in governance among firms could explain our baseline finding. We do not find support for this possibility, as our results indicate that the negative effect of CS on investment efficiency does not change depending on any differences in the quality of the corporate governance of firms.

Our study makes several contributions to the literature. First, we extend the growing literature on CS by providing, for the first time, evidence that CS has real and adverse consequences for a very important firm outcome, namely efficient investing. Prior studies in this stream of literature primarily focus on the determinants of CS (e.g., Athanasakou et al., 2009; Fan et al., 2010; Fan et al., 2019; McVay, 2006; Zalata & Roberts, 2016). Understanding the consequences of CS, particularly with reference to investment efficiency, is also important; this efficiency plays a key role in future firm performance (Cai & Zhang, 2011; Titman et al., 2004).

Furthermore, CS has long been considered a relatively low consequence form of earnings management, explained by the observation that CS does not alter bottom line profit and is not expected to have any future reversing or 'settling-up' consequences (McVay, 2006), at least in terms of bottom-line profit. Recent research has further argued in favor of CS having minimal long-term costs or even positive value-creation effects (Lattanzio & Thomas, 2020) and suggested that managers may enable investors to better predict future earnings by classifying less persistent core expenses as nonrecurring special items (Ha & Thomas, 2021). However, we provide evidence that CS, or a form of earnings management less likely to attract the scrutiny of auditors and regulators (Athanasakou et al., 2009; Cain et al., 2020; McVay, 2006), is not the low consequence form of financial misreporting that it has previously been considered to be, as it is negatively and significantly associated with the efficiency of investment.

Second, we attempt to extend the literature on the association between financial reporting and investment efficiency in at least two ways. First, despite the fact that the conceptual distinction between accrual-based earnings management and CS can be considered as tenuous, we build on research that associates accrual quality or accrual-based earnings management with investment efficiency (e.g., Biddle et al., 2009; Chen et al., 2011; McNichols & Stubben, 2008). Although both the manipulation of accruals and CS do not have any cash flow effects, CS is distinct from this practice, as it does not involve changing GAAP earnings or involve any earnings reduction in future periods as, for example, accrual-based earnings management does

(McVay, 2006). Our findings show that even the absence of any bottom-line-changing consequences in a method of financial misreporting may have adverse consequences on the perceptions of providers of capital to the firm that may be significantly associated with inefficient investing. Second, we build on research associating disclosure that does not change net income, such as management forecast accuracy (Goodman et al., 2014) and the ability to observe whether managers choose to get an audit (Kausar et al., 2016), with investment efficiency. CS, however, is different from these financial reporting attributes. Unlike these attributes, CS reflects the way a firm reports the way it generates profitability for its stakeholders, with additional disclosure about the firm to complement this baseline information. Our findings suggest that the way a firm reports core vs. transitory items on the face of the income statement affects its investment efficiency.

Third, past research has mainly focused on how firms' own production of information influences their investment decisions; it has largely neglected other sources of information which could also help reduce adverse selection costs with a beneficial effect on investment efficiency (Roychowdhury et al., 2019). In our study, we explicitly identify other sources of accounting information that can influence a firm's own adverse selection costs and investment decisions, as we examine the effect of disclosures from peers on efficient investing in a targeted way. By doing so, we contribute to previous research on the determinants of investment efficiency by examining the effect of CS on investment efficiency via both an agency channel and a managerial perception channel. Prior research has largely ignored managerial learning mechanisms when associating financial reporting with investment decisions (Roychowdhury et al., 2019).

Finally, our paper contributes to the literature on the real effects of accounting (Leuz & Wysocki, 2016; Roychowdhury et al., 2019; Shroff, 2020). Ferracutti and Stubben (2019) recently highlighted the importance of understanding which financial statement or disclosed items more strongly help explain managerial investment decisions and whether managers weigh financial information appropriately. We contribute to this stream of research by examining whether the misclassification of items within the income statement is associated with efficient investing, and provide additional insights regarding the impact of earnings manipulation on efficient investing when this manipulation affects operating profit reporting rather than the bottom line.

The rest of the study is organized as follows. In Section 2, we provide a review of the literature and develop the research hypothesis. Section 3 discusses our data and methodology, while Section 4 reports our empirical results. The study concludes with Section 5.

2. Literature review and research hypothesis

2.1. Determinants of investment efficiency

In a market without frictions, firms should invest efficiently by undertaking projects with positive net present values (NPV) (Hayashi, 1982; Modigliani & Miller, 1958). According to the neoclassical theory of investment, the only determinant of a firm's investment policy is the marginal Q ratio (Abel, 1983; Hayashi, 1982), and firms achieve their optimal levels of investment when the marginal benefit of investment is equal to its marginal cost, subject to adjustment costs of capital (Biddle et al., 2009). In reality, however, market frictions, conflicts of interest between managers and shareholders (Jensen & Meckling, 1976), and financing constraints (Myers & Majluf, 1984) cause firms to deviate from optimal levels of investment.

First, managers may deviate from optimal levels of investment when their private interests deviate from those of shareholders because of adverse selection (Chen et al., 2017b). The adverse selection problem suggests that managers possess superior private information about the firm's true value compared to outsiders, so they may time the issuance of capital and issue overpriced capital or issue capital when the firm is overpriced. If capital providers, who are naturally subject to informational disadvantages, suspect or detect this type of behavior, they may respond rationally by discounting new issues through an increase in the cost of funding (Biddle et al., 2009; Chen et al., 2017a) and by squeezing out even reliable borrowers (Fazzari et al., 1988). Second, according to the principal–agent conflict or moral hazard problem, distortions in investment are attributed to the misalignment between managerial incentives and shareholders' interests (Chen et al., 2017b). Instead of maximizing shareholders' wealth, managers may have other private objectives and invest excessively in the presence of enough resources to invest (Biddle et al., 2009; Chen et al., 2017b). If capital providers, however, identify this type of behavior *ex-ante*, they may increase the cost of capital and constrain its supply, leading to deviations from optimal levels of investment *ex-post* (Biddle et al., 2009; Lambert et al., 2007).

2.2. Hypothesis development

We discuss two separate channels through which we expect CS to significantly associate with investment efficiency. These are an agency and a learning channel.

2.2.1. The agency channel

High-quality reporting can improve investment decisions by reducing information asymmetry between managers and investors, which creates market frictions and thus decreases the costs of adverse selection and capital raising (Jung et al., 2014; Lambert et al., 2007, 2012; Roychowdhury et al., 2019). Financial reporting quality can also mitigate agency conflicts among firms' stakeholders by acting as a control mechanism for the external providers of capital (e.g., Biddle et al., 2009; García Lara et al., 2016; Roychowdhury et al., 2019).

CS alters the presentation of different elements within the income statement, and opportunistically reports inflated core earnings without changing bottom line profit, by misclassifying ordinary operating expenses as income-decreasing special items. This managerial behavior is consistent with evidence that the placement of a line item in the income statement is important for investors and affects stock valuation (Bartov & Mohanram, 2014;

Poonawala & Nagar, 2019). Special items reported below operating profit are typically excluded from 'street' earnings used by analysts and other financial statement users (Christensen et al., 2011; Lougee & Marquardt, 2004), as they are considered less relevant when estimating the earnings power of firms (Ali & Zarowin, 1992; Bradshaw & Sloan, 2002; Elliott & Hanna, 1996; Seve & Wilson, 2019). Research consistently shows that investors, especially less sophisticated ones, pay more attention to operating profit than other more transient types of profit (Zalata & Roberts, 2016) and may be unable to distinguish cases of misclassified non-recurring items (Athanasakou et al., 2009). This is because special items are normally less persistent than recurring expenses; this is easily understood upon considering the types of charges comprising special items, i.e., restructuring charges, asset write-offs, and gains or losses on the sale of assets (Cain et al., 2020).

For this reason, financial statement users generally discount income-decreasing special items and exclude them from GAAP earnings when assessing firm performance (Bentley et al., 2018; Bradshaw & Sloan, 2002; Cain et al., 2020). Measures of performance tend to be more value-relevant when they include core expenses and exclude more transitory items (Bartov & Mohanram, 2014), thus giving managers the incentive to misclassify persistent core expenses as transitory income-decreasing special items in order to report higher core profit (Liu & Wu, 2021). Current core earnings are used to predict future earnings (Finger, 1994; Nissim & Penman, 2001), with higher vs. lower current core earnings used to create informed expectations about future profitability. Investors typically consider core earnings as more persistent than non-core earnings (Fairfield et al., 1996; Fan et al., 2019). If managers inflate current core performance through opportunistic CS, investors may incorrectly evaluate the ability of current performance to predict future performance (Doyle et al., 2013; Ha & Thomas, 2021).

If CS obstructs the ability of capital providers to formulate valid expectations about the true core and sustainable profitability of the firm, it naturally gives rise to agency conflicts between insiders and outsiders, and efficient external monitoring is impeded in this respect. Thus, we expect that CS should negatively affect investment efficiency because of its anticipated adverse effect on the accurate formulation of investor expectations about the true and persistent performance of firms.

2.2.2. The managerial perceptions/learning channel

Investment decisions depend on expectations of investment benefits, and these benefits in turn depend on expectations regarding future growth and product demand. Thus, high-quality financial information can help managers themselves form more accurate expectations and better identify investment opportunities, thereby resulting in overall improvements in investment efficiency even in the absence of any adverse selection or moral hazard frictions (McNichols & Stubben, 2008). Roychowdhury et al. (2019) were the first to provide a systematic review of the way in which financial reporting can affect investment efficiency via a learning channel, in addition to the aforementioned agency channel widely examined by past research. This learning channel can work in two ways: a) managers make more informed investment decisions by better understanding their investment opportunities thanks to the investment-related information disclosed by their peers, and/or b) firms and their managers are forced to gather additional information useful for the optimal planning of their investment efforts (Shroff, 2017).

To the extent that CS affects managers' own perceptions of permanent vs. transitory earnings, their investment-related information set could be imperfect and also lead to inefficient investment. Managerial forecasting effectiveness in turn depends on the ability to collect high-quality information about internal operations and the external environment, and on the adequate processing and synthesizing of this information (Goodman et al., 2014). Thus, if managers' own perceptions of permanent profitability are distorted due to CS, this should result in unrealistic information sets being used when making investment decisions. Consequently, by misrepresenting the existence of sustainable performance as reported in firms' own financial statements, CS can also alter managers' perceptions of their firm's ability to sustainably perform in the future. Thus, we expect that CS should be associated with inefficient investing for this reason. To test this channel, we will focus on the richness of firms' peer information environment. This is because if peer environment information reduces adverse selection concerns, it should increase managerial opportunities for learning from peer information, and alleviate any CS-distortion effects creating imperfect information sets for managers when they make corporate investment decisions.

In summary, based on the above arguments in relation to an agency and a managerial perceptions channel, we expect that CS should be negatively associated with firm investment efficiency, and we form the following research hypothesis:

H1: CS is negatively associated with firm-level investment efficiency.

3. Research design and sample selection

3.1. Investment efficiency measure

We measure investment efficiency by focusing on investment responsiveness to growth opportunities. This model is derived from the Q theory of investment, introduced by Tobin (1969) and further developed by Hayashi (1982), which is based on the neoclassical theory of investment. Several studies from accounting, finance, and economics use investment-Q sensitivity to evaluate investment efficiency (e.g., Asker et al., 2015; Badertscher et al., 2013; Bloom et al., 2007; Gutiérrez & Philippon, 2017; Shroff et al., 2014; Shroff, 2020). Higher sensitivity of investment to growth opportunities implies more efficient investment (Badertscher et al., 2013; Shroff et al., 2014).

To measure growth opportunities, past research has largely focused on either Tobin's Q or sales growth (Badertscher et al., 2013). Biddle et al. (2009) state that they explicitly use sales growth instead of Tobin's Q as a proxy for growth opportunities, given that Q can be affected by financial reporting quality because marginal Q is not easy to measure. Following their research, we employ growth in sales as our baseline proxy for investment opportunities.[1] Sales growth has been extensively used as a proxy for investment opportunities in investment-related literature (e.g., Asker et al., 2012; Badertscher et al., 2013; Biddle et al., 2009; Bloom et al., 2007; Kausar et al., 2016; Shin & Stulz, 1998; Whited & Wu, 2006; Wurgler, 2000).

3.2. CS measure

We measure CS as unexpected core earnings if unexpected core earnings are positive and special items are income-decreasing, and zero otherwise, following Joo and Chamberlain (2017) and Anagnostopoulou et al. (2021). This definition is based on the idea that when firms engage in CS, they are likely to have income decreasing special items and positive unexpected core earnings, where the latter capture the amount of core expenses that are misclassified as non-recurring expenses (e.g., Fan et al., 2019; Joo & Chamberlain, 2017). We estimate unexpected core earnings as the residuals from McVay's (2006) model, which has been employed extensively in the CS literature (e.g., Fan et al., 2019; Joo & Chamberlain, 2017; Liu & Wu, 2021).[2] This model is a regression of current core earnings on lagged core earnings, current asset turnover ratio, lagged and current accruals, sales growth, and the negative percentage change in sales.[3]

3.3. Empirical specification

We apply a design similar to Badertscher et al. (2013) and Shroff et al. (2014) to examine whether investment efficiency, expressed in the form of increased sensitivity of investment to

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[1] The use of sales growth as a proxy for investment growth opportunities should be most adequate for production technologies for which the profitability of current and future projects is highly correlated, reflecting the neoclassical model (Badertscher et al., 2013). However, according to Badertscher et al. (2013), when the profitability of new projects is different than the profitability of existing projects, sales growth may be harder to interpret. Nevertheless, we rely on the fact that our sample represents the population of firms for which the effect of CS on investment efficiency is examined, so our sample should not suffer from the overrepresentation of any firm-specific characteristic, which would make this proxy for growth unusable. Our main results remain intact when we use Tobin's Q as a proxy for growth opportunities (reported in Online Appendix).

[2] Our results do not change if we estimate unexpected core earnings using the model by Fan et al. (2010).

[3] We estimate the McVay model cross-sectionally for each industry with at least 20 observations in a given year.

growth opportunities, is lower for firms with higher levels of CS. Specifically, we use the following model:

$$INV_{i,t+1} = \alpha_0 + \alpha_1 SALES\_GR_{i,t} + \alpha_2 CS_{i,t} + \alpha_3 SALES\_GR_{i,t} \times CS_{i,t} + CONTROLS + \varepsilon_{i,t+1} \quad (1)$$

In this model, $INV_{i,t+1}$ is defined as the capital expenditures of firm *i* in year *t+1* scaled by total assets in year *t*, following Bae et al. (2017) and Shroff (2020).[4] *SALES_GR* is the percentage change in sales. The regression of *INV* on *SALES_GR* provides the basis for testing the sensitivity of investment to growth opportunities. *CS* is our test variable and represents the measure of CS. The interaction of *SALES_GR* with *CS* captures the effect of CS on the sensitivity of investment to growth opportunities. Our hypothesis predicts a negative coefficient on *SALES_GR* × *CS* in equation (1).

CONTROLS is a set of control variables selected based on past research (e.g., Badertscher et al., 2013; Shroff et al., 2014; Shroff, 2020). Specifically, we include accruals quality (*AQ*), measured using the Dechow and Dichev (2002) model, and its interaction with our sales growth measure to control for the effect of accruals quality on investment efficiency (Biddle et al., 2009; Chen et al., 2011). We also add variables proxying for firm characteristics that are likely to affect investment level (e.g., Badertscher et al., 2013; Joo & Chamberlain, 2017; Shroff, 2020). These involve cash flows from operations (*CFO*), the natural logarithm of equity market value as a proxy for firm size (*LN*(*MVE*)), cash holdings (*CASH*), firm leverage (*LEVERAGE*), tangibility of assets (*TANGIBILITY*), operating cycle (*OP_CYCLE*), and the proportion of income-decreasing special items that are not classification-shifted (*NCS*). Finally, we include year and industry fixed-effects to account for year- and industry-specific shocks to investment and compute standard errors by employing a two-dimensional cluster at the firm and year level. Detailed definitions of all the variables are provided in Appendix A.

3.4. Sample and data

[4] In our robustness analyses, we also employ other definitions of investment in the form of acquisition outlays and research and development (R&D) expenses. We discuss these analyses in Online Appendix in more detail.

Our main data source is the Compustat Annual File. We exclude all firm-year observations where annual sales are less than one million dollars or average net operating assets are negative, following the CS literature (e.g., Liu & Wu, 2021; McVay, 2006). We also exclude financial firms (SIC codes 6000–6999) because their capital investment behavior and financial reporting environment are significantly different to those of nonfinancial firms (e.g., Bae et al., 2017; Biddle et al., 2009; García Lara et al., 2016). Lastly, to ensure that there exists sufficient data for the estimation of unexpected core earnings, we exclude industry-years with fewer than 20 observations. Consequently, our final sample used for the main analysis consists of 97,184 firm-year observations for the time period 1990–2019.[5]

Insert Table 1 about here.

Table 1 shows descriptive statistics for the variables used in our main analysis. All continuous variables are winsorized at percentiles 1-99% by year. The mean (median) value of future capital expenditures scaled by total assets (*INV*) is 0.065 (0.038), and the mean (median) of the percentage change in sales (*SALES_GR*) is 0.227 (0.083), in line with prior studies (e.g., Asker et al., 2012; Badertscher et al., 2013; Shroff, 2020). Unexpected core earnings (*UECE*) and income-decreasing special items scaled by sales (measured as positive values) (*SI*), which are used to construct our CS proxy (*CS*), have mean values of 0.003 and 0.034, respectively. The mean value of *CS* is 0.027, and this variable gets a positive value for 24.7 percent of the total number of our firm-year observations. These numbers are consistent with those reported in past research (e.g., Joo & Chamberlain, 2017; Liu & Wu, 2021).

4. Empirical findings

4.1. Association between CS and investment efficiency

[5] The starting year of our sample period is justified by data availability from this period onward, similar to García Lara et al. (2016) and Biddle et al. (2009).

Table 2 reports the results of estimating model (1). In column (1), we report results when estimating the model by excluding the CS (*CS*) and accruals quality (*AQ*) variables and their interactions with sales growth (*SALES_GR*) to confirm whether the level of investment is responsive to growth opportunities for our sample firms. As intuitively expected, the estimated coefficient on *SALES_GR* is 0.0100 and significant at the 1 percent level. This implies that firms' investment decisions are associated with growth in sales, consistent with Badertscher et al. (2013). In column (2), we report results for the full model, which includes the *CS* and *AQ* variables and their interactions with *SALES_GR*. The estimated coefficient on *SALES_GR* × *CS* is negative and significant at the 1 percent level. This indicates that CS decreases the sensitivity of investment to growth opportunities and is therefore associated with investment inefficiency, providing support for Hypothesis 1. The estimated coefficient on *SALES_GR* × *AQ* is negatively significant. This implies that accruals quality decreases the sensitivity of investment to growth opportunities and is associated with more inefficient investment, in line with past research (e.g., Biddle et al., 2009). The coefficient on *SALES_GR* × *CS* is -0.0058, while that on *SALES_GR* × *AQ* is -0.0056. Our results for CS appear to be economically significant and suggest that CS is at least as important a driver of investment efficiency as accruals quality.

Insert Table 2 about here.

Turning our attention to control variables, cash holdings (*CASH*), cash flows from operations (*CFO*), the market value of equity (*LN*(*MVE*)), and tangibility of assets (*TANGIBILITY*) are all positively and significantly associated with investment, showing that firms with a higher ability to generate cash and free cash flows, in addition to larger firms and firms with more tangible assets in place, tend to make more capital investments, as one would intuitively expect. On the contrary, leverage (*LEVERAGE*) is observed to be negatively and significantly related to investment, indicating that more leveraged firms are less likely to obtain additional debt financing, which should limit their ability to invest. The behavior of our control variables is generally consistent with previous studies in similar empirical contexts (e.g., Badertscher et al., 2013; Shroff, 2020).

4.2. Economic mechanisms: Implementation of cross-sectional analyses

Our hypothesis is that CS is negatively associated with efficient investment because of agency and managerial learning mechanisms. To confirm the validity of this inference, we examine whether our evidence is more pronounced in settings with lower vs. higher levels of agency problems and with more vs. less learning by managers. This is because the existence of lower vs. higher levels of agency problems and/or managerial learning should affect the strength of the association between CS and investment efficiency, if indeed agency considerations and/or managerial learning represent mechanisms through which CS drives inefficient investment. We describe our examination of the validity of these mechanisms in the following three subsections.

4.2.1. The agency channel based on financing constraints

We examine whether an agency channel explains our findings by focusing on the role of financial constraints. Choi et al. (2020) argue that low information asymmetry between the firm and its capital providers is particularly important so that financially constrained firms invest efficiently. Financially constrained firms already face difficulties in convincing capital providers to grant funding, and this is likely to be even more difficult when they engage in practices that increase information asymmetry between them and their capital providers. Therefore, to the extent that CS aggravates the agency-related factors identified by previous research, which trigger sub-optimal investment, we predict that the negative association between CS and investment efficiency should be more pronounced for more financially constrained firms.

To test this conjecture, we interact proxies for financial constraints with CS and growth opportunities in our baseline model (1). We use two measures of financial constraints (*FC*). Our first measure, (*DELAYCON*), is based on a text-based index of financial constraints on investment, obtained from Hoberg and Maksimovic (2015), where higher (lower) values of this index indicate higher (lower) financial constraints for firms.[6] We sort firms into terciles based on their text-based index of financial constraints and define financially constrained firms as those that are in the top tercile of their industry-year. Our second measure, (*AGE*), is based on firm age. Younger firms are more likely to face financial constraints (Li, 2011). Thus, we sort firms into terciles based on their age and define financially constrained firms as those falling in the bottom tercile of their industry-year.

Table 3 reports the results when estimating model (1) by interacting CS and growth opportunities with our two proxies for financial constraints. The estimated coefficient on $SALES\_GR \times CS \times FC$ is negative and statistically significant at the 10 and 5 percent levels, respectively, for both measures of financial constraints, *DELAYCON* and *AGE*. This result is consistent with our conjecture that the negative effect of CS on investment efficiency, measured in the form of the sensitivity of investment to growth opportunities, is stronger for firms that are more financially constrained.

Insert Table 3 about here.

4.2.2. The agency and managerial perceptions and learning channels based on peer information

Roychowdhury et al. (2019: p. 7) summarize the literature on agency reasons; they explain the association between financial reporting and investment efficiency by commenting on the fact that most of the literature focuses on the investment consequences of accounting information directly provided by firms themselves, while other sources of information could also help reduce adverse selection costs, thus improving investment efficiency. They argue that

[6] We use this index rather than widely used indices from the prior literature (e.g., the Kaplan-Zingales, Whited-Wu, and Hadlock-Pierce indices) as proxies for financial constraints because Farre-Mensa and Ljungqvist (2016) show that these measures do not successfully partition firms into constrained and unconstrained groups in a manner that realistically reflects their inability to secure funding. In addition to using the proxy based on Hoberg and Maksimovic (2015), we further use firm age as a second proxy for constraints in securing financing to increase the validity of our results.

accounting information disclosed by peer firms can inform the stakeholders of economically related firms about their operations and opportunities for growth and performance, with a mitigating effect on adverse selection costs. For this reason, we examine whether the association between CS and investment efficiency is affected by the information environment of peer firms. To the extent that peer environment information decreases information asymmetry, and thereby limits adverse selection costs, we predict that the negative association between CS and investment efficiency should be less pronounced for firms operating in richer external information environments. This is because a rich information environment from peer firms could increase opportunities for managerial learning though improved information sets available to managers, and thus alleviate any CS-caused distortion effects on managerial perceptions through improved managerial learning from peers. The anticipated function of peer-related information for mitigating investment inefficiency is consistent with managerial learning from a firm's peer information environment. This is because peer environment information is likely to increase opportunities for firm management to improve their informational set using information extracted from the relevant environment of peer firms. This conjecture is consistent with the way Roychowdhury et al. (2019) expect the learning channel for explaining efficiency in investment to function. In this way, firms and their managers could compensate for potential distortions in the quality of the information sets they have available when they make investment decisions because of CS-related biases by complementing their investment decision-related information through efficient learning from their peer firms' information environment.

To test our prediction, we interact proxies for peer information with CS and growth opportunities in our baseline model (1). We use two proxies for peer information (*PI*) in the spirit of Shroff et al. (2017). Our first proxy, (*EARNINGS_SYNC*), is the average value of earnings synchronicity in an industry and captures the relevance of peer firms' disclosures to non-disclosing firms. Higher values for this measure imply that firms from particular industries are more likely to be economically linked with each other, and thus information about one firm's future prospects is more likely to convey information related to its peer firms' prospects. Our second proxy, (*ANALYSTS*), is the average analyst coverage for firms in the industry and captures the aggregate amount of information available about peer firms. Higher values for this measure imply a richer information environment for all firms in a particular industry.

Table 4 reports the results when estimating model (1) by interacting CS and growth opportunities with our two proxies for peer environment information. The estimated coefficient on *SALES_GR* × *CS* × *PI* is positive and statistically significant at the 10 and 5 percent levels, respectively, for both measures of peer information, *EARNINGS_SYNC* and *ANALYSTS*. This result is consistent with our prediction that the negative effect of CS on investment efficiency, measured in the form of the sensitivity of investment to growth opportunities, is weaker for firms operating in richer external information environments.

Insert Table 4 about here.

4.3. Supplementary analyses

4.3.1. Opportunistic income-decreasing special items

The very existence and availability of income-decreasing special items gives rise to an opportunity for managers to inappropriately reclassify past, present, and future recurring core expenses into current-period special items in an effort to inflate reported core earnings (McVay 2006). Cain et al. (2020) propose a methodology for partitioning income-decreasing special items into an economically driven vs. an opportunistic component. Based on their methodology, we estimate opportunistic special items and examine how the predicted (or economically explainable) vs. opportunistic component of special items is associated with investment inefficiency. On the one hand, predicted special items could relate to inefficient investing from the moment that the very existence of special items reflects non-repeatable but negative performance, giving rise to obvious concerns for capital providers regarding the future course of the firm. On the other hand, however, opportunistic special items should be expected to be associated with information asymmetry and moral hazard concerns to a greater extent than predicted special items, given that they reflect managerial incentives to achieve profit targets. Thus, we argue that opportunistic special items should be more strongly associated with investment inefficiency, compared to predicted ones.

To test this expectation, we exclude CS and its interaction with growth opportunities from model (1) and include opportunistic special items (*OPP_SI*), predicted special items (*PRED_SI*), and their interactions with growth opportunities.[7] This model is estimated separately for the full sample, for a sample of firms reporting income-decreasing special items (*SI* sample), and for a sample of firms reporting opportunistic special items (*OPP_SI* sample), in the spirit of Cain et al. (2020). Table 5 shows that when interacting *OPP_SI* with *SALES_GR*, the coefficient for this multiplicative term is negatively significant for all three samples, while it is more economically significant in the case of the opportunistic special item sample (coefficient of -0.0208, compared to -0.0137 for the full sample and -0.0160 for the special item sample). However, when interacting *PRED_SI* with *SALES_GR*, we observe no significant coefficient for this multiplicative term in either sample. Collectively, these results indicate that opportunistic special items are more strongly associated with investment inefficiency, than predicted special items. In addition, they appear to be most economically significant for the particular subsample of firms reporting this type of special items, which is not explained by firms' ordinary course of business.

Insert Table 5 about here.

[7] To calculate opportunistic and predicted special items, following Cain et al. (2020), we regress income-decreasing special items on key economic factors that may affect the likelihood of income-decreasing special items occurring, and also their magnitude, using a Tobit regression. This regression is estimated cross-sectionally for each industry-year with data availability for at least 50 observations. The predicted or fitted value from the model represents the economically driven component of special items, and the residual value reflects the opportunistic special items.

4.3.2. Unexpected investment

The magnitude of unexpected investment is seen as an indicator of firms' poor performance (Chen et al., 2017b). Therefore, the negative effect of CS on investment efficiency should be more pronounced for firms with higher vs. lower levels of unexpected investment. This is because the former group consists of firms with greater uncertainty about their ability to convince outsiders to provide them with capital at an acceptable cost so that managers invest in a way optimal for the firm. Thus, firms with higher levels of unexpected investment could be more strongly affected by the aggravating effect of CS on efficient investing because of their weaker-than-average performance, compared to firms with lower levels of unexpected investment.

To test this conjecture, we repeat the estimation of our baseline model (1) for firms with higher (*HIGH_ UI*) and lower (*LOW_ UI*) than the sample median levels of unexpected investment following Chen et al. (2017b). We measure unexpected investment in the form of the deviation of a firm's investment from expected levels by estimating a regression of investment on lagged sales growth (Biddle et al., 2009). The absolute value of firm-specific residuals from this equation, estimated for each year and industry, represents the level of unexpected investment for a firm in a year. Table 6 shows that our main variable of interest, *SALES_GR* × *CS*, is significant in the high, but not in the low, unexpected investment sample. These results support our prediction that the negative effect of CS on investment efficiency is more pronounced for firms with higher levels of unexpected investment.

Insert Table 6 about here.

4.3.3. The quality of corporate governance

One could argue that our results on CS negatively associating with efficient investment could be explained by cross-sectional variation in governance among firms, which might correlate with CS. This is because better-governed firms should be less likely to engage in CS and thus be more likely to invest efficiently. To address this concern, we include proxies for the quality of internal/external governance (*CG*) and their interactions with CS and growth opportunities in model (1). We use the strength of the market for corporate control (*E-INDEX*)[8] and the percentage of institutional investor holdings (*INST_OWN*) as proxies for the quality of external corporate governance (e.g., Biddle et al., 2009; Chen et al., 2017b). We further employ board size (*BRD_SIZE*) and the percentage of independent directors on the board (*BRD_INDEP*) as proxies for the quality of internal corporate governance, in line with Goodman et al. (2014).[9] All four proxies for corporate governance increase with its quality.

Our findings on the role played by corporate governance in explaining the association between CS and investment efficiency are reported in Table 7. We find that the estimated coefficient on *SALES_GR* × *CS* × *CG* is not statistically significant for any of our governance measures. This finding indicates that differences in the quality of governance across firms do not drive our results on the association between CS and investment efficiency. Interestingly, we observe that our governance measures, *E-INDEX* and *INST_OWN*, when interacted with growth opportunities, yield a positive and significant coefficient. This finding implies that better, rather than worse, governance increases the sensitivity of investment to growth opportunities, resulting in more efficient investment, as one would intuitively expect.

Insert Table 7 about here.

4.4. Endogeneity analysis

While our results suggest that CS is associated with investment inefficiency, these results might be subject to several endogeneity concerns. First, there might be potential omitted factors that

[8] This is the entrenchment index of Bebchuk et al. (2009), which measures a firm's anti-takeover protection multiplied by negative one; higher values imply lower anti-takeover protection and thereby stronger market discipline. The value of the index is set to zero if missing, to avoid a substantial decrease in sample size, while a binary indicator variable is included to control for missing data (*E-INDEX-DUM*), following past research (e.g., Biddle et al., 2009).

[9] Goodman et al. (2014) also use audit committee size and CEO duality as governance measures. Our inferences do not change if we employ these proxies.

simultaneously affect both firms' engagement in CS and efficient investing. For instance, it could be the case that information asymmetry between outside investors and corporate managers allows managers to make inefficient investments while also making it possible for them to engage in CS without being detected.[10] Second, there might exist potential reverse causality concerns if inefficient investing actually leads to CS. This could be the case, for example, if overinvesting involves income-decreasing special items, such as restructuring or acquisitions, which create opportunities for CS. Third, given that earnings management proxies suffer from measurement problems, our proxy for CS might comingle the firm's underlying economics with the expense misclassification that we are trying to measure (Leuz & Wysocki, 2016; Roychowdhury et al., 2019). Should this be the case, our results could be attributed to the firm's underlying economics rather than to its accounting practices involving CS. To mitigate these potential endogeneity issues, we implement a number of additional analyses.[11]

First, we estimate our baseline model (1) by using firm fixed effects. The results are reported in column (1) of Panel A in Table 8. We find that the estimated coefficient on our variable of interest, *SALES_GR* × *CS*, is significant and negative. These results are in line with our main findings, as reported in Table 2.

Insert Table 8 about here.

Second, we conduct a 2SLS analysis using CS by peer firms in the previous year as an instrumental variable for this year's level of CS for a firm. Lattanzio and Thomas (2020) find that firms' CS in the current year is affected by their peers' use of such practices. A similar result is documented by Bratten et al. (2016) for firms' discretionary reporting practices. We follow Bratten et al. (2016) and Lattanzio and Thomas (2020) in measuring peer effects

[10] Alternatively, management-related agency concerns may trigger expense misclassification practices, and may also be associated with reluctance on the part of capital providers to supply capital at an economically acceptable cost, thus leading to investment inefficiency.

[11] We are grateful to two anonymous reviewers for identifying these potential endogeneity issues within our research context.

(*PEER_CS*). To do so, we first define peer firms as those that are in the top tercile of total assets in each industry-year. We then calculate the average of these firms' CS level in year *t-1*. Columns (2)–(4) of Panel A in Table 8 show the 2SLS estimation results. In the first-stage regressions, we regress *CS* and its interaction term with *SALES_GR* on the instrumental variable *PEER_CS* and the control variables used in our baseline model (1), following the approach of Badertscher et al. (2013) and Chen et al. (2017b). The results show that CS by firms in the current year is significantly affected by their peers' CS in the previous year. In the second-stage regression, we estimate our baseline model (1) using the predicted values for CS (*Pred*(*CS*)) and its interaction with sales growth (*Pred*(*SALES_GR* × *CS*)) as the regressors obtained from the first-stage regressions. The results indicate that the estimated coefficient on *Pred*(*SALES_GR* × *CS*) is significant and negative. These results are consistent with our main findings, as reported in Table 2.

Third, we estimate our baseline model (1) when this model is augmented with the interactions between growth opportunities and CS measures undertaken in the periods before and after the corporate investment decision. The results are reported in column (5) of Panel A in Table 8. We find that the coefficients on sales growth interacted with CS undertaken before the investment decision are significant and negative. However, the coefficients on sales growth interacted with CS measures following the investment decision are insignificant. These results indicate that investment inefficiency is related to past CS but not to future CS, thus providing support for our hypothesis that CS leads to investment inefficiency.

Fourth, we apply a DID methodology that has been used extensively by recent important investment-related research to deal with measurement problems and establish causality (e.g., Breuer, 2021; Shroff, 2020; Tsai et al., 2021). We make use of 2002 as the event year of an externally imposed shock on how easy it can be for firms to engage in CS; the shock is attributable to the contemporaneous (at the year level) passing of both SOX and the FAS 146 regulation. Joo and Chamberlain (2017) show that these regulations, particularly FAS 146, provide reasons to view 2002 as an intervention year for CS. Their results indicate that the use of CS decreased after 2002 thanks to the stricter verification rules imposed by FAS 146 for special items relating to restructuring charges.

Given that the accounting changes in 2002 affected all listed firms, we follow a continuous DID design to construct a treatment group and a benchmark group of firms. Under this strategy, treatment (benchmark) firms are defined as the ones that are more (less) affected by the exogenous shock (Atanasov & Black, 2016; Bernard et al., 2020; Hu, 2021). We argue that firms with high net operating assets should experience a greater decrease in the use of CS after 2002, compared to firms with lower levels of such assets. This is because prior studies show that the first group of firms are more reliant on CS to inflate earnings than the second group, due to their limited ability to employ other manipulation methods (e.g., Abernathy et al., 2014; Fan et al., 2010). Therefore, firms with high (low) net operating assets are used as our treatment (benchmark) firms, defined as those with pre-FAS 146 average net operating assets above (below) the industry median.

To provide evidence that firms that decreased any engagement in CS following the year 2002 also increased the efficiency of their investments, we estimate the following DID regression model:

$$INV_{i,t+1} = \alpha_0 + \alpha_1 SALES\_GR_{i,t} + \alpha_2 TREAT_{i,t} + \alpha_3 SALES\_GR_{i,t} \times TREAT_{i,t} + \alpha_4 POST_{i,t} + \alpha_5 SALES\_GR_{i,t} \times POST_{i,t} + \alpha_6 TREAT_{i,t} \times POST_{i,t} + \alpha_7 SALES\_GR_{i,t} \times TREAT_{i,t} \times POST_{i,t} + CONTROLS + \varepsilon_{i,t+1} \quad (2)$$

where *TREAT* is an indicator variable equal to one for treatment firms and zero for benchmark firms. *POST* is an indicator variable equal to one in 2003–2006 and zero for 2000 and 2001. This variable is defined following Joo and Chamberlain (2017), who drop 2002 to avoid first-year regulatory transition effects and use a relatively short window period to avoid confounding effects. All other variables have been previously defined.

Panel B in Table 8 reports the DID estimation results. In column (1), we first perform a validation test by regressing CS on *TREAT*, *POST*, and the interactions between *TREAT* and *POST* along with the relevant control variables. The estimated coefficient on $TREAT \times POST$ is negative and significant, indicating that the decrease in CS after 2002 is more pronounced among firms with high net operating assets than among other firms. These results validate our argument that firms with high net operating assets were more responsive to the change in regulations in 2002 and reduced CS to a greater extent than firms with low net operating assets. After this validation test, we perform the DID estimation based on model (2) and report these results in column (2) of Panel B. The estimated coefficient on $SALES\_GR \times TREAT \times POST$ is positive and significant, indicating that the treatment firms invested less inefficiently than benchmark firms after 2002. We interpret this finding as evidence that the exogenous incentive to decrease CS leads to a decline in inefficient investment, providing support for our hypothesis that CS has a causal effect on investment efficiency.

Finally, we perform two additional analyses to deal with potential measurement problems regarding our CS proxy. First, we repeat the estimation of our baseline model (1) for suspect firms, or firms that are more likely to have managed earnings via CS. Earnings management studies typically use suspect firm analysis to provide construct validity for their measures (e.g., Cohen et al., 2008). If our proxy for CS does not suffer from serious measurement problems, then one should expect that our main finding—that CS negatively affects investment efficiency—holds when we consider suspect firms only. We define these firms as the ones that just meet or beat core earnings benchmarks (e.g., Fan et al., 2019; Fan et al., 2010).[12] The results from column (1) of Panel C in Table 8 show that our baseline finding is confirmed for firms that are more likely to have engaged in CS. Second, we repeat the estimation of our baseline

[12] More specifically, a firm is considered as suspect if it reports core earnings from $0.00 to $0.02 per share, or a change in core earnings from $0.00 to $0.02 per share, or analyst forecast errors from $0.00 to $0.02 per share (Fan et al., 2019).

model (1) by excluding firms that report restructuring-related special items. Restructuring events lead to the generation of corresponding special items, which are considered non-recurring. The occurrence of such events could thus trigger the generation of special items, rather than CS representing the triggering factor for their generation, leading to measurement errors when identifying the classification-shifted vs. non-classification-shifted components of special items (Anagnostopoulou et al., 2021). The results from column (2) of Panel C in Table 8 show that our baseline finding holds if we exclude firms that report restructuring-related special items.

Overall, the battery of tests reported in Table 8 suggest that our main findings do not suffer from serious endogeneity concerns related to omitted factors, reverse causality, and measurement problems, although we cannot completely rule out that endogeneity concerns could interfere with the interpretation of our findings.

4.5. Additional robustness controls

We conduct several additional analyses to lend support to and extend our baseline finding; we report these results in Online Appendix in the interest of space. They suggest that our main result is robust to alternative methods of measuring CS and investment opportunities, and that it holds more consistently for capital, compared to non-capital, investments.

5. Conclusion

In this paper, we examine the real effect of CS, a form of earnings management which deliberately increases core earnings without affecting bottom line profit, on corporate investment efficiency. We predict that CS is negatively associated with investment efficiency, manifested in the form of lower sensitivity of investment to growth opportunities. Our prediction is based on the idea that CS (i) accentuates information asymmetries and agency concerns between the firm and its capital providers and (ii) affects managers' own perceptions of permanent vs. transitory earnings, distorting their view of the ability of their own firm to perform sustainably, and ultimately resulting in imperfect investment-related information sets available to them when they make investment decisions.

We find that CS significantly decreases the sensitivity of investment to growth opportunities, indicating that this practice is associated with more inefficient investing. This finding is robust to alternative methods of measuring investment opportunities and CS, and also to a battery of controls for possible endogeneity concerns related to omitted factors, reverse causality, and measurement problems. Although the possibility for an endogenous explanation for our findings cannot be completely ruled out, this battery of tests provides reassurance about potential endogenous factors explaining our findings. Our cross-sectional analysis provides support for our expectation that CS negatively affects investment efficiency via agency and managerial perception distortion mechanisms. Specifically, we observe that the negative effect of CS on investment efficiency is more pronounced for firms facing larger financial constraints. We also observe that the negative effect of CS on investment efficiency becomes less strong when firms' managers appear to learn more from information extracted from peers' information environments, when this kind of information environment could increase opportunities for managerial learning through improvement in managerial information sets thanks to information from peer firms. Thus, a richer peer information environment may compensate for any CS-caused distortions on managerial perceptions, and inadequate investment-related information sets through improved managerial learning from peers.

Overall, our evidence suggests that CS aggravates agency problems and distorts managerial perceptions; it is therefore negatively associated with investment efficiency. By examining the effect of CS on investment efficiency via a managerial perceptions channel in addition to an agency channel, our paper provides insights into how financial reporting quality is associated with inefficient investing through managerial learning mechanisms. The evidence in our paper is important, as it highlights how adversely CS, a method of income manipulation typically considered as relatively low cost, affects a firm outcome, as is efficient investing, which has been linked to reduced future performance for firms. Prior studies mainly examine the determinants of CS, and there is limited previous research investigating the consequences of this practice, which focuses on the IPO context only (Anagnostopoulou et al., 2021; Liu and Wu, 2021). Our study is the first to investigate the real effects of CS in a context unrelated to IPOs and provides evidence that CS can be harmful for firms and investors through its real adverse consequences for firms' informational efficiency.

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Appendix A: Variable definitions

Main variables	
INV	Capital expenditures scaled by lagged total assets.
SALES_GR	The percentage change in sales.
CS	Measure for classification shifting. This is a variable equal to unexpected core earnings (*UECE*) when unexpected core earnings are positive and special items are income-decreasing (*SI*), and zero otherwise. Unexpected core earnings are estimated as the residuals from the McVay (2006) model. The model is a regression of current core earnings on lagged core earnings, current asset turnover ratio, lagged and current accruals, sales growth, and the negative percentage change in sales. The model is estimated cross-sectionally for each industry (2-digit SICs) with at least 20 observations in a given year.
Control variables	
AQ	The residual value from the Dechow and Dichev (2002) model, which is a regression of working capital accruals on the change in revenue, property, plant and equipment (PPE), and lagged, current, and future cash flows. The model is estimated cross-sectionally for each industry with at least 20 observations in a given year.
CASH	Total cash and cash equivalent balance scaled by lagged total assets.
LEVERAGE	Short-term debt plus long-term debt divided by lagged total assets.
CFO	Operating cash flows scaled by lagged total assets.
NCS	The proportion of income-decreasing special items that are not classification-shifted, defined as the difference between income-decreasing special items and *CS*.
LN(MVE)	The natural log of a firm's market value of equity.
TANGIBILITY	The ratio of tangible assets, net PPE, to total assets.
OP_CYCLE	The log of receivables to sales plus inventory to cost of goods sold multiplied by 360.
Additional variables used in cross-sectional and supplementary analyses	
DELAYCON	A variable equal to one for firms that are in the top tercile of their industry-year text-based financial constraint index by Hoberg and Maksimovic (2015), and zero otherwise. We thank Hoberg and Maksimovic (2015) for making a text-based financial constraint index data available to use.
AGE	A variable equal to one for firms that are in the bottom tercile of their industry-year-based age, and zero otherwise. Age is defined as the difference between the first year the firm appears in Compustat and the current year.
EARNINGS_SYNC	Earnings synchronicity, measured using the methodlogy proposed by Shroff et al. (2017), as the average adjusted R-squared obtained by estimating time-series regressions of a firm's quarterly earnings on the aggregate quarterly earnings in its 3-digit NAICS industry.
ANALYSTS	The average number of analyst forecasts per firm within each 3-digit NAICS industry-year.
OPP_SI	Opportunistic income-decreasing special items, measured by obtaining the residuals from the model by Cain et al. (2020). The model is a regression of income-decreasing special items on prior stock returns, change in the book-to-market ratio, change in return on assets, employee decline, M&A activity, discontinued operations, large sales declines, change in sales, current-period operating loss, intensity of operating losses over the prior three years, change in operating cash flows, operating cycle, capital intensity, intangible intensity, and firm size. The model is estimated cross-sectionally for each industry with at least 50 observations in a given year.
PRED_SI	Predicted income-decreasing special items, measured by the fitted values from the model of Cain et al. (2020).

E-INDEX	The entrenchment index of Bebchuk et al. (2009), representing a measure of the strength of outside monitoring through the number of anti-takeover provisions in place multiplied by negative one so that higher values imply lower anti-takeover protection, indicating stronger market discipline. This index is constructed by measuring the number of these provisions (existence of a staggered board, limits on the amendments of bylaws, limits on the amendments of charters, existence of supermajority, golden parachutes, and poison pill) following Bebchuck et al. (2009). The *E-INDEX* takes values from 0 to 6, depending on the number of anti-takeover provisions in place, and when this index is missing, it is assigned the value of zero. We calculate the annual *E-INDEX* for years after 2006 using data from Institutional Shareholder Services (ISS), and values for the index until 2006 are downloaded directly from the website of Lucian A. Bebchuk (http://www.law. harvard.edu/faculty/bebchuk/).
E-INDEX-DUM	An indicator variable that is equal to one if *E-INDEX* is missing, and zero otherwise.
INST_OWN	The percentage of a firm's shares held by institutional investors.
BRD_SIZE	The total number of directors on the board.
BRD_INDEP	The percentage of independent directors on the board.
PEER_CS	The average of peer firms' classification shifting. Peer firms are defined as those that are in the top tercile of total assets in each industry-year.
TREAT	An indicator variable that is equal to one for treatment firms, and zero for benchmark firms. Treatment (benchmark) firms are defined as those with pre-FAS 146 average net operating assets above (below) the industry median.
POST	An indicator variable that is equal to one in 2003–2006, and zero for 2000 and 2001.

Table 1. Descriptive statistics

Variables	N	Mean	25%	Median	75%	SD
INV	97,184	0.065	0.018	0.038	0.076	0.085
SALES_GR	97,184	0.227	-0.030	0.083	0.249	0.782
UECE	97,184	0.003	-0.037	0.007	0.063	0.214
SI	97,184	0.034	0.000	0.000	0.013	0.135
CS	97,184	0.027	0.00	0.000	0.000	0.084
AQ	97,184	0.003	-0.037	0.001	0.041	0.093
CASH	97,184	0.221	0.030	0.104	0.278	0.406
LEVERAGE	97,184	0.255	0.029	0.190	0.368	0.290
CFO	97,184	0.051	0.002	0.077	0.140	0.178
NCS	97,184	0.007	0.000	0.000	0.001	0.126
LN(MVE)	97,184	5.216	3.464	5.149	6.887	2.410
TANGIBILITY	97,184	0.276	0.091	0.204	0.399	0.233
OP_CYCLE	97,184	4.713	4.333	4.791	5.194	0.762

This table reports descriptive statistics for the variables used in our main analysis. *INV* is a measure of investment; *SALES_GR* is the percentage change in sales; *UECE* is unexpected core earnings; *SI* is income-decreasing special items (measured as positive values); *CS* is a measure of classification shifting; *AQ* is a measure of accruals quality; *CASH* is cash holdings; *LEVERAGE* is the leverage ratio; *CFO* is cash flows from operations; *NCS* is the proportion of income-decreasing special items that are not classification-shifted; *LN*(*MVE*) is the natural log of equity market value; *TANGIBILITY* is the tangibility of assets; *OP_CYCLE* is the operating cycle of the firm. See Appendix A for detailed variable definitions and calculations.

Table 2. Association between CS and investment efficiency

Variables	Pr. Sign	(1) *INV*	(2) *INV*
SALES_GR	+	0.0100***	0.0105***
		(0.000)	(0.000)
CS			-0.0294***
			(0.000)
SALES_GR $\times$ *CS*	-		-0.0058***
			(0.004)
AQ			0.0152***
			(0.000)
SALES_GR $\times$ *AQ*			-0.0056*
			(0.052)
CASH		0.0164***	0.0161***
		(0.000)	(0.000)
LEVERAGE		-0.0095***	-0.0096***
		(0.000)	(0.000)
CFO		0.0463***	0.0451***
		(0.000)	(0.000)
NCS			-0.0072***
			(0.000)
LN(MVE)		0.0019***	0.0020***
		(0.000)	(0.000)
TANGIBILITY		0.1331***	0.1331***
		(0.000)	(0.000)
OP_CYCLE		0.0006	0.0003
		(0.173)	(0.484)
Constant		-0.0144***	-0.0127***
		(0.003)	(0.008)
Industry effects		Yes	Yes
Year effects		Yes	Yes
N		97,184	97,184
Adjusted R-squared		0.3442	0.3455

This table provides regression results for model (1), which tests whether CS affects investment efficiency. *INV* is a measure of investment; *SALES_GR* is the percentage change in sales; *CS* is a measure of classification shifting; *AQ* is a measure of accruals quality; *CASH* is cash holdings; *LEVERAGE* is the leverage ratio; *CFO* is cash flows from operations; *NCS* is the proportion of income-decreasing special items that are not classification-shifted; *LN*(*MVE*) is the natural log of equity market value; *TANGIBILITY* is the tangibility of assets; *OP_CYCLE* is the operating cycle of the firm. See Appendix A for detailed variable definitions and calculations. Reported *p*-values are based on standard errors clustered by year and firm. ***/**/* indicate significance at 1%/5%/10% levels, respectively.

Table 3. Effect of financial constraints on the association between CS and investment efficiency

Variables	Pr. Sign	(1) *INV* *FC = DELAYCON*	(2) *INV* *FC = AGE*
SALES_GR		0.0113***	0.0103***
		(0.000)	(0.000)
CS		-0.0160***	-0.0292***
		(0.001)	(0.000)
SALES_GR × *CS*		-0.0060	0.0012
		(0.205)	(0.732)
FC		0.0044***	0.0129***
		(0.000)	(0.000)
SALES_GR × *FC*		-0.0001	-0.0011
		(0.957)	(0.310)
CS × *FC*		0.0019	-0.0033
		(0.810)	(0.607)
SALES_GR × *CS* × *FC*	-	-0.0105*	-0.0090**
		(0.053)	(0.021)
AQ		0.0203***	0.0140***
		(0.000)	(0.000)
SALES_GR × *AQ*		-0.0075*	-0.0054*
		(0.052)	(0.054)
CASH		0.0219***	0.0146***
		(0.000)	(0.000)
LEVERAGE		-0.0116***	-0.0100***
		(0.000)	(0.000)
CFO		0.0353***	0.0470***
		(0.000)	(0.000)
NCS		-0.0081***	-0.0092***
		(0.003)	(0.000)
LN(MVE)		0.0020***	0.0022***
		(0.000)	(0.000)
TANGIBILITY		0.1439***	0.1326***
		(0.000)	(0.000)
OP_CYCLE		0.0006	0.0002
		(0.295)	(0.716)
Constant		0.0042	-0.0167***
		(0.566)	(0.000)
Industry effects		Yes	Yes
Year effects		Yes	Yes
N		43,699	97,184
Adjusted R-squared		0.3884	0.3501

This table provides regression results for model (1), which tests whether CS affects investment efficiency by examining the role of financial constraints for this association. We use the text-based index of Hoberg and Maksimovic (2015) (*DELAYCON*) and firm age (*AGE*) as proxies for financial constraints (*FC*). *INV* is a measure of investment; *SALES_GR* is the percentage change in sales; *CS* is a measure of classification shifting; *AQ* is a measure of accruals quality; *CASH* is cash holdings; *LEVERAGE* is the leverage ratio; *CFO* is cash flows from operations; *NCS* is the proportion of income-decreasing special items that are not classification-shifted; *LN*(*MVE*) is the natural log of equity market value; *TANGIBILITY* is the tangibility of assets; *OP_CYCLE* is the operating cycle of the firm. See Appendix A for detailed variable definitions and calculations. Reported *p*-values are based on standard errors clustered by year and firm. ***/**/* indicate significance at 1%/5%/10% levels, respectively.

Table 4. Effect of peer information on the association between CS and investment efficiency

Variables	Pr. Sign	(1) *INV* *PI = EARNINGS_SYNC*	(1) *INV* *PI = ANALYSTS*
SALES_GR		0.0055***	0.0113***
		(0.000)	(0.000)
CS		-0.0260***	-0.0201**
		(0.000)	(0.015)
SALES_GR × CS		-0.0097***	-0.0146**
		(0.004)	(0.013)
PI		-0.0293***	-0.0024***
		(0.000)	(0.000)
SALES_GR × PI		0.0689***	-0.0005
		(0.000)	(0.444)
CS × PI		-0.0505	-0.0045
		(0.469)	(0.159)
SALES_GR × CS × PI	+	0.0838*	0.0046**
		(0.075)	(0.035)
AQ		0.0156***	0.0152***
		(0.000)	(0.000)
SALES_GR × AQ		-0.0050*	-0.0055*
		(0.076)	(0.056)
CASH		0.0168***	0.0162***
		(0.000)	(0.000)
LEVERAGE		-0.0098***	-0.0097***
		(0.000)	(0.000)
CFO		0.0444***	0.0453***
		(0.000)	(0.000)
NCS		-0.0069***	-0.0069***
		(0.000)	(0.000)
LN(MVE)		0.0020***	0.0020***
		(0.000)	(0.000)
TANGIBILITY		0.1336***	0.1324***
		(0.000)	(0.000)
OP_CYCLE		0.0003	0.0003
		(0.511)	(0.465)
Constant		-0.0093*	-0.0101**
		(0.056)	(0.034)
Industry effects		Yes	Yes
Year effects		Yes	Yes
N		97,184	97,184
Adjusted R-squared		0.3474	0.3460

This table provides regression results for model (1), which tests whether CS affects investment efficiency by examining the role of peer-related information for this association. We use the average values of earnings synchronicity in an industry (*EARNINGS_SYNC*) and average analyst coverage for firms in the industry (*ANALYSTS*) as proxies for peer information environment (*PI*). *INV* is a measure of investment; *SALES_GR* is the percentage change in sales; *CS* is a measure of classification shifting; *AQ* is a measure of accruals quality; *CASH* is cash holdings; *LEVERAGE* is the leverage ratio; *CFO* is cash flows from operations; *NCS* is the proportion of income-decreasing special items that are not classification-shifted; *LN*(*MVE*) is the natural log of equity market value; *TANGIBILITY* is the tangibility of assets; *OP_CYCLE* is the operating cycle of the firm. See Appendix A for detailed variable definitions and calculations. Reported *p*-values are based on standard errors clustered by year and firm. ***/**/* indicate significance at 1%/5%/10% levels, respectively.

Table 5. Association between opportunistic special items and investment efficiency

Variables	Pr. Sign	(1) *INV*	(2) *INV*	(3) *INV*
		Full sample	*SI* sample	*OPP_SI* sample
SALES_GR		0.0109***	0.0123***	0.0132***
		(0.000)	(0.000)	(0.000)
OPP_SI		0.0042	0.0045	0.0023
		(0.395)	(0.347)	(0.716)
SALES_GR $\times$ *OPP_SI*	-	-0.0137**	-0.0160***	-0.0208***
		(0.011)	(0.004)	(0.007)
PRED_SI		-0.0875***	-0.0795***	-0.0776***
		(0.000)	(0.000)	(0.000)
SALES_GR $\times$ *PRED_SI*		-0.0196	-0.0270	-0.0215
		(0.114)	(0.108)	(0.318)
AQ		0.0205***	0.0228***	0.0264***
		(0.000)	(0.000)	(0.000)
SALES_GR $\times$ *AQ*		-0.0063	-0.0153**	-0.0089
		(0.223)	(0.036)	(0.320)
CASH		0.0232***	0.0217***	0.0208***
		(0.000)	(0.000)	(0.000)
LEVERAGE		-0.0084***	-0.0059***	-0.0072***
		(0.000)	(0.000)	(0.000)
CFO		0.0365***	0.0244***	0.0184***
		(0.000)	(0.000)	(0.001)
LN(MVE)		0.0014***	0.0013***	0.0014***
		(0.000)	(0.000)	(0.000)
TANGIBILITY		0.1336***	0.1232***	0.1199***
		(0.000)	(0.000)	(0.000)
OP_CYCLE		-0.0003	-0.0009	-0.0021**
		(0.550)	(0.219)	(0.039)
Constant		0.0250***	0.0184***	0.0307***
		(0.000)	(0.007)	(0.001)
Industry effects		Yes	Yes	Yes
Year effects		Yes	Yes	Yes
N		49,359	22,788	11,413
Adjusted R-squared		0.3582	0.3553	0.3299

This table provides regression results for model (1), which tests whether CS affects investment efficiency by replacing *CS* with measures of opportunistic and predicted special items, estimated separately for the full sample, and for subsamples of firms that possess special items and opportunistic special items. *INV* is a measure of investment; *SALES_GR* is the percentage change in sales; *SI* is income-decreasing special items; *OPP_SI* is opportunistic special items; *PRED_SI* is predicted special items; *AQ* is a measure of accruals quality; *CASH* is cash holdings; *LEVERAGE* is the leverage ratio; *CFO* is cash flows from operations; *LN*(*MVE*) is the natural log of equity market value; *TANGIBILITY* is the tangibility of assets; *OP_CYCLE* is the operating cycle of the firm. See Appendix A for detailed variable definitions and calculations. Reported *p*-values are based on standard errors clustered by year and firm. ***/**/* indicate significance at 1%/5%/10% levels, respectively.

Table 6. Firms with high vs. low unexpected investment

Variables	Pr. Sign	(1) *INV*	(2) *INV*
		HIGH_ UI sample	*LOW_ UI* sample
SALES_GR		0.0127***	0.0042***
		(0.000)	(0.000)
CS		-0.0344***	-0.0150***
		(0.000)	(0.000)
SALES_GR × *CS*	-	-0.0070**	-0.0012
		(0.015)	(0.351)
AQ		0.0095**	0.0155***
		(0.034)	(0.000)
SALES_GR × *AQ*		-0.0038	0.0013
		(0.306)	(0.726)
CASH		0.0190***	0.0061***
		(0.000)	(0.000)
LEVERAGE		-0.0075***	-0.0135***
		(0.000)	(0.000)
CFO		0.0635***	0.0153***
		(0.000)	(0.000)
NCS		-0.0075***	-0.0054***
		(0.007)	(0.001)
LN(MVE)		0.0036***	0.0005***
		(0.000)	(0.000)
TANGIBILITY		0.1664***	0.0526***
		(0.000)	(0.000)
OP_CYCLE		0.0016**	-0.0024***
		(0.024)	(0.000)
Constant		-0.0136**	0.0973***
		(0.016)	(0.000)
Industry effects		Yes	Yes
Year effects		Yes	Yes
N		47,570	47,571
Adjusted R-squared		0.3456	0.3350

This table provides regression results for model (1), which tests whether CS affects investment efficiency, estimated separately for subsamples of firms with high (*High_ UI*) and low unexpected investment (*Low_ UI*). *INV* is a measure of investment; *SALES_GR* is the percentage change in sales; *CS* is a measure of classification shifting; *AQ* is a measure of accruals quality; *CASH* is cash holdings; *LEVERAGE* is the leverage ratio; *CFO* is cash flows from operations; *NCS* is the proportion of income-decreasing special items that are not classification-shifted; *LN*(*MVE*) is the natural log of equity market value; *TANGIBILITY* is the tangibility of assets; *OP_CYCLE* is the operating cycle of the firm. See Appendix A for detailed variable definitions and calculations. Reported *p*-values are based on standard errors clustered by year and firm. ***/**/* indicate significance at 1%/5%/10% levels, respectively.

Table 7. Corporate governance controls

Variables	(1) *INV*	(2) *INV*	(3) *INV*	(4) *INV*
	CG = E-INDEX	*CG = INST_OWN*	*CG = BRD_SIZE*	*CG = BRD_INDEP*
SALES_GR	0.0291***	0.0094***	0.0080	0.0172**
	(0.000)	(0.000)	(0.309)	(0.035)
CS	-0.0284***	-0.0326***	0.0053	0.0132
	(0.000)	(0.000)	(0.835)	(0.664)
SALES_GR × *CS*	-0.0057***	-0.0047**	0.0233	0.0023
	(0.008)	(0.040)	(0.443)	(0.945)
CG	-0.0012***	-0.0060***	-0.0026***	-0.0030
	(0.000)	(0.000)	(0.000)	(0.373)
SALES_GR × *CG*	0.0033***	0.0110***	0.0006	-0.0059
	(0.007)	(0.000)	(0.516)	(0.580)
CS × *CG*	-0.0019	0.0189**	-0.0014	-0.0250
	(0.264)	(0.035)	(0.638)	(0.532)
SALES_GR × *CS* × *CG*	-0.0050	-0.0028	-0.0023	0.0043
	(0.220)	(0.820)	(0.508)	(0.923)
E-INDEX-DUM	0.0173***			
	(0.000)			
SALES_GR × *E-INDEX-DUM*	-0.0192***			
	(0.000)			
AQ	0.0143***	0.0152***	0.0086	0.0104
	(0.000)	(0.000)	(0.230)	(0.157)
SALES_GR × *AQ*	-0.0051*	-0.0056**	-0.0024	-0.0024
	(0.067)	(0.049)	(0.840)	(0.848)
CASH	0.0151***	0.0158***	0.0173***	0.0198***
	(0.000)	(0.000)	(0.000)	(0.000)
LEVERAGE	-0.0099***	-0.0098***	-0.0065***	-0.0080***
	(0.000)	(0.000)	(0.001)	(0.000)
CFO	0.0456***	0.0454***	0.0530***	0.0561***
	(0.000)	(0.000)	(0.000)	(0.000)
NCS	-0.0074***	-0.0072***	-0.0018	-0.0022
	(0.000)	(0.000)	(0.603)	(0.562)
LN(MVE)	0.0030***	0.0022***	0.0019***	0.0004*
	(0.000)	(0.000)	(0.000)	(0.096)
TANGIBILITY	0.1327***	0.1329***	0.1519***	0.1513***
	(0.000)	(0.000)	(0.000)	(0.000)
OP_CYCLE	0.0000	0.0002	0.0003	0.0005
	(0.994)	(0.612)	(0.722)	(0.565)
Constant	-0.0297***	-0.0119**	0.0416**	0.0242
	(0.000)	(0.014)	(0.013)	(0.127)
Industry effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
N	97,184	97,184	17,076	17,076
Adjusted R-squared	0.3486	0.3461	0.4733	0.4694

This table provides regression results for model (1), which tests whether CS affects investment efficiency by examining the role of external and internal corporate governance for this association. We use the entrenchment index of Bebchuk et al. (2009) (*E-INDEX*), institutional investor holdings (*INST_OWN*), board size (*BRD_SIZE*), and board independence (*BRD_INDEP*) as proxies for the quality of external and internal governance. *INV* is a measure of investment; *SALES_GR* is the percentage change in sales; *CS* is a measure of classification shifting; *E-INDEX-DUM* is equal to one if *E-INDEX* is missing, and zero otherwise; *AQ* is a measure of accounting quality; *CASH* is cash holdings; *LEVERAGE* is the leverage ratio; *CFO* is cash flows from operations; *NCS* is the proportion of income-decreasing special items that are not classification-shifted; *LN*(*MVE*) is the natural log of equity market value; *TANGIBILITY* is the tangibility of assets; *OP_CYCLE* is the operating cycle of the firm. See Appendix A for detailed variable definitions and calculations. Reported *p*-values are based on standard errors clustered by year and firm. ***/**/* indicate significance at 1%/5%/10% levels, respectively.

Table 8. Endogeneity controls

Panel A: Firm fixed effects and 2SLS regressions

		Firms fixed effects	2SLS regressions			Lagged and leading CS
			First-stage		Second-stage	
		(1)	(2)	(3)	(4)	(5)
Variables	Pr. Sign	*INV*	*CS*	*SALES_GR × CS*	*INV*	*INV*
SALES_GR		0.0057***	-0.0067***	0.0042***	0.0211***	0.0214***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CS		-0.0295***				-0.0184***
		(0.000)				(0.000)
SALES_GR × CS	-	-0.0044**				-0.0117**
		(0.014)				(0.017)
PEER_CS			0.3682***	-0.0374***		
			(0.000)	(0.000)		
SALES_GR × PEER_CS			0.0227	0.2073***		
			(0.561)	(0.000)		
Pred(*CS*)					-0.3241***	
					(0.000)	
Pred(SALES_GR × CS)	-				-0.5771***	
					(0.000)	
CS_{t-2}						0.0009
						(0.839)
$SALES\_GR \times CS_{t-2}$						-0.0305***
						(0.000)
CS_{t-1}						-0.0100**
						(0.018)
$SALES\_GR \times CS_{t-1}$						-0.0166**
						(0.026)
CS_{t+1}						-0.0345***
						(0.000)
$SALES\_GR \times CS_{t+1}$						-0.0109
						(0.231)
CS_{t+2}						0.0103**
						(0.015)
$SALES\_GR \times CS_{t+2}$						-0.0102
						(0.204)
AQ		-0.0009	-0.0735***	-0.0017	-0.0090**	0.0097**
		(0.732)	(0.000)	(0.313)	(0.034)	(0.013)
SALES_GR × AQ		0.0024	0.0116**	-0.0077*	-0.0009	-0.0043
		(0.337)	(0.020)	(0.065)	(0.844)	(0.570)
CASH		0.0068***	-0.0057***	0.0021**	0.0186***	0.0252***
		(0.000)	(0.000)	(0.042)	(0.000)	(0.000)
LEVERAGE		-0.0179***	0.0097***	0.0007	-0.0086***	-0.0118***
		(0.000)	(0.000)	(0.293)	(0.000)	(0.000)
CFO		0.0369***	-0.0301***	0.0007	0.0415***	0.0622***
		(0.000)	(0.000)	(0.424)	(0.000)	(0.000)
NCS		-0.0061***	-0.1346***	0.0107***	-0.0380***	-0.0058**
		(0.000)	(0.000)	(0.001)	(0.000)	(0.036)
LN(MVE)		0.0073***	0.0016***	0.0005***	0.0025***	0.0012***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TANGIBILITY		0.0042	0.0063***	0.0014**	0.1384***	0.1413***
		(0.332)	(0.001)	(0.044)	(0.000)	(0.000)
OP_CYCLE		0.0012	-0.0003	0.0006**	0.0002	0.0000
		(0.167)	(0.579)	(0.012)	(0.658)	(0.946)
Constant		0.0434***	-0.0027	-0.0054***	-0.0175***	-0.0138*
		(0.000)	(0.658)	(0.007)	(0.002)	(0.086)
Industry effects / Firm effects		Yes	Yes	Yes	Yes	Yes
Year effects		Yes	Yes	Yes	Yes	Yes
N		97,184	92,344	92,344	92,344	68,377
Adjusted R-squared		0.5298	0.1094	0.1050	0.3531	0.3740

Panel B: Difference-in-differences (DID) analysis

		Validation tests		DID results
		(1)		(2)
Variables	Pr. Sign	*CS*	Pr. Sign	*INV*
SALES_GR				0.0056***
				(0.000)
TREAT	+	0.0244***		-0.0059***
		(0.000)		(0.000)
SALES_GR × *TREAT*			-	-0.0029**
				(0.020)
POST		-0.0129***		0.0082***
		(0.000)		(0.000)
SALES_GR × *POST*				0.0078***
				(0.000)
TREAT × *POST*	-	-0.0167***		-0.0001
		(0.000)		(0.955)
SALES_GR × *TREAT* × *POST*			+	0.0041**
				(0.039)
AQ		-0.0574***		0.0220***
		(0.000)		(0.000)
SALES_GR × *AQ*				-0.0115***
				(0.000)
CASH		-0.0081***		0.0130***
		(0.000)		(0.000)
LEVERAGE		0.0036*		-0.0113***
		(0.082)		(0.000)
CFO		-0.0270***		0.0441***
		(0.000)		(0.000)
NCS		-0.0319***		-0.0001
		(0.000)		(0.961)
LN(MVE)		0.0017***		0.0010***
		(0.000)		(0.000)
TANGIBILITY		-0.0068*		0.1426***
		(0.091)		(0.000)
OP_CYCLE		-0.0064***		0.0029***
		(0.000)		(0.000)
Constant		0.0394**		-0.0428***
		(0.013)		(0.000)
Industry effects		Yes		Yes
N		23,412		23,316
Adjusted R-squared		0.0694		0.4312

Panel C: Suspect firm and non-restructuring firm analyses

		Suspect firms	Non-restructuring firms
		(1)	(2)
Variables	Pr. Sign	*INV*	*INV*
SALES_GR		0.0137***	0.0105***
		(0.000)	(0.000)
CS		-0.0342***	-0.0308***
		(0.000)	(0.000)
SALES_GR $\times$ *CS*	-	-0.0180***	-0.0060***
		(0.002)	(0.006)
AQ		0.0091	0.0142***
		(0.264)	(0.000)
SALES_GR $\times$ *AQ*		-0.0095	-0.0056*
		(0.389)	(0.055)
CASH		0.0185***	0.0154***
		(0.000)	(0.000)
LEVERAGE		-0.0112***	-0.0095***
		(0.000)	(0.000)
CFO		0.0523***	0.0433***
		(0.000)	(0.000)
NCS		-0.0014	-0.0115***
		(0.776)	(0.000)
LN(MVE)		0.0011***	0.0025***
		(0.000)	(0.000)
TANGIBILITY		0.1565***	0.1344***
		(0.000)	(0.000)
OP_CYCLE		0.0005	0.0006
		(0.634)	(0.239)
Constant		-0.0067	-0.0173***
		(0.709)	(0.001)
Industry effects		Yes	Yes
Year effects		Yes	Yes
N		17,166	80,395
Adjusted R-squared		0.3682	0.3375

This table reports a series of results on endogeneity controls described in detail in Section 4.5. Panel A reports regression results for model (1), which tests whether CS affects investment efficiency when a) using firm fixed effects (Column [1]); b) when employing a 2SLS model estimation with the use of CS by peer firms in the previous year (*PEER_CS*) as the instrumental variable for this year's level of CS for a firm (Columns [2]–[3] for first-stage and column [4] for second-stage results); and c) when including lagged and leading CS measures (Column [5]). Panel B presents the DID analysis of how exogenous changes in CS due to the passage of SOX and the FAS 146 regulation in 2002 influenced the association between CS and investment efficiency, as described in Section 4.5. Panel C reports regression results for model (1) when a) considering only suspect firms that are more likely to have managed earnings via CS, and b) excluding firms that report restructuring-related special items. *INV* is a measure of investment; *SALES_GR* is the percentage change in sales; *CS* is a measure of classification shifting; *AQ* is a measure of accruals quality; *CASH* is cash holdings; *LEVERAGE* is the leverage ratio; *CFO* is cash flows from operations; *NCS* is the proportion of income-decreasing special items that are not classification-shifted; *LN*(*MVE*) is the natural log of equity market value; *TANGIBILITY* is the tangibility of assets; *OP_CYCLE* is the operating cycle of the firm; *Pred*(*CS*) is the predicted value of CS from the first stage estimation; *Pred*(*SALES_GR* $\times$ *CS*) is the predicted value of *SALES_GR* $\times$ *CS* from the first stage estimation; *TREAT* is an indicator variable equal to one for treatment firms, and zero for benchmark firms; *POST* is an indicator variable equal to one in 2003–2006 and zero for 2000 and 2001. See Appendix A for detailed variable definitions and calculations. Reported *p*-values are based on standard errors clustered by year and firm. ***/**/* indicate significance at 1%/5%/10% levels, respectively.