Does Earnings Management Matter for Strategy Research?*

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Abstract

Strategic management research frequently seeks to explain variation in organizational performance using metrics such as accounting profits scaled by firm assets (ROA). A concern with accrual-based accounting methods, perhaps best illustrated by a large discontinuity in the distribution of ROA around zero for U.S. public firms, is that operational and accounting practices will artificially inflate/deflate accounting profit. In this manuscript we establish that such *earnings management* is common, introduces non-classical noise, and distorts our understanding of broad drivers of firm performance. We conclude with analysis showing that an alternative performance measure rarely used in strategy and economics research, Cash Flows from Operations on Assets (OCFOA), offers a robust vehicle for checking results using accounting profits. Two short demonstrations applied to classic strategic management research questions are included to show how the implications of such studies may change depending on whether one uses a profit-based or cash-flow-based measure of firm performance.

Keywords: earnings management, return on assets, performance, measurement error, bunching

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1 Introduction

Investors, managers, and scholars all rely on accounting-based measures of public firm performance. A cursory search on Google Scholar, for example, yields over 22,000 papers, distributed over multiple fields, containing the terms "Compustat" and "Return on Assets." This prevalence partly reflects a long tradition of using accounting data to study both the drivers of profitability (McGahan and Porter, 1997, 2002), and the persistence of performance (Rumelt et al., 1991; D'Aveni et al., 2010; Bennett, 2020). Moreover, reporting of accounting measures is mandated for publicly traded firms, providing scholars with metrics that are comparable, convenient, and broadly accepted as important.

At the same time, there is a substantial accounting literature on *earnings management*, defined as reporting that aims to "mislead some stakeholders about the underlying economic performance of the company or influence contractual outcomes that depend on reported accounting numbers" (Healy and Wahlen, 1999).[1] Although our impression is that scholars studying firm performance are generally aware that accounting adjustments can obscure the link between real and reported performance, we find very few citations to the relevant accounting research in fields such as strategy, finance, and economics.[2] We speculate that this omission reflects the fact that manipulation, an activity that is by definition hidden, is hard to systematically assess. Moreover, scholars may implicitly assume that any "noise" in accrual accounting will balance out within the firm over time, and that the market will detect non-trivial misreporting. [3]

In this manuscript we first establish that *earnings management* is common, introduces non-classical noise, and distorts our understanding of broad drivers of firm performance. We begin with an analysis of a known discontinuity in the distribution of Return on Assets (ROA) at zero profits, and employ a bunching estimator (Chetty, 2012; Kleven and Waseem, 2013) to estimate that approximately 15 percent of firm-year observations are shifted from

[1]We use the term "earnings manipulation" to describe discretionary reporting decisions permitted under Generally Accepted Accounting Principles (GAAP) that strategically inflate or deflate accounting profits. The term does not imply fraud.

[2]For example, at the time of this writing, the seminal study of earnings management by Burgstahler and Dichev (1997) had been cited over 5,000 times. It received one citation in *Strategic Management Journal*, three in the *Academy of Management Journal*, five in the *Journal of Finance*, and none in the *Quarterly Journal of Economics*.

[3]It is worth noting that some strategy scholars and empiricists in related fields (such as economics and finance) are generally aware that managers can at times manipulate reported earnings, and it is common for authors to conduct (and referees require) robustness checks with alternative specifications. There are even rare examples of scholars using a cash-flow-based measure of performance specifically to address the potential for manipulation. For example, Bertrand and Schoar (2003) raise concern of earnings manipulation specifically as a threat to inference and use operating cash flows over assets, the specific robustness check we suggest. Our aim is to make such practice more common and provide greater precision and evidence of why this type of check is important.

negative to positive profitability. While striking, this shift in the distribution of ROA could reflect endogenous effort (i.e., striving harder when within striking distance of a goal) as well as accounting tricks. Therefore, we next demonstrate that for Cash Flows from Operations on Assets (OCFOA), an alternative accounting measure that is arguably less subject to manipulation, only approximately four percent of observations shift from the negative to positive region, suggesting that the majority of the shift in ROA is driven by manipulation rather than endogenous effort.

Finally, we conduct two short demonstrations of the impact of using a profit-based measure vs. a cash flow-based measure. The first is a decomposition of variance, in the spirit of canonical analyses found in Schmalensee (1985), Rumelt et al. (1991), and McGahan and Porter (1997, 2002), comparing results based on ROA versus OCFOA. We find that earnings management may obfuscate 10 percent or more of the variance in earnings that scholars can predict using these factors; and moreover, the manipulation changes the relative importance of industry-, firm-, and CEO-level factors.

The second demonstration revisits seemingly conflicting evidence in Bennett (2020) regarding trends in the persistence of firm performance. A key finding from Bennett (2020) is that the persistence of performance appears to be monotonically increasing over the past 30 years when an ordinal ranking of firm ROA is analyzed, but the trend is inconsistent (decreasing, increasing, then decreasing) with a cardinal measure of firm ROA. We present evidence that such a discrepancy could be driven by earnings manipulation, as when OCFOA-based measures are used, both the ordinal and cardinal measures increase monotonically over this period. Additionally, the persistence of firm performance is substantially less with OCFOA than with ROA, which could indicate that earnings smoothing causes an overestimate of how long superior performance is sustained.

The issues of performance measurement and the match to theoretical constructs are of long-standing concern in management scholarship (Winter, 1995; Lieberman, 2021). An emerging stream of recent work has addressed deficiencies in accounting measures, such as the distinction between average and marginal profit maximization (Levinthal and Wu, 2010; Shapira and Shaver, 2014), short- versus long-term value creation (Wibbens and Siggelkow, 2020), cleavages between value creation and capture (Lieberman et al., 2017), and the ability of firms to leverage non-owned assets (Barney, 2019). We contribute to this line of work by documenting how accrual accounting may systematically obscure understanding of the relationship between firm policies and outcomes, and by highlighting the value of the relatively simple solution of checking results with a cash-flow-based alternative accounting measure. While we embed our variance decomposition and persistence of performance analyses within broad lines of empirical inquiry, we believe there is much potential for strategy scholars to examine whether and how more specific firm actions are influenced by earnings manipulation.

2 Context: Public Firm Performance Data

Return on Assets (ROA) features prominently in strategy research on the drivers of organizational performance. For example, out of approximately 860 empirical articles published in the *Strategic Management Journal* between 2011 and 2020, we found that 238 articles (27%) reference ROA. The popularity of ROA as a variable of interest in the empirical strategy literature is due to at least three factors. First, ROA is comparable across firms of different sizes, and in theory represents the capability of managers to generate value from a stock resources (Barney, 1991, for example). Second, ROA is a key outcome variable used by investors, making it reasonable to assume that managers also focus on that outcome. Third, and perhaps most importantly, the underlying components of ROA — Net or Operating Income and Total Assets — are part of the mandated reporting requirements for publicly traded U.S. firms, and are therefore readily available to scholars through the Compustat database.

Because our aim in this paper is to illustrate the potential importance of earnings management for Strategy research that takes ROA as an outcome, we also use Compustat data. Table 1 below reports descriptive statistics, and Table 2 correlations, for selected variables from the Compustat database using data from 1992-2018. Each table considers two samples. The first sample comprises all firms publicly traded in the United States (N=210,797). The second sample (N=171,328) excludes firms in the financial sector (standard industrial classification [SIC] codes in the 6000s) or public administration (SIC codes in the 9000s) as is common in many academic studies that utilize ROA. Both samples are unbalanced panels, with firms entering in 1992 or the year they became public, and exiting in 2018 or the year they ceased being public.

[Insert Table 1 approximately here.]

Most of the variables used in our analysis are quite standard. Net Income, Total Assets, and OCF (Net cash flows from operating activities) are incorporated into Compustat from the firm's annual 10-K filings with the SEC. OCF "...is the cash profit the company would have reported had it constructed its income statement on a cash basis rather than an accrual basis" (Easton et al., 2013, p. 2-17).

OCF plays an important role in our analysis, and it can be calculated in two ways: the direct method (i.e., noting the cash received or cash paid for all operating transactions), and the indirect method of starting from Net Income and removing all non-cash gains or losses.[4] At a conceptual level, Net Income – the numerator of ROA – represents the profit or loss of a business using accrual-based accounting, while OCF represents the profit or loss from operations using a cash basis.[5] Specifically, using OCF as a measure of firm performance rather than income-based measures removes the effect of investing and financing effects, the effects of interest, taxes, and special items, and the effects of non-cash book transactions such as depreciation, amortization, or book-value changes in asset or liability valuation. In addition to these specific items that would appear as journal entries in the corporate accounts, OCF is also not sensitive to broad accounting policy decisions such as the choice of inventory valuation method (e.g., LIFO vs. FIFO), when revenue is recognized, or allowances for potential outcomes (such as anticipated customer returns). Because it is less sensitive to various discretionary choices that managers can use to influence reported profit, OCF should be less vulnerable to accounting-based earnings management than ROA.[6]

[Insert Table 2 approximately here.]

ROA in a given year for a given firm is calculated by the authors, following convention, by dividing Net Income by the Total Assets from the prior year. Similarly, OCFOA is calculated by dividing *OCF* by the Total Assets of the prior year.[7] By construction, OCF and Net Income are strongly correlated, as are the two performance measures ROA and OCFOA.[8] Although OCFOA is not widely used as a performance measure in the strategy literature (we found only six instances in our corpus of *SMJ* articles) it is clearly linked to operational performance, and for the reasons described above, less subject to accounting manipulation than ROA.

Earnings Smoothing, the final variable listed in Tables 1 and 2, is well known to account-

[4]Specifically, the items that are removed are typically depreciation/amortization, changes to current non-cash assets (such as accounts receivable, inventory), and changes to current non-cash liabilities (such as accounts payable).

[5]Some scholars use Operating Income or adjusted income such as Earnings Before Interest, Taxes, Depreciation, or Amortization (EBITDA) to calculate ROA. These other income-based measures relieve some of the potential error from earnings management, as they strip out certain sources of accounting-based discretion, but OCF excludes more potential sources for accounting-based manipulation by restricting fully to a cash basis.

[6]There is evidence that firms also use methods in addition to accruals to engage in earnings management (Zang, 2012; Roychowdhury, 2006; Graham et al., 2005). Mismeasurement caused by these other types of activities may not be detected by our analysis. Thus, our estimates are likely to represent a conservative lower bound on the potential impact earnings-management-induced measurement error have on ROA.

[7]Total Assets from the prior year is used in order to avoid time reversal, for instance such that declines in Net Income or OCF early in the year prompt asset depreciation later in the year.

[8]See Figure C.1.

ing scholars (Leuz et al., 2003; Dechow et al., 2010) but less common in strategy research. It is defined as standard deviation of OCFOA divided by the standard deviation of ROA, calculated over the trailing 12 quarters (and therefore computed from quarterly rather than annual data). Earnings Smoothing is constructed such that a higher ratio indicates smoother earnings relative to the underlying cash flows. Many managers prefer smooth earnings paths (Graham et al., 2005), and the intuition behind this variable is that a large discrepancy between variation in operating cash flows and variation in accounting earnings may signal that a firm is intentionally smoothing earnings by boosting profit during poorer quarters and stashing away profits during good ones.[9] It is important to note that while Earnings Smoothing provides some evidence that earnings are being intentionally managed from period-to-period, it does not provide information on whether any specific period's earnings have been shifted, nor what the "true" counterfactual earnings should have been.

Before turning to the analysis, we briefly review the rationale for accrual accounting which, when used properly, can add useful information to reported earnings. For example, suppose a firm incurs a monthly rental expense of $X that is paid in cash 30 days after the 1st of each month. Under cash-based accounting, the firm would show monthly expenses of $X, $0, and $2X for January, February, and March, respectively. In contrast, because of the matching principle, accrual accounting would show an expense of $X in all three months. Because the company incurred the liability when it used the facility, the accrual accounting method shows a truer picture of the financial impact of this use than the cash-based method. In econometric models that use monthly panel data, we might therefore expect ROA to produce a better fit than OCFOA. Similar arguments can be applied to a wide variety of investment and financing activities.

On the other hand, accrual accounting implies a degree of managerial discretion that can be used to obfuscate underlying performance. Suppose, for example, that a firm generates a cash-based loss of $Y in one month by selling product A, and a cash profit of $Y the next month selling product B. If the firm makes an accrual to inflate profits in the first month (e.g., by making a more aggressive prediction about its receivables), and then unwinds that accrual in the next month, the pattern of returns would be $0, $0 under accrual accounting and -$Y, $Y based on cash. Consequently, a regression of "product sold" on profitability

[9]Although there are other measures for earnings management/earnings manipulation that hold value (for example, the Modified Jones method(Dechow et al., 1995)), comparing variation of earnings to variation in cash flows has helpful features for our purpose. Unlike methods that rely on identifying and isolating discretionary accruals, this method covers both "real" income smoothing and "artificial" income smoothing (Ronen and Yaari, 2008). Additionally, this method does not require the existence of a "non-manipulated" period for each firm from which to derive their non-discretionary accrual patterns. Finally, the ratio of standard deviations is more intuitive for a non-accounting audience than detecting anomalies in specific accrual accounts would be.

would produce no clear result if ROA is used as the outcome variable, but would show that product B is associated with greater profit when using OCFOA. This latter example also illustrates why the intuition that earnings manipulation simply "averages out" is not correct. Even if all adjustments are eventually reversed, earnings management can generate bias in statistical analyses when it is correlated with other variables, such as a particular manager or strategy.[10]

The preceding discussion suggests that accrual-based accounting can provide a better picture of performance over time by matching operational decisions to their financial consequences, and smoothing out idiosyncratic and "lumpy" cash flows. At the same time, accruals may obscure true performance, at least for a while. Ultimately, the information content of ROA relative to OCFOA is therefore an empirical question whose answer will depend, among other factors, on the amount of earnings manipulation and its causes.

3 The Amount of Earnings Management

To isolate and quantify a lower bound for the impact of earnings management bias, we leverage a discontinuity in the distribution of firm profit that could be primarily driven by manipulation. [11] Accounting scholars are well aware that there is a discontinuity in reported earnings at the zero-profit threshold, and that this "kink" also appears when earnings are scaled by share-price (Hayn, 1995) or shareholders' equity (Burgstahler and Dichev, 1997). Figure 1 illustrates this discontinuity using an ROA histogram.

[Insert Figure 1 approximately here.]

The left panel of Figure 1 is based on the full sample of all U.S. Public Firms from 1992 through 2018. There is a clear spike in the reported ROA distribution at zero (the vertical solid line). The right panel omits firms with a primary SIC code in the financial, insurance, or public administration industries (SICs in the 6000s and the 9000s). Although the large spike at zero becomes less pronounced in the right panel, there is still a sharp increase in the probability distribution just above zero. Many empirical studies choose to omit firms in the financial sector, and this graph suggests there is a logic to that decision, although (as we show below) it does not eliminate the measurement problem.

In the accounting literature, earnings management is generally accepted as the explana-

[10]When firms exit a data set (e.g., through bankruptcy, acquisition, or going private) we also may not observe the "unwinding" of all accounting adjustments.

[11]For a theoretical model of how manipulation could lead to such a discontinuity, please see Appendix A.

tion for the discontinuous jump in the distribution of reported earnings just above zero (e.g., Burgstahler and Chuk, 2017).[12] We are aware of no prior study, however, that estimates *how much* earnings management occurs around that threshold. To address this gap, and to provide some sense of the overall the size of the potential measurement problem for empirical strategy research, we use a set of methods developed to analyze economic behavior around discontinuities in incentives (Chetty, 2012; Kleven and Waseem, 2013; Kleven, 2016). In particular, Diamond and Persson (2016) suggest a methodology for assessing how much probability mass is shifted across a threshold where there is a "notch" in incentives (as in the simple model presented in Appendix A). We apply their method to the ROA distribution in Figure 1.

At the core of this methodology is a model of the probability distribution of ROA (denoted by x) that takes the following form:

$$P = \sum_{m=1}^{K} \beta_m x^m + \sum_{x=L}^{-1} \alpha_x + \sum_{x=0}^{U} \gamma_x + \epsilon \tag{1}$$

where P is a count of observations at $ROA = x$; the β_m are coefficients of a Kth order polynomial in x; the parameters α_x (γ_x) measure the missing (excess) mass due to earnings manipulation below (above) the zero-profit threshold; and ϵ is an econometric error term. Intuitively, this regression uses a flexible polynomial to estimate the un-manipulated counterfactual ROA distribution on the interval $[L, U]$, and the dummies α_x and γ_x provide a flexible fit to the actual data in that manipulated region. This model assumes that (1) there is a "manipulation zone" around zero – specifically inside the interval $[L, U]$ — where the ROA measure is distorted, (2) outside of that interval we observe an accurate measure of ROA, and (3) the counter-factual (unmanipulated) distribution of ROA is continuous on the interval $[L, U]$, so we can extrapolate from a polynomial estimated on data outside of the manipulation zone to impute the counterfactual values within.

To complete this empirical model of earnings manipulation requires that we select values for the parameters K, U, and L. To do so, we use the cross-validation algorithm proposed in Diamond and Persson (2016), which consists of the following steps:

1. Discretize the underlying ROA data. In practice, we use 200 bins of equal width between ROA values of -1 and 1 (i.e., each bin covers .005 units of ROA).

2. Construct five random samples, by selecting N observations (with replacement) from

[12]Based on citations, this fact does not appear to be widely known to strategic management scholars. For example, Hayn (1995) has not been cited and Burgstahler and Dichev (1997) is cited by only one article in *Strategic Management Journal*.

the actual ROA data. In each random sample, we treat 80% of the observations as a training data set, and 20% as a holdout sample.

3. Perform a grid search, looping over feasible values of (K, L, U), and for each triple

   (a) Estimate equation (1) for given values (K, L, U) on the full dataset. Test the hypothesis that $\sum_{x=L}^{-1} \alpha_x = \sum_{x=0}^{U} \gamma_x$ (i.e., the "missing" mass below zero equals the "excess" mass above). If that test rejects at the 10% level or better, move to the next triple.

   (b) If we cannot reject the hypothesis that missing mass equals excess mass, then estimate equation (1) using the values (K, L, U) on each of the five training samples, and compute the mean squared prediction error (MSE) for the associated holdout sample. Store the sum of the MSE across all five test samples.

4. Choose the values (K, L, U) that produced the lowest aggregate MSE at Step 3, and re-estimate that model on the full data set.

The results of this five-fold cross-validation procedure are displayed in Figure 2. The upper (U) and lower (L) bounds of the region of ROA manipulation are indicated by dashed lines. Gray circles indicate the number of firm-year observations in each ROA bin. Black diamonds represent the counterfactual estimate for that bin imputed from our model.

[Insert Figure 2 approximately here.]

The left panel in Figure 2 plots the actual versus predicted distribution of ROA for the full sample, where the cross-validation procedure selected a 12th degree polynomial with $L = -0.15$ and $U = 0.08$. For that sample, our model implies that 15.5 percent of all firm-year observations were shifted from negative to positive ROA.

The right panel in Figure 2 shows results if we exclude financial and public-sector firms from our sample. For this sample, the best-fit model was a 15-degree polynomial, with $L = -0.15$ and $U = 0.10$. The model implies that 10.5 percent of all non-financial firm-year observations were shifted from negative to positive ROA. This is almost 30 percent less earnings manipulation than we estimate for the full sample, which suggests that manipulation among financial firms, which only comprise about 20 percent of the full sample, could be quite substantial. Nevertheless, our baseline estimates suggest that around 1 in 10 observations in a paper that employs Compustat ROA is prone to systematic measurement error, even when excluding the financial sector. In Appendix B we show that an alternative methodology that replaces the polynomial in equation (1) with a function of the density of OCFOA (under the assumption that OCFOA is not manipulated), yields similar results, at least for the non-financials.

3.1 Earnings Management vs. Endogenous Effort

At the end of Section 2 we noted that there are at least two explanations for the discontinuity in ROA at the zero-profit threshold: earnings manipulation and a "try-harder" effect.[13] Up to this point, we have focused on measuring the scale of the discontinuity (i.e., what share of all reporting is moved from negative to positive) and discussed those results in terms of earnings manipulation. We now consider two complementary approaches that help to rule out explanations other than earnings manipulation. The first method uses the Earnings Smoothing measure described above, and the second exploits the idea that OCFOA is harder to manipulate than ROA.

Figure 3 shows a binned scatterplot of the mean of *Earnings Smoothing* conditional on *ROA*. We have overlaid on this graph a fitted regression line with confidence intervals, and indicated the manipulation region identified as described above using dashed vertical lines. For both the full sample and the sample excluding financial-sector firms, we observe a sharp (discontinuous) increase in earnings smoothing when ROA is just above zero. This indicates that when firms report small positive values of ROA, they also tend to exhibit a sudden increase in the ratio of the variance in accounting earnings to the variance in OCF. Moreover, because these variances are computed *within-firm* (over the trailing 12 quarters), the evidence of earnings manipulation in Figure 3 is not simply an implication of the baseline discontinuity illustrated in Figure 2. Put simply, the firms bunching just above zero in the ROA distribution are *also* characterized by an unusually low level of earnings volatility relative to their cash flows.

[Insert Figure 3 approximately here.]

If we expand our gaze, moving away from the discontinuity at zero ROA to consider the entire manipulated region of the ROA distribution, it becomes clear that Earnings Smoothing is lower at negative levels of ROA, and higher when ROA is positive. This is a natural consequence of accounting conventions. Firms with higher underlying profitability are less constrained in their ability to smooth earnings, because some financial slack is required in order to reallocate resources. After peaking at an ROA of 5 to 10 percent, the relationship

[13] In the literature on bunching, round numbers and psychologically important thresholds are called *focal points*. The effort-based explanation for bunching near focal points has been advanced in other contexts, such as the distribution of marathon finishing times (Allen et al., 2017).

between ROA and Smoothing turns negative, perhaps because managers feel less pressure to manipulate earnings when the business is performing well.

To the extent that our measure of Earnings Smoothing captures what it purports to measure, Figure 3 provides direct evidence against the hypothesis that bunching in the ROA distribution at zero is caused by endogenous effort rather than earnings manipulation. As another test, however, we can apply our cross-validation approach directly to OCFOA to estimate the amount of "cash flow manipulation" at the same threshold. Under the maintained assumption that it is more difficult for CEOs to manipulate cash flow than accounting earnings, we would expect to find less evidence of OCFOA manipulation. Figure 4 shows the results of that exercise.

[Insert Figure 4 approximately here.]

The top two panels in the Figure compare ROA to OCFOA manipulation for the full sample, and the bottom two panels compare ROA to OCFOA manipulation for the non-financials.[14] It is clear even from visual inspection that the size of the discontinuity around zero and the subsequent bunching above zero is dramatically reduced by using the cash-basis performance measure of OCFOA rather than the accrual-basis performance measure of ROA. For the full sample, our estimates imply that four percent of the observations are "shifted" from negative to positive OCF. In the non-financial sample, we estimate that the amount of earnings manipulation is *negative*. Instead of "missing" mass below zero, there are slightly more negative observations that were predicted. This evidence, we interpret as essentially no sign of left-to-right OCFOA manipulation.

3.2 Robustness

The analyses in this section yield three basic facts. First, there is a substantial amount of earnings manipulation (on the order of 15% of all firm-year observations) around the zero-profit threshold. Second, manipulation is especially prevalent among firms in the financial sector. Third, there is much less manipulation of OCFOA, and essentially none for non-financial firms. We have considered a number of supplemental analyses and robustness checks that further support these findings.

First, we checked whether Earnings Smoothing was continuous at the zero-OCFOA threshold, and whether OCFOA was continuous at the zero-ROA threshold. In the Appendix, we show that for non-financial firms, there is no evidence of smoothing to achieve

[14]In the Appendix, we provide the histograms corresponding to each panel in Figure C.2

positive cash flow, and that direct manipulation to post a positive OCF is confined to the financial sector.[15] Both results are consistent with our findings that accounting earnings are more prone to manipulation than cash flows.

Second, as an alternative to the specification in equation (1) that relies on functional form to estimate the counterfactual density of ROA in the interval $[L, U]$, we developed a model that uses OCFOA to predict ROA. This approach rests on the maintained assumption that OCFOA is not manipulated, and as a result, works better for the sample that excludes financial-sector firms. The results, provided in Appendix B, indicate that around 6 percent of firm-year observations in our non-financial sample are manipulated.[16]

Finally, there is a concern that the missing mass in our figures might be caused by a liquidation option for struggling firms. In particular, if those firms most likely to post accounting losses leave the dataset due to bankruptcy, acquisition by another firm, or being taken private, that could produce a "hole" in the earnings distribution just below zero. This hypothesis does not explain the bunching of reported earnings just above zero. Nevertheless, we have replicated our main results on a dataset that excludes firms firms that exit the Compustat before the end of the sample period (regardless of whether the exit was due to bankruptcy, liquidation, leveraged buyout, etc.) with substantially similar results.

4 Earnings Management and Empirical Strategy Research

Having established that there is a large amount of earnings manipulation near the zero-profit threshold, the question remains whether this "matters" for empirical strategy research. To address this question, we apply our insights to two influential lines of studies. The first is the literature on the decomposition of variance of firm performance, which seeks to attribute variation in performance to firm, industry, and macro-economic factors (e.g. Schmalensee, 1985; Rumelt et al., 1991; McGahan and Porter, 2002).[17] The second is the literature on the persistence of performance (Bennett, 2020), which seeks to explain to what extent superior performing firms are able to sustain such performance over time. Our goal is not to replicate prior studies, or to address any of the methodological shortcomings of variance decomposition or persistence measures that are well-documented in previous studies. Rather, we aim to show how the results of this type of analysis change when we move from ROA to OCFOA

[15] See Figure C.3.

[16] See Figure B.1.

[17] One measure of the importance of these papers is common to find their results described in the early chapters of many strategy textbooks (see Rothaermel (2016)).

as a measure of firm performance.

4.1 Variance Decomposition of Firm Performance

In revisiting variance decomposition of firm performance, our analysis will consider two ways in which earning manipulation might matter. First, it may add "classical" measurement error that reduces the overall explanatory power of a model. Second, and more importantly in our view, earnings management might be correlated with other variables (e.g., if it is more prevalent in specific industries, and linked to certain CEOs). To the extent that earnings manipulation is correlated with other factors, it has the potential to introduce bias into analyses that use ROA as an outcome.

The foundational studies in this literature estimated models that might include year, industry, firm, and/or business-unit fixed effects. By comparing the model R-squared for different combinations of variables, it is possible to compute how much total variance is explained by each of the observed factors. One limitation of using OCFOA in this context is that operating cash flows are not required to be reported at the business segment level, and therefore a direct replication of the classic studies is not possible. In particular, our "industry" effects are based on the primary SIC code assigned to the firm as a whole, rather than to an individual business unit. On the other hand, we can extend upon the early papers by using the Execucomp data set to include CEO fixed effects, following later later scholars in this literature stream (e.g. Mackey, 2008)).

Our analysis is based on the following model for the generation of reported accounting profit:

$$r_{t,j,i,k} = \mu + \gamma_t + \alpha_i + \beta_j + \delta_k + \varepsilon_{t,i,j,k} \tag{2}$$

In this equation, $r_{t,j,i,k}$ is either the ROA or OCFOA reported in a given year t by a specific firm j operating within industry i and led by CEO k. μ is the average accounting profit over the entire sample (the constant in the regression models), and the other variables represent fixed effects for the year (γ_t), the industry (α_i), the firm (β_j), and the CEO (δ_k), as well as the error term ($\varepsilon_{t,i,j,k}$).

For the sequential ANOVA model, we incrementally added fixed effects for year, industry, firm, and CEO to gauge the marginal contribution of R-squared gained with the addition of each set of fixed effects. This approach was used by scholars earlier in this literature stream, but has a significant flaw of being sensitive to the order in which the fixed effects are added, as noted prominently by McGahan and Porter (2002) and Mackey (2008). In sequential ANOVA, variance that could be explained by either of two nested levels of fixed effects will be attributed to the first one added to the model.

This drawback is alleviated by the second approach, a simultaneous ANOVA model. In the simultaneous model, variance that could be explained by more than one factor is not attributed to either of them. This has the benefit of avoiding misattribution of explained variance, while it also has the drawback of leading to lower estimates of variance explained for each category, as the ambiguous cases are not attributed at all. However, the total R-squared for the full model with all fixed effects is not understated even if the category breakdown may be (i.e., the total R-squared for the model exceeds that of the sum of the categories).

[Insert Figure 5 approximately here.]

Figure 5 presents the results of the explanatory value of the full models for both ROA and OCFOA, sequential and simultaneous, for both all industry and non-financial industry samples. The key finding here is that our ability to predict/explain variance in OCFOA exceeds that of ROA by approximately 10 percentage points across all specifications. As the entire point of accrual accounting is to add salient information and remove noise from cash-basis performance, the 10 percentage points of explained variance should be considered a fairly conservative lower bound for how much obfuscation appears to be introduced by strategic accounting decisions. Not only are accruals not giving us a clearer picture of underlying financial performance (as they are supposed to do), they are actively worsening the signal-to-noise ratio in the most common measure of performance used in the strategy literature.

If earnings management introduces measurement error in ROA, under what conditions should we be concerned with bias rather than merely a loss of efficiency? If earnings management caused primarily classical measurement error in ROA, it would not cause us great concern when using ROA in our econometric models. When we used ROA as an outcome variable, this would simply reduce the efficiency and increase the standard errors around our coefficients. When ROA was used as an explanatory variable, it would attenuate the coefficient towards zero, which is often toward a more conservative interpretation, i.e., pulling our inference towards the null (Bound et al., 2001). But unfortunately, there is reason to believe that the measurement error caused by earnings management on ROA is non-classical.

The key assumption of classical measurement error is that the error itself is uncorrelated with values of the measure, but also that the error is uncorrelated with other variables in the econometric model (Hyslop and Imbens, 2001). We saw from the analysis in the previous sections that the prevalence/degree of manipulation was not evenly spread across all values of ROA. Indeed, it is concentrated enough in a region of ROA to cause visual discontinuities in the distribution.

In addition to the correlation with ROA itself, there is also reason to suspect that the measurement error from earnings management is correlated with other variables that may be in our econometric equations. An easy way to see this is in looking at the differential impact using OCFOA vs. ROA has on the amount of variance explained in each category of fixed effects in the ANOVA models. Figure 6 shows the breakdown of explained variance for each of the categories of the ANOVA—year, industry, firm, and CEO. Across the models, the relative explanatory power of firm and industry lowered when using ROA rather than OCFOA, while the relative explanatory power of CEO and year increased.[18] In the all industries nested ANOVA model, this effect is large enough to change the rank order of CEO and industry effects by reversing their relative importance.

[Insert Figure 6 approximately here.]

One interpretation of the results in Figure 6 is that certain CEOs are more likely to manipulate earnings, so that moving from ROA to OCFOA as the focal measure of firm performance causes the share of variance attributed to CEO effects to decline, and the share of variance explained by firm and industry-level factors to increase.

4.2 Persistence of Performance

Our second illustration of the difference when using a cash-flow-based measure of performance is to build upon the work of Bennett (2020), who updated a classic strategic management research stream with more current data and additional methods. The research question is to what extent has the persistence of firm performance changed over time, and one of Bennett's primary goals was to try to reconcile conflicting arguments either that increased industry concentration and market power was lengthening the time a high-performing firm could maintain superior profits, or that increased competition was causing temporary performance advantages to erode more quickly. In essence, the first viewpoint would expect the persistence of performance to increase over time while the second viewpoint would expect the persistence of performance to decrease over time.

The main analysis consisted of two primary measures: 1) a "convergence interval" calculated with an Arellano-Bover/Blundell-Bond (ABBB) panel estimating auto-regressive correlation between a given year's profit and the profit from the previous nine periods; and

[18]For tabular format, please see Table C.1.

2) a measure of "rank friction" (Powell and Reinhardt, 2010), or the extent to which the ordinal ranking of firms within an industry (defined as three-digit SIC code) changed from year to year. The results of the first measure are presented as the average number of years it would take for the effects of a shock to firm profits on future profits to dissipate. The results of the second measure reflect the likelihood that a given firm would maintain the same position in the industry's rank order of profit, with a higher number indicating a higher probability of maintaining the same rank. Both of these measures used ROA adjusted to represent "firm-specific profits" (Villalonga, 2004), i.e., the ROA of the business segment in a given period minus the industry average ROA for that period.

While there are many points of insight in the paper, a key observation Bennett (2020) makes is that one might draw different conclusions about the change in profit persistence over time depending on whether a cardinal (convergence interval) vs. an ordinal (rank friction) measure was used. He found that the convergence interval declined from 1985 to 1999, then increased from 1999 to 2009, then decreased again through the end of the sample in 2018. In contrast, the rank friction measure held to a steady positive slope throughout the panel period.

By observing the difference of using a cash-flow-based measure rather than ROA, we gain insight on what may be driving this discrepancy. We constructed a study using the same two measures described above as Bennett (2020) did using ROA, then compare these results when OCFOA is substituted for ROA. This was not a direct replication, as we had to use a different sample for our analysis. While Bennett used the Compustat Segments database, OCF information is not available on the segment level; thus, we used the Compustat Annual Fundamentals database, which has data at the firm level. Additionally, OCF information is only available as early as 1981 for most firms, and complete coverage did not begin occurring until after 1987, when FASB began requiring U.S. public firms to report operating cash flows as part of GAAP. Because a 10-year window is required for each year's ABBB auto-regressive model, our analysis begins in 1990 instead of 1985.

The left panel of Figure 7 shows the results of the convergence interval measure constructed with either ROA (solid line) or OCFOA (dashed line). The first thing to observe is that even though the dataset for our sample was at the firm level (with business units consolidated into the corporate parent for diversified firms), the results for ROA mirror the pattern found in Figure 1 of Bennett (2020), suggesting that Bennett's findings at the business unit level hold at the firm level as well.

[Insert Figure 7 approximately here.]

The differences between these two plots include both the level and the slope. The level shift downward when moving from an ROA-based measure to an OCFOA-based measure can be interpreted as shocks to cash flows dissipating more quickly than shocks to operating profit. This is consistent with widespread earnings smoothing among firms, as the accruals on net would lead to an earnings number closer to previous period earnings than the operating cash flow is to previous period operating cash flow. This shift in itself could cause a researcher to overestimate the persistence of profitability; a researcher might mistakenly infer a manager's capability and willingness to aggressively smooth earnings as an ability to maintain superior underlying performance.

Additionally, the pattern Bennett observed with the persistence of profit declining, then rising, then declining again disappears when a cash-flow-based measure of profit is used instead of ROA. This can be seen by the generally flat or increasing convergence interval levels for OCFOA. One of Bennett's interesting observations was the seeming disconnect between changing levels of ordinal vs. cardinal persistence over time, but when we remove the effect of accounting accruals (and thus, accrual-based earnings manipulation), these measures are no longer in conflict: both increase monotonically from 1990 to 2018.

The right panel of Figure 7 shows the results of the rank friction measure constructed with either ROA (solid line) or OCFOA (dashed line). Again, despite this dataset being at the firm level, the results for ROA are consistent with the pattern observed by Bennett (2020). There is a similar level shift downwards from the ROA-based measure to the OCFOA-based measure, which indicates that a firm's ROA is more likely to be ranked similar to the previous year in its industry than its OCFOA would be to the previous year. This again is consistent with widespread practice of earnings smoothing. Also, the slopes of the two plots are almost identical, implying that the persistence of both ROA and OCFOA have monotonically increased over this period.

The findings described above help to reconcile seemingly conflicting evidence in the persistence of performance literature. When bias from earnings manipulation is removed, the finding is clearer that the persistence of firm performance has been steadily increasing over the last 30 years. This also has implications for some of the proposed mechanisms for increasing power or decreasing competition; for example, when Bennett (2020) notes about the effects of intangible capital "If increases in the importance or prevalence of intangible capital were driving the observed patterns, one would expect a monotonic increase in persistence of performance..." This is indeed what is observed when accruals are removed from the firm performance measure, and so this mechanism remains a more plausible explanation than originally thought.

5 Conclusions

We make four contributions in this study. First, we provide new evidence quantifying the prevalence of earnings management, a well-known problem that has previously resisted precise measurement or quantification. We find evidence that 10 to 15 percent of firm-year observations in Compustat exhibit earnings manipulation. Our estimates also indicate that earnings manipulation is more prevalent in the financial sector, thereby providing a firmer empirical foundation for the "folk wisdom" that one might want to exclude financials when analyzing firm performance with accounting data. These findings augment the literature using regression discontinuity designs (Burgstahler and Chuk, 2017), studies leveraging discretionary accruals (Dechow et al., 1995) or accrual reversals (Dechow et al., 2012), and survey designs targeting chief financial officers (Graham et al., 2005) by employing novel methods from the econometrics literature on bunching.

Second, these bunching methods are employed to evaluate alternative performance measures. We find that OCFOA exhibits less manipulation, and thus provides a method by which scholars can test the sensitivity of models including accounting profits for bias introduced by earnings manipulation. This study thus dovetails with current efforts to rethink and improve how we measure performance (Lieberman, 2021; Lieberman et al., 2017; Wibbens and Siggelkow, 2020).

Third, we deploy our insight about OCFOA to re-evaluate a classic set of strategy papers that uses variance decomposition to understand the drivers of firm-performance (Schmalensee, 1985; Rumelt et al., 1991; McGahan and Porter, 1997, 2002). Our results suggest, counter-intuitively, that we can explain more of the total variance in cash-based rather than accrual-based accounting performance. Moving from ROA to OCFOA also reduces the amount of variance in firm-performance associated with CEO effects, which suggest that some CEOs are more likely to engage in manipulation than others.

Fourth, we demonstrated that the use of OCFOA as a robustness check can help resolve seemingly conflicting results driven by bias from earnings manipulation. For example, our results suggest that inconsistency between how ordinal and cardinal measures of the persistence of performance (Bennett, 2020) have changed over time is resolved when a cash-flow-based measure of performance is used. This could be an example of the concerns raised by Bertrand and Schoar (2003), "that the systematic differences in rate of return on assets across managers may not reflect actual differences in performance but rather differences in aggressiveness of accounting practices or willingness to 'cook the books'." (p.1186) There is evidence that some of our belief in the consistency of sustained performance may be based on widespread earnings smoothing rather than the continuance or furtherance of value creation.

Our findings have implications for empirical work where firm performance is measured using accounting profit. For many studies, restricting the sample to non-financial firms and utilizing OCFOA as a performance measure for accounting profitability offers a simple way to avoid potential econometric problems created by earnings management (as did Bertrand and Schoar (2003)). More generally, researchers should carefully consider whether firms' unobserved propensity to inflate profits could be correlated with key outcomes or explanatory variables. In some cases, such as when ROA serves as an ancillary control variable, this will not be especially problematic. But when ROA is the outcome or explanatory variable, and other variables of interest might be correlated with the propensity to manipulate, researchers should explore sensitivity by using OCFOA. Our findings also suggest that these issues may be particularly salient when exploring the relationship between CEO attributes and firm performance, as this is a case where it may be particularly problematic to mistake accounting aggressiveness for the ability to create and capture value.

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Table 1: Summary Statistics

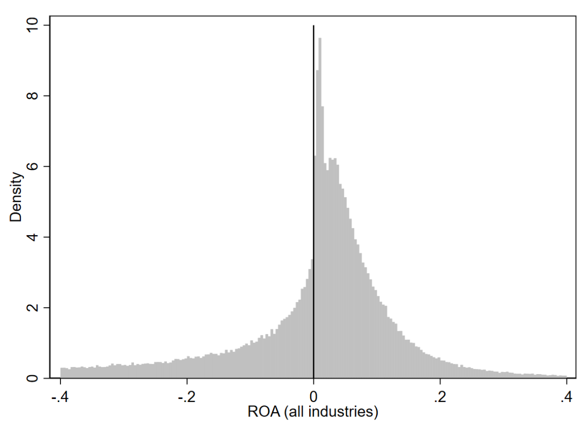
All Industries

Variables	Observations	Mean	Std. Dev.	Min	Max
Fiscal Year	210,797	2005	7.670	1992	2019
Total Assets	210,797	9,127.191	82,896.37	0	3,771,200
Net Income	210,797	161.497	1,306.279	-99,289	99,806.04
ROA	210,797	-0.034	0.224	-1	1
OCF	210,797	369.056	2,570.763	-110,560	166,671.5
OCFOA	210,797	0.031	0.193	-1	0.999
Earnings Smoothing	145,479	2.692	6.311	0	520.836

SICs in 6000s and 9000s Omitted

Variables	Observations	Mean	Std. Dev.	Min	Max
Fiscal Year	171,328	2005	7.670	1992	2019
Total Assets	171,328	3,688.508	16,842.77	0	551,669
Net Income	171,328	145.215	1,211.2	-98,696	98,806.04
OCF	171,328	352.571	1,853.95	-16,856	81,266
ROA	171,328	-0.042	0.236	-1	1
OCFOA	171,328	0.032	0.202	-1	0.999
Earnings Smoothing	117,585	2.109	2.243	0.090	20.544

Figure 1: ROA Histogram: U.S. Public Firms 1992-2018



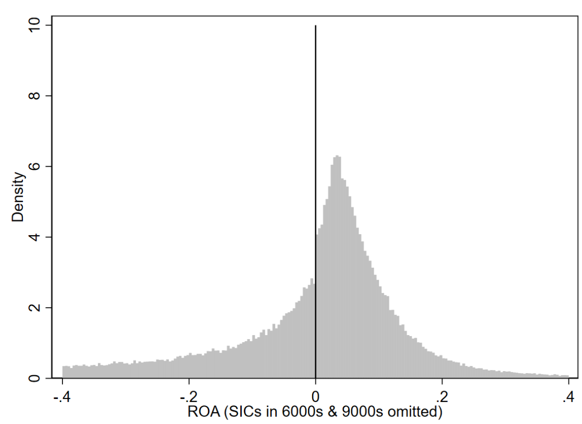


Table 2: Cross-Correlation Table

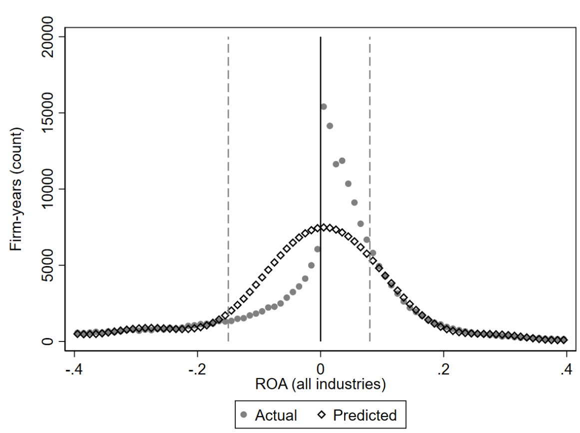
All Industries

Variables	Fiscal Year	Total Assets	Net Income	ROA	OCF	OCFOA	Earnings Smoothing
Fiscal Year	1.000						
Total Assets	0.068	1.000					
Net Income	0.071	0.357	1.000				
ROA	-0.046	0.027	0.106	1.000			
OCF	0.075	0.379	0.546	0.062	1.000		
OCFOA	-0.036	0.007	0.072	0.697	0.079	1.000	
Earnings Smoothing	-0.021	0.109	0.046	0.101	0.010	0.043	1.000

SICs in 6000s and 9000s Omitted

Variables	Fiscal Year	Total Assets	Net Income	ROA	OCF	OCFOA	Earnings Smoothing
Fiscal Year	1.000						
Total Assets	0.115	1.000					
Net Income	0.071	0.605	1.000				
ROA	-0.068	0.082	0.123	1.000			
OCF	0.100	0.875	0.748	0.095	1.000		
OCFOA	-0.040	0.080	0.090	0.718	0.112	1.000	
Earnings Smoothing	-0.097	-0.002	0.021	0.246	-0.002	0.174	1.000

Figure 2: Imputed Vs. Actual ROA



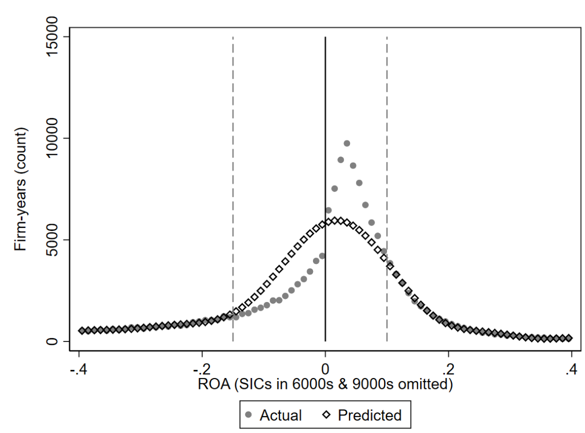


Figure 3: Earnings Smoothing Vs. Reported ROA

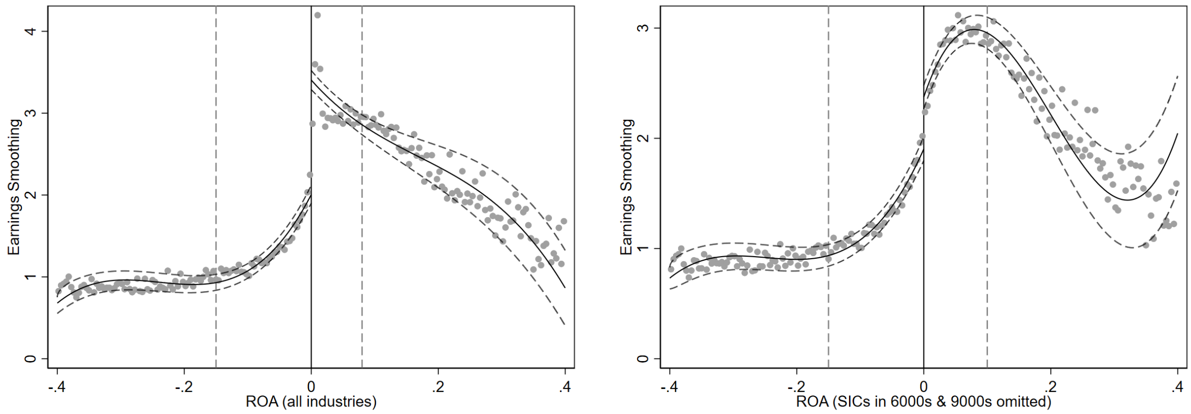


Figure 4: Comparison of Imputed Vs. Actual ROA and OCF

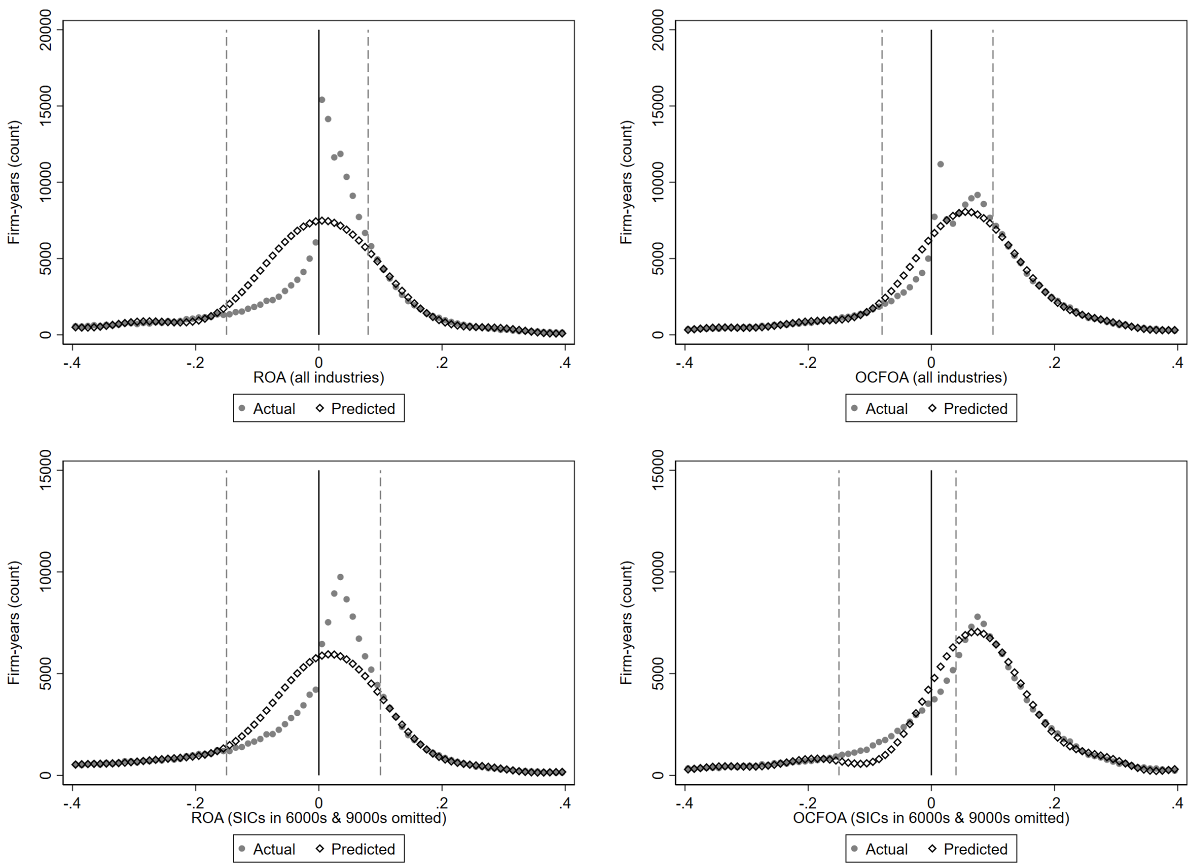


Figure 5: Total Variance of ROA Vs. OCF Explained

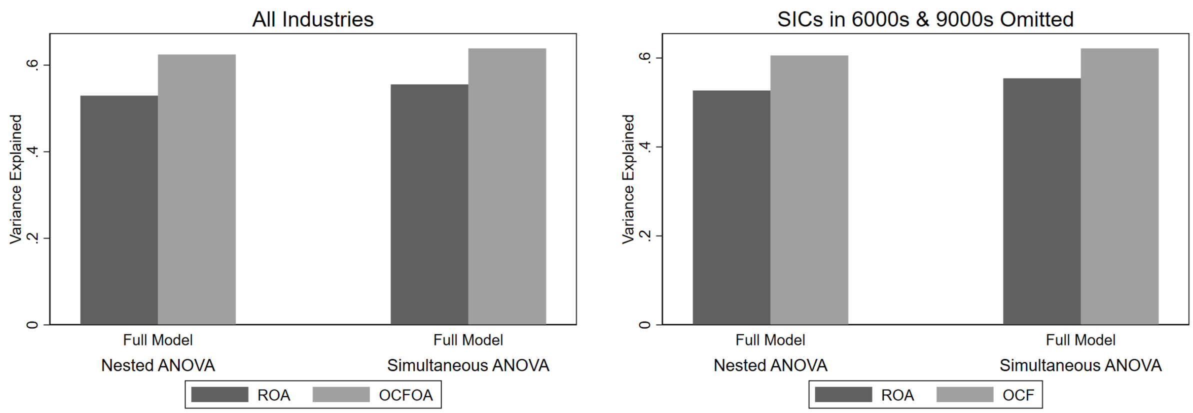


Figure 6: Decomposition of Variance of ROA Vs. OCF

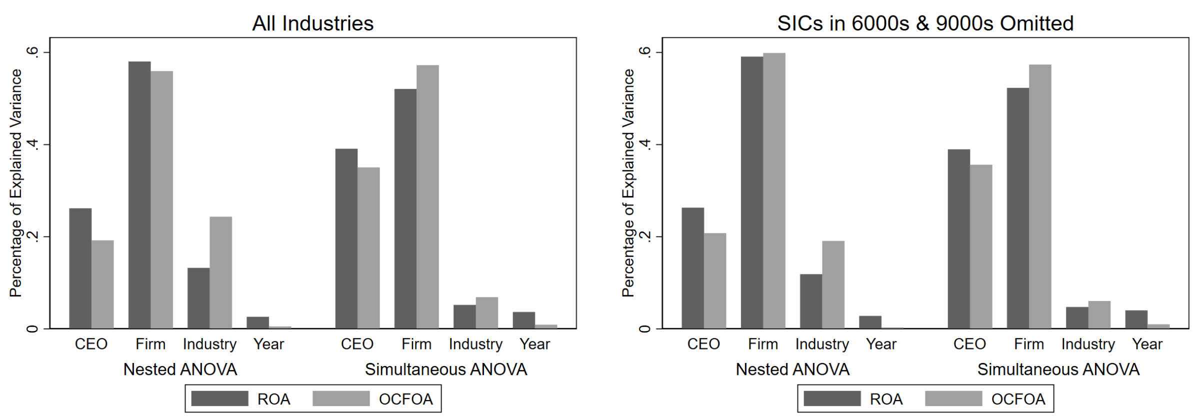
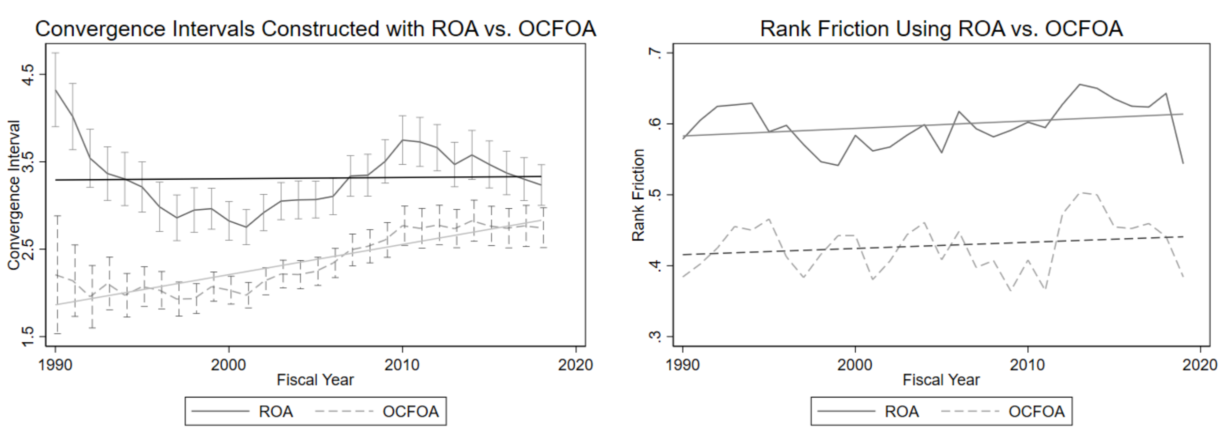


Figure 7: Cardinal vs. Ordinal Measures of Performance Persistence



6 Appendix A: Theoretical Model of Earnings Manipulation and Bunching

This section presents a simplified model of earning management, based on the more general treatment in Kleven (2016). Our model includes a single firm whose true performance is a random variable denoted by π. The CEO observes her firm's performance and makes a report $R = \pi + a$, where a represents accounting adjustments. In our empirical context, R corresponds to publicly reported accounting-based performance measures.

We assume that adjustments incur a quadratic cost $c(a) = \frac{\gamma a^2}{2}$, so unbiased reporting is free, and reporting costs increase (at an increasing rate) with the size of any adjustments. In practice, the costs of earnings management may show up in a wide variety of ways, such as a loss in credibility, managerial distraction, the direct costs of an audit, increased financial constraint, or the cost of "unwinding" an adjustment by under-stating future profits. By adopting a reduced-form quadratic cost function, we are emphasizing expositional clarity and convenience over realism.

The CEO chooses adjustments, a, to maximize her payoff, which takes the following form:

$$\max_a U(a;\pi) = \underbrace{(\pi + a)}_{R} + B \cdot \mathbf{1}_{\{R \geq 0\}} - c(a) \tag{3}$$

where $\mathbf{1}_{\{R\geq 0\}}$ is an indicator function that equals one if and only if the report, R, is non-negative. The CEO's payoff increases linearly with R, to capture the idea that she would generally like to report better performance. Because she also pays a quadratic adjustment cost, $c(a)$, however, there is a limit to the size of any distortions. The parameter B is a "bonus" paid to the CEO for a non-negative report. This bonus could represent an actual payout, a reduced probability of termination, or simply a psychological benefit associated with "not losing money." Regardless of the underlying cause, the bonus produces a discontinuous jump in the marginal benefits of earnings management when $R = 0$. This jump is called a "notch" in the public finance literature.

As a baseline model of earnings manipulation, consider the CEO's report in the absence of a notch (i.e., when $B = 0$). Given the linear quadratic structure of equation (3), the CEO's first-order condition reveals that $a^* = \frac{1}{\gamma}$. The CEO will always make optimistic reports, and the size of her adjustments will naturally decline as the cost of mis-reporting, γ, grows larger.

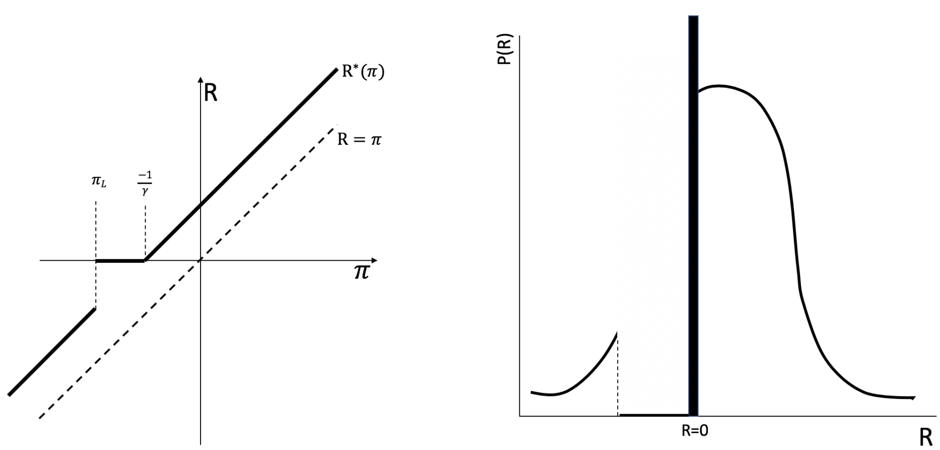
Before considering how a notch affects the CEO's report, it is useful to pause and consider the implications of this baseline model for empirical strategy research. Because the CEO *always* makes adjustments, a researcher never actually observes "true" performance. On the other hand, this may not matter very much. In particular, variation in underlying performance, π, maps directly into variation in the optimal report, $R = \pi + \frac{1}{\gamma}$. For example, in a statistical analysis that seeks to explain how some factor or decision X impacts observed performance R, all reporting distortions can be swept away simply by including a constant term in the regression. Unfortunately, this argument only goes so far. In our model, a^* is constant only because the marginal costs and benefits of adjustments are uncorrelated with π. In general, as we now illustrate for the case of a notch, mis-reporting might be correlated with π, X or both, leading to well-known problems of omitted variables or simultaneity.

To see how this can happen, consider our baseline model with a notch induced by $B > 0$. The CEO now has an incentive to "reach" for the bonus by reporting $R = 0$ (or equivalently, $a = -\pi$), as long as the firm's true performance is close enough to the reporting threshold. In the Appendix, we show that this happens when $\pi > \pi_L \equiv -(\frac{1}{\gamma} + \sqrt{\frac{2B}{\gamma}})$. This implies that the CEO's optimal reporting strategy is:

$$R^*(\pi) = \begin{cases} \pi + \frac{1}{\gamma} & \text{if } \pi \notin [\pi_L, -\frac{1}{\gamma}] \\ 0 & \text{if } \pi \in [\pi_L, -\frac{1}{\gamma}] \end{cases}$$

Figure A.1 graphs this optimal reporting strategy, and illustrates the distribution of R when true performance is normally distributed. As illustrated in right panel, there is a "hole" in the distribution of reports just below $R = 0$, and a spike or mass-point at zero, because all of the firms with true performance in the interval $[\pi_L, -\frac{1}{\gamma}]$ shift their reports upwards to zero. This is the key feature of the model that we will examine in our data.

Figure A.1: Optimal Reporting (left) and the Distribution of Reports (right)



Although the predictions of this simple model are very stark, they can be relaxed. For example, if we allow the marginal cost of adjustment, γ, to vary across firms or introduce an idiosyncratic fixed cost of earnings manipulation, then *some* CEO's may choose to make slightly negative reports. We do not pursue those extensions here because the purpose of the simple model is not to capture every feature of the data set described below. Rather, our aim is to illustrate a set of incentives that can generate bunching in reported profits. We then use the actual bunching observed in our data to illustrate how earnings management can distort empirical strategy research.

A final point about the model that merits some discussion is the interpretation of the CEO's choice. Up to this point, we have labeled the variable a "adjustments" and *assumed* that it represents earnings manipulation. Although we find that interpretation plausible, one could easily re-label a "managerial effort" and argue that a better interpretation of any observed bunching is a try-harder effect induced by the same notch in the CEO's payoff function. To address that concern, we introduce a second performance measure that is harder to manipulate, and show that there is a systematic difference in the amount of bunching across these two outcomes. Because that approach is fundamentally empirical, we now turn to a description of the data.

Derivation of π_L

To find the lower threshold of the "hole" in reported earnings (i.e., π_L), we can look for solutions of $U(\frac{1}{\gamma};\pi) = U(-\pi;\pi)$. At that point, the CEO is indifferent between making a larger adjustment that achieves the bonus B or staying with the locally optimal report $a^* = \frac{1}{\gamma}$. Substituting into equation (3) and simplifying leads to the quadratic equation

$$\frac{\gamma}{2} \cdot \pi^2 + \pi + \left(\frac{1}{2\gamma} - B\right) = 0$$

The roots of this quadratic are $\pi = \frac{-1 \pm \sqrt{2\gamma B}}{\gamma}$. The larger root cannot be the solution, because for $\pi > \frac{-1}{\gamma}$ the CEO would obtain the bonus under her "normal" reporting strategy $a^* = \frac{1}{\gamma}$. This implies that the solution for the lower threshold must be $\pi_L = \frac{-1-\sqrt{2\gamma B}}{\gamma}$, or equivalently, $\pi_L \equiv -(\frac{1}{\gamma} + \sqrt{\frac{2B}{\gamma}})$, as reported in the text.

Appendix B: Alternative Bunching Estimates

Blomquist and Newey (2018) critique the use of bunching estimators in public finance to estimate the tax elasticity of income using kinks or notches in the tax schedule. The core of their argument is that identification rests on functional form assumptions. In particular, within the region where outcomes are assumed to be manipulated, bunching methods impute counterfactual outcomes entirely from extrapolation, rather than any comparison of observed quantities. For example, if the true counterfactual distribution of ROA is highly non-linear around zero, then the estimates of earnings management that we report in Section 4 could be biased.

Setting aside any debate over the practical implications of this critique, there is a natural solution available in our empirical setting. If we assume that OCFOA is not manipulated, then the relationship between OCFOA and ROA helps identify the counterfactual distribution of ROA within the manipulated region. To implement this idea, we use the following model:

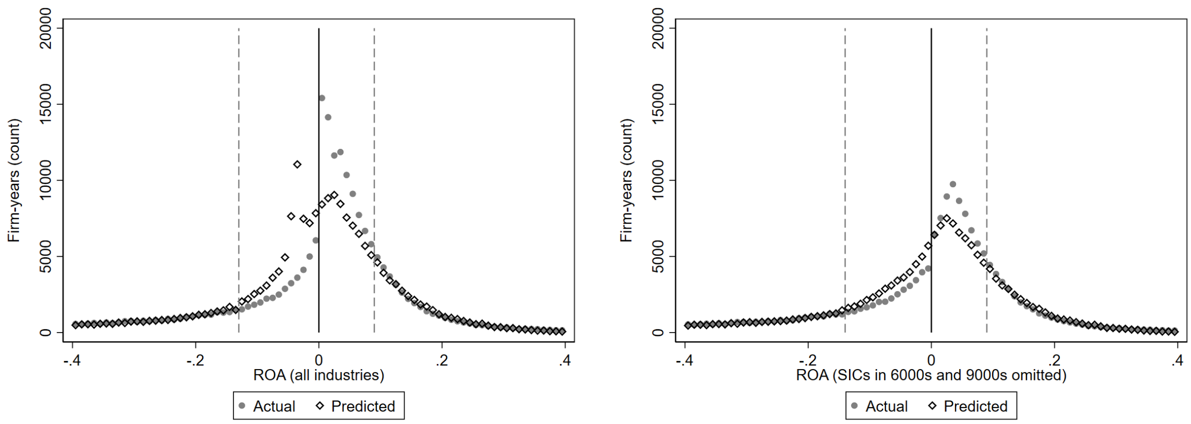
$$P = \beta CF_{x+T} + \sum_{x=L}^{-1} \alpha_x + \sum_{x=0}^{U} \gamma_x + \epsilon \tag{4}$$

where P is the number of observations with ROA equal to x, CF_{x+T} is the number observations with OCFOA equal to $x + T$, and all other parameters are defined as in equation (1). Comparing (4) to (1), it should be clear that we have simply replaced the polynomial previously used to extrapolate ROA in the region $[L, U]$ with a linear function of the OCFOA that is "shifted" by T bins.

The reason we allow for the OCFOA distribution to be shifted relative to ROA is that operating activities are normally a profit center, so OCFOA generally exceeds ROA (e.g., due to taxes, depreciation, *et cetera*). We select a value of T using the cross-validation procedure described in Section 4 of the paper, searching over T rather than K (the degree of the polynomial). Figure B.1 shows the resulting histogram for all firms as well as the non-financial sample. As for earlier figures, the upper (U) and lower (L) bounds of the region of ROA manipulation are indicated by dashed lines, gray circles indicate the number of firm-year observations in each ROA bin, and black diamonds represent the counterfactual estimate for that bin imputed from the model.

For both panels, the cross-validation procedure selected a leftward shift of 5 bins for OCFOA ($T = 5$). The left panel shows the results from the full sample, which has a lower bound (L) of -0.13, an upper bound (U) of 0.09, and a total amount of displaced probability mass of 16.8 percent. The right panel shows the results from the non-financial sample, which has a lower bound (L) of -0.14, an upper bound (U) of 0.09, and a total amount of

Figure B.1: Comparison of Imputed Vs. Actual ROA - Alternative Method



displaced probability mass of 6.4 percent. In both cases, our estimates of total earnings manipulation decline slightly, because the distribution of OCFOA has a more pronounced peak than the counterfactuals based on a polynomial approximation. This can be seen be comparing Figures B.1 and 2.

Finally, we note the spike in the predicted values of ROA just below zero in the left panel. This corresponds to a discontinuity in the distribution of OCFOA for financial firms that can also be observed in the top right panel of Figure 4. We interpret this spike as evidence of real earnings management (i.e., manipulation that also influences OCF) by financial firms. It suggests that the approach used in this Appendix will work better for the non-financial sector, whereas the standard approach of relying on a polynomial extrapolation may be more reliable for the full sample.

Appendix C: Supplemental Tables and Figures

Figure C.1: Binned Scatterplot of ROA and OCFOA

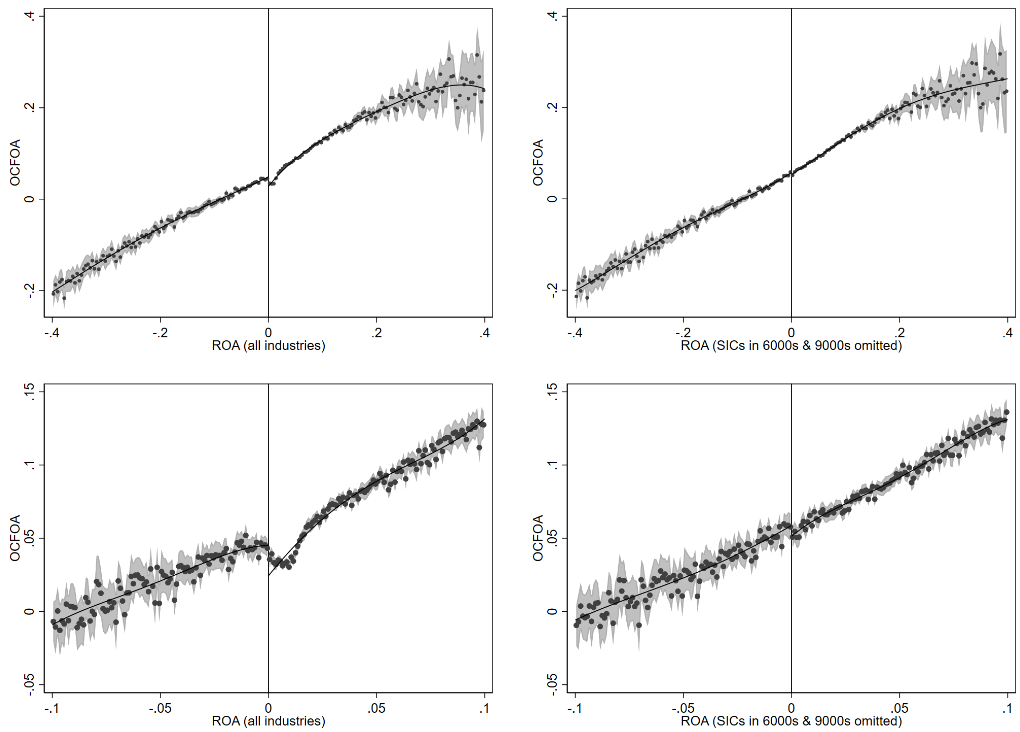


Figure C.2: Comparison of ROA and OCFOA Histograms

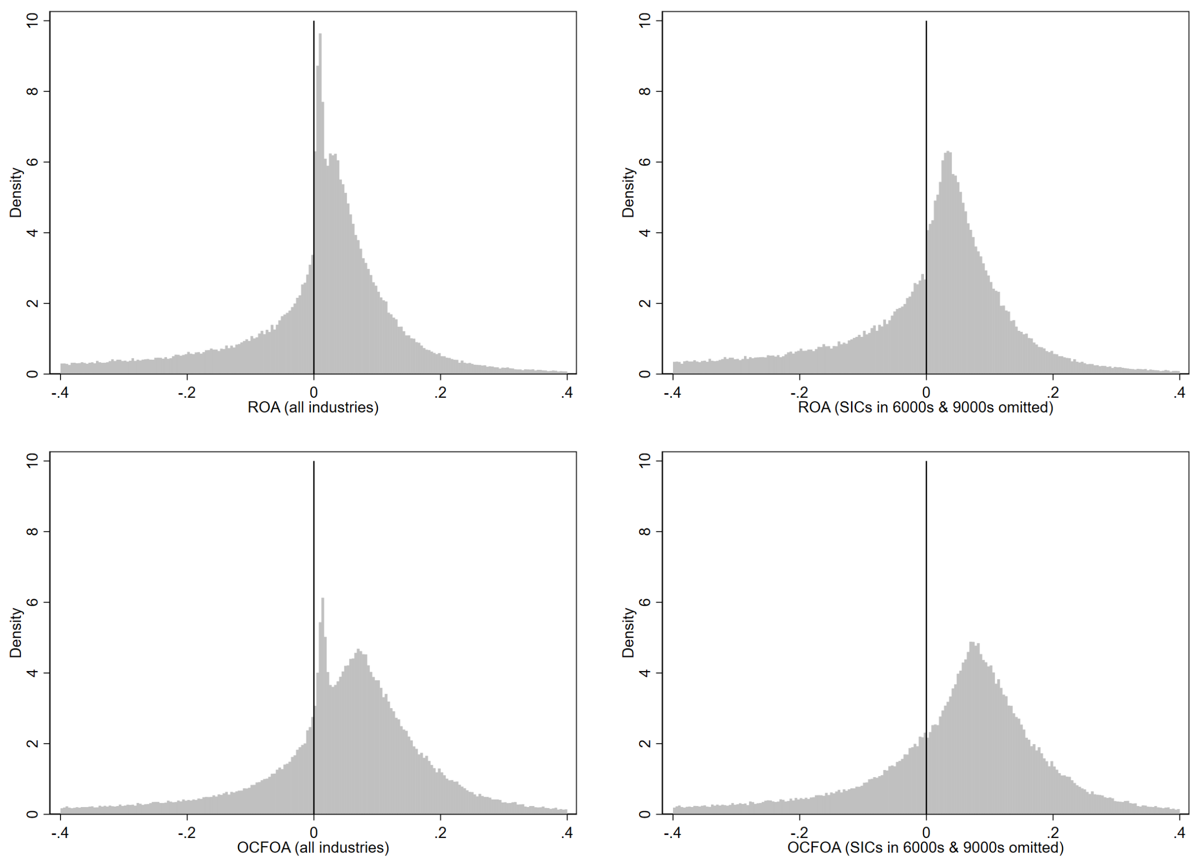


Figure C.3: Comparison of Smoothing Vs. ROA and OCFOA

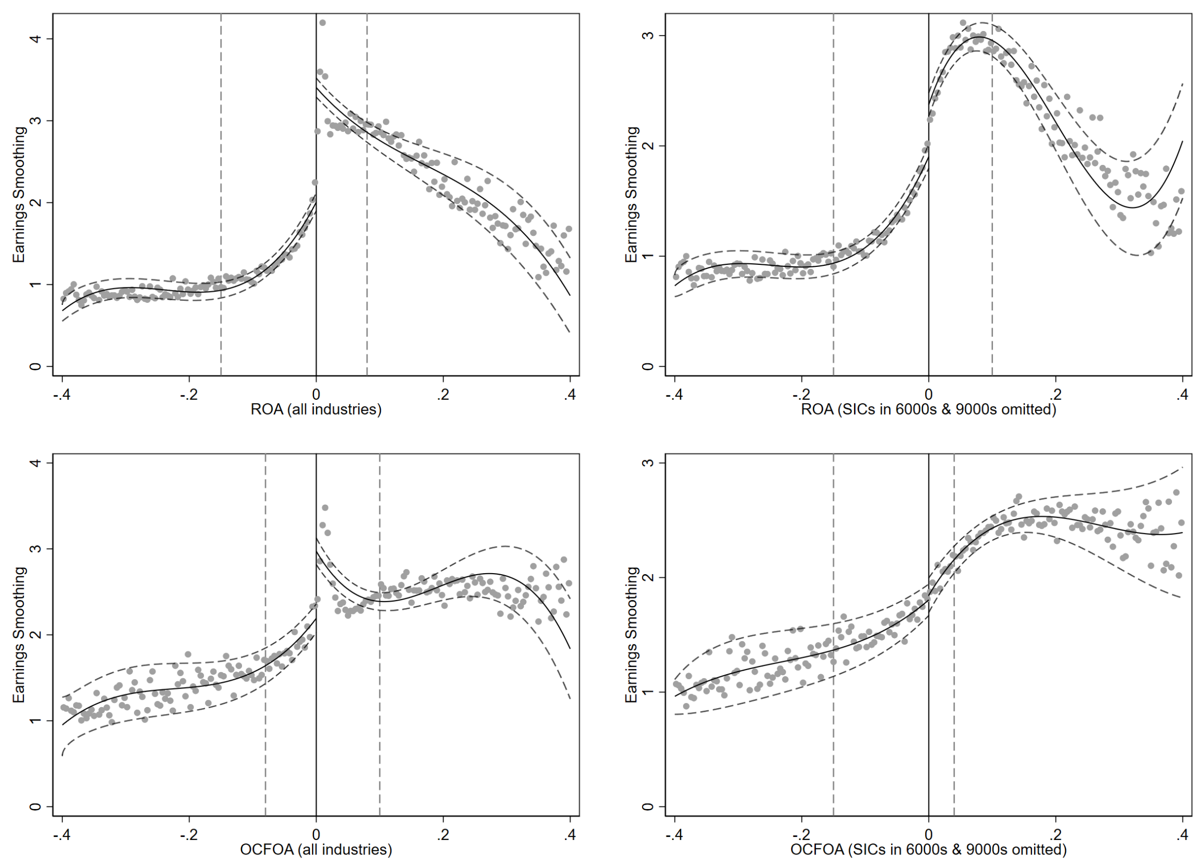


Table C.1: Nested and Simultaneous ANOVA Results

All Industries - Nested ANOVA

Category	ROA Variance Explained	ROA Percentage of Explained Var.	OCFOA Variance Explained	OCFOA Percentage of Explained Var.
Year	.0138	2.61	.0032	0.51
Industry	.0700	13.23	.1520	24.34
Firm	.3071	58.02	.3494	55.95
CEO	.1384	26.15	.1199	19.20
Full Model	.5293	100	.6245	100

All Industries - Simultaneous ANOVA

Category	ROA Variance Explained	ROA Percentage of Explained Var.	OCFOA Variance Explained	OCFOA Percentage of Explained Var.
Year	.0149	3.65	.0033	0.89
Industry	.0212	5.19	.0254	6.86
Firm	.2128	52.07	.2120	57.22
CEO	.1598	39.10	.1298	35.03
Full Model	.5555	100	.6386	100

SICs in 6000s and 9000s Omitted - Nested ANOVA

Category	ROA Variance Explained	ROA Percentage of Explained Var.	OCFOA Variance Explained	OCFOA Percentage of Explained Var.
Year	.0147	2.79	.0019	0.31
Industry	.0624	11.85	.1155	19.07
Firm	.3112	59.07	.3626	59.86
CEO	.1385	26.29	.1257	20.75
Full Model	.5268	100	.6057	100

SICs in 6000s and 9000s Omitted - Simultaneous ANOVA

Category	ROA Variance Explained	ROA Percentage of Explained Var.	OCFOA Variance Explained	OCFOA Percentage of Explained Var.
Year	.0165	3.99	.0038	1.00
Industry	.0196	4.74	.0232	6.05
Firm	.2162	52.30	.2200	57.35
CEO	.1611	38.97	.1366	35.61
Full Model	.5544	100	.6215	100