Detecting Opportunistic Special Items*

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Management Science, Forthcoming

ABSTRACT

The frequency of special items has increased dramatically over time, offering a convenient conduit for the inappropriate classification of past, present, and future recurring expenses as non-recurring. Identifying this misclassification is especially important in light of the pervasive use of non-GAAP earnings in recent periods, as special items offer camouflage for excluded recurring expenses. Building on prior research, we propose a method for identifying the predicted level of special items, attributing any excess to opportunism, and demonstrate the importance of this partitioning for financial statement users. In particular, we provide evidence that the opportunistic portion of special items is associated with lower future earnings, cash flows, and returns. We conclude that this portion of special items is more likely to contain opportunistically misclassified recurring expenses that should have been recognized as such in prior, current, or future periods. Thus, we provide a meaningful partition of special items that should be useful to investors, analysts, creditors, auditors, and regulators, as each of these parties must assess the implications of special items.

Keywords: Special items; transitory items; non-GAAP earnings; earnings quality; earnings management.

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* We appreciate the comments and suggestions of two anonymous reviewers, an anonymous associate editor, Suraj Srinivasan (the managing editor), Mary Billings (FARS discussant), Asher Curtis, Weili Ge, Michelle Hanlon, Doug Hanna, Eddie Riedl, Edgar Rodriguez Vazquez, Doug Skinner, Mike Willenborg, Benjamin Whipple, and workshop participants at London Business School, the University of Arizona, the University of Connecticut, Rutgers University, Yale School of Management, and the FARS midyear conference. An earlier version of this paper was entitled "Qualifying Special Items: An Identification and Examination of Lower-Quality versus Higher-Quality Income-Decreasing Special Items."

1. Introduction

The reporting of special items has increased dramatically over time (Elliott and Hanna 1996; Collins et al. 1997; Donelson et al. 2011) with 50 percent of US publicly traded firms reporting income-decreasing special items by 2016 (Figure 1).[1] The designation of special items as unusual or infrequent is important because it highlights that management expects these charges to be more transitory than recurring expenses (e.g., Lipe 1986; Fairfield et al. 1996). It naturally follows that investors, analysts, and compensation committees typically place less weight on special items than on core earnings (e.g., Elliott and Shaw 1988; Philbrick and Ricks 1991; Dechow et al. 1994; Elliott and Hanna 1996; Gaver and Gaver 1998).

Although the increase in special items largely reflects changes in the economic and regulatory landscape (e.g., Collins et al. 1997; Donelson et al. 2011), it also heightens concerns about the use of special items to manage earnings (e.g., Riedl 2004; Kolev et al. 2008; Cready et al. 2010). In particular, management can misclassify past, present, and future recurring expenses as a current period special item (Barton and Simko 2002; Burgstahler et al. 2002; Riedl 2004; McVay 2006; see examples in Appendix 1). Assessing the composition of special items is particularly important considering the increasing prevalence of "non-GAAP" earnings, with approximately 50 percent of firms reporting non-GAAP earnings by 2013 (see Figure 2 of Bentley et al. 2018). Non-GAAP earnings are more value-relevant than GAAP earnings, which is often attributed to the removal of special items (e.g., Bradshaw and Sloan 2002; Lougee and Marquardt 2004).

[1] The term "special items" refers to unusual or infrequent items that are reported as a separate component of income from continuing operations, and the nature and financial effects of each event or transaction is disclosed on the face of the income statement or in the notes to the financial statements (APB 30; ASC 225-20-45-16). We focus on income-decreasing special items as we expect misclassified recurring expenses to make the income-decreasing special item larger, whereas the predictions for income-increasing special items are more nuanced. We expand on these subtleties in later discussions.

A practical tool for assessing the validity of reported special items is therefore necessary to evaluate the quality of a firm's financial reports. We fill this void by proposing a methodology to predict economically driven special items, the excess of which likely contains opportunistically misclassified recurring expenses from the past, present, and future—hereafter "opportunistic special items." Such a tool is particularly important given the prevalence of non-GAAP earnings. Although academic studies of special items are rife with concerns of manipulation (Barton and Simko 2002; Burgstahler et al. 2002; Atiase et al. 2004; Riedl 2004; McVay 2006; Kolev et al. 2008; and Bens and Johnston 2009, among others), the non-GAAP earnings literature generally treats excluded special items as relatively "safe." Instead, that literature focuses on other exclusions, such as the exclusion of amortization expense, and more recently, stock based compensation expense, as the vehicle for financial reporting manipulation involving non-GAAP earnings (e.g., Doyle et al. 2003; Black and Christensen 2009; Doyle et al. 2013). By partitioning the predicted and opportunistic components of special items, we are able to bridge these two distinct, but clearly related, streams of literature.

Although the type and frequency of specific special items are important to financial statement users, alone these identifiers are insufficient to classify a given special item as opportunistic. A single special item could contain both recurring and transitory expenses (e.g., Borden and Enterasys Networks—both examples in Appendix 1—had actual restructuring charges which contained some misclassified recurring expenses and hence were overstated).

To form an estimate of the economically driven "predicted" component of special items, we build on evidence in prior research on the determinants of special item reporting (e.g., Francis et al. 1996; Riedl 2004; Bens and Johnston 2009; Cready et al. 2010). Specifically, we use a Tobit estimator to jointly model the propensity of reporting income-decreasing special items during a specific year and the magnitude of the charge, inferring the predicted (opportunistic) special item portion as the resultant fitted value (residual). To validate our partition, we examine the association of the special items partitions with future firm performance. We find that our estimate of opportunistic special items is significantly negatively associated with both future earnings and cash flows, on average, whereas predicted special items are not, supporting that our identification of opportunistic special items contains misclassified recurring expenses. Our model, however, could classify less transitory (but still special) expenses as opportunistic. To address this concern, we also examine future abnormal stock returns. We find that opportunistic special items are significantly negatively associated with future abnormal returns, whereas the association is insignificant for predicted special items. In short, these analyses support that our model of special items allows users to isolate the economically driven component of special items, which behave in a manner that is more consistent with the concept of a transitory item (Ohlson 1999).

As additional analyses, we document that our estimate of opportunistic special items are associated with future restatements related to special items (i.e., items first classified as special are restated to recurring expenses) and also document that the probability of just meeting or beating the analysts' consensus forecast is higher when the proportion of opportunistic special items, relative to total special items, is higher. Collectively, we interpret these results as further evidence that we are able to identify some misclassified recurring expenses from the past, present, and future.

The literature on special items is vast. Extant research, however, focuses on either specific types, such as impairments or restructuring charges (Francis et al. 1996; Moehrle 2002; Atiase et al. 2004; Riedl 2004; Bens and Johnston 2009; Lee 2014), total special items (Doyle et al. 2003), the sign of special items (Kinney and Trezevant 1997; Riedl and Srinivasan 2010), or the recurrence of special items (Elliott and Hanna 1996; Cready et al. 2010). In contrast, we propose a systematic approach to assess the validity of income-decreasing special items, with the goal of separating the economically driven, valid, component from the portion more likely to reflect strategic financial reporting.

This partition should be useful to a number of parties interested in assessing the merit of managers' special item designations, as it is extremely difficult to gauge the reasonableness of many special items, such as restructuring charges, especially relying solely on external reports. One example is regulators, who need to decide whether to allow separate reporting of special items. Another is investors and analysts who need to assess the quality of non-GAAP earnings, a central performance indicator that has reached all-time highs in terms of usage (e.g., Bentley et al. 2018) and has again come under SEC scrutiny (Michaels and Rapoport 2016). In addition, our partitioning should also be of interest to auditors, who often waive proposed classification adjustments (Nelson et al. 2002), and due diligence teams valuing target firms for M&A purposes (Skaife and Wangerin 2013). Identifying potentially opportunistic special items also allows financial statement users to more carefully scrutinize prior and future earnings, which would be overstated if recurring expenses from the past and future are shifted into current period special items.

We expect our relatively simple model, which does not require forward-looking information and is relatively easy to implement, to be useful to financial statement users who must assess the implications of special items in real time. As with all regression-based partitioning models, however, our approach has limitations. Most notably, this approach yields a relatively large residual which contains some economically driven special items—it overstates opportunistic special items. Moreover, it does not identify the period from which the recurring expenses are shifted (i.e., the past, present, or future). As a step to resolving these issues, we develop explicit estimates of shifting from the past, present, and future, which may be of greater interest to academics or regulators wishing to assess, ex post, the quality of prior special items. The estimate of opportunistic special items using this more arduous methodology provides a lower-bound estimate of opportunistic special items, and suggests that misclassified recurring expenses make up approximately one-third of special items, on average.

2. Motivation

The components of the income statement are intended to provide information about the underlying economics of a firm's transactions. Fairfield et al. (1996) offer evidence that the persistence of earnings components is generally declining as one moves down the income statement. They find that, on average, core earnings are more than five times as persistent as special items. For example, when forecasting future return-on-equity (their Table 2), the estimated coefficient on special items is 0.123, whereas the coefficient on gross margin is 0.636. This lower persistence of special items is reasonable considering the types of charges comprising special items: e.g., restructuring charges, asset write-offs, and gains or losses on the sale of assets. Consistent with this notion, investors, analysts, and compensation committees generally discount income-decreasing special items, largely excluding them from GAAP earnings in assessing firm performance or determining managerial compensation (e.g., Elliott and Shaw 1988; Philbrick and Ricks 1991; Dechow et al. 1994; Elliott and Hanna 1996; Gaver and Gaver 1998; Bradshaw and Sloan 2002; Bentley et al. 2018).

This differential treatment makes special items a convenient tool for managing earnings (e.g., Elliott and Shaw 1988; Kinney and Trezevant 1997; Burgstahler et al. 2002; Moehrle 2002;

McVay 2006; Bens and Johnston 2009). For example, managers can under-report past expenses, such as depreciation (e.g., by using too large of a residual value or too long of an expected life) which bloats the balance sheet (Barton and Simko 2002; Hirshleifer et al. 2004), and can ultimately be written off as a special item. Thus, managers might view the deceleration of expenses as a low-cost means to manage reported earnings if they plan to write off the accumulated expenses as a special item in a future period. This tactic is especially attractive since the subsequent write-down is typically excluded from non-GAAP earnings, which are the focus of investors and analysts. In other words, the benefit is more than just a timing difference, as the "reversal" of the accrual build-up is discounted by investors.

Managers can also manipulate the classification of expenses within the income statement. McVay (2006) documents that managers misclassify core operating expenses as special items in order to inflate core earnings (see also Fan et al. 2010). Moreover, Robinson (2010) documents managers are willing to incur real costs to classify charges as tax expenses rather than operating expenses. These studies support the notion that managers care about the classification of expenses *within* the income statement.[2] Shifting operating expenses to special items allows managers to report better core performance without changing bottom-line earnings, which may be perceived as beneficial in that analysts, investors, and compensation committees tend to discount the special items, focusing on core earnings. Indeed, McVay (2006) provides some evidence that investors are negatively surprised when these misclassified core expenses recur in future periods.

[2] Kinney and Trezevant (1997) find that managers tend to break out transitory expenses on the face of the income statement, while merely disclosing transitory gains in the footnotes, although Riedl and Srinivasan (2010) suggest that this disclosure choice corresponds to the permanency of the special items. Rather than examine where the special items are reported, we analyze the association of our measure of opportunistic special items with future returns and restatements to corroborate that we identify misclassified expenses, rather than relatively more permanent (but appropriately classified) special items.

Finally, managers may shift future recurring expenses into the current period special item, thereby artificially improving future earnings. Specifically, managers have been accused of engaging in big bath accounting (Moore 1973; Healy 1985; Murphy and Zimmerman 1993; Pourciau 1993; Kirschenheiter and Melumad 2002; Atiase et al. 2004; Bens and Johnston 2009) to improve future earnings; and, the time-series properties of special items support this conjecture (Levitt 1998; Burgstahler et al. 2002; Fairfield et al. 2009; Cready et al. 2010).[3] Thus, special items can contain future expenses, in which case special items will be associated with future unexpected improvements in earnings (e.g., Burgstahler et al. 2002; Atiase et al. 2004; Dechow and Ge 2006). For example, although Atiase et al. (2004) find that firms with losses and multiple restructuring charges tend to improve in the following years, they note that the improvement is more pronounced in earnings than in cash flows, and caveat that they cannot rule out earnings management.[4]

Disentangling the recurring component of special items is difficult for financial statement users, as they generally do not have sufficient information to identify how much of a specific expense represents appropriately classified special items versus misclassified recurring expenses.[5] Referring to the examples in Appendix 1, if an auditor failed to identify and correct such misreporting, is it reasonable to expect a firm outsider to discern shifting at the time of the reporting of the special item?

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[3] Managers have also been found to create reserves that are later reversed into income, allowing them to meet future benchmarks (Moehrle 2002). These reversals should be classified as future income-increasing special items, whereas our model of shifting from the future focuses on future earnings before special items. Thus, our analysis does not encompass this earnings management technique.

[4] Our residual-based estimate of opportunistic special items encapsulates shifting from the past, present, and future. The inclusion of shifting from the future, however, biases against finding negative future outcomes, as the mechanism leads to higher future earnings and stock returns (Burgstahler et al. 2002).

[5] Although in earlier periods the recurrence of special items allowed for a relatively strong indicator of perceived quality (e.g., Elliott and Hanna 1996; Cready et al. 2010), we expect the usefulness of recurrence as a signal of opportunism to decline, as the appropriate application of recent financial standards results in multi-period special items (e.g., SFAS 146, now ASC 420; Lee 2014). As a practical matter, we confirm that our partitioning notably outperforms an analogous partition that treats repeated special items as opportunistic (untabulated).

Considering the feasibility of using special items as a vehicle for managing earnings, a natural question becomes why we observe other, much costlier, types of earnings management. First, firms do not report special items every period. Thus, we posit that opportunistic managers typically capitalize on the existence of a valid special item, using it as camouflage. Second, the valuation and compensation benefits to reporting special items decline as this practice increases in frequency (Elliott and Hanna 1996; Cready et al. 2010). Specifically, as special items recur, financial statement users begin treating them more like recurring earnings. This imposes a natural constraint on how frequently managers can shift past, present, and future expenses into special items.

Even potentially contaminated by the inclusion of past, present, and future recurring expenses, special items remain more transitory than core earnings on average. The inclusion of these recurring expenses, however, reduces the usefulness of the separation of special items from core earnings and evidence supports that current period special items are predictive of both future special items (Francis et al. 1996; Cready et al. 2010) and future core earnings (Burgstahler et al. 2002; McVay 2006; Fairfield et al. 2009; Cready et al. 2010). In sum, we believe that a meaningful assessment of the composition of reported special items would be useful to virtually all financial statement users.

The approach we take focuses on modeling economically motivated special items and treating any income-decreasing special items exceeding this predicted magnitude as opportunistic—likely to contain past, present, and future recurring expenses. Similar to other attempts to partition accounting variables (e.g., identifying discretionary accruals), the methodology we propose trades off feasibility and precision. We conduct a number of tests to verify that the partitioning is meaningful. We first explore whether predicted and opportunistic special items are differentially associated with future earnings (before special items) and operating cash flows. This analysis is motivated by the notion that recurring expenses, misclassified as transitory, will be negatively associated with future earnings and operating cash flows as they recur (Doyle et al. 2003; Kolev et al. 2008).

Clearly, there is natural variation in the permanence of special items that does not reflect opportunism (e.g., Riedl and Srinivasan 2010). Thus, it is possible that the residual of our model contains less transitory, but still appropriately classified, special items. In this case, these expenses would be associated with future earnings and cash flows, but not reflective of intentional misclassification of recurring expenses from the past, present, and future. This argument does not extend to the association between future abnormal stock returns and special items, which we view as clearer evidence that recurring expenses are misclassified as transitory. Specifically, if investors learn of the misclassification over time as the expenses recur, opportunistic special items should be negatively associated with future returns. Investors could also learn of the misclassification if special items are subsequently restated as recurring expenses, yielding a similar prediction. In support of the latter mechanism, we provide several examples of restatements related to the shifting of expenses from the past, present, and future (Appendix 1). For example, in 1992 Borden misclassified concurrent recurring expenses (largely marketing expenses) as one-time charges and was subject to an SEC enforcement action, and in 1996, Sunbeam took a big-bath by writing off future expenses, also attracting the attention of the SEC—both resulted in a restatement. Thus, we expect that the misclassification of recurring expenses as special items should lead to lower future abnormal stock returns, as investors see "transitory" expenses recur.

In summary, we predict economically driven special items and attribute any excess to opportunism. We expect the opportunistic, but not predicted, component will be negatively associated with future earnings, cash flows, and returns. As additional analyses, we explore directly whether opportunistic special items are associated with a higher likelihood of subsequent financial statement restatements or linked to reporting incentives via the likelihood of meeting or narrowly beating the analysts' consensus forecast.

3. Sample Selection, Descriptive Statistics and Measurement of Shifting

3.1 Sample Selection

We obtain financial and market data from Compustat, accounting restatements data from Audit Analytics, equity returns from CRSP, and analysts' forecast error data from IBES. The sample spans 1989 through 2016. We begin the sample in 1989, as we require lagged data from the statement of cash flows. Since some analyses require subsequent data (e.g., future earnings, cash flows, and returns), the time series length varies across specifications. The number of observations varies across tests due to data availability. We scale all continuous financial variables, other than CFO Volatility and Operating Cycle, by Net Sales (Compustat item SALE). We do not consider assets, book value of equity, or market value of equity as scalars since assets and book value of equity are affected by the accumulation of past expenses and the acceleration of future expenses, and market performance is an important predictor of special items. In other words, any of the three deflators is likely to bias the analysis, whereas we have no reason to believe that sales would similarly bias the estimates. We exclude firm-year observations with less than one million in sales to mitigate potential small-denominator problems. We also exclude firm-year observations with a change in fiscal-year end. All continuous variables are winsorized at 1 percent and 99 percent by fiscal year to mitigate the influence of outliers. In addition, we require each industry-year group to have at least 50 observations with non-missing data for the model of economically driven special items, where the industry definition is based on the Fama and French (1997) classification. The full sample comprises 104,495 firm-year observations for 11,991 individual companies.

3.2 Descriptive Statistics

The descriptive statistics for our main variables are presented in Panel A of Table 1; we define the variables in Appendix 2. Mean total assets are approximately \$6.8 billion, and mean sales are approximately \$2.9 billion. We obtain special items (SI) from Compustat; for ease of interpretation, we multiply the variable by negative one, resulting in positive values representing income-decreasing special items. Since the focus of the study is the potential shifting of expenses into special items, we examine only the income-decreasing special items and set the income-increasing special items to zero.[6] Income-decreasing special items as a percentage of sales has a mean of 2.44 and a median of zero.

In Panel B of Table 1 we partition the sample into firm-years with zero or income-increasing special items and firm-years with income-decreasing special items. Firms reporting income-decreasing special items tend to be larger, less profitable and have lower sales growth. We include a correlation table in our online appendix.

[6] Hypothetically, managers could also use income-increasing special items to inflate core earnings, i.e., record the transactions as "recurring." If the tactic were successful, however, the special items in Compustat would be recorded as zero. Because we cannot rely on the same variables and models to identify earnings management using income-increasing special items, we opt to set income-increasing special items to zero. To maximize the sample size, we also set missing values for the special items variable to zero. Prior to setting income-increasing special items to zero, 13.9 percent of the sample had a net income-increasing special item, as reported by Compustat. The mean (median) magnitude of these income-increasing special items is \$84.7 (\$3) million, or 12.6 (0.9) percent of net sales (unwinsorized; not tabulated). Results are not sensitive to the removal of firm-year observations with income-increasing or missing special items (not tabulated).

4. Tests

4.1 Identifying Predicted and Opportunistic Special Items

Much of prior research on the determinants of special items focuses on specific types, such as asset write-offs (Francis et al. 1996; Riedl 2004) and restructuring charges (Bens and Johnston 2009; Lee 2014). These papers often consider both economic determinants and incentives to report special items. We consider only the variables motivated as economic drivers, as we expect incentives drive opportunistic special items. We model the economically driven component of income-decreasing special items as follows:

$$\begin{aligned} SI_{i,t} = {} & \eta + \lambda_1 Returns_{i,t\text{-}1} + \lambda_2 Returns_{i,t\text{-}3,t\text{-}1} + \lambda_3 \Delta BM_{i,t\text{-}3,t\text{-}1} + \lambda_4 \Delta ROA_{i,t\text{-}3,t\text{-}1} \\ & + \lambda_5 Merger_{i,t,\,t\text{-}1} + \lambda_6 EmployeeDecline_{i,t\text{-}1,t} + \lambda_7 DiscontinuedOp_{i,t} \\ & + \lambda_8 LargeSalesDecline_{i,t} + \lambda_9 \Delta Sales_{i,t\text{-}3,t\text{-}1} + \lambda_{10} Loss_{i,t} + \lambda_{11} PctLoss_{i,t\text{-}3,t\text{-}1} \\ & + \lambda_{12} \Delta CFO_{i,t} + \lambda_{13} OpCycle_{i,t\text{-}1} + \lambda_{14} CapitalIntensity_{i,t\text{-}1} \\ & + \lambda_{15} IntangibleIntensity_{i,t\text{-}1} + \lambda_{16} \ln(Assets_{i,t\text{-}1}) + \mu_{i,t} \end{aligned} \quad (1)$$

We identify the economically driven (opportunistic) component of income-decreasing special items, *PredSI* (*OppSI*), as the fitted value (error term).[7] We estimate Equation (1) as a Tobit regression. We do so for two reasons. First, our construct of special items is censored below at zero, with positive values reflecting income-decreasing special items. Second, reported special items stem from a two-step process: managers first determine whether an unusual or infrequent event has occurred during the period, and then assess the dollar amount to recognize as a separate component of income from continuing operations.[8] Since the Tobit estimator nests an assessment of the observed magnitude of the dependent variable within a binary model

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[7] To address instances of delayed reporting of income-decreasing special items and the fact that Compustat item SPI combines income-increasing and income-decreasing special items, reporting the net effect, we apply two filters to the model estimates. First, we set *PredSI* and *OppSI* to zero if the variables are non-zero, but the firm does not report an income-decreasing SI for the period (7.15 percent of the observations). Second, if the firm reports income-decreasing special items, but the error term in the model is negative, we set *OppSI* to zero (8.46 percent of the observations).

[8] Typically, we expect that the choice to misclassify recurring expenses as transitory is conditional on the opportunity. With a restructuring charge comes the opportunity to write off assets that had been previously over-stated through under-expensing, shift current recurring expenses to the charge, and write off unimpaired assets to lower future expenses. Asset write-offs, however, could also feasibly manifest as stand-alone removals of prior intentional deceleration of expenses.

predicting the existence of the variable, it is well-suited for our setting (see Riedl 2004 and Lee 2014 for similar applications).

We estimate the regressions by industry-year to control for industry-specific and macroeconomic factors; to allow sufficient degrees of freedom, we require each industry-year subsample to have at least 50 observations with non-missing data for each variable. This also allows the estimated coefficients on the determinants to vary across industries and time; this is especially important in our setting as prior research finds that the impact of economic determinants has changed over time (e.g., Riedl 2004) and that pooled regressions do not provide as good of a fit when predicting special items (e.g., Bens and Johnston 2009).

Turning to the model variables, following Francis et al. (1996), we include prior stock returns, change in the book-to-market ratio, and change in return-on-assets.[9] Following Donelson et al. (2011), we include three indicator variables for economic events that could lead to special items: a decline in employees from year t–1 to t, M&A activity in year t or t–1, and discontinued operations in year t.[10] Building on the models in Cready et al. (2010), Donelson et al. (2011), and Riedl (2004), we also include large sales declines, change in sales, current period operating loss, intensity of operating losses over the prior three years, and change in operating cash flows to the vector of economic determinants. We conjecture that firms with longer operating cycles and larger recognized tangible and intangible assets are at greater risk of recognizing income decreasing special items, as each of these increases the need for estimates and, thus, the

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9 Because we estimate this model by industry-year, we do not industry-adjust the book-to-market ratio, and we do not include the change in industry return-on-assets or book-to-market ratio. For the same reason, we do not include change in GDP (e.g., Riedl 2004). Also, although Francis et al. (1996) use five-year changes for many of their variables, we only consider three-year changes to maximize the number of observations.

10 Donelson et al. (2011) consider M&A activity in year t only, but we also include t–1 as we expect some integration expenses to flow into the year after the M&A transaction, especially if the deal closes late in the fiscal year. Clearly some of these economic determinants could capture incentives to shift. For example, M&A transactions lead to economically driven M&A expenses, but also may correlate with the desire to present higher earnings.

likelihood of write-downs. Therefore, we include the length of a firm's operating cycle and its capital and intangible intensities. Finally, following Francis et al. (1996) and Cready et al. (2010), we include a measure of firm size.

In Table 2 we present summary results from the 771 industry-year Tobit estimations of Equation (1). The first and second columns present the mean and median industry-year regression coefficients, and the second two columns present the percent of the estimated coefficients that obtain the predicted sign and are significant in the predicted direction (one-tailed test; $p < 0.10$), respectively. For example, 83.9 percent of the industry-year regressions yield a positive coefficient on loss in year *t* and the effect is significant in 57.1 percent of the cases.

Turning to the estimates, lagged returns are inversely related to special items, consistent with special item firms generally experiencing poor performance prior to recognizing the charges. Similarly, firms with increasing book-to-market ratios, as well as companies with declining return-on-assets ratios, tend to have larger special items. Mergers tend to result in special items (with merger and acquisition fees and in-process R&D both typically classified as special items during the sample period), as do declines in employees and, at the median, discontinued operations, consistent with these firms undergoing a business reconfiguration that could lead to restructuring charges or asset impairments. Poorly performing firms (those with losses, and declining sales and cash from operations) tend to have larger special items, as do firms with longer operating cycles, consistent with longer operating cycles leading to greater uncertainty, and thus, estimation errors (Dechow and Dichev 2002). Firms with more assets to impair (tangible or intangible) also have larger special items. Finally, firm size is positively associated with special items, consistent with prior work (e.g., Francis et al. 1996; Cready et al. 2010).

4.2 Test Results

4.2.1 Future Earnings, Cash Flows, and Equity Returns Realizations

To investigate the association between special items and future earnings, cash flows, and equity returns, we estimate variations of the following regression model:

$$\sum_{t+2}^{t+3} Future\ Realizations_t = \phi + \varphi_1 SI_{i,t} + \varphi_2 Controls + \theta' FE + \mu_{i,t} \qquad (2)$$

We cumulate the dependent variables (earnings, cash flows or returns) over the second and third year after the observation date to avoid mechanical associations; the vast majority of cash outflows related to liabilities established as part of the special item in year *t* take place in years *t* and *t*+1 (e.g., severance fees within restructuring charges that are correctly paid to the employees the current and subsequent year). Our intent is to capture expenses that continue to occur into the future, rather than cash outflows related to liabilities associated with predicted special items.[11]

As before, *SI* is a continuous variable, defined as income-decreasing special items scaled by sales, bound below at zero. In the specifications analyzing predicted and opportunistic special items, we substitute *SI* for *PredSI* and *OppSI*. We estimate the models using Ordinary Least Squares, clustering the errors at the firm level. Each model includes industry-year fixed effects, *FE*, to absorb macroeconomic factors.

We consider three samples: 1) all observations with available data for the analysis (full sample), 2) only firms that report income-decreasing special items in year *t* (SI sample), and 3) only firms with opportunistic special items in year *t* (OppSI sample). Although the full sample

[11] Results are similar if we include year *t*+1 in the measurement window or restrict the analysis to year *t*+1 (see the online appendix). As a technical point, to avoid survivorship bias, we retain observations with at least one data point in *t*+2 or *t*+3. That is, if data for *t*+3 are missing, the dependent variable is not coded as missing, but takes on the value of *t*+2. Requiring data for all years does not affect the inferences (not tabulated).

results allow a comparison to extant research, we view the SI and OppSI samples as more informative since our focus is the effects of predicted and opportunistic special items, which, by construction, are only present in firms that report special items during the year.

We report the regression results in Tables 3–5. We first consider future earnings. $\sum_{t+2}^{t+3} NIBTSI_t$ denotes Net Income before Taxes and Special Items (Compustat item PI, adjusted for the Compustat-reported income-decreasing special items), scaled by contemporaneous Net Sales and cumulated over years t+2 and t+3. We focus on earnings before special items to avoid a mechanical relation between current period special items and future period special items (e.g., Francis et al. 1996). Thus, any recurrence of special items should bias against finding evidence of opportunism in our earnings estimations, as shifting future expenses to future special items will increase future recurring earnings. We use pre-tax income to accommodate that Compustat item SPI, which underlies our measure of income-decreasing special items, is reported pre-tax.

Turning to Table 3, we note that in the full sample, special items are not associated with future earnings (t-statistic = 0.12). This non-result is consistent with findings in Doyle et al. (2003) and Fairfield et al. (2009). When we examine firm-years with income-decreasing special items, however, on average special items are negatively associated with future earnings ($\varphi_1 = -0.125$; t-statistic = –1.98), and this coefficient appears slightly higher in the OppSI sample ($\varphi_1 = -0.132$; t-statistic = –2.02).

When we examine the special items components, however, the results differ notably between predicted and opportunistic special items. Specifically, predicted special items are *positively* associated with future earnings in all three samples, consistent with operational improvements resulting, for example, from efficiency gains related to a restructuring charge (e.g., Atiase et al. 2004), whereas the estimated coefficients on opportunistic special items are negative across the board, which is consistent with the recurrence of core expenses. An F-test rejects the null of equivalence between the estimated coefficients on *PredSI* and *OppSI* for each of the samples.

Although opportunistic special items are negatively associated with future earnings, the absolute value of the coefficient is smaller than the coefficient on earnings before taxes and special items (e.g., 0.356 < 1.016 in the sample with opportunistic special items) in each of the samples; F-test not tabulated. This is not surprising considering the noise in the measurement of opportunistic special items. As we note earlier, we do not expect that all of the special items in that category are, in fact, misclassified recurring expenses. Instead, this partition allows for a coarse categorization, isolating the highest-quality special items and documenting the notably different implications of the two categories. When we form the more precise estimate of opportunistic special items (we discuss the methodology in Section 4.3 and the online appendix), the respective coefficient nearly doubles to 0.668 in absolute value (not tabulated). In other words, one dollar of opportunistic special items is associated with lower earnings of 67 cents in years *t*+2 and *t*+3. Although it remains smaller than the estimated coefficient on earnings before taxes and special items, we view the effect as economically significant. In sum, we provide evidence that the opportunistic, but not predicted, component of special items has negative implications for future earnings.

We examine future cash flows in Table 4. $\sum_{t+2}^{t+3} CFO_t$ denotes Cash from Operations (Compustat item OANCF – XIDOC), scaled by contemporaneous Net Sales and cumulated over years *t*+2 and *t*+3. Although the coefficient on total special items is not significant at conventional levels for the full sample (t-statistic = –1.27), the association between special items and future cash flows is significantly negative in the SI and OppSI samples.[12] We again find that this negative association is concentrated in the component of special items we classify as opportunistic. Specifically, the estimated coefficients imply that on average, one dollar of opportunistic special items during the current period corresponds to net operating cash outflows in years *t*+2 and *t*+3 of 25 cents (OppSI sample). This amount is lower than the analogous coefficient in Table 3 of 0.36 because some of the shifting is through depreciation expense, which does not affect cash from operations.

Although the evidence in Tables 3 and 4 supports that the opportunistic component of special items has different implications for future earnings and cash flows than the predicted component, it is possible that the estimated coefficients capture natural variation in the permanence of appropriately classified special items (e.g., Riedl and Srinivasan 2010). Thus, we also examine future returns, which we do not expect to be systematically associated with appropriately classified special items.

Turning to Table 5, $\sum_{t+2}^{t+3} BHAR_t$ denotes cumulative market-adjusted abnormal returns for years *t*+2 and *t*+3, aggregated starting twelve months after the earnings announcement for year *t*. The estimated coefficient on special items is significantly negative in all three samples. When we partition special items into the predicted and opportunistic components, the effect is again concentrated in opportunistic special items. In particular, the estimated coefficient on predicted special items is insignificant, whereas the coefficients on opportunistic special items are significantly negatively associated with future abnormal returns across all three samples, consistent with investors' disappointment as shifted expenses recur. For example, in the full sample the estimated coefficient on opportunistic special items is –0.240 versus –0.091 for

[12] Note that Doyle et al. (2003) do not consider firms with non-zero special items. The insignificant coefficient on special items for the full sample is consistent with the results presented in their Table 3, Panel B.

predicted special items. Even though an F-test fails to reject the null of equivalence, the difference in the magnitude of the estimated coefficients is notable. Turning to economic significance, for the full sample a one standard deviation increase in opportunistic special items implies negative abnormal returns in years t+2 and t+3 of –0.240 × 0.0580 = –1.39 percent. A similar analysis indicates that a one standard deviation increase in predicted special items implies negative abnormal returns in years t+2 and t+3 of –0.091 × 0.0391 = –0.36 percent.

The estimated coefficients on the control variables are generally consistent with expectations: *Momentum* and *Size* are negative, while *BM* is positive (e.g., Carhart 1997; Fama and French 1992). *Beta* is statistically insignificant across specifications, which conflicts with theory, but aligns with extant empirical research (Fama and French 1992). The one exception is the accruals metric we use, $Accruals^{Pre\text{-}SI}$, which is not negative and significant. This is likely because accruals and special items are highly correlated, and much of the "accrual" anomaly is due to special items (Dechow and Ge 2006). Because we cannot separate special items between accruals and cash flows, we remove total special items from the accrual variable. Although we realize the assumption that special items are entirely accruals is not realistic, as a practical matter, if this design choice was simply a re-allocation of accruals into special items, we would expect both predicted and opportunistic special items to be negatively associated with future abnormal returns, which is not the case.

In summary, the results in Tables 3–5 support that the implications of special items for future earnings, cash flows, and equity returns depend on the validity of the special item. In other words, it validates the notion that special items should not be treated as a homogenous group and highlights the importance to investors of exercising due diligence in assessing how much of the reported special items should be considered transitory, thereby increasing the usefulness of non-

GAAP earnings. Although the returns tests provide some confidence that our classification of opportunistic special items includes misclassified recurring expenses, we proceed by corroborating the meaningfulness of our partition with an analysis of subsequent restatements related to special items, as well as an examination of incentives to shift in the next section.

4.2.2. Additional Analysis

In this section we provide two supplemental analyses. We first examine whether the propensity to experience a subsequent restatement related to special items in year *t* increases with the opportunistic component of the special items. Then, we evaluate whether our estimate of opportunistic special items is related to incentives to shift, using the propensity to meet or just beat the analyst forecast as the setting.

4.2.2.1. Future Restatements

As we note previously, Appendix 1 offers several anecdotal examples of restatements related to the intentional misclassification of recurring expenses. Here we investigate the issue in a systematic manner by exploring the association between the special items partitions and subsequent financial restatements. Specifically, we estimate the following regression model:

$$\begin{aligned}\Pr(Restate{=}1){=}F(&\phi+\varphi_1 SI_{i,t}+\varphi_2 ln(AT_{i,t})+\varphi_3 SalesVol_{i,t}+\varphi_4 CFOVol_{i,t}\\&+\varphi_5 \%Loss_{i,t}+\varphi_6 BigN_{i,t}+\varphi_7 OperatingCycle_{i,t}\\&+\varphi_8 \Delta SalesGrowth_{i,t}+\varphi_9 Returns_{i,t}+\theta' FE+\eta_{i,t})\end{aligned} \quad (3)$$

Ideally, *Restate* would take the value of one if a recurring expense is misclassified as special and later restated. In practice, however, it is very difficult to identify restatements related specifically to the misclassification of special items; not only are these relatively rare, but traditional data providers, such as Audit Analytics, do not track them separately.

To work around the issue, we conduct a word search within the restatement descriptions, as provided by Audit Analytics, to identify restatements related to special items. Absent the availability of a well-accepted dictionary, we develop and validate, through spot checks, our own. After removing special characters and spaces, the dictionary comprises: *restruct*, *reorg*, *impair*, *write*, *loss*, *integration*, *onetime*, *transitory*, *special*, *severance*, *year2000*, *settle*, *nonrecurring*, *flood*, *fire*, *disaster*, and *assetretire*. Building on the Audit Analytics restatements database, we define *Restate* as an indicator variable set to one when a company files an accounting- or fraud-based restatement (Audit Analytics item RES_ACCOUNTING = 1 or RES_FRAUD = 1) linked to special items reported during a period overlapping with the examined fiscal year via the algorithm we describe above, zero otherwise. We acknowledge that using this list results in a high number of false positives, but believe the proxy is correlated with our underlying construct of interest. Although this approach introduces noise, the costs of manually verifying each restatement far exceeds the potential benefits, and our identified restatements do contain misclassification examples such as International Rectifier Corp. In untabulated analyses, we find that results weaken when we use all restatements in place of those identified through our dictionary. We begin the analysis in 2000, as this is the first year the relevant data are available through Audit Analytics. We control for firm size, financial and market performance metrics, and measures of oversight (we define the main variables in Appendix 2). To account for remaining un-modeled macro- and industry-specific factors, we also include industry-year fixed effects. We estimate the equation among firm-years with opportunistic special items, using a linear probability model and allowing the standard errors to cluster by firm.[13]

Results are presented in Panel A of Table 6. We note that the propensity to restate for special item-related reasons increases in total special items, providing some validation for the

[13] We take this approach because of claims that binary estimators are susceptible to bias in the presence of indicator variables (e.g., Angrist and Pischke 2009). As a practical matter, inferences remain unaffected when we evaluate the model via a Logit estimator (not tabulated).

adopted methodology for identifying special-items-related restatements. Partitioning the variable into predicted and opportunistic components reveals that the effect is concentrated within opportunistic special items. Although both coefficients are positive, only the coefficient on opportunistic special items is statistically significant. Moreover, although an F-test fails to reject the null of equivalence between the two estimated coefficients, the coefficient on opportunistic special items is over six times larger (e.g., 0.038 versus 0.006, when the full set of controls is included). In terms of economic significance, a one standard deviation increase in opportunistic special items (0.0930; untabulated) is associated with an increase in the unconditional probability of a special-item-related restatement (2.65 percent; untabulated) of 13.34 percent (0.038 × 0.0930 / 0.0265). Thus, we provide some evidence that restatements of special items are concentrated in the opportunistic component of special items.

4.2.2.2. Incentives

An often-cited incentive to manage earnings through special items is meeting the analyst consensus forecast, which generally excludes special items (e.g., McVay 2006; Fan et al. 2010). Thus, as a validity check, we examine the association between the intensity of opportunistic special items and the likelihood of just meeting the analyst forecast (by zero to two cents) in the four fiscal quarters of year *t*.[14]

[14] We focus on the zero to two cents band because strategic use of special items would be most compelling when it allows the firm to meet its reporting target, whereas it would add little value for a firm that already beats the reporting target by a comfortable margin. We consider all four fiscal quarters, rather than only quarters with reported special items, for two reasons. First, considering all fiscal quarters allows the examined period to match our annual measure of opportunistic special items. Second, the special item could influence just meeting the analysts' consensus forecast in quarters other than the one with the special item. For example, lower depreciation rates could facilitate meeting the analyst forecast and then the accumulation could be eliminated with a fourth-quarter asset impairment, or a first-quarter asset impairment that was too high could mechanically lower the depreciation expense for the remaining quarters. Following this line of reasoning, we subsequently extend the examination to the years surrounding special items recognition.

Because special items are endogenous, and often stem from poor performance, we expect special item firms will be less likely to just meet or beat the analyst forecast than their peers. Moreover, we expect the effect to increase with the magnitude of the special item (a firm with a large restructuring charge will be more likely to miss the analyst forecast than a firm with a small restructuring charge). Put differently, considering the sales-deflated predicted and opportunistic special items partitions, as we do in the preceding analyses, raises endogeneity concerns. We address the issue by examining the intensity of opportunistic special items; holding the magnitude of the reported special items constant, the larger the portion attributable to the opportunistic component, the higher the likelihood that shifted recurring expenses have been used to meet the analysts' consensus forecast. If opportunistic special items are used to meet the analysts' consensus forecast, we expect a positive association between the proportion of special items that is opportunistic and the proportion of quarters the firm meets the reporting target. The empirical model takes the form:

$$\%MBE_{t} = \omega + \tau_1 \%OppSI_{i,t} + \tau_2 BM_{i,t} + \tau_3 \ln(AT_{i,t}) + \tau_4 Returns_{i,t} + \theta' FE + \pi_{i,t} \tag{4}$$

where all variables are as defined in Appendix 2 and the *FE* vector comprises industry-year fixed effects. Similar to the restatements analysis, we estimate the equation using a linear probability model, although inferences are not sensitive to using an ordered logit estimator (not tabulated). Finally, we cluster the standard errors by firm.

We present the results in the first two columns of Table 6, Panel B. Consistent with our conjecture, *%OppSI* is significantly positively associated with *%MBE* in both the SI and OppSI samples. In terms of economic significance, moving *%OppSI* from zero to one is expected to increase the unconditional mean of *%MBE* (0.2939 and 0.2959 in the SI and OppSI samples, respectively; untabulated) by between 0.026 / 0.2939 ≈ 8.8 percent and 0.056 / 0.2959 ≈ 18.9

percent. This finding is consistent with the conjecture that managers shift recurring expenses to the special item to meet the analysts' consensus forecast, which generally excludes them.[15]

We next consider *%MBE* in year t–1 and year t+1. We expect that firms with a special item in year t can increase their likelihood of just meeting the analysts' consensus forecast in the adjacent periods through under-expensing in the prior year or shifting future recurring expenses to the special item in year t and, thus, under-expensing in the subsequent year. Thus, we focus on firms that report an income-decreasing special item in year t. We present the results for $\%MBE_{t-1}$ and $\%MBE_{t+1}$ in the second pair and last pair of columns in Panel B of Table 6, respectively.

Consistent with shifting from the past and future representing small amounts over many years, the estimated coefficients are lower than those for $\%MBE_t$. In each specification, however, they are positive and significant, consistent with the notion that shifting from the past and future helps firms to meet or narrowly beat the analysts' consensus forecast in those adjacent periods. Turning to economic significance, moving *%OppSI* from zero to one in the OppSI specifications implies an increase in the unconditional mean of $\%MBE_{t-1}$ of 0.031 / 0.3196 ≈ 9.7 percent and of $\%MBE_{t+1}$ of 0.022 / 0.2999 ≈ 7.3 percent. Collectively, these results provide additional support for the construct validity of our partition of special items, as we find that the proportion of opportunistic special items varies predictably with incentives to misclassify recurring expenses.

[15] As previously noted, it is difficult for financial statement users to disentangle misclassified expenses. To the extent analysts are able to undo the misclassification, however, we expect the magnitude by which managers' non-GAAP earnings exceed analysts' assessments of recurring earnings to increase with %OppSI (i.e., managers exclude the charges but analysts do not). Using data from Bentley et al. (2018) (available at https://sites.google.com/view/kurthgee/), we find support for this conjecture (untabulated). We caution, however, that this result may obtain because managers who shift recurring expenses to special items are also more likely to omit non-special items, such as amortization expense or stock-based compensation expense, from the firm-reported non-GAAP earnings.

4.2.3 Shifting over Time

Although Figure 1 supports that the reporting of income-decreasing special items has increased dramatically over time, the growth in the magnitude of special items as a percentage of sales is more subdued. This is consistent with the mandate of SFAS 146 (now ASC 420), which limits the recognition of liabilities to those actually incurred, curbing the shifting of future expenses to the current special item (e.g., Lee 2014). Indeed, on average, opportunistic special items as percentage of the total reported special item generally decreases through time (Figure 2). The effect is not as stark as the relevant changes to US GAAP would have suggested. The trend, however, is not surprising in light of the effect on special items from the enactment of Regulation G (e.g., Kolev et al. 2008) and the recently renewed focus of the SEC on non-GAAP reporting.

4.2.4. Discussion of Residual-Based Model Limitations

As with all models relying on a residual, we expect that our measure of opportunistic special items contains noise. In this section, we examine two settings where the measurement error is likely to be more pronounced. In the following section, we introduce an alternative model and contrast the pros and cons of both approaches to identify opportunistic special items.

The basis for our model is that, in general, poorly performing firms experience events that lead to the recognition of special items, such as asset impairments and restructuring charges. By identifying the "expected" component of special items, we are able to isolate the "unexpected" or potentially opportunistic component. Thus, we expect our model to yield higher measurement error when well-performing firms recognize special items, as the determinants model will be less likely to predict these special items. To investigate this issue, we partition the sample by industry-year performance tercile, where we measure performance as pre-tax, pre-special items income scaled by lagged total assets.[16] We are sensitive to the econometric challenges arising from partitioning a sample by a construct correlated with the dependent variable in the regression model; hence, we only consider future cash flows and returns. When we re-estimate Equation (2) for future cash flows and returns within the highest and lowest performance terciles (untabulated), we find that the associations between opportunistic special items and subsequent cash flows and returns are consistently more negative within the subsample of poorly performing firms, where we expect the model to fit best.

In addition, the examined "shifting" mechanisms are feasible only if the reported special item can encapsulate prior, current, or future recurring expenses. As previously described, an example is asset impairments, which can include past, current, and future depreciation expense. In fact, shifting is feasible with most types of special items (e.g., M&A integration expenses, restructurings, etc.). We expect, however, that goodwill impairments are less likely to contain expenses shifted from the past and current period. In particular, unlike capital expenditures, there was little subjectivity in the salvage value (zero) or the amortization schedule (40 years) prior to 2002 when amortization of goodwill was eliminated by SFAS 142 (now ASC 350). Moreover, unlike M&A integration charges or restructuring charges, goodwill impairments do not typically include other expenses that could feasibly be misallocated to the special item. Finally, since 2002 goodwill impairments cannot be written off prematurely to avoid future amortization.

To investigate this, we partition the observations with special items between those that do and do not have goodwill impairments (we identify goodwill impairments using Compustat item GDWLIP, which is not well-populated prior to 2000; this research design choice skews the

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[16] We do not consider scaling by sales, as we do in the other analyses, since return on assets yields a more complete measure of profitability, adding operating efficiency to margin (recall return on assets = margin×asset turnover). As a practical matter, this analysis aims to identify settings where the proposed model will perform best and worst. Since shifting from the past increases total assets, it artificially lowers return on assets, pushing the respective observation to the subsample where we conjecture the model to work best.

analysis to the more recent period). We expect our model will perform worse among observations with goodwill impairments than among those with only other types of special items. Our analysis yields results consistent with this conjecture. Specifically, the negative association between our estimate of opportunistic special items and each of the three performance metrics we consider in the main analysis (future earnings, cash flows, and returns; untabulated) is more pronounced among the observations that do not have goodwill impairments as a component of the reported special item.

To summarize, we expect our residual-based model to be less effective when the reported special items are not a result of economic stress, as modeled in Equation (1), and when the reported special items are not as amenable to masking the shifting of past, present, or future recurring expenses.

4.3 An Alternative Approach to Identifying Opportunistic Special Items

4.3.1 Overview

Thus far, we identify the opportunistic component of special items as the residual from industry-year estimations of Equation (1). As we discuss previously, such an approach, even if straightforward to implement and not requiring data from future periods, over-estimates the proportion of special items that are classified as opportunistic. To mitigate this, we propose a more precise methodology that explicitly estimates shifting from the past, present, and future, using the fitted value with respect to the identified shifted expenses as a measure of the opportunistic special items component. Although this methodology is more arduous to implement—it requires data from future periods and adds another layer to the estimation process—it allows us to generate a more precise estimate of the opportunistic component of special items.

4.3.2 Estimating the Fitted-Value of Opportunistic Special Items

To identify the portion of special items that reflects misclassified recurring expenses that should have been reported as such in the past, present, and future, we build on the observation that any misclassification would result in abnormal performance in the respective periods, as the recurring expenses are not recognized as such and thus improve the respective reported recurring earnings. First, we identify measures of abnormal performance in the past (UE_NOA_{t-1}), present (UE_CE_t), and future ($UE\_\Delta CE_{t+N}$); we describe each in the online appendix. Next, we modify Equation (1) by including the respective abnormal performance measures for years *t*-1 through *t*+2, aiming to capture the extent to which the abnormal performance over the examined period reflects shifting to special items. We identify $\widehat{OppSI}$ as the fitted value implied by the estimated coefficients on the four variables and measure $\widehat{PredSI}$ as special items less $\widehat{OppSI}$. If Compustat does not indicate the reporting of income-decreasing special items or $\widehat{OppSI}$ ($\widehat{PredSI}$) is negative, we set $\widehat{OppSI}$ ($\widehat{PredSI}$) to zero.[17]

Although costlier to implement, this approach should suffer from a lower estimation error in identifying the opportunistic component of special items relative to the residual-based model. More so, by construction, it should provide a lower bound for the magnitude of opportunistic special items. Indeed, this fitted value approach identifies a much smaller proportion of special items as opportunistic. To illustrate the point, the fitted value of opportunistic special items ($\widehat{OppSI}$) in the pooled sample has a mean of 0.84 percent of sales, relative to $\widehat{PredSI}$ of 1.87 percent of sales (Table 1, Panel A), implying opportunistic special items comprise 31 percent of

[17] This approach is also subject to limitations. First, it relies on models of abnormal performance (past, present, and future) that may not be a good fit for all firms within an industry-year. Second, as with our residual-based model, it is likely that the estimate of shifting from the past contains some "unintentional" expense accumulation. We corroborate, however, that at least some of the identified abnormal asset build up is intentional, as it correlates with below-industry-average rates of bad debt and depreciation. Third, our estimate of shifting from the future provides a lower bound estimate of the respective opportunistic special items component, as shifting beyond year *t*+2 is ignored.

firm-reported special items, on average (0.84 / [0.84 + 1.87]). This value is notably lower than the coarser estimate based on the residual from Equation (1) that underlies our main analysis, which pegs the figure at 60.4 percent (1.63 / (1.63 + 1.07)). We note that the Pearson correlation between the residual-based and fitted-value based estimates of opportunistic special items is only 35.7 percent among the observations with income-decreasing special items (not tabulated), corroborating that the simplified model suffers from Type I errors (over-identification or false positives), whereas the more complex model potentially suffers from Type II errors (under-identification or false negatives). Statement users interested in assessing special items in real time will necessarily turn to the residual-based estimate of opportunistic special items, which is also easier to implement, but parties interested in identifying the specific type of shifting would benefit from incorporating the models of shifting from the past, present, and future. Overall, we believe the contrast helps illustrate the trade-offs of these two approaches.

4.3.3 Proportion of Shifted Expenses in the Residual-Based Estimate of OppSI

Although the opportunistic component of special items identified by the two methodologies we propose overlap, as we note in the prior section, their correlation is relatively low at 0.357. Considering that the residual-based measure of opportunistic special items invites noise, to gain an insight into how well it captures the shifting of recurring expenses from the past, present, and future, we next regress it on the vector of abnormal performance measures. The model takes the form:

$$OppSI_{i,t} = \eta + \theta_1 UE\_NOA_{i,t-1} + \theta_2 UE\_CE_{i,t} + \theta_3 UE\_\Delta CE_{i,t+1} + \theta_4 UE\_\Delta CE_{i,t+2} + \theta' FE + \omega \qquad (5)$$

Since *OppSI* is censored at zero, we consider a Tobit estimator. Consistent with prior analyses, however, we replicate the analysis using Ordinary Least Squares. As before, we focus on the samples with income-decreasing special items and opportunistic special items, using the full sample as a benchmark.

We present the results in Table 7. Starting with the shifting of past expenses into the current period special items, we expect the estimated coefficient on UE_NOA_{t-1} to be significantly positive, as the opportunistic component of special items should increase in the build-up of unrecognized past core expenses. Indeed, the coefficient on UE_NOA_{t-1} is positive and significant across estimators and samples (Tobit and OLS; full, SI, and OppSI).

Moreover, if managers shift current period core expenses into the special item, we expect a positive association between opportunistic special items and unexpected core earnings. Consistent with this notion, the coefficient on UE_CE_t is positive and significant in all specifications.

Finally, if managers accelerate future core expenses (e.g., depreciation, inventory, or bad debt expense) to the current period special item, we expect the estimate of opportunistic special items to be positively associated with future abnormal performance. Lending support to this line of logic, the estimated coefficients on the future abnormal performance measures are predominantly positive, although insignificant in the SI and OppSI samples. In untabulated analyses we also pool year *t*+1 and *t*+2; the inferences are unaffected. As noted previously, we expect shifting from the future to be released in small amounts over multiple periods limiting the power of the test when focusing on individual years. In sum, we provide evidence that the residual-based measure used in our main analysis is associated with shifting from the past and present.

5. Conclusion

The marked increase in the recognition of special items, coupled with the exclusion of the vast majority of these expenses from non-GAAP earnings, underscores the importance of identifying the economically driven component of special items versus the portion more likely to include misclassified expenses. In particular, anecdotal and academic evidence suggests that managers may shift future core expenses (e.g., depreciation expense as an asset write-off), current core expenses (e.g., marketing expenses as restructuring), or past core expenses (e.g., unrecognized bad debt expense as an asset write-off) into the current period special item. We propose a methodology for identifying the opportunistic component of special items and document that the resultant estimate is associated with negative future earnings, cash flows, and stock returns. As additional analyses, we provide evidence that the proxy positively predicts the recognition of restatements related to special items, that the likelihood of meeting or narrowly beating the analysts' consensus forecast increases in the intensity of the estimated opportunistic special item, and the metric is positively associated with measures of shifting from the past, present, and future.

We recognize that similar to other residual-based measures, this approach likely overstates the proportion of special items that are opportunistic. As such, we also consider a more demanding, yet more precise, procedure for estimating opportunistic special items. Although this approach yields a materially lower estimate of the intensity of opportunistic special items (30 versus 60 percent of total special items) and suggests that special items are, on average, economically driven, the evidence also supports that the misclassification of past, present, and future expenses is not trivial.

Our results are relevant for investors, analysts, creditors, and regulators, each of whom must assess the implications of reported special items. Our alternative estimation procedure (which requires future data) may be useful for auditors and those with a need to assess the implications of special items for firm value (e.g., acquirers, forensic accountants, and lawyers). Our fitted-value estimate should also be useful for researchers wishing to assess the quality of special items, especially considering that special items are the largest, most frequent, and most easily justified exclusion to arrive at non-GAAP earnings, which continue to increase in prominence (e.g., Bradshaw and Sloan 2002; Brown et al. 2012).

Appendix 1
Special Items Shifting Examples in AAERs and Restatements

<table>
<tr><th>Company</th><th>SEC File Date</th><th>Form</th><th>Period(s) Restated</th><th>Shifted from the Past</th><th>Shifted from the Present</th><th>Shifted from the Future</th></tr>
<tr><td rowspan="2">3Com</td><td>3/6/98</td><td>8-K</td><td>1998</td><td></td><td></td><td>X</td></tr>
<tr><td colspan="6">Reduced reported restructuring charge from $426 to $270 million. The restatement related to the “timing and costs associated with product swap-outs; a more accurate recording of costs associated with the elimination of duplicate facilities; and a revision of goodwill write-offs related to acquisitions by USR prior to the 3Com merger.”</td></tr>
<tr><td rowspan="2">Borden</td><td>3/24/98</td><td>8-K</td><td>1992–1993</td><td></td><td>X</td><td>X</td></tr>
<tr><td colspan="6">Reduced reported restructuring charge from $642 to $377.2 million. The restatement was from shifting both current period and future period operating expenses.</td></tr>
<tr><td rowspan="2">Enterasys Networks, Inc.</td><td>7/23/99</td><td>10-K/A</td><td>1997–1998</td><td>X</td><td>X</td><td>X</td></tr>
<tr><td colspan="6">Reclassified certain expenses relating to its business combinations from special charges to cost of sales and SG&A. The reduction of special charges related to expenses recorded for contract employee benefits and contract compensation write-offs of $12.5, software licenses and software tools costs of $7.0, professional fees and some facility costs reclassified to purchase price of $3.2, customer warranty and stock rotation costs of $3.0 and other costs reductions in estimates and classifications of $7.5.”</td></tr>
<tr><td rowspan="2">International Rectifier Corp.</td><td>8/1/08</td><td>10-K</td><td>2003–2007</td><td></td><td>X</td><td></td></tr>
<tr><td colspan="6">Restated special items to operating expenses. Reclassified manufacturing costs related to the consolidation and start up of certain facilities to cost of sales. Reclassified certain expenses concluded to be customary business expenses to their traditional location of presentation as selling and administrative, R&D or other expense. Reclassified severance charges that were unrelated to an announced exit plan or reduction in workforce plan to the classification and function of the employee terminated.</td></tr>
<tr><td rowspan="2">Kimberly-Clark Corp.</td><td>7/21/99</td><td>8-K</td><td>1995–1999</td><td>X</td><td>X</td><td></td></tr>
<tr><td colspan="6">Restated an asset impairment to prior and current year depreciation expense. As they were deemed to have written off assets which actually represented depreciation for prior periods.</td></tr>
</table>

Appendix 2
Variable Definitions

Accruals	=	Total accruals defined as net income minus CFO; Compustat items IB – (OANCF – XIDOC).
$\text{Accruals}^{\text{Pre-SI}}$	=	Total accruals adjusted for income-decreasing special items (Accruals + Special Items).
Assets	=	Total assets; Compustat item AT.
ATO	=	Asset turnover defined as net sales divided by average NOA for the year; Compustat item SALE / $((NOA_t+NOA_{t-1})/2)$; ATO is required to be positive.
Beta	=	Market beta, as reported by Compustat.
BHAR	=	Market-adjusted buy-and hold abnormal return over the respective period.
Big N	=	Indicator variable set to one if the firm is audited by Arthur Andersen, Deloitte & Touche, Ernst & Young, KPMG, or PWC during the year; zero otherwise.
BM	=	Book to market value of equity; Compustat item CEQ_t / $(PRCC\_F_t \times CSHO_t)$.
CapEx	=	Capital expenditures; Compustat item CAPX.
CapitalIntensity	=	Property, plant, and equipment as percentage of total assets (Compustat items PPENT / AT).
CFO	=	Cash from Operations, net of CFO attributable to extraordinary items and discontinued operations; Compustat item OANCF – XIDOC, scaled by Net Sales for the year. If XIDOC is missing, we set it to zero.
CFO Vol	=	CFO Volatility, measured as the standard deviation of CFO for the five years ending in year *t*, divided by the average CFO for the period; at least three non-missing observations are required.
CoreEarnings	=	Operating income before depreciation and amortization; Compustat item OIBDP.
CoreEarningsAD	=	Operating income after depreciation and amortization; Compustat item OIADP.
DiscontinuedOp	=	An indicator variable set to one if the firm reports income from discontinued operations during the year (Compustat item DO); zero otherwise.
EmployeeDecline	=	An indicator variable set to one if the firm reports a decline in the number of employees (Compustat item EMP) from year *t-1* to year *t*; zero otherwise.
%GAAPLoss	=	Percentage of years where the company reported negative income before extraordinary items and discontinued operations (Compustat item IB) for the five years ending in year *t*; at least three non-missing observations are required.
HighROA	=	Indicator variable set to one if the firm is in the top industry-year ROA quintile; zero otherwise.
IndSI	=	The industry average, excluding firm *i*, of declared income-decreasing special items scaled by net sales for the fiscal year.
%IndSI	=	The percentage of firms in the industry group that declared income-decreasing special items for the fiscal year, excluding firm *i*.
IntangibleIntensity	=	Intangible assets as percentage of total assets (Compustat items INTAN / AT).
LargeSalesDecline	=	Indicator variable set to one if the firm is in the bottom industry-year sales growth quintile; zero otherwise.
Loss	=	Indicator variable set to one if the firm reports net pre-tax loss before special items, extraordinary items and discontinued operations (Compustat item IP – SPI) for the fiscal year; zero otherwise.
%Loss	=	Percentage of years where Loss = 1 over the specified measurement period.

%MBE	=	Percentage of quarters during the fiscal year when the analysts' forecast error is between zero and three cents per share. The benchmark consensus forecast is the latest for the quarter, measured at least three days prior to the respective earnings announcement.
$Merger_{t,t-1}$	=	Indicator variable set to one if the firm underwent M&A activity during the current or prior year, as reported by Compustat (positive value of Compustat item AQS, "acquisitions sales contribution"); zero otherwise.
Momentum	=	Buy-and-hold market-adjusted return for the six months ending with the earnings announcement date for the year.
MVE	=	Market value of equity; Compustat items $PRCC\_F_t \times CSHO_t$.
NegSalesGrowth	=	Sales Growth when the variable is negative; zero otherwise.
NIBT	=	Net income before taxes (Compustat item PI).
NIBTSI	=	Net income before special items and taxes (Compustat item PI, adjusted for income-decreasing special items, as reported by Compustat).
NOA	=	Net operating assets defined as operating assets minus operating liabilities where Operating Assets are calculated as Total Assets minus Cash and Short Term Investments (Compustat items AT – CHE) and Operating Liabilities are defined as Total Assets minus Short and Long Term Debt, Stockholders' Equity and Minority Interest (Compustat items AT – DLTT – DLC – SEQ – MIB). If minority interest is not reported by Compustat, we set it to zero.
OpCycle	=	Log-transformed sum of days inventory outstanding and receivables outstanding, where either is set to zero, if missing; Compustat items $[365/(COGS_t/(INVT_t+INVT_{t-1})/2))]$ and $[365/(SALE_t/(RECD_t+RECD_{t-1})/2))]$, respectively.
OppSI	=	The residual of Equation (1), estimated by industry-year. The variable is set to zero if no income-decreasing special items are reported or the estimate is below zero.
$\widehat{\text{OppSI}}$	=	Estimate of the amount of past, current, and future core expenses shifted to special items; see equation below. This variable is set to zero if no income-decreasing special items are reported or the estimate is below zero. $\widehat{OppSI_{i,t}} = \widehat{\theta_1} \times UE\_NOA_{i,t-1} + \widehat{\theta_2} \times UE\_CE_{i,t} + \widehat{\theta_3} \times UE\_\Delta CE_{i,t+1} + \widehat{\theta_4} \times UE\_\Delta CE_{i,t+2}$
%OppSI	=	OppSI / (OppSI + PredSI)
PredSI	=	The fitted value of Equation (1), estimated by industry-year. The variable is set to zero if no income-decreasing special items are reported or the estimate is below zero.
$\widehat{\text{PredSI}}$	=	Special Items–minus $\widehat{\text{OppSI}}$. The variable is set to zero if no income-decreasing special items are reported or the estimate is below zero.
Returns	=	Change in market value of equity for the fiscal year; Compustat items $(PRCC\_F_t \times CSHO_t - PRCC\_F_{t-1} \times CSHO_{t-1})/(PRCC\_F_{t-1} \times CSHO_{t-1})$.
Sales	=	Net sales; Compustat item SALE.
Sales Growth	=	Sales growth; Compustat items $(SALE_t - SALE_{t-1}) / SALE_{t-1}$.
Sales Vol	=	Sales Volatility, measured as the standard deviation of net sales for the five years ending in year *t*, divided by the average net sales for the period; at least three non-missing observations are required.
Special Items (SI)	=	Income-decreasing special items or zero; Compustat item SPI×(–1), for SPI < 0, 0 otherwise.

SumSI = Sum of SI as proportion of Sales over the specified period.

UE_CE = Unexpected core earnings; we estimate the coefficients below by year and industry, excluding firm *i*, and use these coefficients to calculate firm *i*'s predicted CE. We then subtract the predicted CE from reported CE.

$$CoreEarnings_{i,t} = \alpha + \beta_1 CoreEarnings_{i,t-1} + \beta_2 ATO_{i,t} + \beta_3 Accrual_{i,t-1} + \beta_4 Accrual_{i,t} + \beta_5 SalesGrowth_{i,t} + \beta_6 NegSalesGrowth_{i,t} + \varepsilon_{i,t}$$

UE_ΔCE = Unexpected change in core earnings; we estimate the coefficients below by year and industry, excluding firm *i*, and use these coefficients to calculate firm *i*'s predicted ΔCE. We then subtract the predicted ΔCE from reported ΔCE.

$$\Delta CoreEarningsAD_{i,t+1} = \alpha'' + \beta_1'' \widehat{CoreEarnings}AD_{i,t} + \beta_2'' \Delta \widehat{CoreEarnings}AD_{i,t} + \beta_3'' \Delta ATO_{i,t+1} + \beta_4'' SalesGrowth_{i,t+1} + \beta_5'' NegSalesGrowth_{i,t+1} + \varepsilon_{i,t+1}''$$

UE_NOA = Unexpected NOA; we estimate the coefficients below by year and industry, excluding firm *i*, and use these coefficients to calculate firm *i*'s predicted NOA. We then subtract the predicted NOA from reported NOA.

$$NOA_{i,t} = \delta + \gamma_1 CapEx_{i,t} + \gamma_2 SalesGrowth_{i,t} + \gamma_3 NegSalesGrowth_{i,t} + \gamma_4 Merger_{i;t,t-1} + \gamma_5 \mathrm{OperatingCycle}_{i,t} + u_{i,t}$$

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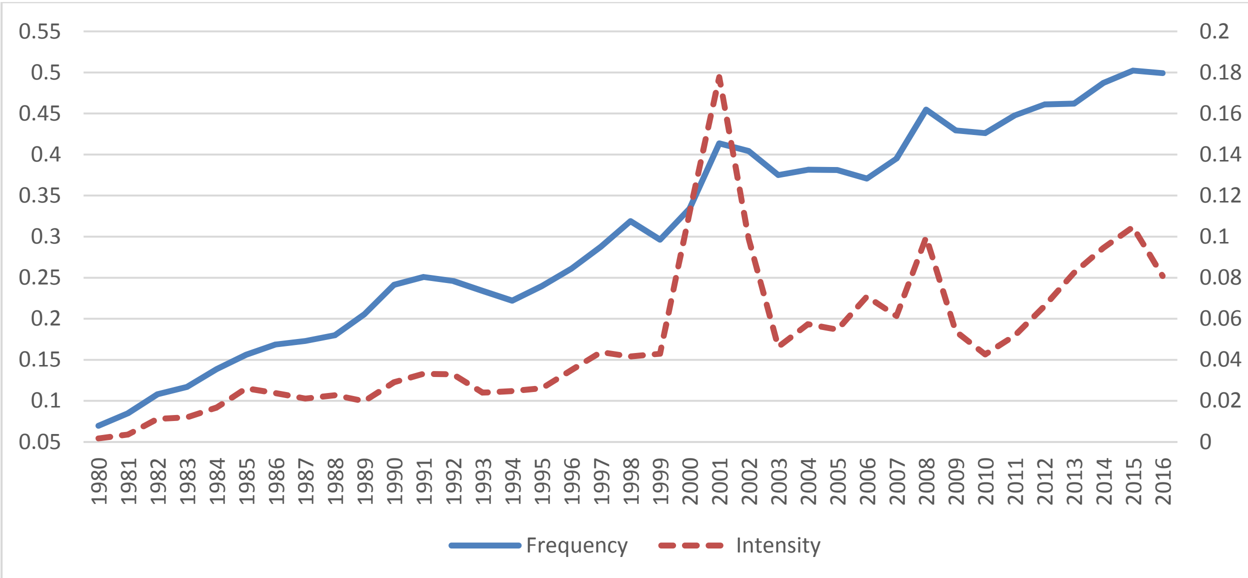
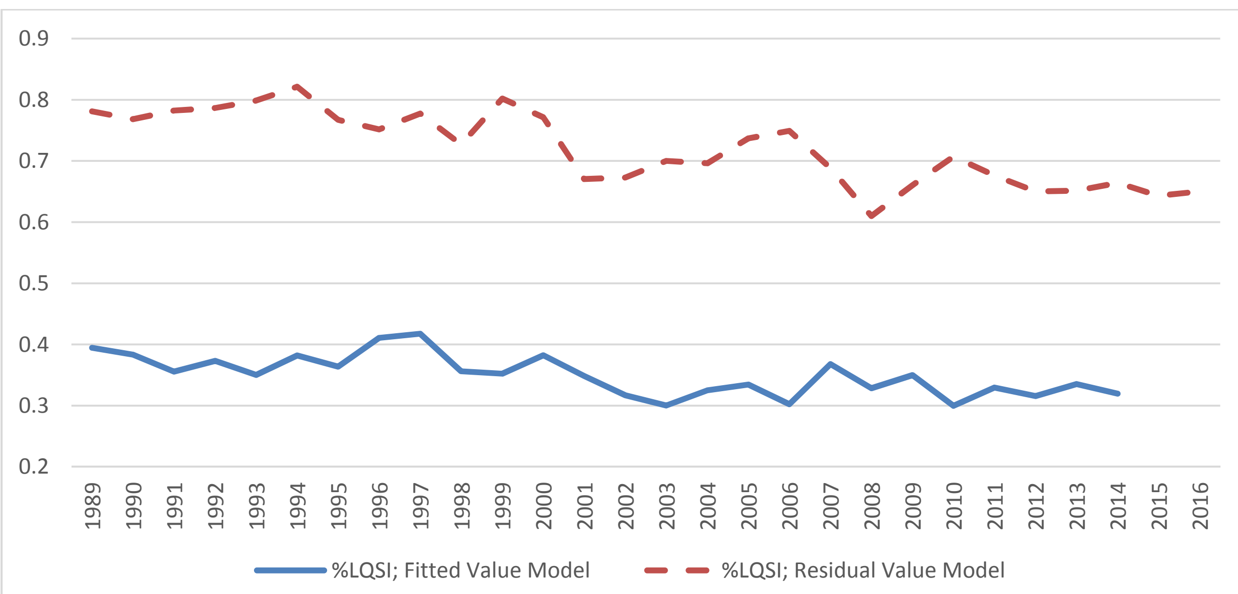
Figure 1: Incidence and Intensity of Income-decreasing Special Items through Time



The graph reflects the frequency (solid line; left axis) and intensity (dashed line; right axis), as percentage of net sales, income-decreasing special items by fiscal year among firms with positive total assets and sales, as reported by Compustat. Intensity is winsorized at 99% by fiscal year.

Figure 2: OppSI Intensity



The graph presents the time-series of the ratio of estimated opportunistic to total special items. The dashed line corresponds to the main model used in the paper, where the proportion of opportunistic special items is based on the model residual, and the solid line reflects the fitted value model estimates, referenced in Section 4.3.

Table 1

Panel A: Descriptive Statistics, Pooled Sample

	# Obs.	Mean	Q1	Median	Q3	StdDev
Total $Assets_t$	104,495	6,757.96	67.66	403.91	2,192.44	32,022.35
Net $Sales_t$	104,495	2,908.08	51.45	259.87	1,318.69	9,600.77
Pre-tax $Income_t$ / Net $Sales_t$	104,495	–0.0301	–0.0227	0.0540	0.1347	0.4992
Core $Earnings_t$ / Net $Sales_t$	101,350	0.0861	0.0426	0.1168	0.2301	0.4128
Special $Items_t$ / Net $Sales_t$	104,495	0.0244	0.0000	0.0000	0.0102	0.0842
Sales $Growth_t$	104,495	0.0925	–0.0420	0.0599	0.1789	0.2955
$Loss_t$	104,495	0.2537	0.0000	0.0000	1.0000	0.4351
ATO_t	100,083	2.5032	0.7598	1.6233	2.8436	3.4591
BM_t	104,078	0.5808	0.2976	0.5453	0.8922	1.6474
$OppSI_t$	104,495	0.0163	0.0000	0.0000	0.0043	0.0580
$PredSI_t$	104,495	0.0107	0.0000	0.0000	0.0000	0.0391
$\widehat{\mathrm{OppSI}}_t$	90,972	0.0084	0.0000	0.0000	0.0000	0.0322
$\widehat{\mathrm{PredSI}}_t$	90,972	0.0187	0.0000	0.0000	0.0035	0.0716
$NIBTSI_t$ / Net $Sales_t$	104,495	–0.0003	–0.0018	0.0622	0.1429	0.4443
$\sum_{t+2}^{t+3} \mathrm{NIBTSI}_t/\mathrm{Net\ Sales}_t$	83,275	0.0416	0.0046	0.1188	0.2670	0.6725
CFO_t / Net $Sales_t$	104,495	0.0696	0.0210	0.0876	0.1879	0.3541
$\sum_{t+2}^{t+3} \mathrm{CFO}_t/\mathrm{Net\ Sales}_t$	83,141	0.1626	0.0517	0.1678	0.3500	0.5502
$\sum_{t+2}^{t+3} \mathrm{BHAR}_t$	67,581	0.0805	–0.3941	–0.0352	0.3296	0.8489

Panel B: Descriptive Statistics, Observations with Income-Decreasing Special Items versus No Income-Decreasing Special Items

Variables	Income-Decreasing Special Items			No Income-Decreasing Special Items			Equality of Means / Medians
	# Obs.	Mean	Median	# Obs.	Mean	Median	
Total $Assets_t$	42,788	8,828.02	682.60	61,707	5,322.57	208.15	0.01 / 0.01
Net $Sales_t$	42,788	3,857.55	465.95	61,707	2,249.71	167.37	0.01 / 0.01
Pre-tax $Income_t$/Net $Sales_t$	42,788	–0.0983	0.0255	61,707	0.0171	0.0719	0.01 / 0.01
Core $Earnings_t$/Net $Sales_t$	41,772	0.0713	0.1109	59,578	0.0966	0.1208	0.01 / 0.01
Special $Items_t$/Net $Sales_t$	42,788	0.0596	0.0163	61,707	0.0000	0.0000	0.01 / 0.01
Sales $Growth_t$	42,788	0.0770	0.0442	61,707	0.1032	0.0707	0.01 / 0.01
$Loss_t$	42,788	0.3086	0.0000	61,707	0.2156	0.0000	0.01 / 0.01
ATO_t	41,140	2.4643	1.5708	58,943	2.5304	1.6651	0.01 / 0.01
BM_t	42,634	0.5025	0.5218	61,444	0.6350	0.5606	0.01 / 0.01
$OppSI_t$	42,788	0.0397	0.0087	61,707	0.0000	0.0000	0.01 / 0.01
$PredSI_t$	42,788	0.0262	0.0000	61,707	0.0000	0.0000	0.01 / 0.01
$\widehat{\mathrm{OppSI}}_t$	36,228	0.0210	0.0015	54,744	0.0000	0.0000	0.01 / 0.01
$\widehat{\mathrm{PredSI}}_t$	36,228	0.0471	0.0089	54,744	0.0000	0.0000	0.01 / 0.01
$NIBTSI_t$ / Net $Sales_t$	42,788	–0.0302	0.0480	61,707	0.0204	0.0719	0.01 / 0.01
$\sum_{t+2}^{t+3} \mathrm{NIBTSI}_t/\mathrm{Net\ Sales}_t$	32,625	0.0242	0.1086	50,650	0.0528	0.1258	0.01 / 0.01
CFO_t / Net $Sales_t$	42,788	0.0572	0.0829	61,707	0.0781	0.0910	0.01 / 0.01
$\sum_{t+2}^{t+3} \mathrm{CFO}_t/\mathrm{Net\ Sales}_t$	32,588	0.1491	0.1642	50,553	0.1714	0.1705	0.01 / 0.01
$\sum_{t+2}^{t+3} \mathrm{BHAR}_t$	27,275	0.0934	–0.0237	40,306	0.0717	–0.0441	0.01 / 0.01

All variables are as defined in Appendix 2. All continuous variables are winsorized at 1% and 99% by fiscal year. The last column reports the p-values for a t-test for equality of means and median test for equality of medians.

Table 2
Determinants of Special Items

	Predicted Sign	Dependent Variable = SI			
		Estimated coefficients		*% of coefficients with*	
		Mean	*Median*	*E[sign]*	*p < 0.10*
Intercept	–	–0.178	–0.138	90.7%	71.9%
$Returns_{t-1}$	–	–0.007	–0.002	54.3%	18.9%
$Returns_{t-3,t-1}$	–	–0.003	–0.000	52.9%	15.7%
$\Delta BM_{t-3,t-1}$	+	0.004	0.001	52.8%	21.5%
$\Delta ROA_{t-3,t-1}$	–	–0.029	–0.018	54.6%	22.8%
$Merger_{t,t-1}$	+	0.024	0.020	72.5%	32.6%
$EmployeeDecline_{t-1,t}$	+	0.017	0.013	71.2%	23.0%
$DiscontinuedOp_{t}$	+	–0.006	0.004	55.8%	18.4%
$LargeSalesDecline_{t}$	+	0.022	0.013	65.0%	32.0%
$\Delta Sales_{t-3,t-1}$	–	–0.004	–0.001	51.6%	17.5%
$Loss_{t}$	+	0.060	0.044	83.9%	57.1%
$PctLoss_{t-3,t-1}$	+	0.008	0.009	55.4%	23.0%
ΔCFO_{t}	–	–0.050	–0.023	59.9%	29.8%
$OpCycle_{t-1}$	+	0.004	0.003	59.5%	21.9%
$CapitalIntensity_{t-1}$	+	0.006	0.009	53.8%	18.2%
$IntangibleIntensity_{t-1}$	+	0.100	0.086	74.6%	45.0%
$\ln(AT_{t-1})$	+	0.011	0.007	85.5%	52.5%
Pseudo-R^2		0.460	0.454		
# Industry-Year Regressions		771			
# Observations		104,495			
# Firms		11,991			

SI is income-decreasing special items scaled by sales. All variables are as defined in Appendix 2 and Δ is the first-differences operator. The "E[sign]" ("p < 0.10") column indicates what proportion of the estimated coefficients from the industry-year Tobit regressions obtain the predicted sign (are in the predicted direction and significant at p < 0.10 under a one-tailed test). All continuous variables are winsorized at 1% and 99% (0% and 99% if bound from below by zero) by fiscal year.

Table 3
Regressing Future Pre-Tax, Pre-SI Income on Predicted and Opportunistic Special Items

	Predicted Sign	**Dependent Variable =** $\sum_{t+2}^{t+3} NIBTSI_t$					
		Full Sample		***SI Sample***		***OppSI Sample***	
SI_t	**?**	**0.007** **(0.12)**		**–0.125** **(–1.98)**		**–0.132** **(–2.02)**	
$PredSI_t$	**?**		**0.388** **(3.85)**		**0.222** **(2.06)**		**0.415** **(2.30)**
$OppSI_t$	**–**		**–0.137** **(–1.70)**		**–0.266** **(–3.22)**		**–0.356** **(–3.66)**
$NIBTSI_t$	+	1.036 (46.49)	1.038 (46.66)	1.024 (31.08)	1.028 (31.22)	1.012 (28.12)	1.016 (28.29)
Sales $Growth_t$	?	–0.078 (–6.30)	–0.076 (–6.09)	–0.091 (–5.00)	–0.087 (–4.80)	–0.107 (–5.25)	–0.103 (–5.05)
Ind-Year Fixed Effects		*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
# Observations		83,275	83,275	32,625	32,625	25,972	25,972
# Firms		9,664	9,664	7,621	7,621	7,300	7,300
Adj. R^2		0.412	0.412	0.413	0.413	0.416	0.417
$PredSI_t = OppSI_t$			0.001		0.001		0.001

The dependent variable is Net Income before Taxes and Special Items scaled by contemporaneous Sales cumulated over years *t*+2 through *t*+3. All variables are as defined in Appendix 2. All continuous variables are winsorized at 1% and 99% (0% and 99% if bound from below by zero) by fiscal year. The full sample comprises all observations with sufficient data to estimate OppSI; the SI (OppSI) sample further requires the recognition of income-decreasing special items (identification of OppSI) in year *t*. All models are estimated using OLS and include industry-year fixed effects. The standard errors are clustered by firm. We report the t-statistics in brackets below the estimated coefficients. The main variable(s) of interest are in bold.

Table 4
Regressing Future Cash Flows on Predicted and Opportunistic Special Items

	Predicted Sign	**Dependent Variable = $\sum_{t+2}^{t+3} CFO_t$**					
		Full Sample		***SI Sample***		***OppSI Sample***	
SI_t	**?**	**–0.056**		**–0.120**		**–0.126**	
		(–1.27)		**(–2.61)**		**(–2.61)**	
$PredSI_t$	**?**		**0.207**		**0.115**		**0.147**
			(2.62)		**(1.35)**		**(1.07)**
$OppSI_t$	**–**		**–0.163**		**–0.222**		**–0.250**
			(–2.74)		**(–3.65)**		**(–3.39)**
CFO_t	+	1.048	1.049	1.057	1.059	1.037	1.039
		(47.59)	(47.74)	(36.43)	(36.61)	(33.19)	(33.31)
Sales $Growth_t$	?	–0.022	–0.021	–0.022	–0.019	–0.026	–0.024
		(–2.23)	(–2.07)	(–1.53)	(–1.35)	(–1.63)	(–1.52)
$Accruals^{Pre\text{-}SI}_t$	+	0.345	0.346	0.360	0.363	0.369	0.371
		(14.84)	(14.90)	(10.29)	(10.34)	(10.05)	(10.12)
Ind-Year Fixed Effects		*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
# Observations		83,141	83,141	32,588	32,588	25,943	25,943
# Firms		9,650	9,650	7,615	7,615	7,294	7,294
Adj. R^2		0.458	0.458	0.463	0.463	0.467	0.467
$PredSI_t = OppSI_t$			0.001		0.002		0.030

The dependent variable is CFO scaled by contemporaneous Sales cumulated over years *t*+2 through *t*+3. All variables are as defined in Appendix 2. All continuous variables are winsorized at 1% and 99% (0% and 99% if bound from below by zero) by fiscal year. The full sample comprises all observations with sufficient data to estimate OppSI; the SI (OppSI) Sample further requires the recognition of income-decreasing special items (identification of OppSI) in year *t*. All models are estimated using OLS and include industry-year fixed effects. The standard errors are clustered by firm. We report the t-statistics in brackets below the estimated coefficients. The p-value of the test on coefficient equivalence, $PredSI_t = OppSI_t$, is two-tailed. The main variable(s) of interest are in bold.

Table 5
Regressing Future Returns on Predicted and Opportunistic Special Items

	Predicted Sign	Dependent Variable = $\sum_{t+2}^{t+3} BHAR_t$					
		Full Sample		*SI Sample*		*OppSI Sample*	
SI_t	**?**	**–0.212**		**–0.271**		**–0.254**	
		(–4.02)		**(–4.78)**		**(–4.39)**	
$PredSI_t$	**?**		**–0.091**		**–0.167**		**–0.258**
			(–0.72)		**(–1.24)**		**(–1.31)**
$OppSI_t$	**–**		**–0.240**		**–0.306**		**–0.268**
			(–2.98)		**(–3.63)**		**(–2.74)**
$Beta_t$	+	0.009	0.008	0.002	0.001	–0.004	–0.004
		(1.34)	(1.28)	(0.22)	(0.16)	(–0.43)	(–0.43)
$Momentum_t$	–	–0.081	–0.080	–0.099	–0.099	–0.105	–0.105
		(–6.76)	(–6.73)	(–5.68)	(–5.65)	(–5.22)	(–5.22)
$Accruals^{Pre\text{-}SI}_t$	–	0.038	0.039	0.041	0.043	0.045	0.044
		(1.69)	(1.73)	(1.21)	(1.24)	(1.20)	(1.19)
BM_t	+	0.024	0.025	0.020	0.020	0.017	0.017
		(3.70)	(3.70)	(2.87)	(2.88)	(2.39)	(2.37)
$\ln(MVE_t)$	–	–0.009	–0.009	–0.013	–0.012	–0.012	–0.012
		(–3.96)	(–3.90)	(–4.09)	(–3.98)	(–3.36)	(–3.35)
Ind-Year Fixed Effects		*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
# Observations		45,593	45,593	21,023	21,023	16,327	16,327
# Firms		6,175	6,175	4,908	4,908	4,681	4,681
Adj. R^2		0.115	0.115	0.127	0.126	0.123	0.122
$PredSI_t = OppSI_t$			0.390		0.441		0.970

The dependent variable is market-adjusted buy-and-hold returns cumulated over years *t*+2 through *t*+3 starting the month after the earnings announcement for year T. All variables are as defined in Appendix 2. All continuous independent variables are winsorized at 1% and 99% (0% and 99% if bound from below by zero) by fiscal year. The full sample comprises all observations with sufficient data to estimate OppSI; the SI (OppSI) Sample further requires the recognition of income-decreasing special items (identification of OppSI) in year *t*. All models are estimated using OLS and include industry-year fixed effects. The standard errors are clustered by firm. We report the t-statistics in brackets below the estimated coefficients. The p-value of the test on coefficient equivalence, $PredSI_t = OppSI_t$, is two-tailed. The main variable(s) of interest are in bold.

Table 6
Panel A: Future Accounting Restatements on Special Items

	Predicted Sign	**Dependent Variable = *Restate***			
SI_t	?	**0.024** (2.68)		**0.026** (2.72)	
$PredSI_t$	?		**0.005** (0.16)		**0.006** (0.20)
$OppSI_t$	+		**0.035** (2.39)		**0.038** (2.42)
Controls		*Not Included*	*Not Included*	*Included*	*Included*
Industry-Year Fixed Effects		*Included*	*Included*	*Included*	*Included*
# Observations		25,379	25,379	25,199	25,199
# Firms		7,256	7,256	7,226	7,226
Adj. R^2		0.012	0.012	0.013	0.013
$PredSI_t = OppSI_t$			0.457		0.436

This panel provides the estimation of Equation (3) in Section 4.2.2.1. Restate is an indicator variable set to one if the fiscal year overlaps with a restatement period for the company and the restatement is 1) classified as related to accounting issues or fraud, and 2) the description of the restatement contains at least one of the key words related to SI. All other variables are as defined in Appendix 2. All continuous variables are winsorized at 1% and 99% (0% and 99% if bound from below by zero) by fiscal year. The sample comprises observations with OppSI > 0 in year *t*. All models are estimated using a linear probability model and include industry-year fixed effects. The standard errors are clustered by firm. We report the t-statistics in brackets below the estimated coefficients. The p-value of the test on coefficient equivalence, $PredSI_t = OppSI_t$, is two-tailed. The main variable(s) of interest are in bold.

Panel B: Regression of Analyst Benchmark Outcomes on %OppSI

		Dependent Variable =					
	Predicted Sign	**$\%MBE_t$**		**$\%MBE_{t-1}$**		**$\%MBE_{t+1}$**	
		SI Sample	***OppSI Sample***	***SI Sample***	***OppSI Sample***	***SI Sample***	***OppSI Sample***
$\%OppSI_t$	+	**0.026** (4.88)	**0.056** (5.53)	**0.015** (2.79)	**0.031** (3.06)	**0.012** (2.08)	**0.022** (1.98)
Controls		*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
Industry-Year Fixed Effects		*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
# Observations		27,606	21,618	26,616	20,776	24,686	19,378
# Firms		5,966	5,655	5,753	5,430	5,404	5,131
Adj. R^2		0.099	0.108	0.111	0.119	0.099	0.105

This panel provides the estimation of Equation (4) in Section 4.2.2.2. Regressions are estimated using a linear probability model. $\%MBE_t$ is the ratio of the quarters in the one year window of fiscal year t where the median consensus analyst forecast error is between zero and two cents per share. All other variables are as defined in Appendix 2. t-statistics are reported in brackets below the estimated coefficients. The errors are clustered by firm. The variable of interest is in bold. The SI Sample comprises firm-year observations with income-decreasing special items and sufficient data to estimate the proportion of opportunistic special items; the OppSI sample further requires the identification of OppSI during the period. The continuous variables, other than %MBE and %OppSI, are winsorized at 1% and 99% by fiscal year. The main variable of interest is in bold.

Table 7
Regression of OppSI on proxies for shifting from the past, present, and future

	Predicted Sign	**Dependent Variable = OppSI**					
		Tobit			**OLS**		
		Full Sample	***SI Sample***	***OppSI Sample***	***Full Sample***	***SI Sample***	***OppSI Sample***
UE_NOA_{t-1}	+	0.004	0.007	0.009	0.003	0.007	0.009
		(6.26)	(7.84)	(9.53)	(8.23)	(8.54)	(9.38)
UE_CE_t	+	0.064	0.065	0.070	0.033	0.059	0.070
		(10.34)	(8.42)	(8.53)	(9.65)	(8.44)	(8.39)
$UE\_\Delta CE_{t+1}$	+	0.017	–0.002	0.008	0.006	0.002	0.008
		(3.48)	(–0.34)	(1.23)	(2.36)	(0.34)	(1.21)
$UE\_\Delta CE_{t+2}$	+	0.013	0.000	0.006	0.004	0.003	0.006
		(2.96)	(0.09)	(1.07)	(2.02)	(0.56)	(1.06)
Industry-Year Fixed Effects		*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
# Observations		74,505	29,442	23,303	74,505	29,442	23,303
# Firms		8,964	7,031	6,711	8,964	7,031	6,711
Pseudo-R^2		0.439	–0.084	–0.077			
Adj. R^2					0.047	0.093	0.127

OppSI is the estimate of opportunistic special items measured as the residual from Equation (1). The full sample comprises firm-year observations with sufficient data to measure OppSI; the SI > 0 subsample further requires the reporting of an income-decreasing special item during the period. The standard errors are clustered by firm. We report the t-statistics in brackets below the estimated coefficients. Variable(s) of interest are in bold. All variables are as defined in Appendix 2. All continuous variables are winsorized at 1% and 99% (0% and 99% if bound from below by zero) by fiscal year.

Online Appendix to "Detecting Opportunistic Special Items"

Online Appendix A

A.1 Abnormal Past Performance (UE_NOA)

We estimate abnormal past performance via the model described by Equation (A.1). We use Net Operating Assets (NOA), which has been linked to balance sheet bloat (Barton and Simko 2002; Hirshleifer et al. 2004), as a proxy for the accumulation of assets (e.g., accounts receivable, inventory, equipment) that should have been expensed in the normal course of business. For example, a manager might recognize too little bad debt expense, or might depreciate equipment too slowly, both of which will result in the accumulation of past expenses as assets (e.g., net A/R or net PP&E) on the balance sheet. An alternative approach would entail examining unexpected earnings performance over a discrete set of prior years, analogous to our measure of shifting from the future we discuss below. Such a design, however, would only capture shifting over a limited period, whereas asset bloat allows for assessing the cumulative effect.

Ideally, we would isolate asset accumulation related to the intentional under-expensing of past assets; however, some asset accumulation may be due to errors in the estimation of needed inventory or industry downturns. Moreover, both DeFond (2002) and Choy (2003) note that industry is a necessary control when assessing net operating assets. Thus, to lower the likelihood that industry-wide and macroeconomic shocks are bundled into the error term, we estimate Equation (A.1) below within industry and year. The abnormal NOA model we consider takes the form:

$$NOA_{i,t} = \delta + \gamma_1 CapEx_{i,t} + \gamma_2 SalesGrowth_{i,t} + \gamma_3 NegSalesGrowth_{i,t} + \gamma_4 Merger_{i;t,t-1} + \gamma_5 \text{OperatingCycle}_{i,t} + u_{i,t} \quad \text{(A.1)}$$

Following prior research (e.g., Hirshleifer et al. 2004), we measure NOA as the difference between Operating Assets and Operating Liabilities. We scale NOA by Sales, to be consistent with the scaling of special items. As predictors, we consider Sales Growth and Capital Expenditures, since the accumulation of assets could be due to a decrease in product demand or in anticipation of an expansion in operations. We allow for a separate slope for decline in sales to account for asymmetric ratcheting (Anderson et al. 2003). We also include an indicator variable for merger or acquisition activity in years *t* or *t*–1, as we expect M&A to result in shocks to NOA. Finally, we include the length of the firm's operating cycle, as it directly relates to asset build-up. To avoid bias from the reporting choices of each examined firm, we estimate the necessary industry-year coefficients excluding firm *i*.

We apply the estimated coefficients to calculate firm *i*'s predicted NOA. We retain the regression residual as a measure of UE_NOA. We present the mean and median coefficient in Table A.1, Panel A; the mean R^2 is 30.4 percent.[18]

As initial support for the claim that our measure of past abnormal performance is in part a function of intentional accumulation of past expenses, we document a significantly negative correlation between abnormal net operating assets and industry-year-median adjusted allowance for bad debts and depreciation rates (Table A.2). In particular, abnormal net operating assets are higher when the firm's percentage of allowance for doubtful accounts is below the industry median and when the firm's depreciation rate is below the industry median. Although by itself the estimate could capture assets that are more productive, coupled with the subsequent reporting of an income-decreasing special item, the observed effect points to a systematic under-estimation of recurring expenses. The associations are persistent year-over-year, consistent with the stickiness of both depreciation rates and allowance for doubtful accounts estimates. In other words, if the abnormal net operating assets were a result of good performance, or unanticipated shocks to the firm or industry, we would not expect to find a systematically negative relation with these previously recorded subjective accounting estimates.

Turning to assessing the quality of special items, if managers delay normal operating expenses and later write them off as special items, the subsequently reported special items should increase in

[18] We do not include the level of NOA in the prior period as an explanatory variable as this specification would model the unexpected *change* in NOA, rather than the level of NOA. As a practical matter, if we include NOA_{t-1} as an explanatory variable in model (A.1), the average (median) R^2 jumps to 75.8 percent (80.2 percent). Although modeling the change in NOA weakens the observed effects, the main inferences we report are unaffected (not tabulated).

abnormal net operating assets. Thus, we expect unexpected net operating assets at the end of year *t*–1 to be positively associated with income-decreasing special items in year *t*. Consistent with this conjecture, we document a positive correlation between income-decreasing special items (SI_t / Net $Sales_t$) and unexpected net operating assets (UE_NOA_{t-1}; untabulated).

A portion of the estimated abnormal net operating assets likely reflects superior past performance. This component, however, should not be associated with subsequent income-decreasing special items. In other words, the refinement to the methodology to estimate opportunistic special items we propose attributes only the component of abnormal net operating assets associated with special items, not the entire value of UE_NOA, to the accumulation of past expenses.

A.2 Abnormal Current Performance (UE_CE)

Next, we turn to abnormal current performance. We base our model of abnormal core earnings on McVay (2006), as follows:

$$CoreEarnings_{i,t} = \alpha + \beta_1 CoreEarnings_{i,t-1} + \beta_2 ATO_{i,t} + \beta_3 Accrual_{i,t-1} + \beta_4 Accrual_{i,t} + \beta_5 SalesGrowth_{i,t} + \beta_6 NegSalesGrowth_{i,t} + \varepsilon_{i,t} \quad \text{(A.2)}$$

where we define Core Earnings as Operating Income before Depreciation and Amortization for the year, as reported by Compustat (Compustat item OIBDP), scaled by Net Sales for the year. Like McVay (2006), we focus on earnings before depreciation and amortization to avoid mechanical reductions in current period depreciation and amortization expense resulting from current-period asset write-downs. The vector of controls includes the prior period level of core earnings in Equation (A.2) as core earnings should persist. We also consider the asset turnover ratio (ATO), as special items may be associated with firm strategy, and core earnings (which, when scaled by Sales, approximate a firm's profit margin) is expected to shift with asset turnover (Nissim and Penman 2001). We include both prior period and current period accruals; holding earnings constant, accruals yield less persistent earnings than cash flows (Sloan 1996). Current period accruals are included by McVay (2006) as a performance control, as extreme performance is highly correlated with changes in accrual levels (DeAngelo et al. 1994). Mindful of potential endogeneity, we also consider an alternate model of current period shifting proposed by Fan et al. (2010), which excludes this variable, as a robustness check; inferences are not affected (untabulated). Finally, we include sales growth—as sales increase, fixed costs per sales dollar are expected to be lower—and allow the coefficient to vary for sales declines, as Anderson et al. (2003) find that costs are more sensitive to activity increases than to equivalent decreases.

We estimate the Equation (A.2) coefficients by year and industry, excluding firm *i*. Similar to the NOA approach, estimating the model by industry-year allows the coefficients on each of the variables to vary by industry-year and pushes industry and macro-economic shocks to the predicted value. We measure unexpected core earnings (UE_CE) as the difference between the reported and predicted values of Core Earnings.

We present the mean and median estimates from the industry-year regressions in Table A.1, Panel B. The mean R^2 of the model is 79.2 percent and the coefficients are generally in the predicted direction and are comparable to those reported in McVay (2006). Our arguments indicate unexpected current core earnings to increase in income-decreasing special items.[19] In other words, as core expenses are misclassified as special items, we expect unexpected core earnings to become more positive.

A.3 Abnormal Future Performance (UE_ΔCE)

We operationalize abnormal future performance through the unexpected improvements in earnings over the two years after reporting of the respective income-decreasing special item. We acknowledge that benefits gained by accelerating depreciation or other recurring expenses to the current period special item often extend beyond the next two years. We opt for a two-year window as a compromise between capturing the full economic effect of shifting future recurring expenses and the

[19] If managers shift core expenses to special items every period, our expectations models would be based on artificially inflated core earnings figures, thereby weakening the power of our tests. Investors, however, should begin to weight repeat special items more in line with recurring earnings (Elliott and Hanna 1996; Cready et al. 2010). Thus, managers are precluded from using special items to manage earnings every period if they desire the lower weighting on these charges.

associated data costs and measurement challenges associated with considering a longer horizon.[20] Hence, our future abnormal performance measure captures a lower bound of the effects of shifting from the future.[21] As a proxy for abnormal performance resulting from shifting of recurring expenses from the future, we consider the residual from the following model:

$$\Delta CoreEarningsAD_{i,t+1} = \alpha'' + \beta_1'' \widehat{CoreEarningsAD}_{i,t} + \beta_2'' \Delta \widehat{CoreEarningsAD}_{i,t} + \beta_3'' \Delta ATO_{i,t+1} + \beta_4'' SalesGrowth_{i,t+1} + \beta_5'' NegSalesGrowth_{i,t+1} + \varepsilon_{i,t+1}'' \quad \text{(A.3)}$$

This model is an adaptation of Equation (A.2). We apply four adjustments. First, we consider future core earnings *after* depreciation and amortization (Compustat item OIADP) to allow for the acceleration of future depreciation and amortization via the write-off of a productive asset. Second, we consider a changes, rather than levels, analysis. We take this approach with the aim of capturing the annual increment of overstated earnings. To adapt the model to changes, we include both the level and the change in core earnings, as mean reversion is expected to vary based on the level of earnings (Freeman et al. 1982). We also consider the change, rather than the level, in asset turnover. Third, since we require abnormal core earnings estimates based on pre-managed earnings, we consider the fitted values of the level and change in core earnings, rather than the reported (and potentially managed) values.[22] Finally, we do not include accruals in the model, as inter-period shifting affects accruals.

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[20] Ideally, we would use a measure of cumulative shift of future expenses, analogous with the shifting of expenses from the past, UE_NOA, model. The described annual metric we use as a substitute poses a need to compromise between power of the tests on one hand, and sample attrition and survivorship bias, on the other. As a practical matter, we confirm that power of the test is a non-trivial issue with such a specification by annualizing the NOA measure (i.e., we model the change in NOA), noting that the results from shifting from the past only for years *t*-1 and *t*-2 notably weakens the inferences (not tabulated).

[21] Ideally, as with the shifting of past expenses, we would like to consider a measure that reflects all future years of shifted expenses; for example, abnormal net operating assets at the end of year *t*. Theoretically, the abnormally low portion of net operating assets would reflect future expenses that were written off prematurely. It is possible, however, that net operating assets are abnormally low for performance-related reasons, and this abnormally low component of net operating assets would be correlated with special items, but not be reflective of opportunism. It is also possible that our measure of future write-offs could be capturing desirable levels of conservatism or performance improvements following a turn-around effort. These alternative explanations, however, would not predict an association with future restatements, or an association with lower future earnings and cash flows in year *t*+3. Moreover, these concerns extend only to shifting from the future, which comprises only 40 percent of our estimate of opportunistic special items for the mean company with positive OppSI (not tabulated).

[22] We estimate the fitted values using a version of Equation (A.2), which focuses on the level and change in core earnings after, rather than before, depreciation and amortization. This ensures consistency between the left- and right-hand side variables.

As before, we form our estimate of the future change in core earnings by year and industry, where the coefficients are estimated excluding firm *i*. Thus, we derive the unexpected change in future earnings (UE_ΔCE) as the reported value less the predicted value of the metric. We present the mean and median results of the estimation for year $t + 1$ in Table A.1, Panel C. The mean and median R^2 is over 40 percent.

As with our other measures of abnormal performance, we conjecture the unexpected change in future earnings would be positively associated with income-decreasing special items. Specifically, if managers accelerate future core expenses into a current period special item, then, we expect income-decreasing special items to increase in unexpected future earnings. Consistent with this notion, we note a small, but statistically significant, positive correlation between special items and both $UE\_\Delta CE_{t+1}$ and $UE\_\Delta CE_{t+2}$ (untabulated). An alternative interpretation of this correlation is that our estimate of shifting from the future captures real economic improvements highlighting the need to examine future cash flows and returns to present a more complete depiction of the underlying relations.

Table A.1: Model Fit Statistics

Panel A: Model of Abnormal NOA

	Mean		Median		
	Coefficient	t-statistic	Coefficient	t-statistic	% p ≤ 0.10
Intercept	0.637	2.20	0.349	1.63	61.6%
$CapEx_t$	2.853	5.45	2.612	4.35	77.2%
$SalesGrowth_t$	0.067	0.21	0.006	0.04	25.0%
$NegSalesGrowth_t$	–1.012	–0.80	–0.411	–0.57	35.2%
$Merger_{t,t-1}$	0.045	0.73	0.081	0.46	27.0%
$OperatingCycle_t$	0.014	0.63	0.040	0.65	55.2%
R^2	0.304		0.271	# industry-years: 1,090	

Panel B: Model of Abnormal Core Earnings

	Mean		Median		
	Coefficient	t-statistic	Coefficient	t-statistic	% p ≤ 0.10
Intercept	0.038	1.57	0.028	1.38	52.3%
$CoreEarnings_{t-1}$	0.785	16.51	0.785	14.54	99.2%
ATO_t	–0.001	–0.33	–0.001	–0.30	24.9%
$Accrual_{t-1}$	–0.181	–2.60	–0.158	–2.36	66.6%
$Accrual_t$	0.256	4.28	0.208	3.41	72.7%
$SalesGrowth_t$	0.093	2.05	0.059	1.68	54.7%
$NegSalesGrowth_t$	0.427	2.44	0.291	2.24	61.8%
R^2	0.792		0.812	# industry-years: 1,057	

Panel C: Model of Abnormal Changes in Core Earnings

	Mean		Median		
	Coefficient	t-statistic	Coefficient	t-statistic	% p ≤ 0.10
Intercept	0.012	0.90	0.012	0.79	40.0%
Fitted $CoreEarningsAD_t$	–0.163	–3.05	–0.165	–2.43	66.8%
Fitted $\Delta CoreEarningsAD_t$	–0.017	–0.09	–0.029	–0.19	45.0%
ΔATO_{t+1}	0.007	0.61	0.005	0.49	26.6%
$SalesGrowth_{t+1}$	0.105	1.90	0.065	1.29	48.0%
$NegSalesGrowth_{t+1}$	0.459	2.78	0.360	2.45	66.4%
R^2	0.421		0.413	# industry-years: 1,056	

We estimate the individual models by industry-fiscal year, where the industries are defined over the Fama and French (1997) classification. The sample spans fiscal years 1987–2013, 1988–2014, and 1989–2016 for Panel A, B, and C, respectively. The "% p ≤ 0.10" column reports the percentage of industry-fiscal year groups where the respective estimated coefficient is significant at 10 percent under a two-tailed test.

Table A.2
Correlation Matrix – Unexpected NOA and Intentional Expense Accumulation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) UE_NOA_t	-	**–0.0376**	**–0.1147**	**–0.2099**	**–0.0396**	**–0.1264**	**–0.2137**
		(0.001)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**
(2) $\%DoubtfulAccounts\_Adj_t$	**–0.0081**	-	0.0414	0.0663	0.8285	0.0461	0.0588
	(0.010)		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
(3) $DepreciationRate(Gross)\_Adj_t$	**–0.0593**	0.0420	-	0.6384	0.0302	0.8472	0.5265
	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)	(0.001)
(4) $DepreciationRate(Net)\_Adj_t$	**–0.1063**	0.0845	0.6736	-	0.0691	0.5892	0.8816
	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)
(5) $\%DoubtfulAccounts\_Adj_{t-1}$	**–0.0073**	0.7730	0.0281	0.0864	-	0.0438	0.0669
	(0.021)	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)
(6) $DepreciationRate(Gross)\_Adj_{t-1}$	**–0.0650**	0.0502	0.7643	0.5557	0.0492	-	0.6586
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)		(0.001)
(7) $DepreciationRate(Net)\_Adj_{t-1}$	**–0.1028**	0.0711	0.4799	0.7968	0.0829	0.7064	-
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	

Pearson (Spearman) correlations are below (above) the diagonal. UE_NOA is the residual from model 1. %DoubtfulAccounts is the ratio of Estimated Doubtful Receivables to Total Receivables plus Estimated Doubtful Receivables (Compustat items $RECD_t$ / ($RECT_t$ + $RECD_t$)). DepreciationRate(Gross) is the ratio of depreciation expense to average gross PPE (Compustat items (DP_t – AM_t) / (($PPEGT_t$ + $PPEGT_{t-1}$)/2)). DepreciationRate(Net) is the ratio of depreciation expense to average gross PPE (Compustat items (DP_t – AM_t) / (($PPENT_t$ + $PPENT_{t-1}$)/2)). _Adj signifies that the variables are deviations from the industry-year median. p-values are reported in brackets below the correlation coefficients.

Table B
Correlation Matrix – Main Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) $PredSI_t$	-	0.3375 (0.001)	–0.2536 (0.001)	–0.3138 (0.001)	–0.1528 (0.001)	–0.1547 (0.001)	–0.0158 (0.001)
(2) $OppSI_t$	0.4110 (0.001)	-	–0.3025 (0.001)	–0.3710 (0.001)	–0.2306 (0.001)	–0.2090 (0.001)	–0.0197 (0.001)
(3) CFO_t	–0.1629 (0.001)	–0.1922 (0.001)	-	0.7658 (0.001)	0.5367 (0.001)	0.6505 (0.001)	0.0295 (0.001)
(4) $NIBTSI_t$	–0.2149 (0.001)	–0.2504 (0.001)	0.7412 (0.001)	-	0.6119 (0.001)	0.5842 (0.001)	0.0315 (0.001)
(5) $\sum_{t+2}^{t+3} \text{NIBTSI}$	–0.0972 (0.001)	–0.1427 (0.001)	0.5310 (0.001)	0.6055 (0.001)	-	0.7515 (0.001)	0.1255 (0.001)
(6) $\sum_{t+2}^{t+3} \text{CFO}$	–0.0959 (0.001)	–0.1270 (0.001)	0.6401 (0.001)	0.5696 (0.001)	0.7424 (0.001)	-	0.0839 (0.001)
(7) $\sum_{t+2}^{t+3} \text{BHAR}$	–0.0057 (0.139)	–0.0079 (0.041)	0.0323 (0.001)	0.0265 (0.001)	0.1266 (0.001)	0.0876 (0.001)	-

Pearson correlations for the full sample (firm-years with current income-decreasing SI) are below (above) the diagonal; p-values are reported in brackets below the coefficients. All variables are as defined in Appendix 2 of the main paper and scaled by Sales. All continuous variables are winsorized at 1% and 99% (0% and 99% if bound from below by zero) by fiscal year.

Table C.1
Panel A: Regressing Future Pre-Tax, Pre-SI Income on Predicted and Opportunistic Special Items

	Predicted Sign	**Dependent Variable = $\sum_{t+1}^{t+3} NIBTSI_t$**					
		Full Sample		***SI Sample***		***OppSI Sample***	
SI_t	**?**	**–0.118** **(–1.56)**		**–0.338** **(–4.21)**		**–0.347** **(–4.25)**	
$PredSI_t$	**?**		**0.351** **(2.52)**		**0.068** **(0.46)**		**0.297** **(1.25)**
$OppSI_t$	**–**		**–0.308** **(–3.09)**		**–0.536** **(–5.13)**		**–0.641** **(–5.35)**
$NIBTSI_t$	+	1.530 (52.33)	1.532 (52.47)	1.493 (34.35)	1.497 (34.45)	1.483 (31.87)	1.487 (32.06)
Sales $Growth_t$	?	–0.091 (–5.49)	–0.088 (–5.33)	–0.108 (–4.57)	–0.104 (–4.46)	–0.133 (–4.89)	–0.123 (–4.75)
Industry-Year Fixed Effects		*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
# Observations		93,520	93,520	37,405	37,405	29,700	29,700
# Firms		10,749	10,749	8,546	8,546	8,180	8,180
Adj. R^2		0.468	0.468	0.460	0.460	0.466	0.466
$PredSI_t = OppSI_t$			0.001		0.001		0.002

The dependent variable is Net Income before Taxes and Special Items scaled by contemporaneous Sales cumulated over years *t*+1 through *t*+3. All variables are as defined in Appendix 2. All continuous variables are winsorized at 1% and 99% (0% and 99% if bound from below by zero) by fiscal year. The full sample comprises all observations with sufficient data to estimate OppSI; the SI (OppSI) Sample further requires the recognition of income-decreasing special items (identification of OppSI) in year *t*. All models are estimated using OLS and include industry-year fixed effects. The standard errors are clustered by firm. We report the t-statistics in brackets below the estimated coefficients. The main variable(s) of interest are in bold.

Panel B: Regressing Future Cash Flows on Predicted and Opportunistic Special Items

	Predicted Sign	**Dependent Variable = $\sum_{t+1}^{t+3} CFO_t$**					
		Full Sample		***SI Sample***		***OppSI Sample***	
SI_t	**?**	**–0.120** **(–2.24)**		**–0.228** **(–4.14)**		**–0.232** **(–4.11)**	
$PredSI_t$	**?**		**0.233** **(2.31)**		**0.097** **(0.92)**		**0.113** **(0.68)**
$OppSI_t$	**–**		**–0.263** **(–3.59)**		**–0.375** **(–5.01)**		**–0.396** **(–4.56)**
CFO_t	+	1.607 (62.10)	1.608 (62.33)	1.606 (44.75)	1.609 (44.99)	1.583 (40.74)	1.585 (40.90)
Sales $Growth_t$	?	–0.018 (–1.32)	–0.016 (–1.17)	–0.004 (–0.21)	–0.001 (–0.05)	–0.014 (–0.67)	–0.012 (–0.58)
$Accruals^{Pre\text{-}SI}_t$	+	0.456 (16.51)	0.458 (16.57)	0.461 (10.60)	0.464 (10.65)	0.484 (10.25)	0.486 (10.29)
Industry-Year Fixed Effects		*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
# Observations		93,415	93,415	37,364	37,364	29,664	29,664
# Firms		10,741	10,741	8,532	8,532	8,166	8,166
Adj. R^2		0.525	0.525	0.529	0.530	0.534	0.535
$PredSI_t = OppSI_t$			0.001		0.001		0.021

The dependent variable is CFO scaled by contemporaneous Sales cumulated over years t+1 through t+3. All variables are as defined in Appendix 2. All continuous variables are winsorized at 1% and 99% (0% and 99% if bound from below by zero) by fiscal year. The full sample comprises all observations with sufficient data to estimate OppSI; the SI (OppSI) Sample further requires the recognition of income-decreasing special items (identification of OppSI) in year t. All models are estimated using OLS and include industry-year fixed effects. The standard errors are clustered by firm. We report the t-statistics in brackets below the estimated coefficients. The p-value of the test on coefficient equivalence, $PredSI_t = OppSI_t$, is two-tailed. The main variable(s) of interest are in bold.

Panel C: Regressing Future Returns on Predicted and Opportunistic Special Items

	Predicted Sign	Dependent Variable = $\sum_{t+1}^{t+3} BHAR_t$					
		Full Sample		*SI Sample*		*OppSI Sample*	
SI_t	**?**	**–0.126** **(–1.73)**		**–0.297** **(–3.77)**		**–0.337** **(–4.21)**	
$PredSI_t$	**?**		**0.134** **(0.71)**		**–0.172** **(–0.88)**		**–0.051** **(–0.17)**
$OppSI_t$	**–**		**–0.242** **(–2.27)**		**–0.395** **(–3.50)**		**–0.481** **(–3.45)**
$Beta_t$	+	–0.003 (–0.29)	–0.003 (–0.38)	0.002 (0.19)	0.002 (0.18)	–0.006 (–0.52)	–0.007 (–0.61)
$Momentum_t$	–	–0.096 (–6.92)	–0.095 (–6.88)	–0.119 (–5.53)	–0.119 (–5.52)	–0.126 (–5.33)	–0.126 (–5.30)
$Accruals^{Pre\text{-}SI}_t$	–	0.077 (2.92)	0.078 (2.96)	0.108 (3.03)	0.107 (2.98)	0.105 (2.79)	0.106 (2.82)
BM_t	+	0.059 (5.68)	0.059 (5.68)	0.054 (5.02)	0.054 (5.01)	0.054 (5.11)	0.054 (5.08)
$\ln(MVE_t)$	–	–0.012 (–3.81)	–0.012 (–3.85)	–0.024 (–5.78)	–0.024 (–5.77)	–0.025 (–5.33)	–0.025 (–5.36)
Industry-Year Fixed Effects		*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
# Observations		51,675	51,675	24,331	24,331	18,818	18,818
# Firms		6,971	6,971	5,569	5,569	5,286	5,286
Adj. R^2		0.116	0.116	0.116	0.116	0.121	0.121
$PredSI_t = OppSI_t$			0.131		0.380		0.285

The dependent variable is market-adjusted buy-and-hold returns cumulated over years t+1 through t+3 starting the month after the earnings announcement for year T. All variables are as defined in Appendix 2. All continuous independent variables are winsorized at 1% and 99% (0% and 99% if bound from below by zero) by fiscal year. The full sample comprises all observations with sufficient data to estimate OppSI; the SI (OppSI) Sample further requires the recognition of income-decreasing special items (identification of OppSI) in year t. All models are estimated using OLS and include industry-year fixed effects. The standard errors are clustered by firm. We report the t-statistics in brackets below the estimated coefficients. The p-value of the test on coefficient equivalence, $PredSI_t = OppSI_t$, is two-tailed. The main variable(s) of interest are in bold.

Table C.2
Panel A: Regressing Future Pre-Tax, Pre-SI Income on Predicted and Opportunistic Special Items

	Predicted Sign	**Dependent Variable = $NIBTSI_{t+1}$**					
		Full Sample		***SI Sample***		***OppSI Sample***	
SI_t	**?**	**–0.066** **(–2.51)**		**–0.162** **(–5.42)**		**–0.173** **(–5.56)**	
$PredSI_t$	**?**		**0.083** **(1.72)**		**–0.042** **(–0.82)**		**0.012** **(0.14)**
$OppSI_t$	**–**		**–0.128** **(–3.52)**		**–0.231** **(–5.73)**		**–0.266** **(–5.68)**
$NIBTSI_t$	+	0.669 (67.82)	0.669 (67.98)	0.645 (41.41)	0.646 (41.50)	0.637 (38.01)	0.638 (38.22)
Sales $Growth_t$	?	–0.016 (–2.57)	–0.016 (–2.45)	–0.028 (–3.24)	–0.028 (–3.19)	–0.034 (–3.25)	–0.033 (–3.16)
Industry-Year Fixed Effects		*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
# Observations		93,520	93,520	37,405	37,405	29,700	29,700
# Firms		10,749	10,749	8,546	8,546	8,180	8,180
Adj. R^2		0.525	0.525	0.522	0.522	0.522	0.522
$PredSI_t = OppSI_t$			0.001		0.005		0.019

The dependent variable is Net Income before Taxes and Special Items scaled by contemporaneous Sales for year *t*+1. All variables are as defined in Appendix 3. All continuous variables are winsorized at 1% and 99% (0% and 99% if bound from below by zero) by fiscal year. The full sample comprises all observations with sufficient data to estimate OppSI; the SI (OppSI) Sample further requires the recognition of income-decreasing special items (identification of OppSI) in year *t*. All models are estimated using OLS and include industry-year fixed effects. The standard errors are clustered by firm. We report the t-statistics in brackets below the estimated coefficients. The p-value of the test on coefficient equivalence, $PredSI_t = OppSI_t$, is two-tailed. The main variable(s) of interest are in bold.

Panel B: Regressing Future Cash Flows on Predicted and Opportunistic Special Items

	Predicted Sign	Dependent Variable = CFO_{t+1}					
		Full Sample		*SI Sample*		*OppSI Sample*	
SI_t	**?**	**–0.029**		**–0.084**		**–0.082**	
		(–1.53)		**(–4.30)**		**(–4.01)**	
$PredSI_t$	**?**		**0.074**		**0.008**		**0.011**
			(2.07)		**(0.22)**		**(0.18)**
$OppSI_t$	**–**		**–0.068**		**–0.128**		**–0.129**
			(–2.59)		**(–4.63)**		**(–3.97)**
CFO_t	+	0.690	0.690	0.675	0.676	0.670	0.671
		(73.22)	(73.41)	(48.73)	(48.91)	(43.98)	(44.14)
Sales $Growth_t$	?	–0.002	–0.002	0.008	0.009	0.005	0.006
		(–0.48)	(–0.36)	(1.20)	(1.32)	(0.65)	(0.72)
$Accruals^{Pre\text{-}SI}_t$	+	0.189	0.190	0.173	0.174	0.185	0.186
		(17.62)	(17.66)	(10.75)	(10.79)	(10.30)	(10.35)
Industry-Year Fixed Effects		*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
# Observations		93,393	93,393	37,357	37,357	29,658	29,658
# Firms		10,739	10,739	8,529	8,529	8,164	8,164
Adj. R^2		0.562	0.562	0.566	0.566	0.570	0.570
$PredSI_t = OppSI_t$			0.004		0.007		0.087

The dependent variable is CFO scaled by contemporaneous Sales cumulated for year *t*+1. All variables are as defined in Appendix 3. All continuous variables are winsorized at 1% and 99% (0% and 99% if bound from below by zero) by fiscal year. The full sample comprises all observations with sufficient data to estimate OppSI; the SI (OppSI) Sample further requires the recognition of income-decreasing special items (identification of OppSI) in year *t*. All models are estimated using OLS and include industry-year fixed effects. The standard errors are clustered by firm. We report the t-statistics in brackets below the estimated coefficients. The p-value of the test on coefficient equivalence, $PredSI_t = OppSI_t$, is two-tailed. The main variable(s) of interest are in bold.

Panel C: Regressing Future Returns on Predicted and Opportunistic Special Items

	Predicted Sign	Dependent Variable = $BHAR_{t+1}$					
		Full Sample		*SI Sample*		*OppSI Sample*	
SI_t	**?**	**0.120** **(2.39)**		**0.026** **(0.48)**		**–0.003** **(–0.05)**	
$PredSI_t$	**?**		**0.442** **(3.87)**		**0.264** **(2.28)**		**0.567** **(2.77)**
$OppSI_t$	**–**		**–0.043** **(–0.67)**		**–0.109** **(–1.60)**		**–0.251** **(–2.98)**
$Beta_t$	+	0.017 (4.63)	0.016 (4.38)	0.026 (4.62)	0.025 (4.45)	0.019 (3.12)	0.018 (2.83)
$Momentum_t$	–	–0.050 (–5.89)	–0.049 (–5.83)	–0.066 (–5.07)	–0.066 (–5.05)	–0.062 (–4.18)	–0.061 (–4.10)
$Accruals^{Pre\text{-}SI}_t$	–	0.027 (1.75)	0.028 (1.84)	0.026 (1.16)	0.028 (1.24)	0.022 (0.92)	0.027 (1.10)
BM_t	+	0.035 (5.27)	0.035 (5.28)	0.034 (4.07)	0.034 (4.07)	0.040 (4.92)	0.040 (4.91)
$\ln(MVE_t)$	–	–0.007 (–4.92)	–0.007 (–5.26)	–0.013 (–6.31)	–0.014 (–6.58)	–0.013 (–5.46)	–0.013 (–5.63)
Industry-Year Fixed Effects		*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
# Observations		51,627	51,627	24,294	24,294	18,792	18,792
# Firms		6,970	6,970	5,567	5,567	5,283	5,283
Adj. R^2		0.131	0.132	0.144	0.144	0.152	0.153
$PredSI_t = OppSI_t$			0.001		0.012		0.002

The dependent variable is market-adjusted buy-and-hold returns cumulated for year *t*+1 starting the month after the earnings announcement for year T. All variables are as defined in Appendix 3. All continuous independent variables are winsorized at 1% and 99% (0% and 99% if bound from below by zero) by fiscal year. The full sample comprises all observations with sufficient data to estimate OppSI; the SI (OppSI) Sample further requires the recognition of income-decreasing special items (identification of OppSI) in year *t*. All models are estimated using OLS and include industry-year fixed effects. The standard errors are clustered by firm. We report the t-statistics in brackets below the estimated coefficients. The p-value of the test on coefficient equivalence, $PredSI_t = OppSI_t$, is two-tailed. The main variable(s) of interest are in bold.