Advances in Accounting 60 (2023) 100642

Contents lists available at ScienceDirect

Advances in Accounting

journal homepage: www.elsevier.com/locate/adiac

Accruals and firm life cycle: Improving regulatory earnings management detection[☆]

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ARTICLE INFO

Editor: Dennis Caplan

JEL classification codes:
L21
L25
M410

Keywords:
Accruals
Life cycle
Earnings management
Misspecification

ABSTRACT

Regulators have invested considerable energy into developing analytical tools to better detect earnings management. We propose that firms in similar life cycle stages (LCSs) face similar strategic concerns, managerial pressures, growth prospects, etc., and that the commonality in these factors contribute to the "normal" accruals generating process. Consistent with this prediction, we simulate various earnings management conditions and find that accruals models are misspecified in detecting manipulation within particular LCSs; in particular, introduction, shakeout, and decline firms are over-identified as manipulators, while growth and mature firms are under-identified as manipulators when LCS is *not* used to estimate accruals. Weighted average performance across life cycle stages reveals that LCS estimation of discretionary accruals substantially improves successful detection and reduces Type I errors relative to other grouping alternatives. The combined improvement across both Type I and Type II errors is over 70% for both the modified Jones and discretionary revenue models of accruals-based earnings management.

1. Introduction

> "The identification of false positives can be costly, not only for the registrant erroneously tagged as engaging in earnings management, but for staff who has expended resources to investigate further. However, if the number of false positives can be kept to a manageable level, the use of quantitative models regarding discretionary accounting choices could be a powerful tool for staff who may be interested in the full range of behaviors associated with earnings management, and not merely as a way to potentially identify fraud."
> Craig Lewis, Chief Economist and Director, Division of Risk, Strategy, and Financial Innovation; U.S. Securities & Exchange Commission (SEC), 2012.

In recent years, the SEC has invested considerable energy into developing analytical tools to better detect earnings management and fraud.[1] The Accounting Quality Model (AQM) is a model that "allows us

☆ The authors appreciate the helpful comments of Editor Dennis Caplan, two anonymous reviewers, Kris Allee, Mark Anderson, Jim Cannon, Amanda Convery, Joshua Coyne, Patty Dechow, Jodi Gissel, Jing He, Jennifer Joe, Sam Lee, Qinghua Ling, Zhejia Ling, Nir Yehuda, Kevin Rich, Ikseon Suh, Quinn Swanquist, Laura Swenson, Joe Wall, and the workshop participants at the University of Alabama, Iowa State University, Marquette University, University of Delaware, University of Memphis, University of Mississippi, the 2017 University of Calgary Conference on the Convergence of Financial and Managerial Accounting, and the 2017 EuroMed Academy of Business Conference at Sapienza University of Rome.

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[1] Earnings management is a serious concern for regulators. To underscore its prevalence, Dichev, Graham, Harvey, and Rajgopal (2016) interview chief financial officers (CFOs) regarding their views on earnings management. The surveyed CFOs believe that 20% of firms intentionally distort earnings, even while adhering to generally accepted accounting principles (GAAP). They also state that comparison to peers is one of the most important factors in understanding earnings management, since comparisons can help flag potential earnings distortions.

https://doi.org/10.1016/j.adiac.2023.100642
Received 16 July 2021; Received in revised form 27 December 2022; Accepted 6 January 2023
Available online 27 January 2023
0882-6110/

[the SEC] to discern whether a registrant's financial statements stick out from the pack, while taking into account the contemporaneous attributes of that pack." (Lewis, 2012). Given regulators' increased reliance on data analytic techniques, we hypothesize that earnings management detection models improve when those models' are estimated on economically homogenous populations. The AQM model, and the academic models upon which it is based, detect earnings management by the estimation of discretionary accruals, i.e., accounting estimates that are subject to managerial discretion. Discretionary accruals are modeled as total accounting accruals minus expected, or normal, accruals.[2] These models, however, take a problematic one-size-fits-all approach to estimating the normal accruals-generating process. (Dopuch, Mashruwala, Seethamraju, & Zach, 2012). The resulting measurement error in discretionary accruals results in costly enforcement inefficiencies (and ultimately a deadweight loss) for regulators.

When normal accruals are misspecified, discretionary accruals are also measured with error, which reduces the power to detect earnings management and increases the likelihood of spurious over-identification of earnings management firms. Therefore, increasing the homogeneity of the sample of firms used to determine the normal accrual process improves estimations of normal accruals and ultimately the efficient detection of earnings management (Ecker, Francis, Olsson, & Schipper, 2013; Zarowin, 2015). This targeted identification of potential earnings management firms results in a more efficient allocation of constrained monitoring resources. While prior earnings management literature has used industry, size, and performance to estimate normal accruals, accrual characteristics also vary predictably across firm life cycle stages (LCSs) (Aharony, Falk, & Yehuda, 2006; Black, 1998; Chen, Yang, & Huang, 2010; Krishnan, Myllymaki, & Nagar, 2018). In this study, we examine firm LCS (introduction, growth, mature, shake-out, or decline) as a critical economic characteristic upon which regulators can organize firms to improve estimates of normal accruals, thereby improving earnings management model specification and detection. We suggest that models that group by firm LCS can better capture the risks, product competition, and strategic pressures unique to each LCS, which manifest in the underlying accruals-generating processes.

We estimate discretionary accruals using two common discretionary accruals models: the modified Jones model (Dechow, Sloan, & Sweeney, 1995; Jones, 1991) and the discretionary revenue model (Stubben, 2010). These models do not include any future-period accrual or cash flow information, making them most analogous to models that regulators implement in real time.[3] We run both models across varying estimation partitions used in prior literature (industry, size, performance, and growth) in addition to the firm-specific LCS proxy developed by Dickinson (2011). We first demonstrate that differences in the accrual generating process vary across firm lifecycle stages. We then simulate earnings management for the various estimation groupings in both the modified Jones and discretionary revenue models. We focus on both model specification and earnings management detection (which are both sources of inefficiency for regulators).

We find that estimating managerial discretion by firm LCS yields superior detection rates for growth and mature firms, which comprise over 70% of the sample population. We also find that relative to LCS, non-LCS estimation partitions result in substantial misidentification of earnings management (Type I errors). Specifically, when LCS is not used as the grouping variable, firms in the introduction, shakeout, and decline stages are over-identified as manipulators; similarly, growth and mature stages are under-identified. Including LCS information in the modified Jones and discretionary revenue accruals models both remedies the misspecification problem and increases detection power such that we see a 12% (52%) reduction in Type I errors and 53% (36%) improvement in detection for the modified Jones Model (discretionary revenue model) over the best-performing non-LCS variable. Finally, we validate our results against a sample of actual earnings manipulators identified from SEC AAER filings.

Our contribution to the literature and to regulators is twofold. First, we examine the role of firm LCS in increasing homogeneity among samples used to identify earnings management firms (via the estimation of normal accruals and the resulting discretionary accruals). Second, we find that firm LCS is successful in creating better-specified discretionary accruals estimates. Similar to findings in prior research, discretionary accruals models are grossly misspecified, and we pinpoint that misspecification to be most prevalent in the early and late LCSs. Estimating the discretionary accruals grouped by LCS overcomes that misspecification. Additionally, we find substantial improvement in detection for growth and mature firms, which constitute approximately 70% of the sample population, without introducing misspecification. Our tests investigating earnings management by LCS provide important context for optimizing discretionary accruals models.

The SEC continues to evolve its data analytic capabilities and indicates that peer comparison is important for earnings management detection.[4] Our results suggest that LCS is a meaningful peer comparison mechanism. Existing literature has examined the relation between accruals and firm life cycle from the investor perspective (Aharony et al., 2006; Black, 1998; Chen et al., 2010; Krishnan et al., 2018). We complement this literature by explicitly examining LCS's role in identifying earnings management from the regulatory screening perspective with the goal of better allocating scarce regulatory resources.

2. Background and hypotheses development

2.1. Accounting accruals

Zarowin (2015) provides several reasons why managers use accruals to manage earnings: 1) the judgment and subjectivity inherent in accruals provide an opportunity for adjusting earnings; 2) managers can adjust accruals at the end of the accounting period to meet or beat a revealed earnings target (i.e., analyst forecast, prior management guidance, etc.); and 3) managing accruals does not compromise real performance in the way that real earnings management does. To detect potential earnings management, we decompose total accruals into two (unobserved) components: normal (expected) accruals and discretionary accruals.

[2] The SEC states, "Our Accounting Quality Model extends the traditional approach by allowing discretionary accrual factors to be a part of the estimation. Specifically, we take filings information across all registrants and estimate total accruals as a function of a large set of factors that are proxies for discretionary and non-discretionary components. Further, we decompose the discretionary component into factors that fall into one of two groups: factors that *indicate* earnings management or factors that *induce* earnings management. Discretionary accruals are calculated from the model estimates and then used to screen firms that appear to be managing earnings most aggressively" (Lewis, 2012).

[3] Lewis (2012) specifically identifies the modified Jones model in his description of AQM. The modified Jones model estimates normal (i.e., nondiscretionary) accruals using a linear function of the change in cash revenues and property, plant, and equipment (PPE) (Dechow et al., 1995). Alternatively, Stubben (2010) measures discretion based on the receivables accrual to capture premature recognition of revenue. He makes this choice because revenue management is the most prevalent form of earnings management reported in the Security and Exchange Commission's (SEC) Accounting and Auditing Enforcement Releases (AAERs).

[4] For example, in a 2016 presentation at the Center for Accounting Research and Education (CARE) Conference (Center for Accounting Research and Education, 2016), an SEC official discussed the advancement of inline XBRL filing data, which facilitates comparison of key metrics across pre-defined peer groups.

2.2. Accruals and growth

The normal portion of accruals is derived from the firm's industry, strategy choices, opportunities for growth, etc. McNichols (2000) argues that accounting research lacks a theoretical framework to predict how accruals behave in the absence of discretion. Building on that point, Fairfield, Whisenant, and Yohn (2003) suggest high levels of discretionary accruals may be due to earnings management or growth in net operating assets and their related accruals.

Additionally, accruals activity first consists of the origination of the accounting accrual and then its subsequent reversal. This means the observable level of discretionary accruals is really a net accrual: current period originations less current period reversals. When the firm is growing, originations are higher than reversals. This growth eventually converges to normal profitability levels (i.e., a steady state), where originations and reversals are approximately equal each year. Accruals, then, consist of two components: (1) an investment component that is positively related to growth and (2) a component related to converting cash flows to accruals to overcome timing issues (or vice versa), which is unrelated to growth (Hribar & Yehuda, 2015). Conversely, if the firm is contracting, reversals are often higher than originations. We will later demonstrate that accrual originations and reversals (i.e., the first component) vary systematically by firm LCS.

2.3. Discretionary accruals models

We concentrate our analyses on two discretionary accruals models. The SEC specifically cites the modified Jones model as a foundation for its AQM, used in their enforcement activities. We also use the discretionary revenue model because prior research demonstrates over 70% of SEC enforcement actions and earnings restatements involve revenue misstatement (Dechow & Schrand, 2004; Stubben, 2010).[5]

The modified Jones model estimates normal accruals as a linear function of the change in cash revenues and PPE (Dechow et al., 1995). Normal accruals are generally estimated annually by industry, with the discretionary portion of accruals (the proxy for earnings management) computed as the difference between total and normal accruals (i.e., the residual). Stubben (2010) (referred to as the revenue model, hereafter) estimates revenue-based earnings management by examining the change in accounts receivable (instead of the change in total accruals) as a function of revenue change. He finds that, overall, the revenue model produces less-biased estimates of discretion than the modified Jones model; specifically, the revenue model is more effective at (but also limited to) detecting premature recognition of revenue.

2.4. Model specification issues

While the discretionary portion of accruals provides insight into earnings management behavior, discretionary accruals models suffer from misspecification due to measurement error and correlated omitted variables (Bernard & Skinner, 1996; Dechow et al., 1995; Dechow, Hutton, Kim, & Sloan, 2012; Guay, Kothari, & Watts, 1996; Kang & Sivaramakrishnan, 1995; Stubben, 2010; Thomas & Zhang, 2001). The models possess low power for detecting actual earnings management and are more imprecise in regions of extreme performance, which is where discretion detection becomes increasingly important (Dechow et al., 1995; Kothari, Leone, & Wasley, 2005). The resulting misspecification leads to both Type I (detecting earnings management when none exists, i.e., a false positive) and Type II errors (failure to detect earnings management when it does exist, i.e., a false negative). Both types of errors result in either misallocating or under-allocating scarce regulatory investigation resources. We assert that LCS is one such correlated omitted variable that captures the patterns of accrual originations and reversals.

2.5. Estimation groupings

As mentioned above, existing models of earnings management have been criticized for producing biased and imprecise measurements of discretionary accruals. Zarowin (2015) states, "… estimation methods assume that observations in the estimation model are homogeneous, but even firms within an industry have varying characteristics, and individual firms change over time." He further indicates that holding coefficients constant for a heterogeneous group of firms adds noise to normal accruals. Thus, increasing homogeneity among firms in the estimation sample improves specification of the normal accruals-generating process. We discuss each estimation grouping used in prior research below and propose firm LCS as an important additional grouping.

2.6. Industry

Discretionary accruals estimation historically relied on time series data by firm to estimate normal accruals. However, a sufficiently long time series of data eliminates younger firms from analysis. In response, researchers adopted an industry-level cross-sectional approach (DeFond & Jiambalvo, 1994; Subramanyam, 1996), which assumes that firms within the same industry should have similar accrual generating processes. For example, Lewellen and Resutek (2019) show that changes in product markets explain accrual behavior and its relation to earnings. Industry also influences earnings management behavior; Bagnoli and Watts (2000) find firms manage earnings more when compensation relies on relative performance evaluation (i.e., competition against peers). However, using industry alone to model normal accruals does not consider differences in strategy or competitive advantages of firms within the industry. Owens, Wu, and Zimmerman (2017) state:

Profit maximization via innovation and strategy differentiation presents an inherent challenge to the intra-industry homogeneity assumption. Further, technological innovations, regulatory changes, and entry by new (or existing) firms (what we call "business model shocks") cause firms to frequently alter their existing business strategies. These frequent business model revisions/shocks present an inherent challenge to the firm stationarity assumption, and likewise decrease intra-industry homogeneity …

Further, Dopuch et al. (2012) find significant differences in the accruals generating process related to sales, inventory, and credit policies within industries, which suggests industry may not fully mitigate undesirable heterogeneity in normal accruals estimation.

2.7. Size

Ecker et al. (2013) state that similarly sized firms are homogenous in growth, risk, and monitoring (e.g., analyst following, institutional investors, Big Four auditor, etc.), which are factors that also influence the accruals process. They argue that size is persistent, which improves stationarity of the accruals generating process. Overall, they find that size-based estimation samples outperform industry-based samples with respect to discretionary accrual detection. Size also attenuates sample attrition because each size grouping is populated, whereas some industries lack sufficient data to estimate normal accruals. We expect LCS will capture additional differences in strategy, risk and other economic-based characteristics that are unrelated to size.

[5] We do not test the earnings quality measure developed by Dechow and Dichev (2002) because this measure incorporates future operating cash flows into its estimation of normal performance. Thus, from a regulatory standpoint, the model would invoke a look-ahead bias as regulators would not have access to future cash flows to identify suspect firms in real time.

2.8. Performance

Kothari et al. (2005) indicates estimating accruals based on performance matching (e.g., return on assets) reduces estimation errors in regions of extreme performance. Discretionary accruals are computed by subtracting normal accruals (estimated for a set of control firms matched on industry and ROA) from total accruals. However, Dechow et al. (2012) reports that performance matching on ROA "… mitigates misspecification in samples with extreme ROA but exaggerates misspecification in samples with extreme firm size" (p. 278). They also point out that performance matching increases the standard error of the test statistic, which reduces the power of the model to detect earnings management.

Of course, performance is linked to growth. Collins, Pungaliya, and Vijh (2017) demonstrate that several factors contribute to model misspecification in the Jones model (and its variations) including contemporaneous sales growth and future expected growth. Accordingly, they use sales growth and the market-to-book ratio to capture expected growth, along with ROA, to capture the performance matching used in Kothari et al. (2005). While the inclusion of growth improves model performance, there may be additional operational and strategy factors that govern the generation (and reversal) of accruals. We suggest firm LCS adds incrementally to the variables used in prior studies to estimate normal accruals.

2.9. Firm life cycle

Healy (1996, pp. 112-113) states "current models … do a poor job of capturing how accruals are affected by a firm's stage in its life cycle. In a growth phase, accruals patterns are likely to be quite different from those during periods of stability or decline." Further, Dickinson (2011, p. 1969) states, "Business firms are evolving entities, with the path of evolution determined by internal factors (e.g., strategy choice, financial resources, and managerial ability) and external factors (e.g., competitive environment and macroeconomic factors). Firm LCSs are distinct phases that result from changes in these factors, many of which arise from strategic activities undertaken by the firm."

In addition to accruals earnings management, prior literature has investigated earnings management through real economic activity (Cohen, Pandit, Wasley, & Zach, 2020; Eldenburg, Gunny, Hee, & Soderstrom, 2011). Srivastava (2019) finds that models of real earnings management (REM) are misspecified because they do not incorporate differences in competitive strategy across firms. Specifically, he states that "…the cost patterns and cash profitability of firms in a given industry could differ because firms are in different stages of their life cycles" (p. 1278). Xie, Chang, and Shiue (2022) directly examines the use of real earnings management across firm LCS and finds both differing levels and types of real earnings management. For example, they report more sales-related earnings management in early LCSs as opposed to expense management. Their findings are consistent with firms in different LCSs confronting different competitive pressures, strategic concerns, and mechanisms by which they might manage earnings. Their findings provide strong motivation for this study and offer conceptual support for our hypothesis that accruals-based earnings management will also differ across LCSs. Thus, our study complements the important real earnings management findings of Srivastava (2019) and Xie et al. (2022).[6]

Differences arise in two ways between each LCS's accruals generation. First, firms in different LCSs should differ in how specific accruals originate and reverse. Yu, Hyun, and Anderson (2019) document differences across LCSs for key accrual accounts, including accounts receivable, change in accounts receivable, PPE, change in PPE (all variables used in this study), and performance ratios like profit margin and asset turnover.[7] For example, introduction and decline firms turn over their receivables more slowly than growth and mature firms. Thus, we expect an equivalent increase in sales to increase the accounts receivable balance to a greater degree for introduction and decline firms than for growth and mature firms.

Second, LCS has an indirect effect on the likelihood of earnings management. Given the riskier profiles of firms in introductory and decline life cycle stages (Dickinson, 2011; Shahzad, Lu, & Fareed, 2019), changes in underlying economics such as sales or the level of PPE investment resolve uncertainty about future prospects, which eases the need to manage accruals. As an example, an increase in sales for a mature firm (i.e., a steady state firm) will correspond to a proportional increase in accruals. However, an increase in sales for an introduction firm (i.e., a riskier firm than a mature firm) is a more meaningful signal about long-term prospects and lessens the need for outside financing. Thus, the increase in revenue for an introduction firm reduces the need to manage accruals more pronouncedly than for a mature firm. Similarly, Yu et al. (2019) document different levels of PPE and differential market pricing for PPE turnover across LCSs. They report positive future returns from PPE turnover in introduction and decline stages (though not in the other three stages). This means the ability to generate revenues from invested long-term assets is a particularly important signal for firms in the introduction or decline stages. To summarize, we contend that earnings management models potentially capture risk and growth prospects via the accrual accounts differentially by LCS.[8] Thus, pooling firms across different LCSs within the same normal accrual estimation sample will contain measurement error and impede the estimation of resulting normal and abnormal accruals. Thus, we predict:

H1. : The normal accruals generating process differs by firm LCS.

Firm LCS can be determined by a firm's cash flow patterns (Dickinson, 2011). A primary strength of using cash flow patterns to classify firms into LCSs is that cash flows are unaffected by accruals-based earnings management. At the same time, the propensity to use accruals to achieve earnings targets is likely driven by firm LCS. Therefore, using the cash flow-based method of deriving firm LCS achieves a measure of normal accruals that is free from potential endogeneity.

We expect firm life cycle to improve estimation groupings for several reason, in addition to commonality in the accruals generating process within LCSs. For instance, firms in the same industry face the same markets for capital and inputs, such as materials and labor. Regulatory environments and demand for products and/or services lead to industry commonalities. For these reasons, industry membership should affect operating and market performance (Cheng, 2005; Fairfield, Ramnath, & Yohn, 2009; Gebhardt, Lee, & Swaminathan, 2001; Soliman, 2008). However, industry membership and firm LCS are distinct phenomena; Dickinson (2011) reports that most industries contain the full range of firm LCSs within a given industry. Therefore, firm life cycle adds incremental information to industry membership.

With respect to firm size, Ecker et al. (2013) state that larger firms

[6] Cantrell and Dickinson (2020) find that firm LCS conditional on the LCS of the industry (i.e., conditional life cycle) coincides with the theories of leader and laggard behavior and leads to systematic and predictable operating and market performance outcomes. Their finding also supports the notion that firms in different life cycle stages face differing risks, competitive pressures, and strategic concerns.

[7] Additionally, we document changes in accrual-related ratios across life cycle stages such as receivables turnover and PPE turnover. These ratios are presented in Table 4 and discussed in Section IV of the paper.

[8] It is also the case that introduction and growth firms have relatively newer PPE (with less accumulated depreciation) than the other stages. Thus, for introduction and growth firms, the use of accelerated depreciation would result in larger differences between income and cash flows from operations (specifically, accruals that are more negative) leading to a direct difference in accrual generation across life cycle stages related to PPE.

are likely to be mature. Yet, Dickinson (2011) demonstrated that firm size and firm LCS are nonlinearly related such that firm LCS produces different groupings than using firm size to form groups. Smaller firms are likely either introduction or decline firms, each of which has different ramifications for future profitability and performance, and likewise accruals. A similar non-linear relation exists between profitability and LCSs, such that profitability increases from introduction through growth and peaks in the maturity stage before falling to the shake-out and decline phases. Therefore, we predict firm LCS will result in greater homogeneity than the previously used groupings and thereby will produce a better-performing measure of discretionary accruals. We posit the improved performance will lead to a reduction in both Type I and Type II errors in estimating accruals models.

H2. : Estimation by LCS will improve the specification and power of each of the accruals models as compared to estimating the models by industry, size, performance, or growth measures.

3. Research design

In this section, we discuss 1) the discretionary accruals models used in this study, 2) the grouping mechanisms for the estimation sample including firm life cycle proxy, 3) the method of examining accrual originations, and 4) the process used to simulate earnings management.

3.1. Discretionary accruals models

We employ two discretionary accruals models: the modified Jones model and the discretionary revenue model.

3.1.1. Modified Jones model

The modified Jones model (Dechow et al., 1995; Jones, 1991) estimates nondiscretionary accruals by modeling total accruals as a function of the change in cash revenues and gross property, plant, and equipment (PPE). Gross PPE controls for accruals explained by nondiscretionary depreciation expense:

$$AC_{it} = \alpha + \beta_1(\Delta R_{it} - \Delta AR_{it}) + \beta_2 PPE_{it} + \varepsilon_{it} \tag{1}$$

The accruals variable, AC_{it}, is calculated as income before extraordinary items (IB) minus cash flows from operations (OANCF). Change in revenues (ΔR_{it}) is computed from revenues (REVT), the change in accounts receivable (ΔAR_{it}) is computed from the statement of cash flows (RECCH), and gross property, plant, and equipment (PPE_{it}) is taken directly from Compustat (PPEGT). We estimate this regression by alternative grouping partitions, with the predicted values representing normal accruals for each group. The residuals, computed as actual accruals minus predicted values, measure discretionary accruals.

3.1.2. Discretionary revenue model

Stubben (2010) examines premature revenue recognition via the change in accounts receivable:

$$\Delta AR_{it} = \alpha + \beta_1 \Delta R1\_3_{it} + \beta_2 \Delta R4_{it} + \varepsilon_{it} \tag{3}$$

Where ΔAR_{it} is the year-over-year change in the accounts receivable balance, $\Delta R1\_3_{it}$ is the year-over-year change in revenues of the first three quarters of the year, and $\Delta R4_{it}$ is the year-over-year change in revenues for the fourth quarter of the year. Stubben utilizes quarterly revenue because managers tend to use more discretion in the fourth quarter to meet annual earnings targets. Thus, the residuals from this model capture unexplained discretionary revenues (which are uncollected at year-end), such as prematurely recognized revenues.

3.2. Estimation sample groupings

To determine which grouping will produce the greatest homogeneity for estimating normal accruals, we form our estimation samples (discussed below) grouping by industry membership, firm size, performance, growth, and firm LCS.

3.2.1. Industry membership

We define industry-based estimation on 2-digit SIC codes. Ecker et al. (2013) reports considerable sample attrition using industry membership because some industries lack sufficient observations to reliably estimate normal accruals. Consistent with prior studies, we require ten firm-year observations per industry-year for inclusion in industry groups.

3.2.2. Firm size

We define size-based estimation by lagged total assets by year. Unlike the industry estimation, size quintiles will not suffer from sample attrition as all firm-years can be grouped into a size quintile. Ecker et al. show that size-based estimation samples detect discretionary accruals at least as well as industry-based samples.

3.2.3. Performance and growth

Collins et al. (2017) demonstrate that incorporating performance and growth improve the specification of accruals models, so we initially form estimation groups alternatively on quintiles of ROA, market-to-book (MB), and sales growth (SG) by year.

3.2.4. LCS

Dickinson (2011) uses the combination of a firm's net operating, investing, and financing cash flows (determined by sign) to categorize firm years into life cycle stage (introduction, growth, mature, shakeout, or decline).[9,10,11]

[9] Dickinson (2011) explains "there are three cash flow types (operating, investing, and financing) and each can take a positive or negative sign which results in $2^3 = 8$ possible combinations. The eight patterns are collapsed into five stages as follows" (p. 1974):

	1 Introduction	2 Growth	3 Mature	4 Shake-Out	5 Shake-Out	6 Shake-Out	7 Decline	8 Decline
Preditcted sign								
Cash flow from operating activities	−	+	+	−	+	+	−	−
Cash flow from investing activities	−	−	−	−	+	+	+	+
Cash flow from financing activities	+	+	−	−	+	−	+	−

[10] Partitioning across quintiles of size, performance and growth results in estimating models on samples with similar number of observations. Life cycle also includes five subsamples, though not evenly balanced. Industry membership results in many more subsamples, which are significantly smaller. Partitioning into smaller sample sizes may help increase the homogeneity of samples, increasing model specification. But the smaller sample sizes also reduce the power of the tests. Ultimately, we are interested in model detection from a regulatory perspective. Thus, we allow the trade-off between homogeneity and power to manifest itself in the model detection rates.

[11] Dickinson (2011) defines shakeout by exception meaning that the firm does not fit into the other LCS patterns. To the extent that shake-out firms are dissimilar to each other (or should be classified in other stages), partitioning by LCS should be less successful at detecting manipulation, working against our findings. Thus, we utilize the LCS identification provided by Dickinson to maintain comparability with other studies.

Table 1
Sample selection.

Selection of data observations using Compustat North America data 1989–2017	
Selection Criteria	# Firm Years
Annual Dataset for 1988–2017* (U.S. Only)	264,059
Observations after joining annual and quarterly data	252,342
With data for required for cash flow patterns	204,957
With data for all other variables needed	123,453
Observations after 1988	119,520
With data from parent companies only	90,121
From NYSE, NASDAQ, or AMEX	89,881
Non-regulated industries	78,854

* 1988 is needed for variable construction. Final data set covers 1989–2017. Data starts in 1989 since that is the first year that cash flow data is readily available. Cash flow data is needed for life cycle variables.

3.3. Accrual origination and reversals

We suggest that firm LCS affects the pattern of accrual originations and reversals, which provides rationale for its potential success as a grouping variable. Prior research examines accrual originations and reversals (Allen, Larson, & Sloan, 2013; Dechow et al., 2012) using the Dechow-Dichev (2002) earnings quality measure, which requires one-year-ahead operating cash flows. Regulators, however, are interested in detecting earnings management in the current period, so they prefer an ex ante measure of accrual originations.[12] Fedyk, Singer, and Sougiannis (2020) develop an ex ante measure of accrual originations and reversals by focusing on extreme magnitudes of originations and reversals. Likewise, we classify a firm as originating positive (or negative) accruals when the firm falls in the top (or bottom) two deciles on the magnitude of current accruals and also falls in the top (or bottom) three deciles of working capital. An accrual reversal is defined as the first net accrual in a year subsequent to the originating accrual that is of the opposite sign and is at least 50% of the magnitude of the originating accrual.

3.4. Simulated earnings management

We use simulations to test the specification and power of discretionary accrual models by varying levels of seeded manipulation (Dechow et al., 1995; Ecker et al., 2013; Kothari et al., 2005; Stubben, 2010). We examine both Type I and Type II errors in each model estimation. Type I errors occur when the null hypothesis that earnings are not systematically managed is rejected, but there is no earnings manipulation; conversely, Type II errors occur when the null hypothesis is not rejected, but there is earnings manipulation. We investigate Type I errors by analyzing rejection frequencies for partitions of firms in which we *have not* introduced artificial earnings manipulation. We would expect each model to reject the null hypothesis of no earnings management 5 % of the time (assuming a 95% confidence interval). Type II errors are investigated by artificially inducing a fixed and known amount of accruals to each firm-year (Dechow et al., 1995). Ideally, each model will reject the null hypothesis with 100% frequency because we have actually seeded known amounts of manipulation into the data. Consequently, Type I errors provide evidence of model specification performance, while Type II errors provide evidence of the power to detect earnings management.

3.4.1. Simulation process

Using the alternative estimation grouping partitions, we simulate earnings management into each sample (Dechow et al., 1995; Ecker et al., 2013; Stubben, 2010). We repeat the following steps for each discretionary accrual model:

(1) We select a random subsample of 100 firm-year observations (firm-event-years) with replacement (in initial tests this selection is from the entire pooled sample, while in subsequent tests this selection is from particular life cycle stages). These firm-event-years do not change throughout the iteration of the steps listed here.
(2) We simulate discretionary accrual manipulation for both revenues and expenses. To manipulate revenues we add either zero, one, or 5 %[13] of lagged total assets to the change in revenues, the change in fourth-quarter revenues, and the receivables accrual. To manipulate expenses we add zero, one, or 5 % of lagged total assets multiplied by the gross margin percentage to current accruals. These manipulations are performed on each of the 100 firm-event-years.
(3) We use the original sample minus the 100 manipulated firm-event-years to estimate discretionary accruals for both the modified Jones and revenue models. These models are estimated separately for a given partition (i.e., industry, size, ROA, market-to-book, sales growth, or LCS). In other words, we estimate the model (either the modified Jones or revenue model) by a given partition, such as industry, and complete the following steps before repeating the process for a different partition.
(4) We use the unique coefficient estimates from the given partition to calculate estimates of discretionary accruals for the 100 firm-event-years. Thus, we calculate a distinct measure of discretionary accruals by partition for each model.
(5) Finally, we calculate the mean estimate of discretion (signed discretionary accruals) from the 100 firm-event-years by partition for each model and test whether the mean is significantly greater than zero.
(6) We repeat this process 1000 times in initial tests. In subsequent tests where firm-event-years are selected from specific life cycle stages, we reduce the iterations to 500 to conserve computation time.
(7) We report the percentage of the means from the 1000 iterations that are significantly greater than zero; that is the percentage of times each model rejects the null hypothesis of no manipulation.

We then repeat these seven steps changing the partition selected in step 3 and completing the testing procedure. A rejection rate of 5 % is expected when manipulation is not introduced, and based on a 95% confidence interval, an actual rejection rate below 2 % or above 8 % indicates that the test is misspecified (Collins et al., 2017; Ecker et al., 2013; Kothari et al., 2005; Stubben, 2010). When manipulation is introduced, however, the rejection rate should be 100%.

4. Sample, descriptive statistics, and results

4.1. Sample data and descriptive statistics

The sample period spans from 1989 (the first year that statement of cash flow data is available) through 2017. We include domestic firms listed on the major U.S. exchanges that contain sufficient data to

[12] The need for an ex ante measure that captures accrual originations stems from the regulatory desire to identify earnings management that exceeds the discretion within GAAP at the earliest possible point. Lewis (2012) notes the need for "contemporaneous" information and describes uses of the AQM model in the current year, such as the Division of Corporate Finance filing review process, that would not allow sufficient time for the accruals to unwind.

[13] Dechow et al. (1995) indicates that one to 5 % of total assets are economically plausible amounts of earnings management. However, they test between zero and 100% accrual manipulation in 10 percentage point increments. Ecker et al. (2013) test between zero and 20% accrual manipulation using two percentage point increments.

Table 2
Sample descriptive statistics ($n = 78{,}854$).

Panel A: Overall Means					
Variable	Mean	Std Dev	Q1	Median	Q3
AC	(0.07)	0.13	(0.11)	(0.06)	(0.01)
ΔAR	0.02	0.06	(0.01)	0.01	0.03
ΔR	0.13	0.35	(0.01)	0.08	0.22
ΔR1_3	0.09	0.27	(0.01)	0.06	0.17
ΔR4	0.04	0.11	(0.01)	0.02	0.06
PPE	0.57	0.45	0.24	0.45	0.80
AR	0.19	0.16	0.08	0.16	0.26
INV	0.15	0.16	0.01	0.10	0.22
AP	0.10	0.09	0.04	0.07	0.12

Panel B: Means by Life Cycle					
Variable	Introduction	Growth	Mature	Shakeout	Decline
AC	(0.04)	(0.07)	(0.08)	(0.06)	(0.05)
ΔAR	0.05	0.03	0.01	0.01	0.01
ΔR	0.21	0.23	0.09	0.01	(0.01)
ΔR1_3	0.15	0.16	0.07	0.00	(0.01)
ΔR4	0.07	0.07	0.02	0.01	0.01
PPE	0.44	0.67	0.61	0.43	0.33
AR	0.24	0.21	0.18	0.16	0.14
INV	0.20	0.14	0.14	0.12	0.10
AP	0.13	0.10	0.09	0.07	0.08

Table 2 reports descriptive statistics for variables used in this study. These statistics represent the 78,854 firm-year observations ranging from 1989 through 2017 as described in Table 1. We deflate all variables by lagged total assets and winsorize at the 1% and 99% levels by year.
We define these variables as follows:
AC = annual current accruals, calculated by earnings before extraordinary items (IB) - cash from operations (OANCF).
ΔAR = change in accounts receivable, taken from the statement of cash flows (RECCH).
ΔR = change in annual revenues (REVT).
ΔR1_3 = change in revenues of the first three quarters of the year.
ΔR4 = change in revenues of the fourth quarter.
PPE = end of fiscal year gross property, plant, and equipment (PPEGT).
AR = end of year receivables (RECT).
INV = end of year total inventories (INVT).
AP = end of year trade accounts payable (AP).

compute the accruals models and life cycle measures. Following Stubben (2010), we exclude firms in regulated industries (financial, insurance, and utilities) because their revenues and accruals are not comparable to the rest of the population. Our final sample is comprised of 78,854 firm-year observations (the sample selection procedure is outlined in Table 1). We deflate all continuous dependent variables by lagged total assets. Variables are winsorized by year at the 1st and 99th percentiles.

Descriptive statistics in Table 2, Panel A, show that mean (median) accruals are −7% (−6%) of lagged assets, consistent with Stubben (2010). The mean (median) change in receivables is 2% (1%) of lagged total assets, while the mean (median) change in revenue is 13% (8%).

4.2. Investigating differences in the accruals generating process by LCS

Differences in accrual components across LCSs will indicate that accrual originations vary by LCS. Table 2, Panel B reports the means of each descriptive statistic from Panel A, broken down by LCS. As expected, the growth and mature stage generate the largest magnitude of accruals. We also observe that introduction and growth firms have the highest changes in receivables and sales. Property, plant, and equipment (PPE) are a larger share of lagged total assets for growth and mature firms. The proportion of current assets and liabilities (accounts receivable, inventory, and accounts payable) to lagged total assets are larger for introduction firms, indicating that their accruals impact operations as compared to firms in the other stages.

Table 3
Accrual Originations and Reversal Interval by LCS.

Panel A: Positive Originating Accruals				
	N	% of the Total Sample	Average Years Until Reversal	
Introduction	2245	22.95%	3.56	***
Growth	3319	14.20%	3.92	***
Mature	1847	5.59%	3.45	***
Shakeout	507	6.50%	3.05	
Decline	399	8.28%	3.00	
Total	8317	10.55%	3.61	

Panel B: Negative Originating Accruals				
	N	% of the Total Sample	Average Years Until Reversal	
Introduction	945	9.66%	2.73	***
Growth	1786	7.64%	3.10	
Mature	1754	5.30%	3.15	***
Shakeout	754	9.66%	2.92	***
Decline	671	13.92%	2.62	
Total	5910	7.49%	3.00	

Panel C: Total Originating Accruals				
	N	% of the Total Sample	Average Years Until Reversal	
Introduction	3190	32.61%	3.33	***
Growth	5105	21.83%	3.65	***
Mature	3601	10.89%	3.31	***
Shakeout	1261	16.16%	2.97	**
Decline	1070	22.19%	2.77	
Total	14,227	18.04%	3.36	

Table 3 reports the originating accruals and the average years until the subsequent reversal following the methodology of Fedyk et al. (2020) by firm life cycle. We classify a firm as originating positive (negative) accruals when the firm falls in the top (bottom) two deciles on the magnitude of current accruals and also falls in the top (bottom) three deciles of working capital. Similar to past literature that focuses on accruals reversals, we use current period accruals and exclude the impact of non-current or investing accruals. However, the distribution of originating accruals follows a similar pattern when using the accrual definition used throughout the remainder of the paper. An accrual reversal is defined as the first net accrual in a year subsequent to the originating accrual that is of the opposite sign and at least 50% of the magnitude of the originating accrual. T-tests determine that the accrual reversals are statistically significantly different than adjacent LCSs. Specifically, ** and *** denote that the average years to reversal between the LCS and the immediate subsequent LCS statistically significantly differ at the 5% and 1% levels respectively (two-tailed).

In Table 3, we examine accrual originations and reversals by LCS. *t*-tests determine whether the accrual reversals are significantly different from those in adjacent LCSs. We see that positive (income increasing) originating accruals (Panel A) are more likely to occur in the introduction and growth stages while negative originating accruals (Panel B) are more prevalent in decline. This analysis further validates that introduction and growth is where positive accruals origination usually takes place, so isolating those firms when estimating normal accruals is likely to result in better model specification. We also see that there are systematic differences in the reversals across most LCSs (Panel C). Notably, regulators are interested in accrual originations rather than reversals; originations are where managerial intervention is likely to occur. Overall, the results indicate that firm LCS systematically affects the composition of accruals, along with their originations (and reversals) consistent with H1 and supports incorporating LCS into the estimation of normal accruals.

Table 4
Regression Coefficients by LCS.

Panel A: Regression Coefficients - Modified Jones Model: AC = (ΔR - ΔAR) + PPE				
	Intercept	*ΔR-ΔAR*	*PPE*	*Adj R^2*
Introduction	(0.03)	0.06	(0.07)	0.06
Growth	(0.04)	0.01	(0.05)	0.06
Mature	(0.06)	0.02	(0.03)	0.03
Shakeout	(0.05)	0.02	(0.02)	0.02
Decline	(0.04)	0.01	(0.03)	0.02

Panel B: Regression Coefficients - Revenue Model: ΔAR = ΔR1_3 + ΔR4				
	Intercept	*ΔR1_3*	*ΔR4*	*Adj R^2*
Introduction	0.02	0.05	0.30	0.37
Growth	0.01	0.03	0.22	0.27
Mature	0.00	0.02	0.26	0.27
Shakeout	0.00	0.04	0.24	0.27
Decline	0.01	0.04	0.29	0.32

Panel C: Accrual Related Ratios					
	Introduction	Growth	Mature	Shake-Out	Decline
Receivables Turnover	10.36 times	13.15	13.86	11.15	9.41
Collection Period	68.31 days	58.47	53.89	64.20	73.23
Allowance / AR	7.46%	5.19	5.26	6.51	9.30
Inventory Turnover	15.16 times	19.25	16.61	15.74	17.03
Days Sales in Inventory	89.52 days	62.20	68.38	81.02	82.15
PPE Turnover	14.50 times	10.11	10.09	13.15	10.96
PPE Percentage Used	47.84%	43.79	50.09	53.33	55.08
Payables Turnover	16.55 times	18.71	19.29	20.48	18.14
Days Expenses in Payables	34.10 days	33.59	28.79	30.47	32.62

Table 4, Panels A and B report regression coefficients by LCS for the modified Jones model and revenue model, respectively. Chow tests reveal statistically significant (5% level two-tailed test) structural differences in the models across each LCS relative to the other LCSs for each regression model in all five LCSs. Panel C reports common financial ratios related to accrual accounts by LCS. Variable definitions can be found in Table 2. We deflate all variables by lagged total assets and winsorize at the 1% and 99% levels by year. Ratios are defined as follows:
Receivables Turnover = revenues / average receivables.
Collection Period = (average receivables x 365) / revenues.
Allowance / AR = allowance for doubtful accounts / receivables.
Inventory Turnover = cost of goods sold / average inventory.
Days Sales in Inventory = (average inventory x 365) / cost of goods sold.
PPE Turnover = revenues / average net property, plant, and equipment.
PPE Percentage Used = accumulated depreciation / gross property, plant, and equipment.
Payables Turnover = (cost of goods sold + selling, general, and administrative expense) / average accounts payable.
Days Expenses in Payables = (average accounts payable x 365) / (cost of goods sold + selling, general, and administrative expense).

4.3. *Testing accruals model performance using simulations*

If the normal accruals generating process differs by LCS, we expect to see differences across LCSs in the regression coefficients of the two accruals models. In Table 4, we report regression parameters from the modified Jones and revenue models in Panels A and B, respectively. The adjusted R-squared reveals that the revenue model (Panel B) demonstrates higher explanatory power than the modified Jones model (Panel A) in every LCS. We also note that the coefficients vary across the LCSs in both models, which indicates that LCS possesses explanatory power for accruals. Furthermore, Chow tests reveal statistically significant structural differences in the estimated models between LCSs, again consistent with H1.

In Table 4, Panel C, we compute several financial ratios to shed light on how each accrual component varies by LCS. We find that growth and mature firms report higher receivables turnover and lower average collection periods, indicating that they are effective in extending and collecting credit sales. The allowance for doubtful accounts is a smaller percentage of receivables for growth and mature firms, suggesting either higher-quality credit customers or the use of discretion to underreport the allowance account thereby increasing earnings. Growth firms also have higher inventory turnovers and carry less inventory than other stages. On the other hand, introduction and shake-out firms report higher PPE turnover, suggesting they are more efficient with a smaller asset base (introduction) or have maximized their operating efficiency (shake-out). As expected, we find a higher proportion of PPE used in mature, shake-out and decline stages.

In normal circumstances, a lower payables turnover is desirable, which indicates a firm uses the maximum credit period offered by vendors. As expected, introduction firms carry the most days' expenses in payables. Conversely, mature firms rely on vendor credit to a lesser extent; alternatively, perhaps mature firms are better able to take advantage of purchase discounts. Overall, the ratio analysis indicates that introduction (and often shake-out and decline) firms are fundamentally different from growth and mature firms with respect to common accruals.

4.3.1. *Testing for misspecification with no manipulation*

First, we investigate whether the two accruals models are well-specified when estimated by various estimation groupings by year including: 1) SIC2 industry, 2) size quintile, 3) ROA quintile, 4) market-to-book (MB) quintile, 5) sales growth (SG) quintile, and 6) LCS. Results are provided in the first column (0 % manipulation) in Table 5, Panels A and B for the modified Jones and revenue models, respectively. Recall that based on a 95% confidence interval, a rejection rate below 2 % or above 8 % indicates that the model is misspecified. In both models (Panels A and B), we observe rejection rates of close to 5 % for each of the six estimation samples, consistent with acceptable model

Table 5
Rejection rates under varying revenue manipulation simulations.

Panel A: Modified Jones Model	Seeded Rates		
Sample Partitions	0%	1%	5%
Industry Year	6.50%	30.40%	98.90%
Size Year	6.90%	30.20%	99.20%
ROA Year	6.60%	32.80%	99.80%
Market-to-Book Year	7.00%	30.50%	99.00%
Sales Growth Year	6.60%	31.50%	99.20%
Life Cycle Year	6.70%	31.60%	99.30%

Panel B: Revenue Model	Seeded Rates		
Sample Partitions	0%	1%	5%
Industry Year	4.30%	44.10%	99.60%
Size Year	4.30%	45.50%	100.00%
ROA Year	3.80%	42.80%	100.00%
Market-to-Book Year	4.00%	42.80%	100.00%
Sales Growth Year	4.60%	43.70%	100.00%
Life Cycle Year	5.00%	42.60%	100.00%

Table 5 presents results of simulations for 1000 random samples of 100 firm-years. The seeded rates indicate the percent of lagged assets induced as revenue and expense manipulation in each of the samples. We estimate regression equations based on sample partitions as described above. The rejection rates are the percent of the 1000 samples where the mean estimate of discretion is significantly greater than zero (α = 0.05).

specification. More importantly, each estimation grouping performs about equally well, seemingly inconsistent with the prediction in H2 regarding Type I errors. However, this tabulation reports the results on a pooled basis. In later tables, we report the results by LCS and find evidence for H2 is supported.

4.3.2. Testing for earnings management detection with seeded manipulation

Next, we investigate the earning management detection rates for each model when we seed earnings manipulation at both one and 5 % of lagged assets (the second and third columns of Table 5, Panels A and B). Again, we use the six estimation groupings described in the previous section and we expect to see rejection rates of 100% because the manipulation is present by construction. All estimation groupings detect the manipulation with ROA slightly outperforming the other variables in the modified Jones model, and with size slightly outperforming in the revenue model. Again, H2 is not supported. However, we report the average model performance for each model while pooling together *all* firms across stages. It is possible that results are different when we tabulate performance *by* LCS. We explore that possibility in the next section.

4.4. Re-examining the results by LCSs

While Table 5 shows that the models are not misspecified on average, it is possible that the models are misspecified or have better detection rates for specific LCSs. We know firms differ considerably by LCS in accrual generation/reversals (as demonstrated in Tables 2 and 3), yet pooling the results mask these differences across LCS. Thus, we retabulate the results by LCS in Table 6 (the modified Jones model) and Table 7 (the revenue model).

4.4.1. Estimation results by LCSs – modified Jones model

First, we re-examine the results by LCS for seeded manipulation. For brevity, we restrict the subsequent analysis to the one and 0 % seeded conditions. We compute a weighted average for each grouping, which weights each rejection rate by the relative number of observations in each LCS (reported in Table 6, Panel A). This computation facilitates comparison across estimation groupings weighted by each LCS proportion. We also extend the analysis by examining combinations of the various grouping variables, which allows for non-overlapping information to incrementally improve the homogeneity of the estimation samples.

In Table 6, Panel B, we report successful detection in the presence of manipulation. In Table 6. Panel C, we report the detection rate when there is no manipulation present (in other words, Type I errors, or false positives). As such, a high-performing estimation grouping will have a high detection rate in Panel B and a low misspecification rate in Panel C. The results of each panel need to be considered jointly as an estimation grouping will only be useful if it can both detect manipulation when present and avoid false positives when manipulation is not present.

Let us first turn our attention to the performance of the single characteristic groupings in Table 6, Panels B and C, where we compare the groupings used in prior literature and LCS univariately. We see that among univariate variables, LCS performs the strongest in the weighted average summary metric, derived primarily from improved detection in the growth and mature stages. LCS detects 54.20% (38.40%) of the manipulated observations for mature (growth) firms compared to 33.40% (34.20%) for the next best univariate grouping. Because growth and mature observations represent more than 70%[14] of the total firm-years, it is necessary to consider the weighted average results. Additionally, these results must also be considered in the context of the false

[14] There are 56,450 firms in the growth and mature stages (23,380 + 33,070) which represents 71.6% of the 78,854 total observations.

Table 6
Examination of Type I and Type II Errors by LCS – Modified Jones Model.

Panel A: Sample by LCS	
Observations in Introduction Stage	9781
Observations in Growth Stage	23,380
Observations in Mature Stage	33,070
Observations in Shakeout Stage	7802
Observations in Decline Stage	4821
Total Sample Size	78,854

Panel B: Successful Detection (Detection under 1% Manipulation)

Sample Partitions	Intro Firms	Growth Firms	Mature Firms	Shake-Out Firms	Decline Firms	Weighted Average
Industry Year	30.80%	34.20%	23.40%	46.20%	25.40%	29.90%
Size Year	40.20%	23.60%	28.00%	42.60%	25.40%	29.49%
ROA Year	98.40%	6.00%	0.80%	57.80%	99.20%	26.10%
Market-to-Book Year	35.00%	25.40%	33.40%	41.20%	21.00%	31.24%
Sales Growth Year	37.40%	25.80%	26.00%	52.60%	34.40%	30.50%
Life Cycle Year	11.20%	38.40%	54.20%	32.00%	9.80%	39.27%
ROA Year (Industry FE)	97.00%	11.00%	0.60%	62.40%	97.60%	27.69%
ROA Year (Ind & LC FE)	15.00%	49.60%	61.60%	43.00%	11.80%	47.38%
LC Year (Ind & ROA FE)	14.20%	47.40%	64.80%	43.20%	10.80%	47.93%
LC Year (Ind & Size FE)	12.20%	37.00%	57.00%	32.40%	9.40%	40.17%
LC Year (Ind, ROA, & Size FE)	13.80%	48.00%	64.20%	43.00%	11.00%	47.80%

Examination of Type I and Type II Errors by LCS – Modified Jones Model

Panel C: Type I Errors (Detection under No Manipulation)

Sample Partitions	Intro Firms	Growth Firms	Mature Firms	Shake-Out Firms	Decline Firms	Weighted Average
Industry Year	23.40%	5.60%	0.60%	14.00%	22.60%	7.58%
Size Year	29.60%	3.60%	0.60%	14.60%	22.60%	7.82%
ROA Year	97.40%	0.20%	0.00%	20.20%	99.00%	20.19%
Market-to-Book Year	25.40%	3.40%	1.40%	12.60%	19.80%	7.20%
Sales Growth Year	26.80%	3.20%	0.60%	19.00%	30.20%	8.25%
Life Cycle Year	8.00%	7.40%	5.80%	7.00%	8.60%	6.84%
ROA Year (Industry FE)	96.80%	0.40%	0.00%	20.60%	95.80%	20.02%
ROA Year (Ind & LC FE)	6.60%	6.60%	6.00%	7.20%	7.40%	6.46%
LC Year (Ind & ROA FE)	5.80%	6.40%	6.40%	8.40%	7.40%	6.58%
LC Year (Ind & Size FE)	5.80%	7.40%	4.60%	10.20%	7.00%	6.28%
LC Year (Ind, ROA, & Size FE)	5.80%	6.60%	6.00%	8.00%	6.80%	6.40%

Table 6 reports results of simulations for random samples of 100 firm-years for the Modified Jones Model. Panel B reports results where we induce revenue and expense manipulation at 1% each to the random samples. We first estimate the regressions on the original sample (after removing the selected firms) using the partitions named in Panel B above. Then, we scored the random sample of 100 manipulated firms based on their respective life cycles to obtain an estimate of discretion, a process that we iterated 500 times. The rejection rates presented in Panel B above indicate the percent of the 500 replications where the mean estimate of discretion was significantly greater than zero ($\alpha = 0.05$). The Weighted Average column shows the Implied Detection Rate, calculated by weighting the detection rate by the number of firm-year observations within the LCS and summing across all LCSs. Panel C reports the results where we repeat the above procedure, but do not induce any revenue or expense manipulation into the random sample. With no seeded manipulation, rejections represent false positives or Type I errors, and the Weighted Average column shows the Implied False Positive Rate.

Table 7
Examination of Type I and Type II Errors by LCS – Revenue Model.

Panel A: Sample by LCS	
Observations in Introduction Stage	9781
Observations in Growth Stage	23,380
Observations in Mature Stage	33,070
Observations in Shakeout Stage	7802
Observations in Decline Stage	4821
Total Sample Size	78,854

Panel B: Successful Detection (Detection under 1% Manipulation)

Sample Partitions	Intro Firms	Growth Firms	Mature Firms	Shake-Out Firms	Decline Firms	Weighted Average
Industry Year	96.20%	35.60%	21.60%	37.00%	60.80%	38.92%
Size Year	95.80%	40.60%	19.80%	33.40%	54.40%	38.86%
ROA Year	98.80%	32.40%	9.20%	40.60%	86.80%	35.04%
Market-to-Book Year	97.40%	34.40%	17.80%	39.80%	63.20%	37.55%
Sales Growth Year	97.60%	27.20%	19.80%	43.40%	66.60%	36.84%
Life Cycle Year	22.40%	42.20%	60.40%	48.20%	33.20%	47.42%
ROA Year (Industry FE)	98.80%	29.80%	16.40%	39.40%	82.40%	36.90%
ROA Year (Ind & LC FE)	27.80%	46.00%	64.60%	51.40%	38.60%	51.62%
LC Year (Ind & ROA FE)	24.00%	48.20%	65.40%	54.40%	39.20%	52.47%
LC Year (Ind & Size FE)	23.00%	48.40%	60.20%	53.00%	37.20%	49.97%
LC Year (Ind, ROA, & Size FE)	25.20%	48.40%	65.80%	55.60%	40.80%	53.07%

Examination of Type I and Type II Errors by LCS – Revenue Model

Panel C: Type I Errors (Detection under No Manipulation)

Sample Partitions	Intro Firms	Growth Firms	Mature Firms	Shake-Out Firms	Decline Firms	Weighted Average
Industry Year	76.40%	3.20%	0.40%	4.00%	13.80%	11.83%
Size Year	71.00%	5.00%	0.40%	3.00%	10.00%	11.37%
ROA Year	90.40%	3.20%	0.20%	4.80%	35.60%	14.90%
Market-to-Book Year	77.60%	3.40%	0.60%	4.60%	14.60%	12.23%
Sales Growth Year	81.60%	2.80%	1.20%	5.80%	18.00%	13.13%
Life Cycle Year	4.60%	5.20%	5.60%	6.60%	4.40%	5.38%
ROA Year (Industry FE)	88.60%	3.00%	0.20%	4.20%	27.60%	14.07%
ROA Year (Ind & LC FE)	4.20%	4.80%	6.60%	5.40%	4.20%	5.50%
LC Year (Ind & ROA FE)	5.00%	4.60%	6.40%	6.40%	4.80%	5.59%
LC Year (Ind & Size FE)	6.00%	4.60%	6.60%	6.80%	5.20%	5.87%
LC Year (Ind, ROA, & Size FE)	5.40%	4.60%	6.20%	7.00%	5.00%	5.63%

Table 7 reports results of simulations for random samples of 100 firm-years for the Revenue Model. Panel B reports results where we induce revenue and expense manipulation at 1% each to the random samples. We first estimate the regressions on the original sample (after removing the selected firms) using the partitions named in Panel B above. Then, we scored the random sample of 100 manipulated firms based on their respective life cycles to obtain an estimate of discretion, a process that we iterated 500 times. The rejection rates presented in Panel B indicate the percent of the 500 replications where the mean estimate of discretion was significantly greater than zero ($\alpha = 0.05$). The Weighted Average column shows the Implied Detection Rate, calculated by weighting the detection rate by the number of firm-year observations within the LCS and summing across all LCSs. Panel C reports the results where we repeat the above procedure, but do not induce any revenue or expense manipulation into the random sample. With no seeded manipulation, rejections represent false positives or Type I errors, and the Weighted Average column shows the Implied False Positive Rate.

positive rate in Table 6, Panel C, where rejection rates should be approximately 5 % by chance when zero manipulation is introduced.

Table 6, Panel C, shows that among univariate groupings, the rejection rates for introduction firms are higher than expected across all estimation samples (ranging from 23% to 97%) except for the LCS sample, which rejects the null 8 % of the time. ROA is particularly misspecified for introduction firms with a rejection rate over 97%.[15] In other words, the modified Jones model is well-specified for introduction firms when normal accruals are estimated using only other introduction firms in the estimation sample, but other groupings produce high Type I errors for introduction firms. The model is similarly misspecified for shake-out and decline firms for all estimation groupings except LCS. The modified Jones model performs relatively well under all groupings for growth firms (ROA under-rejects and LCS slightly over-rejects). For mature firms, the modified Jones model actually under-rejects for all estimation samples except for LCS. Overall, the weighted average result reveals LCS as the closest to the expected value of 5 % (and that interestingly, ROA is extremely misspecified even when proportional LCS weights are applied). Taken together, the results in Table 6, Panels B and C, show that the LCS estimation grouping provides both the highest weighted average successful detection rate (lowest Type II error rate) and the lowest weighted average Type I error rate among the univariate

[15] This result highlights the need to consider Table 6, Panels B and C, in conjunction. The ROA estimation grouping appeared to successfully identify 98.4% of introduction firms as manipulators when manipulation was present, but when no manipulation was present it continued to identify 97.4% of firms as manipulators.

groupings, improving detection by 25.7% and reducing Type I errors by 5 % over the next best performing groupings.[16]

Next, we seek to determine whether combinations of grouping variables improve earnings management detection (the last five rows on Table 6, Panels B and C). We begin by combining industry and ROA to compare to prior literature (Kothari et al., 2005). We then build on this combination adding LCS, to examine whether the combination of LCS with the other characteristics from prior literature offers incremental improvement compared to the ROA-industry combination (as well as on the univariate LCS grouping).[17] Examining the ROA-industry combination grouping reveals a lower successful detection rate and a higher Type I error rate than LCS alone. Thus, we see that the LCS grouping in isolation outperforms the ROA-industry combination.

Next, we see that adding LCS to create a ROA-industry-LCS combination improves successful detection (relative to both the ROA-industry combination and univariate), with a comparable Type I error rate to the univariate LCS. We also see that selecting ROA or LCS as the primary grouping variable (ROA-industry-LCS versus LCS-industry-ROA) results in very similar results both for detection and Type I errors, suggesting the construction of the combinations is fairly interchangeable. Importantly, all combinations that include LCS are well-specified and outperform groupings from prior literature.[18]

To summarize the results of Table 6, partitioning on life cycle information (univariately or in combination) improves the Modified Jones Model's ability to detect manipulation across life cycles stages compared to partitions from prior literature. *And* partitions that include life cycle information (univariately or in combination) reduce the Modified Jones Model's Type I errors across life cycles stages compared to partitions from prior literature.[19] Collectively these findings support H2.

4.4.2. *Estimation results by LCSs – Revenue Model*

We report the results from the revenue model in Table 7. Again, Panels B and C must be jointly interpreted. Panels B and C show patterns of misspecification, similar to the modified Jones model, but more pronounced. For example, all non-LCS groupings from prior literature show extremely high successful detection rates for introduction firms in Panel B. However, they also each show extremely high Type I errors in Panel C (i.e., incorrect rejection rates ranging from 71% to 90%), suggesting that the revenue model labels nearly all introduction firms as manipulators regardless of the presence of manipulation. Similar, though less severe, misspecification exists for decline firms when LCS is not present in the estimation grouping. The univariate LCS grouping improves detection for growth and shake-out firms and especially for mature firms (Panel B). LCS detects manipulation for mature firms over 60% of the time, whereas the next highest grouping is industry with a detection rate of 21.60%. Consequently, LCS produces the highest weighted average detection at 47.42%, compared to 38.92% for industry.

Importantly, Panel C reports that all LCS grouping rejection rates are within the expected range. The weighted average column highlights that the revenue model is best specified when using LCS univariately (rejection rates of 5.38% as compared to the next-best performing grouping, size, at 11.37%). Even though the revenue model is prone to misspecification in the early and late lifecycle stages using the non-LCS groupings, this misspecification can be remedied by estimating the model using LCS grouping.

The combination of grouping variables — i.e., adding industry, ROA, and size controls to the LCS primary grouping (last row of Panel B) — further improves detection power over the univariate grouping for all life cycle stages, especially for growth, mature, and shakeout firms. All multivariate groupings that include LCS are at least as well-specified as using LCS alone. Thus, similar to Table 6, we find that including life cycle information (univariately or in combination) improves the revenue model's successful detection and reduces its Type 1 errors, supporting H2.[20]

In reconciling the results in Tables 6 and 7 with those in Table 5, we make the following observations. First, while both models appear to be well-specified in the pooled results (the 0 % column in Table 5), we see that each model can be poorly specified in various estimation groupings (other than LCS groupings) when reported *by* LCS. Put differently, Tables 6 and 7 reveal that the initial conclusion of well-specified models in Table 5 is misleading. LCS is capturing a fundamentally different construct than the other grouping variables as evidenced by the substantially higher LCS detection rates for growth and mature firms (using either model). Likewise, rejection rates for introduction and decline firms are severely misspecified using all groupings other than LCS. Thus, we find support for H2 for both Type I and Type II errors. Additionally, the inclusion of LCS in combination with estimation groupings from prior literature outperforms those same groupings from prior literature on a univariate basis.[21]

4.5. *Additional analyses*

In the next several sections, we seek to rule out alternative explanations and further validate our findings.

4.5.1. *Controlling for effects of financial crisis*

In untabulated analyses, we conduct our tests across subsamples excluding the financial crisis of 2007–2009 and within the financial crisis of 2007–2009. In each subsample, we find similar results to our primary analysis, suggesting our result is not driven by the financial crisis but holds within that period.

4.5.2. *Falsification test on random estimation grouping*

It is possible that using LCS as an estimation grouping and then reporting results by that same partition are tautologically driving our results. To eliminate that concern, we use a random number generator to form estimation groups (e.g., quintiles based on an ordered sort of the random numbers) and then report our results by the same random number-sorted quintiles. The results in Table 8 do not exhibit the same patterns of misspecification reported in Tables 6 or 7. Nor does the random number grouping provide the lowest weighted average false positive rate. In fact, both accruals models (modified Jones in Panel A and the revenue model in Panel B) return rejection rates that lack much variation. Therefore, our tabulation methodology does not appear to drive our results.

[16] Life cycle groupings result in a weighted average of 39.27% successful detection, which is an 8.03 percentage-point increase over market-to-book. Taking that increase over market-to-book's detection rate of 31.24% results in a percentage increase in improvement of 25.7%.

[17] We used fixed effects in the regression models to control for the effects of the nonprimary grouping variables. We use ROA or LCS as the primary grouping variables as opposed to industry to avoid sample attrition.

[18] In Appendix B, we partition the sample into size and ROA quintiles and find patterns of misspecification resulting in poorer model performance in comparison with the results in Table 6.

[19] Under-detection and over-detection each presents costs and inefficiencies to regulators. Measuring/weighting the costs associated with Type I and Type II errors is beyond the scope of the study. However, including life cycle to improve both successful detection and reduce Type I errors requires no trade-off and would result in an increase in model performance under all weighting schemes.

[20] Again, improving both detection and reducing Type I errors simultaneously leads to model improvement regardless of the weighting scheme between Type I and Type II errors.

[21] As an additional benefit, the combination of LCS with industry, ROA, and size as constructed in this paper does not lead to sample attrition typically seen when grouping on industry membership. The construction of the four-way combination in this paper partitions primarily on LCS (zero attrition) and then includes fixed effects to control for the other three grouping variables.

Table 8
Falsification Tests - Rejection Rates for No Manipulation by Random Number – Test for Type 1 Errors.

Panel A: Modified Jones Model

Sample Partitions	Random Quintile 01	Random Quintile 02	Random Quintile 03	Random Quintile 04	Random Quintile 05	Weighted Average
Industry Year	7.80%	9.00%	6.00%	6.00%	6.00%	6.96%
Size Year	7.40%	10.60%	5.80%	6.80%	7.00%	7.52%
Life Cycle Year	7.00%	9.60%	7.00%	7.60%	6.80%	7.60%
ROA Year	5.40%	7.60%	4.60%	5.60%	4.80%	5.60%
Market-to-Book Year	7.20%	10.60%	7.20%	7.60%	6.60%	7.84%
Sales Growth Year	6.00%	10.20%	6.20%	7.20%	6.80%	7.28%
Random Variable Year	6.00%	10.00%	7.20%	7.20%	7.00%	7.48%

Panel B: Revenue Model

Sample Partitions	Random Quintile 01	Random Quintile 02	Random Quintile 03	Random Quintile 04	Random Quintile 05	Weighted Average
Industry Year	3.40%	4.40%	4.00%	4.20%	6.40%	4.48%
Size Year	2.80%	4.20%	4.40%	3.60%	5.40%	4.08%
Life Cycle Year	3.40%	4.60%	5.60%	3.60%	5.20%	4.48%
ROA Year	2.60%	3.60%	5.40%	4.40%	4.00%	4.00%
Market-to-Book Year	2.60%	4.00%	4.40%	3.60%	4.80%	3.88%
Sales Growth Year	2.80%	4.00%	5.00%	3.80%	4.40%	4.00%
Random Variable Year	3.20%	4.60%	5.00%	4.20%	4.20%	4.24%

Table 8 reports results of simulations for random samples of 100 firm-years. We do not induce any manipulation to the random samples. We first estimate the regressions on the original sample (after removing the selected, but not manipulated, firms), partitioning by year only, and using a combination of variables named in the table above. Then, we score a random sample of 100 firms based on their respective quintile of a randomly generated number to obtain an estimate of discretion, a process that we iterate 500 times. The rejection rates presented above indicate the percent of the 500 replications where the mean estimate of discretion was significantly greater than zero ($\alpha = 0.05$). However, now with no seeded manipulation, rejections represent false positives or Type I errors. The Weighted Average column shows the Implied False Positive Rate.

4.5.3. *Validation through examination of AAER data*

We next attempt to validate our results on a sample of firms for which the SEC filed Accounting and Auditing Enforcement Releases [AAERs] for a specific firm-year. We examine 841 AAER firm-year observations from the years 1988 to 2013. We delete AAER observations where enforcements: 1) were brought against the auditor when there was no misstatement, 2) were related to bribes, 3) were disclosure-related with no misstatement, or 4) were related to revenues or earnings being understated. Table 9, Panel A, indicates the number of enforcement actions by LCS, and we observe that the growth and mature stages contain the most enforcement actions (230 and 147, respectively).

We then estimate the discretionary accruals (implied residuals) for each AAER firm-year observation by the various estimation groupings. As positive residuals are consistent with income-increasing discretionary accruals, we report the portion of the sample for which the implied residuals were positive.[22] Reporting the percentage of positive accruals has the additional benefit of providing a comparable statistic to the detection rates in the prior tables.

In Table 9, Panel B, we report the percentage of positive residuals for the AAER observations using the modified Jones model. We note that LCS has the highest detection power for growth firms, which encompass a substantial portion of the AAER observations. LCS also provides the second-highest detection rates for mature and shake-out firms, behind industry and sales growth, respectively. Because of LCS's high performance relative to the other groupings, LCS again has the highest weighted average detection rate of all groupings, although grouping by industry is almost as high.[23] It is also critical to consider that regulators are not only concerned with detection, but also Type I errors. Given all firms in this sample have been identified as manipulators, it is not possible to consider the impact of Type I errors as reported in Table 6.

In Panel C, we repeat the analysis using the revenue model and find that examining the results by LCS is important because the revenue model detection of earnings management varies considerably across stages. Similar to Panel B, the weighted average detection rates are similar across model partitions. Size provides the highest detection rate at 56.93% with the four-way combination of Life cycle, industry, size and ROA closely behind at 56.74%. These results again understate the benefit of including life cycle information, as Table 7 shows a substantial reduction in Type I error rates when life cycle is included for the Revenue model. Thus, the AAER sample shows that detection rates for the most extreme manipulators are similar when life cycle is included for both models, before considering Type I errors. Overall, this validation is encouraging, given that a sizable portion of LCS's contribution to the estimation process was in resolving misspecification (Type I errors, or false positives). When regulators investigate firms prompted by false positive identifications, the resulting inefficiency leads to a deadweight loss and the misallocation of valuable resources. This issue can be partially resolved by including LCS as an estimation grouping in regulators' AQM models.

Predictably, the overall detection rates are higher for the AAER firms than for the seeded manipulation, given that the seeded manipulation was chosen at a modest level relative to actual earnings management violations. Regulators have expressed a need for discretionary accruals models to inform "the full range of behaviors associated with earnings management, and not merely as a way to potentially detect fraud" (Lewis, 2012). Given that LCS performs as well as extant grouping variables for extreme earnings manipulators (the AAER sample), and outperforms for more modest manipulation (the seeded manipulation sample), regulators will benefit by incorporating LCS information into their analyses.

[22] Regulators are most concerned with income-increasing accruals when investigating potential earnings manipulation.

[23] Weighted average calculations for both successful detection and Type I errors are based on the LCS distribution of the AAER sample.

Table 9
AAER discretionary accrual analysis.

Panel A: AAER Sample by LCS			
Observations in Introduction Stage	80	Observations in Shakeout Stage	45
Observations in Growth Stage	230	Observations in Decline Stage	25
Observations in Mature Stage	147	Total Sample Size	527

Panel B: Percentage of Observations with Positive Residual - Modified Jones Model

	Intro	Growth	Mature	Shakeout	Decline	WAvg
Industry Year	76.25%	60.00%	67.62%	62.22%	48.00%	64.21%
Size Year	73.75%	61.30%	53.06%	60.00%	48.00%	60.15%
ROA Year	82.50%	46.09%	36.05%	55.56%	56.00%	50.09%
Market-to-Book Year	75.00%	61.74%	58.50%	62.22%	48.00%	62.24%
Sales Growth Year	73.75%	61.30%	53.06%	68.89%	48.00%	60.91%
Life Cycle Year	70.00%	63.48%	65.99%	64.44%	48.00%	64.52%
ROA Year (Industry FE)	78.75%	54.35%	40.82%	46.67%	56.00%	53.70%
ROA Year (Industry & LC FE)	65.00%	63.04%	61.22%	51.11%	36.00%	60.53%
LC Year (Ind & ROA FE)	66.25%	62.17%	59.18%	48.89%	36.00%	59.58%
LC Year (Ind & Size FE)	65.00%	63.48%	57.82%	46.67%	32.00%	59.20%
LC Year (Ind, ROA, & Size FE)	68.75%	63.91%	56.46%	53.33%	44.00%	60.72%

Panel C: Percentage of Observations with Positive Residual - Revenue Model

	Intro	Growth	Mature	Shakeout	Decline	WAvg
Industry Year	73.75%	52.61%	44.22%	40.00%	68.00%	53.13%
Size Year	73.75%	60.87%	44.90%	42.22%	64.00%	56.93%
ROA Year	77.50%	55.22%	38.10%	46.67%	72.00%	53.89%
Market-to-Book Year	73.75%	54.78%	38.78%	46.67%	60.00%	52.75%
Sales Growth Year	76.25%	50.87%	38.78%	44.44%	64.00%	51.42%
Life Cycle Year	60.00%	56.52%	46.26%	53.33%	56.00%	53.89%
ROA Year (Industry FE)	77.50%	55.22%	39.46%	46.67%	68.00%	54.08%
ROA Year (Ind & LC FE)	58.75%	56.52%	51.70%	42.22%	56.00%	54.27%
LC Year (Ind & ROA FE)	65.00%	57.83%	48.98%	53.33%	52.00%	55.79%
LC Year (Ind & Size FE)	60.00%	59.13%	48.98%	44.44%	60.00%	55.22%
LC Year (Ind, ROA, & Size FE)	66.25%	60.43%	46.94%	53.33%	56.00%	56.74%

Table 9, Panels B and C report the percentage of residuals greater than zero in each LCS estimated by each partition. A positive residual is consistent with the model identifying the firm as a potential manipulator. Given the sample is restricted to AAER firms with income increasing earnings manipulations, larger values correspond to greater and more accurate detection. The Weighted Average (WAvg) column shows the Implied Detection Rate, calculated by weighting the percentage of positive residuals by the number of firm-year observations within the LCS and summing across all LCSs. Weighted Average calculations for successful detection are based on the distribution of the AAER sample; however, inferences remain the same if weighted on the entire sample.

5. Conclusion

Prior literature traditionally relies on industry as the sole classification variable by which to estimate discretionary accruals used to identify earnings management. More recent literature introduces firm size and performance/expected growth as alternatives to industry partitioning. We propose that models using firm LCS will increase the homogeneity of estimation samples, as firms in similar LCSs face similar strategic concerns, managerial pressures, growth prospects, etc. Consistent with this prediction, this study demonstrates that LCS improves estimation sample homogeneity in both the modified Jones and revenue models of discretionary accruals. Critically, we find that both models are misspecified and lack power when LCS is not considered, leading to increased Type I and Type II errors.

The results indicate that the inclusion of LCS in the estimation process mitigates both types of errors. We further demonstrate that the accruals generating process, specifically accrual origination and reversals, varies substantially by LCS, which likely contributes to the improvement of the normal accruals estimation process. The results have significant implications for regulators who allocate scarce resources to investigate firms suspected of earnings management based upon quantitative modeling. Standard setters may also consider the implications of LCS when promulgating future accounting measurement and disclosure decisions to improve the representational faithfulness of accounting information reported to investors, creditors, and other financial statement users.

Data availability

All data are publicly available from sources identified.

Appendix A

A.1. Summary of variable definitions, financial ratios, discretionary accruals models and life cycle measure

A.1.1. Variable definitions

AC = annual current accruals, calculated by earnings before extraordinary items (IB) - cash from operations (OANCF)
ΔAR = change in accounts receivable, taken from the statement of cash flows (RECCH)
ΔR = change in annual revenues (REVT)
ΔR1_3 = change in revenues of the first three quarters of the year
ΔR4 = change in revenues of the fourth quarter
PPE = end of fiscal year gross property, plant, and equipment (PPEGT)
AR = end of year receivables (RECT)
INV = end of year total inventories (INVT)
AP = end of year trade accounts payable (AP)

A.1.2. Financial Ratios

Receivables Turnover = revenues / average receivables.
Collection Period = (average receivables x 365) / revenues.
Allowance / AR = allowance for doubtful accounts / receivables.
Inventory Turnover = cost of goods sold / average inventory.
Days Sales in Inventory = (average inventory x 365) / cost of goods sold.
PPE Turnover = revenues / average net property, plant, and equipment.
PPE Percentage Used = accumulated depreciation / gross property, plant, and equipment.
Payables Turnover = (cost of goods sold + selling, general, and administrative expense) / average accounts payable.
Days Expenses in Payables = (average accounts payable x 365) / (cost of goods sold + selling, general, and administrative expense).
Modified Jones Model:

$$AC_{it} = \alpha + \beta_1(\Delta R_{it} - \Delta AR_{it}) + \beta_2 PPE_{it} + \varepsilon_{it}$$

Discretionary Revenue Model:

$$\Delta AR_{it} = \alpha + \beta_1 \Delta R1\_3_{it} + \beta_2 \Delta R4_{it} + \varepsilon_{it}$$

A.1.3. Life cycle measure

Dickinson (2011) explains "there are three cash flow types (operating, investing, and financing) and each can take a positive or negative sign which results in $2^3 = 8$ possible combinations. The eight patterns are collapsed into five stages as follows" (p. 1974):

	1	2	3	4	5	6	7	8
	Introduction	Growth	Mature	Shake-Out	Shake-Out	Shake-Out	Decline	Decline
Preditcted sign								
Cash flow from operating activities	−	+	+	−	+	+	−	−
Cash flow from investing activities	−	−	−	−	+	+	+	+
Cash flow from financing activities	+	+	−	−	+	−	+	−

Appendix B

In this appendix, we report the results of our analysis conducted across quintiles of size and ROA instead of life cycle stages (LCS). Similar to our results related to firm LCS, prior literature has shown that firms of similar size (Ecker et al., 2013) and profitability (Collins et al., 2017) have similar characteristics that increase the homogeneity of the accruals generating process. Thus, we would expect estimation groupings that include size to outperform those that do not include size across size quintiles and estimation groupings that include ROA to outperform those that do not include ROA across ROA quintiles. Critically for this study, we are interested in estimation groupings that combine LCS with these other factors documented by prior literature to determine if estimation groupings that include LCS perform at least as well across size and ROA quintiles as those groupings excluding LCS. Given the benefits of including LCS in reducing Type I and Type II errors across life cycle stages, if estimation groupings that include LCS perform at least as well as other groupings across size and ROA quintiles, then LCS groupings represent an improvement over the current literature.

B.1. Simulation process

We perform the same simulation process as in our primary analysis, re-summarized here. Using the alternative estimation groupings, we simulate earnings management into each sample (Dechow et al., 1995; Ecker et al., 2013; Stubben, 2010). We repeat the following steps for each discretionary accrual model:

(1) We select a random subsample of 100 firm-year observations (firm-event-years) with replacement from particular quintiles of size or ROA. These firm-event-years do not change throughout the iteration of the steps listed here.
(2) We simulate discretionary accrual manipulation for both revenues and expenses. To manipulate revenues we add either zero, one, or 5 %[24] of lagged total assets to the change in revenues, the change in fourth-quarter revenues, and the receivables accrual. To manipulate expenses we add zero, one, or 5 % of lagged total assets multiplied by the gross margin percentage to current accruals. These manipulations are performed on each of the 100 firm-event-years.
(3) We use the original sample less the 100 manipulated firm-event-years to estimate discretionary accruals for both the modified Jones and revenue models. These models are estimated separately for a given partition (i.e., industry, size, ROA, market-to-book, sales growth, or LCS). In other words, we estimate the model (either the modified Jones or revenue model) by a given partition, such as industry, and complete the following steps before repeating the process for a different partition.
(4) We use the unique coefficient estimates from the given partition, to calculate estimates of discretionary accruals for the 100 firm-event-years. Thus, we calculate a distinct measure of discretionary accruals by partition for each model.
(5) Finally, we calculate the mean estimate of discretion (signed discretionary accruals) from the 100 firm-event-years by partition for each model and test whether the mean is significantly greater than zero.
(6) We repeat this process 500 times where firm-event-years are selected from specific quintiles of size or ROA.
(7) We report the percentage of the means from the 500 iterations that are significantly greater than zero; that is the percentage of times each model rejects the null hypothesis of no manipulation.

We then repeat these seven steps changing the partition selected in step 3 and completing the testing procedure. A rejection rate of 5 % is expected when manipulation is not introduced, and based on a 95% confidence interval, an actual rejection rate below 2 % or above 8 % indicates that the test is misspecified. When manipulation is introduced, however, the rejection rate should be 100%.

B.2. Results

Table A1 reports the results for analyses across size quintiles. Panels B and C report results for the modified Jones model. Detection rates in the presence of manipulation (successful detection) are reported in Panel B, with the LCS estimation grouping combined with fixed effects to capture industry, ROA and size performing the best. Similarly, the same four-way combination has the lowest level of Type I errors reported in Panel C. Therefore, the four-way combination outperforms on both dimensions, increasing detection and reducing Type I errors, Thus, the combination of LCS along with the other characteristics documented in prior literature outperforms the size measure by itself, even when we conduct tests across quintiles of size. Results are directionally similar but with smaller differences for the revenue model reported in Panels D and E. The combination of LCS with industry, ROA and size again exhibits the highest detection rate at 58.4% compared to 57.44% for size alone. The Type I error rate slightly favors size alone at 4.44% with the four-way combination at 5.16%. Thus, for the Revenue model, life cycle in combination with characteristics identified in prior literature performs roughly as well as size alone in overall model performance across sizes. Taken together, LCS in combination with characteristics documented in prior literature performs at least as well and can improve traditional models in detection across samples based on varying firm size.

Table A2 reports the results for analyses across ROA quintiles. Panels B and C report results for the modified Jones model. Across ROA quintiles, the estimation groupings that exclude ROA report very high detection in Panel B in the presence of manipulation but claim high detection in Panel C when no manipulation is present. Thus, estimation groupings without ROA demonstrate very high Type I errors, limiting their ability to efficiently detect earnings management firms. For example, the sales growth grouping provides the highest detection rate of 77.80%; however, it also reports a "false positive" rate of 59.44% when no manipulation was present. While this study does not measure the relative benefit of detection and cost of identification for regulators, such a high false positive rate would seem to disqualify this grouping from any practical use. Three models in Panel C report Type I error rates that are consistent with the model being well specified for that grouping. And in each case ROA is included in that grouping. Importantly, among those three groupings the four-way combination including LCS performs the best in detection rate at 56.60% compared to 47.28% for ROA alone. Thus, the combination of LCS along with the other characteristics documented in prior literature outperforms the ROA measure by itself, even when we conduct tests across quintiles of ROA. In Panel E, we see estimation groupings without ROA are generally not as highly misspecified for the revenue model as for the modified Jones model, although misspecification still exists when ROA is not present. For those models that do not exhibit misspecification in Panel E, Panel D again shows that the four-way combination still reports the highest detection rate. The combination of LCS with industry, ROA and size exhibits a detection rate of 52.28% compared to 44.80% for ROA alone. Taken together, LCS in combination with characteristics documented in prior literature provides Type I error rates similar to traditional models that include ROA and outperforms those well-specified models in detection. Thus, the combination of LCS with industry, ROA and size performs at least as well and can improve upon traditional models in detection across samples of firms of different profitability levels.

In summation, the totality of the results in this appendix support the inclusion of LCS information along with firm characteristics established in the literature, as the combinations perform at least as well and generally outperform any single firm characteristic in detecting earnings management when samples are considered across size or profitability.

[24] Dechow et al. (1995) indicates that one to 5 % of total assets are economically plausible amounts of earnings management. However, they test between zero and 100% accrual manipulation in 10 percentage point increments. Ecker et al. (2013) test between zero and 20% accrual manipulation using two percentage point increments.

Table A1
Examination of Type I and Type II Errors by Size Quintiles – Both Models.

Panel A: Sample by Size Quintiles	
Observations in Size Quintile 1	15,770
Observations in Size Quintile 2	15,771
Observations in Size Quintile 3	15,771
Observations in Size Quintile 4	15,771
Observations in Size Quintile 5	15,771
Total Sample Size	78,854

Panel B: Modified Jones Model - Successful Detection (Detection under 1% Manipulation)

Sample Partitions	Size Quintile 1	Size Quintile 2	Size Quintile 3	Size Quintile 4	Size Quintile 5	Weighted Average
Industry Year	12.60%	31.00%	32.00%	38.40%	88.40%	40.48%
Size Year	20.80%	26.60%	32.00%	44.60%	64.60%	37.72%
ROA Year	43.80%	45.60%	22.80%	15.20%	57.00%	36.88%
Market-to-Book Year	9.00%	25.60%	27.60%	46.60%	94.60%	40.68%
Sales Growth Year	9.60%	29.80%	28.40%	44.80%	92.20%	40.96%
Life Cycle Year	5.00%	27.40%	32.20%	54.40%	95.20%	42.84%
LC Year (Ind & ROA FE)	26.60%	42.80%	38.40%	44.80%	84.80%	47.48%
LC Year (Ind & Size FE)	25.00%	27.80%	36.40%	47.00%	67.20%	40.68%
LC Year (Ind, ROA, & Size FE)	27.40%	31.80%	41.20%	61.20%	80.60%	48.44%

Panel C: Modified Jones Model - Type I Errors (Detection under No Manipulation)

Sample Partitions	Size Quintile 1	Size Quintile 2	Size Quintile 3	Size Quintile 4	Size Quintile 5	Weighted Average
Industry Year	2.00%	9.00%	7.40%	5.40%	32.00%	11.16%
Size Year	5.20%	7.80%	7.40%	6.60%	7.80%	6.96%
ROA Year	19.20%	17.40%	2.80%	0.40%	0.80%	8.12%
Market-to-Book Year	1.40%	7.40%	6.00%	7.40%	50.20%	14.48%
Sales Growth Year	2.20%	9.00%	5.40%	7.20%	38.20%	12.40%
Life Cycle Year	1.00%	8.60%	6.60%	12.80%	56.40%	17.08%
LC Year (Ind & ROA FE)	6.00%	10.80%	5.80%	3.20%	10.20%	7.20%
LC Year (Ind & Size FE)	7.60%	5.80%	7.20%	7.40%	6.20%	6.84%
LC Year (Ind, ROA, & Size FE)	6.60%	6.00%	7.20%	5.80%	4.80%	6.08%

Examination of Type I and Type II Errors by LCS – Modified Jones Model.

Panel D: Revenue Model - Successful Detection (Detection under 1% Manipulation)

Sample Partitions	Size Quintile 1	Size Quintile 2	Size Quintile 3	Size Quintile 4	Size Quintile 5	Weighted Average
Industry Year	44.20%	55.80%	51.00%	43.40%	75.80%	54.04%
Size Year	30.40%	34.60%	48.80%	77.60%	95.80%	57.44%
ROA Year	58.00%	55.60%	45.80%	24.80%	42.60%	45.36%
Market-to-Book Year	51.40%	55.60%	47.60%	26.20%	44.20%	45.00%
Sales Growth Year	56.00%	52.80%	46.00%	23.80%	49.40%	45.60%
Life Cycle Year	39.80%	49.20%	50.20%	44.00%	73.80%	51.40%
LC Year (Ind & ROA FE)	38.80%	49.00%	55.00%	57.40%	81.40%	56.32%
LC Year (Ind & Size FE)	32.20%	42.00%	50.60%	73.80%	89.80%	57.68%
LC Year (Ind, ROA, & Size FE)	33.00%	42.00%	51.20%	74.20%	91.60%	58.40%

Examination of Type I and Type II Errors by LCS – Modified Jones Model

Panel E: Revenue Model - Type I Errors (Detection under No Manipulation)

Sample Partitions	Size Quintile 1	Size Quintile 2	Size Quintile 3	Size Quintile 4	Size Quintile 5	Weighted Average
Industry Year	9.80%	12.20%	3.80%	1.00%	0.80%	5.52%
Size Year	4.60%	5.40%	3.00%	6.20%	3.00%	4.44%
ROA Year	20.20%	13.20%	3.40%	0.20%	0.00%	7.40%
Market-to-Book Year	14.80%	14.00%	3.40%	0.00%	0.00%	6.44%
Sales Growth Year	16.00%	12.40%	3.00%	0.20%	0.00%	6.32%
Life Cycle Year	8.20%	9.60%	4.60%	0.40%	1.00%	4.76%
LC Year (Ind & ROA FE)	9.00%	8.20%	5.00%	1.40%	3.20%	5.36%
LC Year (Ind & Size FE)	7.00%	5.20%	4.60%	3.60%	5.60%	5.20%
LC Year (Ind, ROA, & Size FE)	6.60%	5.40%	4.40%	3.60%	5.80%	5.16%

Table A1 reports results of simulations for random samples of 100 firm-years for the Modified Jones and Revenue Models. Panels B and E reports results where we induce revenue and expense manipulation at 1% each to the random samples in the Modified Jones Model and Revenue Model respectively. We first estimate the regressions on the original sample (after removing the selected firms) using the partitions named in the table above. Then, we scored the random sample of 100 manipulated firms based on their respective size quintiles to obtain an estimate of discretion, a process that we iterated 500 times. The rejection rates presented above indicate the percent of the 500 replications where the mean estimate of discretion was significantly greater than zero ($\alpha = 0.05$). The Weighted Average column shows the Implied Detection Rate, calculated by weighting the detection rate by the number of firm-year observations within the size quintiles and summing across all quintiles. Panels C and F report the results where we repeat the above procedure, but do not induce any revenue or expense manipulation into the random sample. However, now with no seeded manipulation, rejections represent false positives or Type I errors, and the Weighted Average column shows the Implied False Positive Rate.

Table A2

Examination of Type I and Type II Errors by ROA Quintiles – Both Models.

Panel A: Sample by ROA Quintiles	
Observations in ROA Quintile 1	15,770
Observations in ROA Quintile 2	15,771
Observations in ROA Quintile 3	15,771
Observations in ROA Quintile 4	15,771
Observations in ROA Quintile 5	15,771
Total Sample Size	78,854

Panel B: Modified Jones Model - Successful Detection (Detection under 1% Manipulation)

Sample Partitions	ROA Quintile 1	ROA Quintile 2	ROA Quintile 3	ROA Quintile 4	ROA Quintile 5	Weighted Average
Industry Year	0.00%	84.00%	99.20%	99.60%	99.20%	76.40%
Size Year	0.00%	83.20%	99.80%	99.80%	99.80%	76.52%
ROA Year	13.80%	58.00%	68.20%	60.00%	36.40%	47.28%
Market-to-Book Year	0.00%	85.40%	100.00%	99.40%	100.00%	76.96%
Sales Growth Year	0.00%	89.40%	99.80%	99.80%	100.00%	77.80%
Life Cycle Year	0.00%	83.40%	100.00%	100.00%	100.00%	76.68%
LC Year (Ind & ROA FE)	15.20%	65.60%	79.80%	73.40%	45.80%	55.96%
LC Year (Ind & Size FE)	0.00%	71.20%	99.60%	100.00%	100.00%	74.16%
LC Year (Ind, ROA, & Size FE)	15.40%	66.80%	80.40%	73.60%	46.80%	56.60%

Panel C: Modified Jones Model - Type I Errors (Detection under No Manipulation)

Sample Partitions	ROA Quintile 1	ROA Quintile 2	ROA Quintile 3	ROA Quintile 4	ROA Quintile 5	Weighted Average
Industry Year	0.00%	23.00%	80.20%	85.40%	97.00%	57.12%
Size Year	0.00%	20.80%	88.60%	92.40%	97.80%	59.92%
ROA Year	5.20%	4.20%	5.20%	2.20%	5.60%	4.48%
Market-to-Book Year	0.00%	23.40%	89.00%	91.60%	98.80%	60.56%
Sales Growth Year	0.00%	24.60%	87.20%	88.60%	96.80%	59.44%
Life Cycle Year	0.00%	18.60%	94.80%	98.80%	99.80%	62.40%
LC Year (Ind & ROA FE)	7.20%	6.60%	4.00%	5.40%	4.20%	5.48%
LC Year (Ind & Size FE)	0.00%	9.20%	86.40%	93.00%	98.60%	57.44%
LC Year (Ind, ROA, & Size FE)	7.80%	6.20%	4.60%	5.40%	4.40%	5.68%

Examination of Type I and Type II Errors by LCS – Modified Jones Model

Panel D: Revenue Model - Successful Detection (Detection under 1% Manipulation)

Sample Partitions	ROA Quintile 1	ROA Quintile 2	ROA Quintile 3	ROA Quintile 4	ROA Quintile 5	Weighted Average
Industry Year	8.20%	39.40%	53.40%	65.80%	79.40%	49.24%
Size Year	5.40%	31.80%	57.40%	68.80%	86.20%	49.92%
ROA Year	30.20%	57.80%	54.80%	48.00%	33.20%	44.80%
Market-to-Book Year	6.60%	41.00%	58.00%	57.00%	70.80%	46.68%
Sales Growth Year	12.20%	40.40%	44.40%	47.00%	81.40%	45.08%
Life Cycle Year	0.60%	30.20%	58.20%	74.80%	95.20%	51.80%
LC Year (Ind & ROA FE)	32.40%	66.40%	63.20%	58.20%	40.00%	52.04%
LC Year (Ind & Size FE)	1.20%	36.20%	68.20%	81.80%	93.60%	56.20%
LC Year (Ind, ROA, & Size FE)	33.00%	66.40%	64.20%	58.20%	39.60%	52.28%

Panel E: Revenue Model - Type I Errors (Detection under No Manipulation)

Sample Partitions	ROA Quintile 1	ROA Quintile 2	ROA Quintile 3	ROA Quintile 4	ROA Quintile 5	Weighted Average
Industry Year	0.60%	1.00%	1.80%	6.00%	27.60%	7.40%
Size Year	0.40%	0.80%	4.00%	7.80%	38.00%	10.20%
ROA Year	4.60%	4.40%	4.00%	2.80%	5.20%	4.20%
Market-to-Book Year	0.60%	1.80%	5.40%	5.60%	25.00%	7.68%
Sales Growth Year	0.40%	1.80%	2.40%	3.40%	33.40%	8.28%
Life Cycle Year	0.00%	0.40%	5.00%	11.20%	64.20%	16.16%
LC Year (Ind & ROA FE)	4.80%	5.00%	3.60%	4.20%	5.60%	4.64%
LC Year (Ind & Size FE)	0.00%	0.60%	5.60%	15.80%	51.40%	14.68%
LC Year (Ind, ROA, & Size FE)	4.00%	5.00%	4.20%	4.80%	6.40%	4.88%

Table A2 reports results of simulations for random samples of 100 firm-years for the Modified Jones and Revenue Models. Panels B and E reports results where we induce revenue and expense manipulation at 1% each to the random samples in the Modified Jones Model and Revenue Model respectively. We first estimate the regressions on the original sample (after removing the selected firms) using the partitions named in the table above. Then, we scored the random sample of 100 manipulated firms based on their respective size quintiles to obtain an estimate of discretion, a process that we iterated 500 times. The rejection rates presented above indicate the percent of the 500 replications where the mean estimate of discretion was significantly greater than zero ($\alpha = 0.05$). The Weighted Average column shows the Implied Detection Rate, calculated by weighting the detection rate by the number of firm-year observations within the size quintiles and summing across all quintiles. Panels C and F report the results where we repeat the above procedure, but do not induce any revenue or expense manipulation into the random sample. However, now with no seeded manipulation, rejections represent false positives or Type I errors, and the Weighted Average column shows the Implied False Positive Rate.

References

Aharony, J., Falk, H., & Yehuda, N. (2006). *Corporate life cycle and the relative value-relevance of cash flow versus accrual financial information*. School of Economics and Management Bolzano.

Allen, E., Larson, C., & Sloan, R. (2013). Accrual reversals, earnings and stock returns. *Journal of Accounting and Economics., 56*, 113–129.

Bagnoli, M., & Watts, S. (2000). The effect of relative performance evaluation on earnings management: A game-theoretic approach. *Journal of Accounting and Public Policy., 19*(4/5), 271–309.

Bernard, V., & Skinner, D. (1996). What motivates managers' choice of discretionary accruals. *Journal of Accounting and Economics., 22*(1–3), 313–325.

Black, E. L. (1998). Life-cycle impacts on the incremental value-relevance of earnings and cash flow measures. *Journal of Financial Statement Analysis., 4*(1), 40–56.

Cantrell, B., & Dickinson, V. (2020). Conditional life cycle: An examination of operating performance for leaders and laggards. *Management Science., 66*(1), 433–451.

Center for Accounting Research and Education. (2016). CARE Conference: Perspectives on Fraud, Proceedings. viewed at https://www.youtube.com/watch?v=IvrLWXW6IwE&feature=youtu.be (accessed 15 October 2020).

Chen, X., Yang, W., & Huang, D. (2010). Corporate life cycle and the accrual model: An empirical study based on Chinese listed companies. *Frontiers of Business Research in China, 4*(3), 580–607.

Cheng, Q. (2005). What determines residual income? *The Accounting Review, 80*(1), 85–112.

Cohen, D., Pandit, S., Wasley, C. E., & Zach, T. (2020). Measuring real activity management. *Contemporary Accounting Research., 37*(2), 1172–1198.

Collins, D., Pungaliya, R., & Vijh, A. (2017). The effects of firm growth and model specification choices on tests of earnings management in quarterly settings. *The Accounting Review., 92*(2), 69–100.

Dechow, P., & Dichev, I. (2002). The quality of accruals and earnings: The role of accrual estimation errors. *The Accounting Review., 77*(Supplement), 35–59.

Dechow, P., Hutton, A., Kim, J., & Sloan, R. (2012). Detecting earnings management, a new approach. *Journal of Accounting Research., 50*(2), 275–334.

Dechow, P., & Schrand, C. (2004). *Earnings quality*. Charlottesville, VA: The Research Foundation of CFA Institute.

Dechow, P., Sloan, R., & Sweeney, A. (1995). Detecting earnings management. *The Accounting Review., 70*(2), 193–225.

DeFond, M., & Jiambalvo, J. (1994). Debt covenant violation and manipulation of accruals. *Journal of Accounting and Economics., 17*(1–2), 145–176.

Dichev, I., Graham, J., Harvey, C., & Rajgopal, S. (2016). The misrepresentation of earnings. *Financial Analysts' Journal., 72*(1), 22–35.

Dickinson, V. (2011). Cash flow patterns as a proxy for firm life cycle. *The Accounting Review., 86*(6), 1969–1994.

Dopuch, N., Mashruwala, R., Seethamraju, C., & Zach, T. (2012). The impact of a heterogeneous accrual-generating process on empirical accrual models. *Journal of Accounting, Auditing and Finance., 27*(3), 386–411.

Ecker, F., Francis, J., Olsson, P., & Schipper, K. (2013). Estimation sample selection for discretionary accruals models. *Journal of Accounting and Economics., 56*(2–3), 190–211.

Eldenburg, L. G., Gunny, K. A., Hee, K. W., & Soderstrom, N. (2011). Earnings management using real activities: Evidence from nonprofit hospitals. *The Accounting Review., 86*(5), 1605–1630.

Fairfield, P., Ramnath, S., & Yohn, T. (2009). Do industry-level analyses improve forecasts of financial performance? *Journal of Accounting Research., 47*(1), 147–178.

Fairfield, P., Whisenant, S., & Yohn, T. (2003). The differential persistence of accruals and cash flows for future operating income versus future profitability. *Review of Accounting Studies., 8*(2–3), 221–243.

Fedyk, T., Singer, Z., & Sougiannis, T. (2020). The accrual anomaly, accrual originations, accrual reversals, and resolution of uncertainty. *Contemporary Accounting Research., 37*(2), 635–1325.

Gebhardt, W., Lee, C. M. C., & Swaminathan, B. (2001). Toward an implied cost of capital. *Journal of Accounting Research., 39*, 135–176.

Guay, W., Kothari, S. P., & Watts, R. (1996). A market-based evaluation of discretionary accruals models. *Journal of Accounting Research., 34*(Supplement), 83–105.

Healy, P. (1996). Discussion of a market-based evaluation of discretionary accrual models. *Journal of Accounting Research., 34*(Supplement), 107–115.

Hribar, P., & Yehuda, N. (2015). The mispricing of cash flows and accruals at different life-cycle stages. *Contemporary Accounting Research., 32*(3), 1053–1072.

Jones, J. (1991). Earnings management during import relief investigations. *Journal of Accounting Research., 29*(2), 193–228.

Kang, S., & Sivaramakrishnan, K. (1995). Issues in testing earnings management and an instrumental variable approach. *Journal of Accounting Research., 33*(2), 355–367.

Kothari, S. P., Leone, A., & Wasley, C. (2005). Performance matched discretionary accrual measures. *Journal of Accounting and Economics., 39*, 163–197.

Krishnan, G. V., Myllymaki, E., & Nagar, N. (2018). *Does financial reporting quality vary across firm life cycle? Working Paper*. Bentley University, Aalto University and Indian Institute of Management.

Lewellen, J., & Resutek, R. J. (2019). Why do accruals predict earnings? *Journal of Accounting and Economics., 67*, 336–356.

Lewis, C. (2012). Speech to the Financial Executives International Committee on Finance and Information Technology. https://www.sec.gov/news/speech/2012-spch121312cmlhtm.

McNichols, M. (2000). Research design issues in earnings management studies. *Journal of Accounting and Public Policy., 19*(4–5), 313–345.

Owens, E., Wu, J., & Zimmerman, J. (2017). Idiosyncratic shocks to firm underlying economics and abnormal accruals. *The Accounting Review., 92*(2), 183–219.

Shahzad, F., Lu, J., & Fareed, Z. (2019). Does firm life cycle impact corporate risk taking and performance? *Journal of Multinational Financial Management., 51*, 23–44.

Soliman, M. (2008). The use of DuPont analysis by market participants. *The Accounting Review., 83*(3), 823–853.

Srivastava, A. (2019). Improving the measures of real earnings management. *Review of Accounting Studies., 24*(4), 1277–1316.

Stubben, S. (2010). Discretionary accruals as a measure of earnings management. *The Accounting Review., 85*(2), 695–717.

Subramanyam, K. (1996). The pricing of discretionary accruals. *Journal of Accounting and Economics., 22*, 249–281.
Thomas, J., & Zhang, X. (2001). Identifying unexpected accruals: A comparison of current approaches. *Journal of Accounting and Public Policy., 19*(4–5), 347–376.
Xie, X., Chang, Y., & Shiue, M. (2022). Corporate life cycle, family firms, and earnings management: Evidence from Taiwan. *Advances in Accounting., 56* (early online).
Yu, D., Hyun, S., & Anderson, M. C. (2019). *DuPont analysis and firm life cycle. Working Paper*. Ryerson University, University of North Carolina Greensboro and University of Calgary.
Zarowin, P. (2015). *Estimation of discretionary accruals and the detection of earnings management. The Oxford Handbook of Strategy Implementation* (pp. 481–496). Oxford University Press.