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Has accounting gone bad?

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ABSTRACT

We investigate two aspects of earnings smoothing via accruals that are consistent with accounting rule changes causing a decline in accounting quality. First, since 2000 accruals cause earnings to be far more volatile than cash flow from operations (CFO). We find this surprising result is unrepresentative, driven by the disproportionate influence of firms with negative CFO and low total assets (the deflator). We consider three other deflators—sales, market capitalization, and number of shares—as well as different diagnostics to determine distortion caused by deflation. We find number of shares performs best, and volatility of earnings is only about half that of CFO. Second, "smoothing coefficients", slopes from annual cross-sectional regressions of accruals on CFO, have become less negative over time. This trend too is likely due to changes in operating characteristics, not changes in accounting rules. It is related mainly to a decline in the level of working capital, especially inventories, and is unrelated to factors such as increases in negative special items and the fraction of firms reporting losses.

Keywords: Earnings quality; deflation by total assets; smoothing; persistence

Data Availability: Data are available from the public sources indicated in the text.

Online Appendix: Available at this link.

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1. Introduction

Accrual accounting converts cash inflows and outflows to revenues and expenses to generate earnings, a performance measure designed to be more informative than net cash flows. Intuition and evidence (e.g., Dechow 1994) suggest that accruals offset some of the volatility in operating cash flows, leading to smoother earnings. A smoother earnings stream is desirable as it improves measures of "accounting quality" (AQ), such as persistence, predictability, matching, and value relevance.[1] We investigate trends in earnings smoothing due to accruals because an emerging stream of research suggests that AQ is in decline (e.g., Dichev and Tang, 2008). Potential reasons for this decline include changes in accounting rules that result in more one-time items, more conditional conservatism, poorer matching between revenues and expenses, and increased emphasis on mark-to-market accounting for balance sheets (e.g., Bushman et al. 2016).

While our interest is in comparing the relative variances of earnings and operating cash flows, we find it convenient to focus on a "smoothing coefficient", the slope from regressions of operating accruals (ACC) on cash flow from operations (CFO).[2] Because earnings (EARN) is the sum of CFO and ACC, the variance of EARN equals the sum of the variances of CFO and ACC plus twice their covariance. For EARN to be smoother than CFO, the covariance of ACC and CFO and the smoothing coefficient (covariance divided by the variance of CFO) need to be sufficiently negative to offset the variance of ACC.

Our objective is to understand two empirical regularities that suggest a decline in earnings smoothing via accruals. First, since 2000 the variance of EARN has been increasing relative to the

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1 Smoother earnings due to accruals can arise both from following the rules of accrual accounting and from managerial efforts to smooth reported earnings. We do not distinguish between these two smoothing sources.

2 We limit our analysis to the slope of this regression because the other measures investigated —such as explained variance (R^2) and unexplained variance (of residuals)—are not comparable across samples.

variance of CFO, and now exceeds it substantially. Relatedly, smoothing coefficients have turned *positive*, and become increasingly positive over time. Why are accruals increasing the variance of EARN, relative to CFO variance, rather than decreasing it as they are commonly expected to? The second empirical finding we investigate is the steady decline in the magnitude of the negative smoothing coefficients documented in Bushman et al. (2016), hereafter BLZ. Is this decline in the smoothing role of accruals due to changes in accounting rules/practices? Or is it due to underlying economic changes, such as changes in the types of firms represented in the sample (e.g., manufacturing versus service) and changes in firms' operations (e.g., lower investments in working capital)?

To motivate the first investigation, we update the main results of BLZ, based on annual cross-sectional regressions of ACC on CFO, both deflated by total assets. We start our sample period in 1990 to obtain consistent measures of CFO based on statement of cash flow data. We find the variance of EARN exceeds considerably the variance of CFO over this period, reaching levels eight times as high, and the smoothing coefficient increases from –0.1 to 1.[3]

We investigate whether the results observed for the simple regression of ACC on CFO are also observed when we add lagged and lead values of CFO, as proposed by the Dechow and Dichev (2002), or DD, model.[4] Including these additional regressors results in similar trends but different levels for the slope on contemporaneous CFO: it increases from about –0.4 in the early 1990s to zero in the early 2000's, and plateaus at that level thereafter. Although the slope does not turn positive, as it does for the simple regression, the implication from the zero slope is again that

3 BLZ estimate the smoothing coefficient is close to zero during this period. This difference in results arises because they delete firms with total assets less than $10 million (see also Christensen et al. 2019).

4 We employ the extension of the DD model proposed by Francis et al. (2006) and include changes in revenue and the level of PP&E as additional explanatory variables (see Christensen et al. 2019).

accruals no longer play a smoothing role as the variance of EARN exceeds that of CFO.[5]

We suspect that the deflator used may explain these puzzling results because the evidence in a second strand of the literature suggests that earnings volatility is considerably *lower* than CFO volatility (e.g., Cheong and Thomas 2017). The deflator employed there is the number of shares (NS). We confirm that using per share data removes both puzzling aspects of the results observed for asset-deflated data. The smoothing coefficient is always substantially negative, increases from −0.7 in 1990 to −0.4 in 2018, and the variance of EARN is only about half that of CFO. The results for the DD model for per share data are similar: the smoothing coefficient increases from about −0.5 to just above −0.4 over our sample period.

We examine several diagnostics and alternative deflators to determine which set of results observed are representative of the underlying relation. We consider time-series regressions by firm, replacing the levels of ACC and CFO with their unexpected components, and two other deflators (sales and market capitalization). We also estimate undeflated regressions that include the deflators as additional regressors (Lev and Sunder 1979, and Barth and Kallapur, 2006). Our diagnostics suggest that the per share results are reliable. While the per share results differ from those for other deflators for the popular specification (annual, cross-sectional regressions based on levels), they resemble the results for all other specifications for all four deflators.

We find it puzzling that deflating by total assets flips the sign of the smoothing coefficient, given that both deflators—AT and NS—are positive. The results in Ball and Shivakumar (2006) suggest that firms with negative CFO might play a role. Their Table 3, Panel A reveals that the slope for positive CFO is quite negative and the slope for negative CFO is positive, albeit of smaller

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[5] BLZ find similar trends in their Figure 2, although the levels are different: their smoothing coefficient remains negative throughout their sample period.

magnitude.[6] Perhaps the aggregate results based on deflation by total assets assign too much weight to the subset with negative CFO.

To investigate this possibility, we report mean levels of ACC for ventiles of CFO and see a clear separation of the sample based on the sign of CFO. Whereas firm-years with positive values of CFO (CFO+) exhibit a negative ACC/CFO relation, firm-years with negative values of CFO (CFO−) exhibit a positive ACC/CFO relation. Returning to annual cross-sectional regressions, we find the CFO− group exhibits levels and trends for smoothing coefficients similar to those for the overall sample: they increase from just above zero in the 1990s to just over 1 in the 2010s. In contrast, the CFO+ group is associated with a smoothing coefficient of around −0.5 over the sample period. Even though the CFO− group represents only 30 percent of the sample, it dominates because it is associated with variances of CFO and magnitudes of means of ACC and CFO that are many times higher than those for the CFO+ group.[7] Further examination reveals that these large variances and means are due to a subset of firms with very low values of AT.

The evidence in Denis and McKeon (2018) potentially explains why partitioning on the sign of CFO identifies different populations. They find that firms with negative CFO exhibit very different operating characteristics and financial policies. These firms tend to be early-stage firms making large investments in R&D and brand-building. They issue equity at regular intervals (primarily private placements), hold the funds raised as cash balances, and run down those balances to cover negative CFO and investments each year. The median "runway" for these

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6 The trend for slopes reported in Figure 3 of BLZ also suggest that the slope becomes positive after 1990 for the subsample with negative CFO.

7 We show algebraically (see Appendix 3) that the combined slope is a weighted average of the CFO− and CFO+ slopes, and the weights are a function not only of the proportion of firms in the two groups but also their CFO variances as well as the differences between the two groups in their means for ACC and CFO.

firms—post-issue cash balances scaled by monthly cash burn rates—is between 6 and 18 months.[8] We find this group is also more likely to have negative working capital (non-cash), which increases the odds of negative accruals (Chu 2019). It is likely that assets are depressed because their investments in R&D and brand-building are not capitalized. The resulting asset-deflated values for CFO and ACC are exaggerated. Switching to per share data presents a different picture. Negative smoothing coefficients are observed for both CFO+ and CFO− groups.

In sum, the higher EARN volatility, relative to CFO, and the positive and increasing smoothing coefficients observed are not due to a reversal of the smoothing role of accruals over time. It is a distortion caused by a subset of firms in the CFO− group with very low values of AT.[9] We encourage research on accruals and earnings to also consider using per share data and to confirm results based on alternative deflators and specifications. We also believe it is relevant that managers, investors, and market intermediaries all emphasize per share numbers.

To investigate the second question—why smoothing coefficients have become less negative over time—we employ an alternative approach, different from those considered in BLZ and Srivastava (2014). We first separate ACC news into four components: short-term accruals (STACC), relating to changes in noncash current assets and current liabilities; one-time items (CCACC) relating to write-offs and other applications of conditional conservatism; depreciation and amortization (D&A); and all other items (OTH). We find that the reduction in smoothing

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8 Srivastava (2014) also develops the notion of two populations to explain declining AQ, with cohorts of newly listed firms being fundamentally different because their investments tend to be in intangible assets, such as those created by expenditures on R&D and customer brands. While both papers appeal to intangibles, partitioning firms with negative CFO is not equivalent to cumulating newly listed firms. Some newly listed firms are mature firms with positive CFO, either because they are mature at listing (e.g., previously public firms taken private) or because their investments are successful and caused CFO to turn positive. The typical run of negative CFO for firms in Denis and McKeon's (2018)sample is four years.

9 Deleting firms with "low" values of total assets eliminates a substantial fraction of firms, and the choice of cutoff seems arbitrary.

coefficient magnitudes is due mainly to STACC. We split STACC further into five components—changes in accounts receivable, inventory, accounts payable, taxes payable, and other working capital accruals—and find that the most relevant components are changes in inventory and accounts receivable (to a lesser extent). A key finding is that the decline in smoothing from these items appears to be due to a decline in the levels of inventory and accounts receivable. That is, observed trends for the smoothing coefficient are due to changes in the underlying economics and operations of sample firms, not accounting rule changes.

Our main takeaway is that the smoothing role of accruals appears to be alive and well. We find consistently negative smoothing coefficients for all specifications that are not affected unduly by the CFO− group. The general decline observed in the magnitude of smoothing coefficients is unlikely to be due to changes in accounting rules that affect accruals. The two items that explain much of the reduction in smoothing coefficients—accounts receivable and inventory—are not associated with major rule changes. More likely, the reduction in smoothing coefficients is due to declining levels of those two current assets, which leads to lower across-firm variation in changes in those levels, relative to corresponding variation in CFO.

Another takeaway is that patterns observed for smoothing coefficients should be interpreted with caution. Trends vary depending on the specification and deflators used. Cross-sectional regressions of ACC on CFO have the potential to be affected disproportionately by a subset of unusual firms with negative CFO that also have very low values of commonly used deflators, such as total assets, sales, and market capitalization. As suggested by our analysis of the DD model, similar inferences might arise for other measures of accounting quality that are derived from the same popular specification.

The remainder of the paper is organized as follows. Section 2 reviews the prior literature, Section 3 describes the sample selection process, Section 4 provides results, and Section 5 concludes.

2. Background

Prior research views operating accruals as the difference between earnings and operating cash flows (e.g. Hribar and Collins 2002). That is, earnings (EARN) is the sum of operating cash flows (CFO) and operating accruals (ACC). Given that the objective of accrual accounting is to create a better measure of performance than net cash flows, it seems reasonable to expect EARN to be less volatile than CFO. Lower EARN volatility should improve matching, persistence, and predictability, three desirable attributes of a performance measure. And lower EARN volatility should improve value relevance, the association with stock returns, a fourth desirable attribute.

To be sure, there are reasons why ACC might *increase* EARN volatility, relative to CFO volatility. Examples include conditional conservatism and efforts to reflect fair values on balance sheets. In such cases, EARN volatility increases because current earnings reflect the value impact of expected future events, not yet reflected in CFO. Managers might also increase EARN volatility by taking large write-offs or "big baths". It is possible that accounting rules and managerial behavior have changed over the years to cause these effects to increase in importance.

As described in the Introduction, the variance of EARN is lower than the variance of CFO, if the covariance of ACC and CFO is sufficiently negative, i.e., if the magnitude of twice the covariance exceeds the variance of ACC. The negative covariance that is required to smooth EARN relative to CFO also determines the smoothing coefficient or the slope of the regression of ACC on CFO, which equals that covariance divided by the variance of CFO. We examine both the relative variances of EARN and CFO as well as the smoothing coefficient to infer the extent of EARN smoothing. As in prior research, we estimate the smoothing coefficient as the slope (β)

from a regression of the level of ACC on the level of CFO;

$$ACC = \alpha + \beta CFO + \varepsilon_t,$$

$$\beta = \frac{Cov(ACC, CFO)}{Var(CFO)}$$

The evidence (e.g., Dechow, 1994) suggests that EARN is less volatile than CFO and a better measure of performance. There have also been efforts to model the accruals process (e.g., Dechow et al. 1998 and Frankel and Sun 2018), with a negative CFO/ACC relation in mind.

However, the evidence in recent years suggests that the variance of EARN is increasing and the CFO/ACC relation is becoming less negative. BLZ focus directly on variation over time in the smoothing role of accruals and document a steady decline in the smoothing coefficient to levels close to zero. Given that the variance of accruals is positive, a covariance close to zero (reflected in smoothing coefficients close to zero) implies that EARN volatility exceeds CFO volatility. Nallareddy et al. (2020) in untabulated results confirm that the smoothing role of accruals is also declining overseas. Their study shows that the decline in smoothing is accompanied by increased cash flow persistence both in the U.S. and in the international sample.

Other studies examining temporal changes in the properties of accounting numbers include Givoly and Hayn's (2000) study of the changing degree of accounting conservatism; Dichev and Tang's (2008) study of the changing degree of matching between revenues and expenses; Srivastava's (2014) analysis of the effect of newly listed firms on the time-series changes in earnings quality attributes; and the study of time-series variation in accruals quality by Christensen et al. (2019).

The most common specification used in prior research predicting accruals, cash flows, and earnings is to estimate cross-sectional regressions based on levels of annual data, deflated by average total assets. As described in Appendix 2, there has been a change over time in the specifications used. In earlier research, some studies estimated firm-by-firm time-series regressions, focused on the unexpected components rather than levels, relied on quarterly data, and deflated by number of shares. While theory and conceptual reasons guide these choices, there is evidence that results are sensitive to the choices made. For example, Nallareddy et al. (2020) find that the relative ability of CFO and EARN to predict next year's CFO flips when they switch from annual to quarterly data.

3. Sample and descriptive results

Table 1 provides details of the sample selection process. Our main sample includes 137,434 firm-years between 1990 and 2018. Our sample period begins in 1990 to allow consistent measures of CFO and ACC based on cash flow statements (see Appendix 1 for details of variables). Firms started reporting cash flow statements from 1988, and we move forward two years to allow collection of lagged values of asset-deflated variables, which requires one additional lag to compute average total assets. We exclude non-US firms and firms in the financial sector (SIC 6000-6999) and require non-missing values for EARN, CFO, average total assets, and number of common shares used to compute basic EPS. We trim firm-years that lie in the extreme 1 percent of the annual distributions for asset-deflated EARN, CFO, and ACC. We trim, rather than Winsorize, to maintain strict equality between EARN and the sum of CFO and ACC.

As described in the remaining panels of Table 1, we consider four other samples derived from our main sample. First, to replicate BLZ, we exclude approximately 27,000 firm-years with average total assets (AT) less than \$10 million. Second to estimate firm-specific time-series regressions, we exclude approximately 19,000 firm-years from our main sample because they relate to firms with fewer than six years of non-missing data. Third, to estimate the contribution of different components of ACC, we lose about 4,000 firm-years because we require non-missing cash flow statement data for depreciation and amortization, and changes in accounts receivable and inventory. We also lose about 3,000 firm-years because we require at least 10 observations per 2-digit SIC code. Finally, to replicate the Francis et al. (2005) adaptation of the Dechow and Dichev (2002) model, we require non-missing data for the relevant variables as well as a minimum of 20 observations per 2-digit SIC code.

Table 2, Panel A provides distributional statistics for key variables for the main sample. The first three rows describe asset-deflated EARN, CFO, and ACC, and the next three rows describe the corresponding per share amounts. As explained in Section 4.1, we introduce per share numbers because results in a different strand of prior research suggest different inferences from those suggested by asset-deflated numbers. The distributions in the first two rows are left-skewed and associated with extreme negative values: the means are negative even though medians are positive. This skewness is possibly due to firms with low levels of total assets being more likely to report negative EARN and CFO. The corresponding rows for per share data are associated with positive means and medians for both EARN and CFO. Accruals are expected to be negative (because of depreciation and amortization), and both means and medians for asset-deflated and per share ACC are negative.

Panel B in Table 2 reports Pearson and Spearman correlations for pairwise combinations of these six variables. In general, EARN is expected to be strongly positively related to CFO, less strongly positively related to ACC, and CFO is expected to be negatively related to ACC. Focusing on Pearson correlations, the expected positive relation between EARN and CFO is observed for both asset-deflated and per share data, but the weaker positive relation between EARN and ACC is observed only for per share data. It is strongly positive for asset-deflated data. And the expected negative relation between CFO and ACC is also only observed for per share data. It is strongly positive for asset-deflated data, which runs counter to the smoothing role for accruals. Also, the Pearson correlations between the two deflated versions of the same variable (e.g., EARN/AT and EAN/SHR) are only weakly positive. As suggested by the results in Panel A, the extreme negative values created by asset-deflation appear to create unexpected Pearson correlations.

Additional confirmation that asset deflation causes extreme values is obtained when we switch to Spearman correlations, which are less affected by extreme values. The unexpected positive relation between asset-deflated CFO and ACC is now negative. The unexpectedly strong positive relation between asset-deflated EARN and ACC is now less positive, and the correlations between the two deflated versions of the same variable are now considerably more positive.

4. Results

Figure 1, Panel A provides the time-series of the variance of asset-deflated EARN estimated in each annual cross-section, as well as the three components of that variance: the variances of ACC and CFO and two times their covariance. Beginning in the late 1990's, the variance of EARN is visibly higher than that of CFO and that gap increases substantially over time. The variance of EARN is almost eight times the variance of CFO in some years during the most recent decade. The second surprising result is that the covariance term is substantially positive and increasing over time. Rather than smooth the volatility of CFO, accruals are clearly adding to that volatility. These results suggest that the various desirable attributes of accruals, such as persistence and predictability of EARN, are deteriorating over our sample period.

Consistent with the increasing trend for the covariance term reported in Panel A, the results in Panel B of Figure 1 suggest that the slopes of year by year regressions of ACC on CFO are positive and increasing over time. Again, this is an unexpected result as accruals are expected to be negatively related to CFO if they are to smooth the volatility of CFO. While the increasing R^2

might suggest an improved association between ACC and CFO, the positive slope driving that association raises questions about how it should be interpreted.

Our Panel B results differ from those in BLZ for the overlapping years because BLZ impose a filter that AT exceed \$10 million. Untabulated results confirm their results when we impose the same filter. The smoothing coefficient increases from about -0.4 and the adjusted R^2 decreases from about 0.15 in 1990 to levels close to zero by the late 1990s and hover around zero thereafter. Given that the filter excludes almost 27,000 firm years, representing nearly 20 percent of the available observations at that point, we elect to retain all firms and offer more general results.

4.1 Role of deflator choice

Although the prior literature has offered different explanations for declining AQ, we focus on a new explanation. We believe it is related to the popular approach that deflates accounting data by total assets. We do so because the evidence in a different strand of research suggests that the volatility of per share EARN may be lower than that of per share CFO.[10] Cheong and Thomas (2018), for example, show that seasonally-differenced quarterly earnings per share (EPS) are less volatile than seasonally-differenced per share CFO. That study also documents managerial efforts to smooth earnings further by increasing the negative correlation between seasonally-differenced CFO and ACC. Also, the descriptive results in Table 2, Panel B suggest that asset-deflation creates extreme negative values that cause a positive Pearson correlation between CFO and ACC. The Spearman correlation for asset-deflated data as well as both Spearman and Pearson correlations for per share data are negative.

To investigate potential distortion due to asset deflation we repeat the Figure 1 analyses based on per share data. The results reported in Figure 2 confirm our conjecture. The variance of

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10 We thank Sudipta Basu for pointing out this seeming contradiction between the two strands of research.

EARN in Panel A is about half of the variance of CFO, and the covariance is substantially negative. And the smoothing coefficient in Panel B is now quite negative, varying between –0.7 in the early 1990s and –0.4 by 2018. The trend for adjusted R^2 in Panel B is declining for per share data, unlike the increasing trend in Figure 1 for asset-deflated data.

4.2. Repeat analysis on Dechow/Dichev (2002) model.

To explore the potential for the bias due to asset deflation to carry over to other measures of accounting quality, we consider the model from Dechow and Dichev (2002). Whereas the regression specification considered so far is a simple regression of ACC on contemporaneous CFO, the DD model includes lead and lagged CFO. We continue to focus on the slope on contemporaneous CFO and check to see whether the findings from the simple regression carry over to the DD model. That is, does the slope on CFO switch from positive to negative when we replace asset-deflated numbers with per share numbers? To make the DD model more comprehensive, we use the covariates proposed by Francis et al. (2005), which include the level of PP&E and changes in revenues as additional control variables that explain ACC. We follow BLZ and estimate the model annually across the entire sample, rather than within industries.

The results reported in Panels A and B of Figure 3 describe trends for the coefficient on contemporaneous CFO and the adjusted R^2 for regressions based on asset-deflated and per share data, respectively. The results reported for asset-deflated numbers in Panel A differ slightly from those reported in Figure 1, Panel B. The slope on CFO in Figure 5 is close to zero, rather than the positive values observed in Figure 1. However, the inference is the same. There is no smoothing role for accruals, and the variance of EARN is higher than that for CFO. Switching to per share numbers in Panel B of Figure 5 yields the same effect observed when we switch the deflator from Figure 1 to Figure 2. The slope on CFO is clearly negative when the DD model is estimated on per share data, which leads to the opposite inference: accruals continue to play a smoothing role as they cause EARN to be smoother than CFO. Finding that asset-deflated data also substantially bias the smoothing coefficient in a different setting suggests that other AQ measures based on asset-deflated data might be similarly biased.

4.3 Partition sample by sign of CFO.

Next, we attempt to understand better why opposite results are observed for per share and asset-deflated data. In particular, how can the smoothing coefficients switch sign between Figures 1 and 2 when both deflators—total assets and number of shares—are positive? Identifying the source of the difference may be relevant for other studies using asset-deflated data.

We turn to the possibility that the cross-sectional relation between ACC and CFO is positive for a subset of firms. We do so because the results in Ball and Shivakumar (2006) show different slopes for positive and negative CFO subsamples. That study emphasizes conditional conservatism and the difference between the slopes for good and bad news (represented by positive and negative CFO), rather than whether the two slopes are of different sign. Regardless, the results in their Table 3, Panel A for the CF model reveal that the slope for positive CFO is quite negative and the slope for negative CFO is positive, albeit of smaller magnitude. Similar results documenting a nonlinear ACC/CFO relation are noted in BLZ's Figure 3, Panel B.

We examine nonlinearity in our sample by forming ventiles based on asset-deflated CFO and report the mean levels of asset-deflated ACC for each ventile in Panel A of Figure 4. The inverted V-shape that emerges confirms that the slope for positive (negative) CFO is negative (positive). While the two slopes in our sample appear to be of similar magnitude, the distributions of asset-deflated ACC and CFO are skewed. Even though about 70 percent of the sample is in the positive CFO group, the mass is dispersed more for the negative CFO group. The corresponding results reported in Panel B for per share data also show nonlinearity, but the slopes and distribution are different than those in Panel A. The slope is near zero for negative CFO in Panel B, and that mass is relatively tightly distributed, whereas the positive CFO group exhibits a negative slope and is more dispersed.

The main finding from the results in Figure 4 is that separating the sample into CFO+ and CFO– provides a possible explanation for why changing the deflator changes the sign of the smoothing coefficients in Figures 1 and 2. The combined slope is a weighted average of the separate slopes for the CFO– and CFO+ groups, but the weights given to those two slopes differs across the two deflators: the slope for the CFO– group is weighted more (less) for asset-deflated (per share) data. Intuitively, the regression slopes reported in Figures 1 and 2 for the overall sample impose a linear fit on the inverted V-shaped relations in Panels A and B of Figure 4, respectively. Because the left (right) leg of the inverted V is considerably longer for asset-deflated (per share) data , the combined slope is positive (negative).

Appendix 3 derives the formal relation between the combined slope and the slopes for the two partitions. The weights assigned to the slopes for the CFO– and CFO+ partitions are a function not only of the fractions of the overall sample in the two partitions, but also the respective variances for CFO. In addition, the product of the differences between the CFO means and ACC means for the two partitions is added to the slope. (See the formula for the numerator in equation (1) of Appendix 3.) Because the CFO variance is considerably larger for the CFO– (CFO+) group for asset-deflated (per share) data in Figure 4, Panel A (Panel B), that group's slope is weighted more. Also, because the product of the difference between mean CFO and mean ACC for the two groups is positive for asset-deflated data in Panel A, the combined slope becomes even more positive. In Panel B, that product is negative, and the combined slope becomes even more negative.

We investigate next why the dispersion of the two legs of the inverted V-shapes in Figure 4 varies across the two deflators. One possibility is that deflators create bias in the estimated ACC/CFO relation by inducing a relation between the deflated values and the deflator.[11] Ideally, deflators capture scale accurately and deflated values of CFO and ACC are unrelated to scale. To investigate this possibility, we form deciles based on asset deflated and per share CFO separately for the CFO- and CFO+ groups. Table 3, Panel A (Panel B) reports the mean values of asset-deflated (per share) CFO and ACC as well as the level of total assets (number of shares) for the two sets of deciles.

The means for asset-deflated CFO and ACC in Panel A describe the same patterns reported in Figure 4, Panel A for the CFO+ and CFO– groups. Decile 1 (10) refers to the most negative (most positive) decile for the CFO– (CFO+) group. Turning to the deflator, the mean level of total assets (AT) for the CFO+ group exhibits an inverted U shape: approximately \$1.5 billion at the two ends and approximately \$3.5 billion in the middle. This level of variation seems small compared to the variation in mean AT exhibited by the CFO– group: it increases more than a hundred-fold, from \$6 million for decile 1 to about \$700 million for decile 10. In effect, the lower AT values for low deciles inflate both CFO/AT and ACC/AT and make them both more negative. As discussed above, this strong correlation between deflated CFO/AT and AT induces a spurious positive relation between CFO/AT and ACC/AT for the CFO– group. It also increases the variance of CFO/AT for this group as well as the magnitudes of the means for CFO/AT and ACC/AT, both of which cause the positive smoothing coefficient for the CFO – group to carry a disproportionately larger weight in determining the overall smoothing coefficient.

The results in Panel B for per share data suggest a positive relation between per share CFO

[11] See Lev and Sunder (1979) for an in-depth discussion of deflation, and the potential for biases.

and the deflator, number of shares. The number of shares increases from 42 million to 147 million shares for CFO+. That is, the more extreme deciles of CFO+ are associated with more shares, which *understates* mean values of per share CFO and ACC. As a result, the variances for CFO and means for both CFO and ACC are understated. For CFO– the number of shares stays relatively constant for most deciles, although it increases sharply for decile 10. Importantly, the more extreme (lower) deciles of CFO– are not associated with fewer shares. As a result, the smoothing coefficient for this group is not overstated, as it is for asset-deflated data. Also, the smoothing coefficient for the CFO– group does not carry a disproportionately larger weight in determining the overall smoothing coefficient because the variances of CFO and the means for CFO and ACC are not overstated.

Overall, the higher variance of EARN relative to that of CFO and the positive sign of the smoothing coefficient observed in Figure 1 for asset-deflated data, are distortions created by firms with understated total assets in the extreme negative CFO– deciles. Deflation by total assets overstates CFO/AT and ACC/AT for those deciles, which overstates the variance of CFO and means of CFO and ACC. Together these two effects create a positive smoothing coefficient for this group and also carry a disproportionate weight in the overall smoothing coefficient .

Figure 5 offers a description of trends underlying the aggregate results reported in Figure 4. Panel A of Figure 5 reports the annual smoothing coefficients for asset-deflated data for the CFO+ and CFO– groups represented by the inverted V-shape in Panel A of Figure 4. The results suggest that the trend observed for the overall coefficient in Figure 1, Panel B reflects mainly the positive and increasing smoothing coefficient for the CFO– group. The CFO+ group, which is severely underweighted in the overall coefficient, even though it represents about 70 percent of the sample, is associated with a strong negative smoothing coefficient, about -0.5, that remains relatively constant over time. The year by year results in Panel B for per share data are consistent with the average pattern reported in Panel B of Figure 4. While the smoothing coefficient for CFO– hovers around zero, the smoothing coefficient for CFO+ is strongly negative, varying between −0.75 and −0.4.

4.4. Deflation by total assets versus number of shares.

Given the distortion associated with asset-deflated data, we take the opportunity to consider the pros and cons of using asset-deflated data versus per share data. Because accruals appear on the balance sheet as assets and liabilities, total assets is a natural choice for deflation. And the number of shares appears to be a poor choice because it is an arbitrary number, one that can be easily changed by stock splits or reverse splits. However, as described below we see reasons why the use of per share data might be preferred.

First, while the number of shares appears arbitrary, it is a choice that managers make. Given the emphasis that managers and other stakeholders place on earnings per share, there could be an implied understanding that per share numbers can be compared across peers and over time, without additional deflation. That is, managers use stock splits/dividends and reverse splits to bring per share earnings (and share prices) within a target range. Figures A4 and A5 in the online appendix plot some key parameters of the cross-sectional distribution of per share earnings and asset-deflated earnings, respectively. between 1960 and 2018. Since 1990, the beginning of our sample period, the distribution is remarkably stationary. The first quartile fluctuates around a loss of $0.50 per share, the median lies just above zero, and the third quartile increases from just above $0.50 to $1.50. These results are consistent with the number of shares being chosen to ease comparisons of per share earnings over time and across peers. The contrast with asset-deflated earnings in Figure A5 is stark. The left tail of the distribution and the mean vary substantially over time.

Second, there is evidence that managers smooth earnings, especially "core" earnings that exclude non-recurring items. Smoothing increases earnings predictability, which improves the ability of current earnings to signal managers' estimates of future earnings. Cheong and Thomas (2018) provide considerable evidence of managers using accruals to smooth quarterly per share earnings. The negative correlation between unexpected per share CFO and ACC, proxied by seasonal differences, is very high, around −0.75. Also, the extent of smoothing increases with share price—indicated by that negative correlation increasing from −0.69 for the smallest price decile to −0.85 for the largest price decile. This differential smoothing is designed to make the volatility of per share earnings be similar in the cross-section.

Third, many relevant stakeholders, including investors and analysts, view per share numbers as the relevant investment base to analyze and communicate. This emphasis is likely related to managerial emphasis on per share numbers. We do not see references to a dollar of total assets as the relevant investment base, which in effect converts deflated earnings and its components to a return on assets measure.

Finally, asset deflation creates a mismatch that reduces cross-sectional and time-series comparability. The numerator reflects flows to equityholders, whereas the denominator includes financing provided by all stakeholders, including debtholders and suppliers. Cross-sectional variation in capital structure and liabilities owed to different stakeholders reduces comparability of asset-deflated numbers across firms. And time-series variation in the use of those liabilities as well as variation in the accounting for liabilities (tendency to book more off-balance sheet items, such as operating liabilities and deferred compensation) impairs comparisons over time.

4.5 Alternative deflators and specifications.

We acknowledge that researchers may have concerns about per share data. We also acknowledge that there are other deflators that are available to scale accounting data. To provide additional evidence on whether deflation by number of shares offers a reasonable way forward, we consider two additional deflators—sales and market value of equity—and alternative specifications beyond the annual cross-sectional regressions estimated so far. As we conduct a large number of analyses, we provide those results separately in the Online Appendix. Figures and Tables in the Online Appendix include an "A" before the number to distinguish them from those in the paper Below is a summary of the main findings.

First, we repeat the cross-sectional analyses in Panel B of Figures 1 and 2 for the two additional deflators (see Figure A1). The smoothing coefficients for sales are positive and resemble those for asset-deflated data in Figure 1. The coefficients for market value of equity are negative but tend toward zero by the end of the sample period. These results are inconclusive: deflation by assets and sales suggests accruals make EARN more volatile than CFO, per share data suggests the opposite, and market value deflation falls in between.

Second, we follow the approach suggested by Lev and Sunder (1979) and Barth and Kallapur (2006) to examine potential bias caused by deflation: confirm that the deflated regressions provide results similar to undeflated regressions that include the deflator as an additional regressor. We find consistently negative smoothing coefficients in all years for all four deflators for the undeflated regressions (see Figure A2). We also consider weighted least squares (WLS) regressions to reduce (increase) the influence of small (large) firms. Again, we generally observe negative smoothing coefficients for all deflators; with one exception: the coefficient is positive in some years for sales (see Figure A3).

Third, we switch from annual cross-sectional analyses to time-series regressions by firm and repeat the analyses in Table 5 of BLZ. We too find negative smoothing coefficients that are declining in magnitude over time for asset-deflated data (see Table A1). Similar results are observed for per share data. That is, time-series results for asset-deflated data differ from corresponding cross-sectional results, but they resemble the cross-sectional and time-series results for per share data.

Finally, we extend our investigation in Table 3 of an induced relation between deflated variables and the deflator. Observing a relation increases the potential for biased estimates. We find a strong negative relation between sales-deflated CFO/ACC and sales for the CFO− group (see Table A2), similar to our findings for total assets. Market value deflation does not appear to induce a strong relation with deflated CFO/ACC similar to the results observed for per share data.

Overall, the results suggest that the results based on per share data are the most reliable, as they produce the same results across all specifications—deflated, undeflated, WLS, and time-series regressions—and they do not induce a relation between deflated data and the deflator. Also, they resemble the results for all specifications other than deflated, cross-sectional regressions for the other three deflators. Sales and total assets appear to be the deflators that are biased the most in cross-sectional regressions because firms with negative CFO and low values of those two deflators distort the overall estimates. Given these results, we limit the remaining discussion to per share data.

4.6 Levels versus news.

We investigate next if the negative relation between ACC and CFO expected by the smoothing role of accruals is more evident in the unexpected components of ACC and CFO, relative to the levels that have been considered so far. As in prior work, we predict current period

ACC and CFO using their respective lagged values. Noting different ACC/CFO relationships for CFO+ and CFO- groups suggests that we allow for nonlinearity based on the sign of the lagged variable. Untabulated results confirm that the relation with lagged values for both CFO and ACC are nonlinear. The slope for CFO is positive, but less positive for the smaller subset with negative values of lagged CFO. The slope for ACC is also positive for negative values of lagged ACC, but turns negative for the smaller subset with positive values of lagged ACC.

We estimate unexpected components (or news) of per share CFO and ACC for each firm-year based on these nonlinear models using lagged values. The models are estimated separately each year by 2-digit SIC industry code. Our results for smoothing coefficients based on ACC and CFO news are reported in Figure 6, with Panel A describing the overall sample and Panel B providing separate results for the CFO+ and CFO- partitions. For reference, we also report in Panel A the smoothing coefficients based on ACC/CFO levels reported in Figure 2, Panel B. The results in Panel B should be compared with the corresponding trends reported for ACC/CFO levels in Figure 5, Panel B for the two partitions.

The main difference between the ACC/CFO news and levels regressions is that the smoothing coefficient for the CFO- partition is consistently negative for news in Figure 6, Panel B, whereas it oscillates around zero for levels in Figure 5, Panel B. The trends for ACC/CFO news for the overall sample and the CFO+ group are relatively similar to those reported for levels in Figure 5. Switching from levels to news suggests a stronger smoothing role for accruals, with no evidence of a positive smoothing coefficient for either partition based on the sign of CFO.

4.7 Upward trend in smoothing coefficients.

While the smoothing coefficients are always negative for both partitions in Figure 6, there is a clear drift upwards, suggesting that they become less negative over time. If so, there is the potential that while the smoothing role of accruals has remained over time, it has declined in importance. BLZ examine the following six explanations for the (more dramatic) decline they report for their sample. To assist with separating the different explanations, we find it convenient to view CFO and ACC as each consisting of two components, one that appears in contemporaneous earnings and one that does not. CFO1 (CFO2) is the component that appears in EARN for the current (a prior or future) year. And ACC1 (ACC2) is the component that appears in EARN for the current year (offsets CFO2).

BLZ first examine “economic-based cash flow shocks” which correspond to increases in the variance of CFO due to increased variance in CFO1, the portion that appears in contemporaneous earnings. Second, they consider “timing-related cash flow shocks” which correspond to increases in the variance of CFO2, the portion that does not appear in current earnings and is offset by ACC2. Third, they consider “non-timing related accruals”, which corresponds to ACC1 (depreciation, write-offs, etc.) that appear in contemporaneous EARN. More ACC1 should reduce the ACC/CFO negative correlation, which depends on ACC2 & CFO2. Fourth, they investigate “poor matching between revenues and expenses” based on Dichev/Tang regressions, Fifth, they consider intangible intensity from Srivastava (2014). Finally, they examine asymmetric recognition of gains versus losses or conditional conservatism (Ball and Shivakumar). They conclude that the explanations based on non-timing related accruals and poor matching are associated with significant coefficients when explaining the time trend in the DD measure of AQ. However, they note that multicollinearity is high, which inflates standard errors, making it harder to find significance for any specific explanation.

In untabulated results we plot trends for the variables underlying all six explanations proposed by BLZ against the increasing trend for the smoothing coefficient shown in Panel A of

Figure 6. None of the six trends resemble that for our smoothing coefficient. Our results likely differ because of differences between the variables and samples between the studies. In particular, much of the upward trend in the smoothing coefficient documented by BLZ occurs prior to our sample period.

We consider a different approach to find an explanation for the observed upward trend in the smoothing coefficient. We follow Dutta et al. (2017) and decompose ACCR into four components: short-term accruals (STACC), one-time items that reflect conditional conservatism (CCACC), depreciation and amortization (D&A), and all other accruals (OTHER). Figure 7 describes our findings from this approach. We first confirm (untabulated results) that the upward drift observed in the Figure 6 for the main sample is replicated in the subset of the combined sample with non-missing accrual component data analyzed in Figure 7.

We also decompose the smoothing coefficient, which equals the ratio of the standard deviations of ACC and CFO news multiplied by their correlation. Panel A of Figure 7 describes how the three vary over time. While the standard deviation of ACC news is more volatile, the standard deviations for both CFO and ACC news exhibit a shallow U-shape. The correlation coefficient increases from –0.6 to –0.3 over the sample period. As described below, we return to the two standard deviations when we seek to isolate the trends underlying the smoothing trend.

We then turn to the decomposition of ACC news. The results in Panel B indicate that the upward drift in Panel A of Figure 6 is reflected mainly in the smoothing coefficient associated with news for one accrual component: STACC. The annual drift (slope from regression of smoothing coefficient on time) for the coefficient on ACC/CFO news in Figure 6 Panel A is 0.0074. The corresponding annual drifts for news in STACC, CCACC, D&A, and Other are 0.0054, 0.0008, 0.0014, and 0.0000, respectively. That is, the relation between CFO news and news in working capital changes (ΔWC)—changes in current assets (non-cash) and current liabilities—has become less negative over time, whereas the other relations have remained relatively unchanged. The relatively flat line for the positive correlation between CFO news and news in CCACC (one-time items) is surprising as it suggests that the increased frequency and magnitude of one-time items does not affect much the overall smoothing coefficient.

STACC captures mostlyACC2, the offset to CFO2, which is the portion of CFO that does not flow through to current earnings. As a result, the decline in the smoothing coefficient is likely not due to changes in accounting rules, such as increased conditional conservatism or the increasing emphasis on fair values and the balance sheet over the income statement (See extensive discussion in BLZ.)

We continue the decomposition process further and report in Panel C the smoothing coefficients for news in changes in three components of working capital: accounts receivable, inventory, and accounts payable.[12] We drop taxes payable, and other working capital items because they exhibit flat trends. We find that two components—accounts receivable and inventory—exhibit the rising trend observed in Figure 6, Panel A. Accounts payable is associated with a weaker rising trend. The annual drifts from regressions of smoothing coefficients on time for news in accounts receivable (AR), inventory (INV), and accounts payable (AP) are 0.0026, 0.0030, and 0.0008, respectively. AR and INV appear to be more important than AP.

As described above, smoothing coefficients are a function of the standard deviations of news in changes in the three working capital accounts as well as the standard deviation of CFO

[12] Changes in current assets show up as positive, and changes in current liabilities are negative. A negative smoothing coefficient for accounts receivable (for example) means that unexpected increases in CFO are associated with unexpected decreases in accounts receivable. And unexpected increases in CFO are associated with unexpected increases in accounts payable. The smoothing coefficient will become less negative if levels of accounts receivable and accounts payable decline.

news. Panel D of Figure 7 provides the time-series of those four cross-sectional standard deviations As shown in Panel A, CFO news exhibits a shallow U-shape: it declines in the early 1990s, and then stays relatively constant until the early 2010s, before it starts to increase. The standard deviations for the three working capital accounts exhibit a downward trend that continues through to the early 2000's, before they level off. Because the working capital accounts do not rise thereafter, the increase exhibited by CFO during the last decade explains why all three smoothing coefficients become less negative toward the end of the sample period. As noted for the smoothing coefficients in Panel C, the decline in standard deviations is more evident for AR and INV.

At a general level, two possibilities exist for the relative decline in the standard deviation of news relating to these working capital accounts: there has been a decline over time in a) average levels of those accounts, and b) cross-sectional heterogeneity in those levels. For example, the variance of news related to inventory changes should decline if inventory levels decline over time or if inventory levels become more homogenous in the cross-section. To investigate the first possibility, we report median levels for the three working capital accounts in Panel F of Figure 9. The results suggest that much of the decline in variance exhibited in Panel E is explained by a decline in the levels of the two accounts.[13]

Overall, our results suggest that the decline in the smoothing coefficient observed for our sample is likely due to operational factors that determine the levels of accounts receivable and inventory that firms in each cross-section choose to hold. Any role played by changes in accounting rules, if it exists, is likely to be much smaller. This conclusion is consistent with those in BLZ and Srivastava. Our contribution is that we use a different approach that allows us to pinpoint the specific accruals components that are more relevant. Also, we are able to isolate the declining

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[13] Nallareddy et al. (2020) also document declines in median non-cash working capital over a similar sample period.

balance sheet levels for those working capital accounts as the mechanism for the decline in smoothing coefficients.

5. Conclusions

The seeming decline in accounting quality has attracted research interest over the past three decades. Although multiple measures of accounting quality have been proposed and investigated, similar declining trends are observed for all measures. One measure, the slope from cross-sectional regressions of accruals on cash flows from operations, exhibits an unexpected sign flip. This slope, which we refer to as the smoothing coefficient, is expected to be negative because accruals are generally expected to cause earnings to be less volatile than cash flows. And yet, the smoothing coefficient has turned positive during the 1990's and become more positive over time. Perhaps even more puzzling, earnings volatility now exceeds cash flow volatility by many orders of magnitude.

Explanations proposed in prior research for the general decline in accounting quality run the gamut, from changes in accounting rules to changes in the type of firms represented in annual samples. Ever-increasing, positive smoothing coefficients are harder to explain. We find that the result is not generalizable. While it is observed for the popular specification—cross-sectional regressions based on asset-deflated levels of the two variables—it is not observed for per share data and it is not observed for any deflator for any other specification. These results all suggest that earnings volatility is well below that for cash flows and the correlation between accruals and cash flows is reliably negative. We also find that the reason why the smoothing coefficient turns positive for this popular specification is a subset of start-up firms that have negative operating cash flows and low total assets. These firm-years are associated with very large negative values of asset-deflated accruals and cash flows, which cause the overall smoothing coefficient to turn positive.

We propose that researchers consider using per share data rather than asset-deflated data. The per share data provide consistent results across all specifications and similar results are observed for both positive and negative CFO partitions, and for other deflators for all specifications other than annual cross-sectional regressions. They eliminate the distortion created by the subset of firms that unduly affect asset-deflated cross-sectional regressions. Per share data are more comparable across firms and over time, relative to asset-deflated data. In addition, discussions among managers, investors, and intermediaries are all in terms of per share numbers.

As with the choice of deflator, we encourage researchers to investigate the sensitivity of their findings to other empirical choices. Do the results hold for quarterly and annual data, for both unexpected components and levels of relevant variables, and for time-series and cross-sectional regressions? To be sure, these choices should be guided by theory. But in the absence of theory, documenting the specific choices that substantially affect results is useful, as it suggests further avenues for inquiry.

While switching to per share data returns the smoothing coefficient to its expected negative value, there is clear indication that the coefficient has become less negative over time. We follow an approach that differs from those followed in prior research and decompose accruals into its components and find that the trend is attributable to working capital accruals. Further decomposition reveals that the overall trends are due to changes in inventory and accounts receivable. Indeed, the decline in the smoothing coefficient for these accrual components is mainly due to a decline in the levels of these accounts. We conclude that the declining trend observed for smoothing coefficients is unlikely to be due to changes in accounting rules. Rather, it is due to cross-sectional heterogeneity and changes in the operations of sample firms.

APPENDIX 1
Variable definitions

Label	Definition
EARN	Earnings measured from the statement of cash flows as income before extraordinary items (IBC) scaled by average total assets (AT) or number of shares (SHR).
CORE	Core earnings scaled by average total assets measured as CORE = CFO + STACC +D&A.
CFO	Operating cash flow measured from the statement of cash flows as net cash flow from operating activities minus the cash portion of extraordinary items and discontinued operations scaled by average total assets (AT) or number of shares (SHR).
ACC	Total accruals scaled by average total assets (AT) or number of shares (SHR) measured as ACC= EARN - CFO.
STACC	Short-term accruals measured from the statement of cash flows as the change in accounts receivable, plus the change in inventory, minus the change in accounts payable and accrued liabilities, minus the change in accrued income taxes, plus the net change in other current assets scaled by average total assets (AT) or number of shares (SHR).
CCACC	Conditionally conservative accruals measured as special items minus extraordinary items and discontinued operations scaled by average total assets (AT) or number of shares (SHR).
D&A	Depreciation and amortization accruals from the statement of cash flows scaled by average total assets (AT) or number of shares (SHR).
OTH	Other accruals measured as OTH = ACC - STACC - CCACC - D&A.
AR	Account receivables (RECTR) measured from the balance sheet scaled by average total assets (AT) or number of shares (SHR)
AP	Account payable (AP) measured from the balance sheet scaled by average total assets (AT) or number of shares (SHR)
INV	Inventory (INVT) measured from the balance sheet scaled by average total assets (AT) or number of shares (SHR)
Pct(loss)	Percentage of firms with negative earnings before extraordinary items (IBC)
Std(OI-PTI)	Cross-sectional standard deviation of the difference between operating income after depreciation (OIADP) and pretax income (PI)
SG&A Intensity	SG&A intensity measured as selling, general, and administrative expense (XSGA) scaled by total expenses, where total expenses are equal to sales (SALE) minus earnings before extraordinary items (IBC)
Std(CFO)	Cross-sectional standard deviation of CFO per share calculated annually
AR(CFO_CHG)	Cross-sectional lag-one autocorrelation coefficients of CFO changes calculated annually

Rsq(DT)	The adjusted R-squared from the Dichev and Tang (2008) model, run annually

This appendix provides the variable definitions along with the corresponding Compustat data item mnemonics. The unexpected component, or news, is estimated for all variables as the residual from annual cross-sectional regressions of current values on lagged values of that variable, within 2-digit SIC industries, allowing for different slopes for positive and negative values of the lagged variable.

Appendix 2: Change over time in the specification used when predicting earnings, cash flows and accruals.

This Appendix describes relevant features of a selected subset of prior research. It is intended to show rough trends over time for four aspects of the specifications used when investigating earnings, cash flows, and accruals: whether unexpected components (news or surprise) are estimated or levels used; whether firm-specific time-series regressions or cross-sectional regressions are estimated; the deflator used (total assets or per share); and whether quarterly or annual data are examined.

Paper	**Unexpected components?**	**Cross-sectional/time-series/pooled**	**Deflator**	**Quarterly or Annual data**	**Research question**
Ball and Brown (1968)	Yes	Pooled	Undeflated and per share	Annual	Do earnings reflect information in stock returns?
Watts (1975), Foster (1977), Griffin (1977), and Brown & Rozeff (1979)	Yes	Time-series	Per share	Quarterly	Forecasting EPS using Box Jenkins models.
Kormendi and Lipe 1987	Yes	Time-series	Per share	Annual	Linking earnings persistence to ERC
Bernard and Stober (1989)	Yes	Cross-sectional and time-series	Total assets	Annual and quarterly	Is ERC higher for CFO component of EARN than ACC component?
Jones (1991)	Yes	Tine-series	Total assets	Annual	Predicting discretionary accruals
Dechow (1994) (Table 2)	Yes	Time-series	Per share	Annual	Whether accrual makes earnings better performance measure
Sloan (1996)	No	Pooled and cross-sectional	Total assets	Annual	Accrual anomaly
Dechow, Kothari and Watts 1998	Yes	Tine-series	Per share	Annual	Build model of earnings, cash flows and accruals.
Pfeiffer et al. (1998)	Yes	Cross-sectional	Per share	Annual	Incremental information content of funds-based earnings component

Paper	Unexpected components?	Cross-sectional/time-series/pooled	Deflator	Quarterly or Annual data	Research question
Dechow and Dichev (2002)	No	Time-series/ Industry/ Pooled	Total Assets	Annual	Accounting quality measure based on model of accruals that includes lead and lagged cash flows
Hanlon (2005)	No	Pooled	Total Assets	Annual	Impact of large book-tax differences on pricing of earnings, accruals, and cash flows
Jayaraman (2008)	No	Time-series (for volatility measures)	Total Assets	Annual	Relation between informed trading and volatility of earnings and cash flows
Barth, Landsman and Lang (2008)	Yes	Pooled	Total Assets and per share	Annual	Does IAS adoption improve accounting quality
Frankel and Sun (2018)	Yes	Pooled	Total Assets	Annual	Improved prediction of accruals using cash flow properties

Appendix 3. **Slope of a pooled regression based on samples drawn from two populations.**
Consider two samples 1 and 2 in proportion p and $1-p$, respectively, so that $x = px_1 + (1-p)x_2$ and $y = py_1 + (1-p)y_2$

Define regression slope coefficients:

$$b = \frac{Cov(y,x)}{Var(x)};\ b_1 = \frac{Cov(y_1,x_1)}{Var(x_1)};\ b_2 = \frac{Cov(y_2,x_2)}{Var(x_2)}$$

Start with numerator of pooled coefficient:

$$Cov(y,x) = E(yx) - E(y)E(x) =$$

$$pE(y_1x_1) + (1-p)E(y_2x_2) - E(py_1 + (1-p)y_2)\,E(px_1 + (1-p)x_2) =$$

$$pE(y_1x_1) + (1-p)E(y_2x_2) - p^2E(y_1)E(x_1) - p(1-p)E(y_1)E(x_2) - p(1-p)E(y_2)E(x_1) - (1-p)^2E(y_2)E(x_2) =$$

Collect terms:

$$pE(y_1x_1) - p^2E(y_1)E(x_1) + (1-p)E(y_2x_2) - (1-p)^2E(y_2)E(x_2) - p(1-p)(E(y_1)E(x_2) + E(y_2)E(x_1)) =$$

Add/subtract terms:

$$pE(y_1x_1) - pE(y_1)E(x_1) + pE(y_1)E(x_1) - p^2E(y_1)E(x_1) + (1-p)E(y_2x_2) - (1-p)E(y_2)E(x_2) + (1-p)E(y_2)E(x_2) - (1-p)^2E(y_2)E(x_2) - p(1-p)(E(y_1)E(x_2) + E(y_2)E(x_1)) =$$

$$pCov(y_1x_1) + p(1-p)E(y_1)E(x_1) + (1-p)Cov(y_2x_2) + p(1-p)E(y_2)E(x_2) - p(1-p)\big(E(y_1)E(x_2) + E(y_2)E(x_1)\big) =$$

$$pCov(y_1x_1) + (1-p)Cov(y_2x_2) + p(1-p)[E(y_1)E(x_1) + E(y_2)E(x_2) - E(y_1)E(x_2) - E(y_2)E(x_1)]$$

It follows that the numerator is given by

$$Cov(y,x) = pVar(x_1)b_1 + (1-p)Var(x_2)b_2 + p(1-p)E(y_1 - y_2)E(x_1 - x_2) \tag{1}$$

Rewrite denominator of pooled coefficient:

$$Var(x) = E(x^2) - E(x)E(x) = \ldots = pVar(x_1) + (1-p)Var(x_2) + p(1-p)E(x_1 - x_2)E(x_1 - x_2)$$

Together, it follows that

$$b = \frac{pVar(x_1)b_1 + (1-p)Var(x_2)b_2 + p(1-p)E(y_1 - y_2)E(x_1 - x_2)}{pVar(x_1) + (1-p)Var(x_2) + p(1-p)E(x_1 - x_2)E(x_1 - x_2)}$$

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TABLE 1
Sample selection

This table presents the steps followed when collecting our main sample. We also provide the additional steps taken to generate four other samples. b) Sample used to replicate BLZ; c) Sample used for time-series analysis; d) sample for the ACC component analysis; and e) DD Sample based on Francis et al. (2005) regressions.

a) Main sample: 1990-2018	
Firm-years excluding financial industry (SIC 6000-6999) with available data for: average total assets, common shares used to calculate EPS basic, CFO, and EARN	195,816
Less:	
Firms not incorporated in the US	147,650
Trim all variables at 1% and 99%	137,434
b) BLZ sample : 1990-2018	
Firm-years excluding financial industry (SIC 6000-6999) with available data for: average total assets, common shares used to calculate EPS basic, CFO, and EARN	195,816
Less:	
Firms not incorporated in the US	147,650
Firms with average total assets < 10 million	120,834
Trim all variables at 1% and 99%	112,358
c) Time-series sample: 1990-2018	
Firm-years excluding financial industry (SIC 6000-6999) with available data for: average total assets, common shares used to calculate EPS basic, CFO, and EARN	195,816
Less:	
Firms not incorporated in the US	147,650
Firms with fewer than 6 years' observations	128,599
d) Component analysis sample: 1990-2018	
Firm-years excluding financial industry (SIC 6000-6999) with available data for: average total assets, common shares used to calculate EPS basic, current and lag CFO, EARN, Change in Receivables, Change in Inventory, and Depreciation	143,571
Less:	
Firms not incorporated in the US	116,526
Firms with fewer than 10 observations per 2-digit SIC-year	113,899
Trim all variables at 1% and 99%	103,353
e) DD sample based on FLOS regression: 1990-2018	
Firm-years excluding financial industry(SIC 6000-6999) with available data for: average total assets, common shares used to calculate EPS basic, CFO(t-1) CFO(t), CFO(t+1), EARN, Change in Revenue, PPE, Change in Receivables, Change in inventory	134,937
Less:	
Firms not incorporated in the US	108,457
Firms with fewer than 20 observations per 2-digit SIC-year	100,560

TABLE 2
Descriptive statistics

This table presents descriptive statistics. Panel A reports the empirical distributions of key variables. Panel B reports Pearson pairwise correlations. * indicates significant correlations at 5%. The sample includes 137,434 firm-year observations from 1990 to 2018. Details of all variables are provided in Appendix 1.

Panel A: Empirical distributions for key variables

Variable	N	Mean	Std.	Lower Quartile	Median	Upper Quartile	Min	Max
EARN/AT	137,434	-0.21	0.93	-0.15	0.01	0.07	-27.14	0.51
CFO/AT	137,434	-0.05	0.42	-0.06	0.06	0.12	-9.10	0.46
ACC/AT	137,434	-0.16	0.65	-0.13	-0.06	-0.01	-24.10	0.65
EARN/SHR	137,434	0.30	1.70	-0.33	0.09	1.01	-16.34	14.93
CFO/SHR	137,434	1.26	2.32	-0.06	0.44	2.04	-6.790	24.21
ACC/SHR	137,434	-0.96	1.81	-1.34	-0.37	-0.02	-23.95	5.17

Panel B: Pairwise correlations.
Pearson (Spearman) correlations are below (above) the main diagonal.

	EARN/AT	CFO/AT	ACC/AT	EARN/SHR	CFO/SHR	ACC/SHR
EARN/AT	1	0.743*	0.488*	0.821*	0.610*	0.012*
CFO/AT	0.800*	1	-0.058*	0.601*	0.798*	-0.443*
ACC/AT	0.919*	0.500*	1	0.398*	-0.024*	0.551*
EARN/SHR	0.194*	0.237*	0.125*	1	0.708*	-0.035*
CFO/SHR	0.194*	0.317*	0.072*	0.633*	1	-0.604*
ACC/SHR	-0.066*	-0.183*	0.024*	0.128*	-0.687*	1

TABLE 3
Variation in the deflator across CFO deciles for CFO + and CFO – groups.

Firms are partitioned each year based on the sign of CFO, into CFO + and CFO – groups. Each group is then partitioned into deciles based on asset-deflated CFO and CFO per share. Mean values (across all years) are then reported for each decile for deflated CFO and ACC as well as the deflators—total assets (AT) and # of shares.

Panel A: Portfolio means for asset-deflated data.

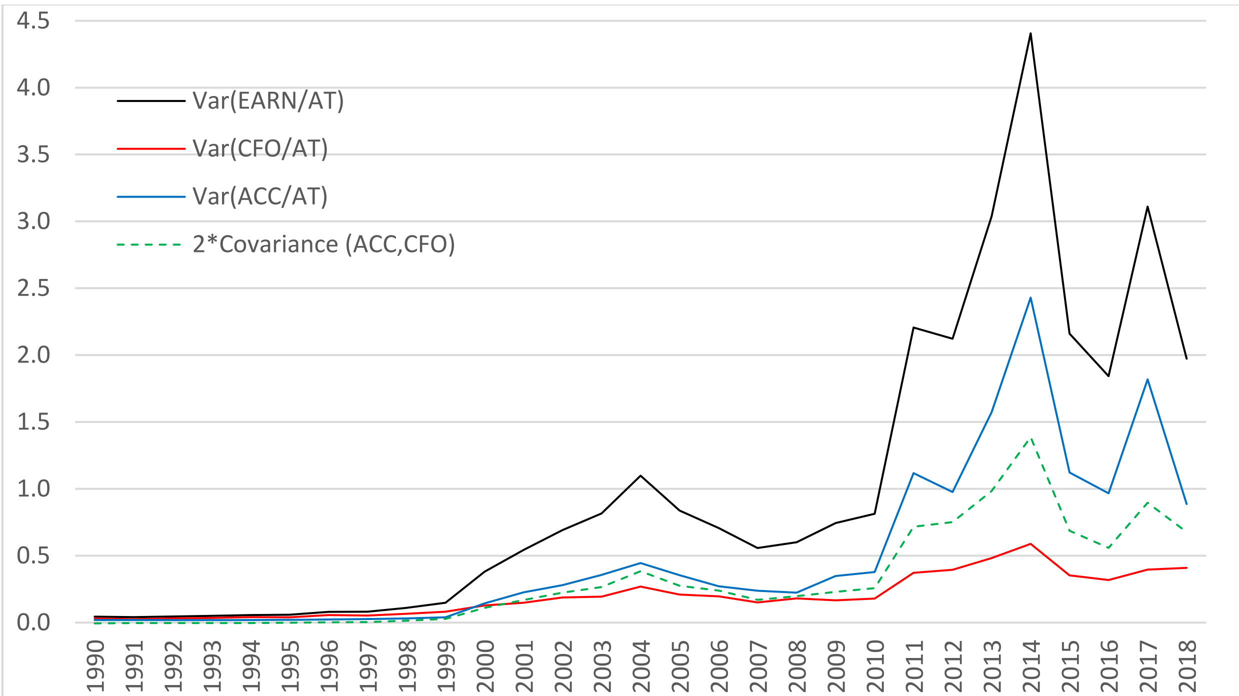
	CFO +			CFO -		
Decile	CFO/AT	ACC/AT	AT ($MN)	CFO/AT	ACC/AT	AT ($MN)
1	0.01	-0.06	1,379	-1.66	-1.35	6
2	0.04	-0.05	2,844	-0.72	-0.51	15
3	0.06	-0.05	4,312	-0.46	-0.29	29
4	0.07	-0.06	3,709	-0.31	-0.24	47
5	0.09	-0.07	3,224	-0.22	-0.18	68
6	0.10	-0.07	3,158	-0.15	-0.16	90
7	0.12	-0.08	3,499	-0.10	-0.13	154
8	0.15	-0.09	3,016	-0.06	-0.09	222
9	0.18	-0.11	2,179	-0.03	-0.08	361
10	0.27	-0.16	1,543	-0.01	-0.08	699

Panel B: Portfolio means for per share data.

	CFO +			CFO -		
Decile	CFO/share	ACC/share	# of shares (MN)	CFO/share	ACC/share	# of shares (MN)
1	0.05	-0.17	42	-1.91	-0.13	24
2	0.22	-0.33	39	-1.01	-0.21	25
3	0.47	-0.46	42	-0.67	-0.24	26
4	0.80	-0.61	56	-0.46	-0.22	28
5	1.20	-0.80	76	-0.31	-0.20	30
6	1.67	-1.00	111	-0.21	-0.18	31
7	2.25	-1.31	115	-0.13	-0.19	34
8	3.05	-1.77	127	-0.07	-0.11	38
9	4.28	-2.49	139	-0.03	-0.10	56
10	7.42	-4.63	147	-0.01	-0.06	223

FIGURE 1Time-series of variances of EARN and its components and smoothing coefficient from ACC/CFO regressions: deflator is average total assets (TA)

Panel A: Variance of EARN, CFO, and ACC and 2*Covariance (ACC, CFO), deflated by TA



Panel B: Slope and adj. R^2 for regressions of ACC on CFO, deflated by total assets.

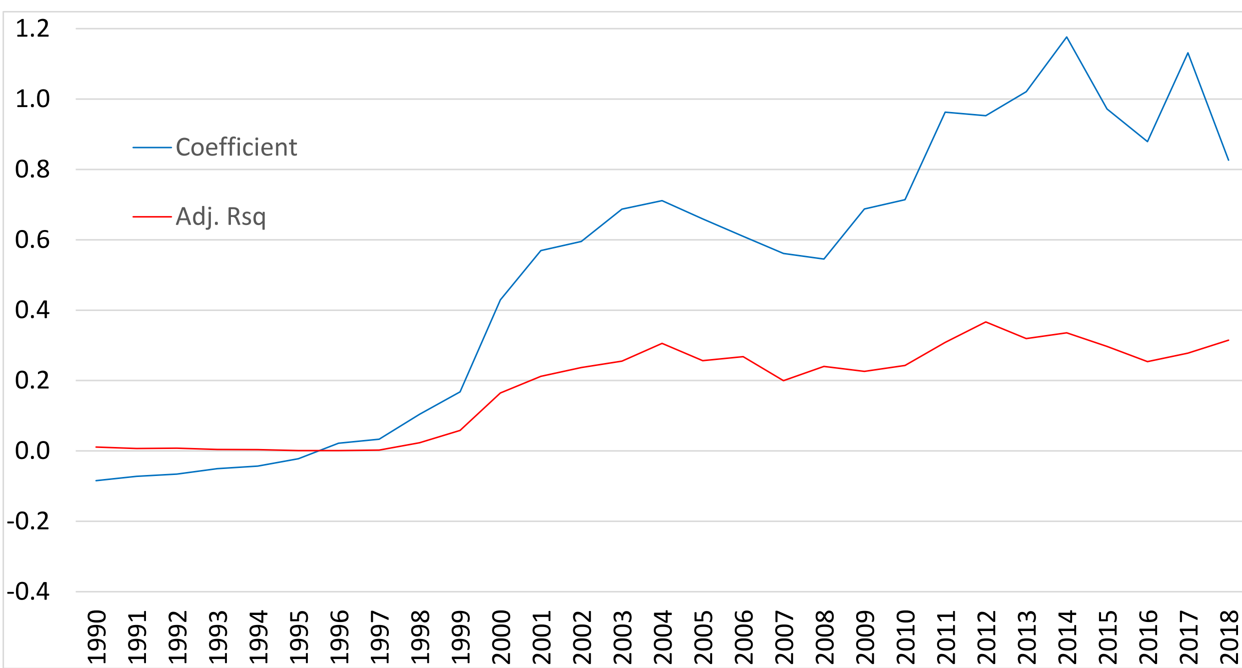
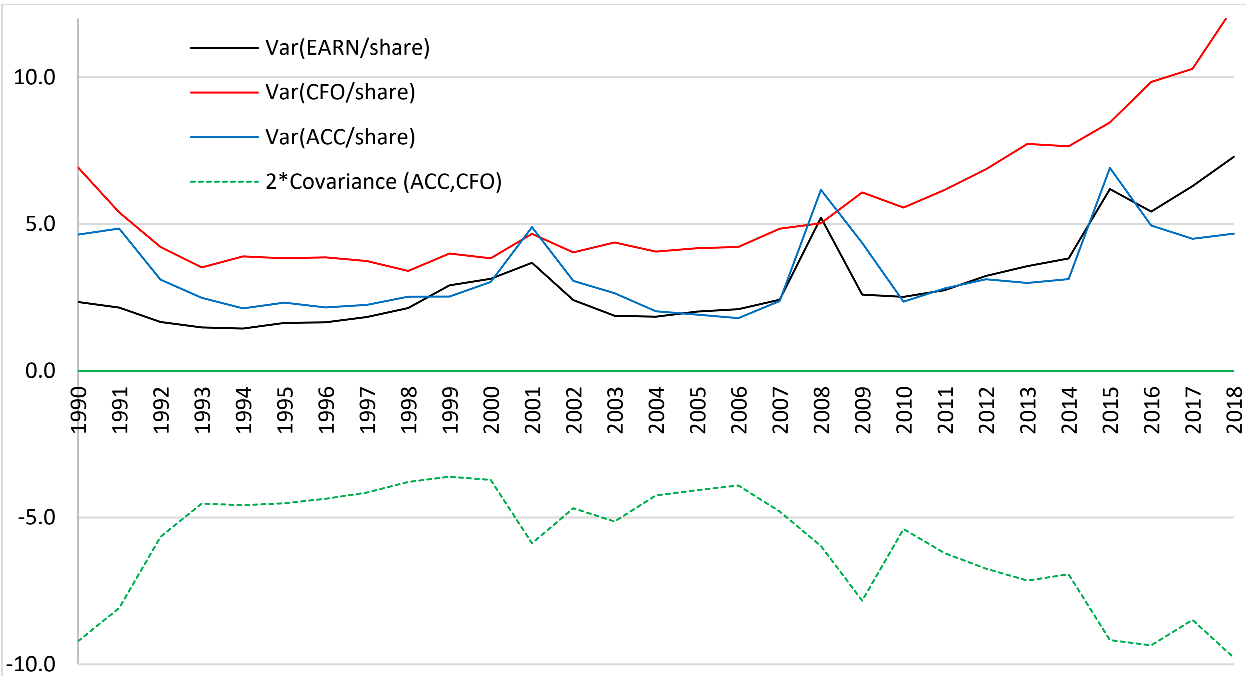


FIGURE 2 Time-series of variances of EARN and its components and smoothing coefficient from ACC/CFO regressions: per share data

Panel A: Variance of EARN, CFO, and ACC and 2*Covariance (ACC, CFO), per share data



Panel B: Slope and adj. R^2 for regressions of ACC on CFO, per share data.

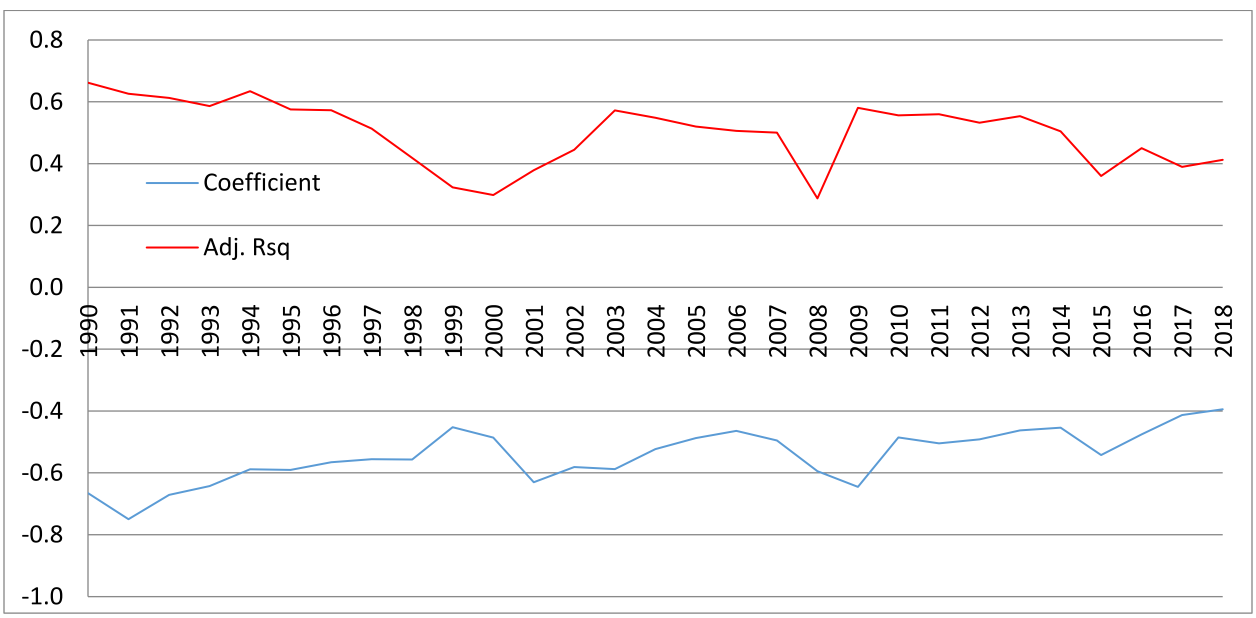
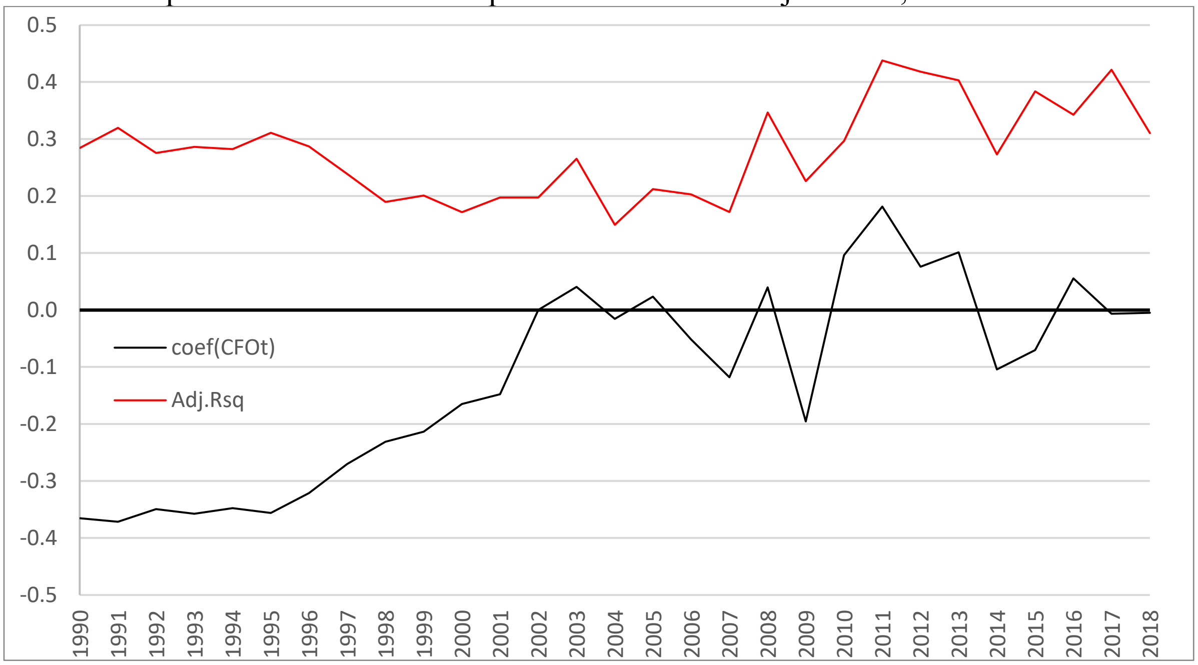


FIGURE 3 Switch from simple regression to multiple regression in Dechow/Dichev model

We estimate annual cross-sectional regressions for the Dechow/Dichev specification (includes CFO lags and leads to the ACC/CFO regressions). We also include changes in Sales and levels of net PP&E per Francis et al. (2005). Panel A (B) provides results for asset-deflated (per share) data. The corresponding results for ACC/CFO regression are in Panel A of Figures 1 and 2.

Panel A: Slope coefficient for contemporaneous CFO and adjusted R^2, for asset-deflated data.



Panel B: Slope coefficient for contemporaneous CFO and adjusted R^2, for per share data.

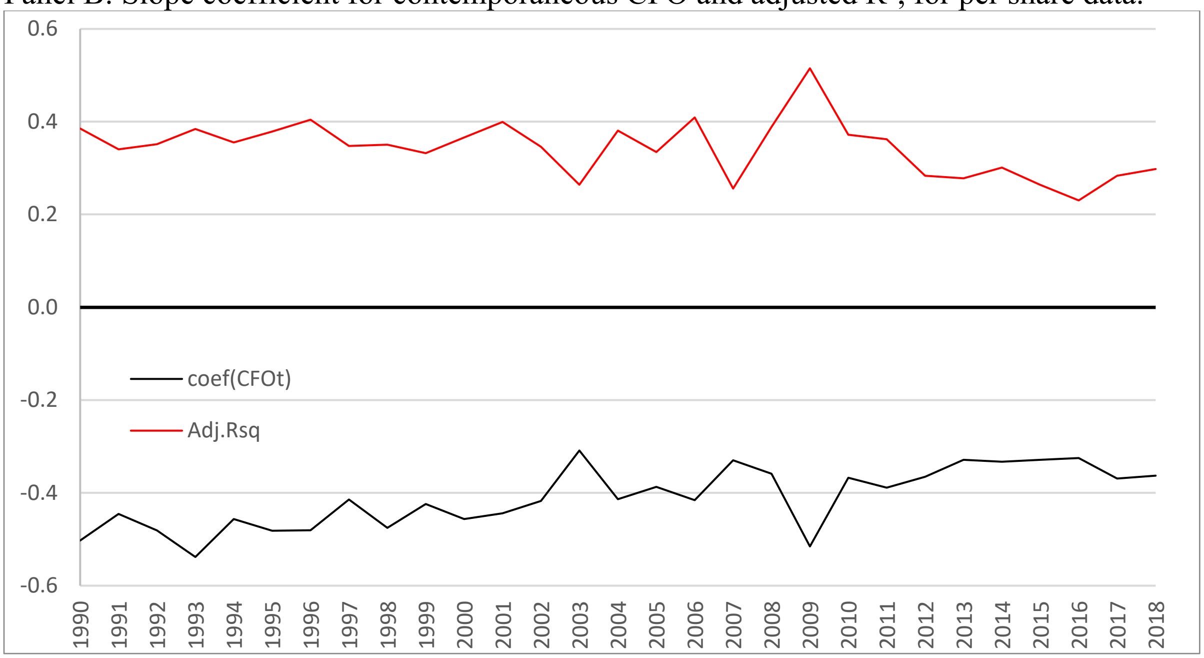
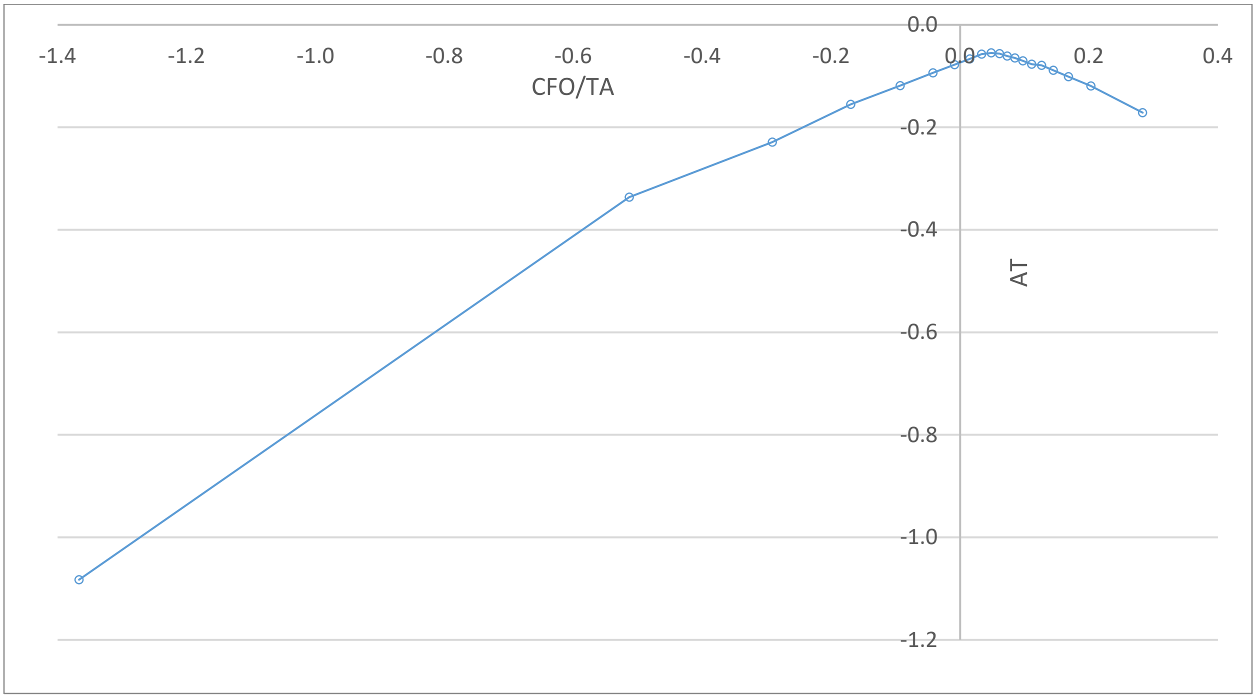


FIGURE 4 Nonlinear relation between ACC and CFO (based on sign of CFO)

Panel A: Mean ACC for CFO ventiles, both deflated by total assets (AT)



Panel B: Mean ACC for CFO ventiles, both based on per share data

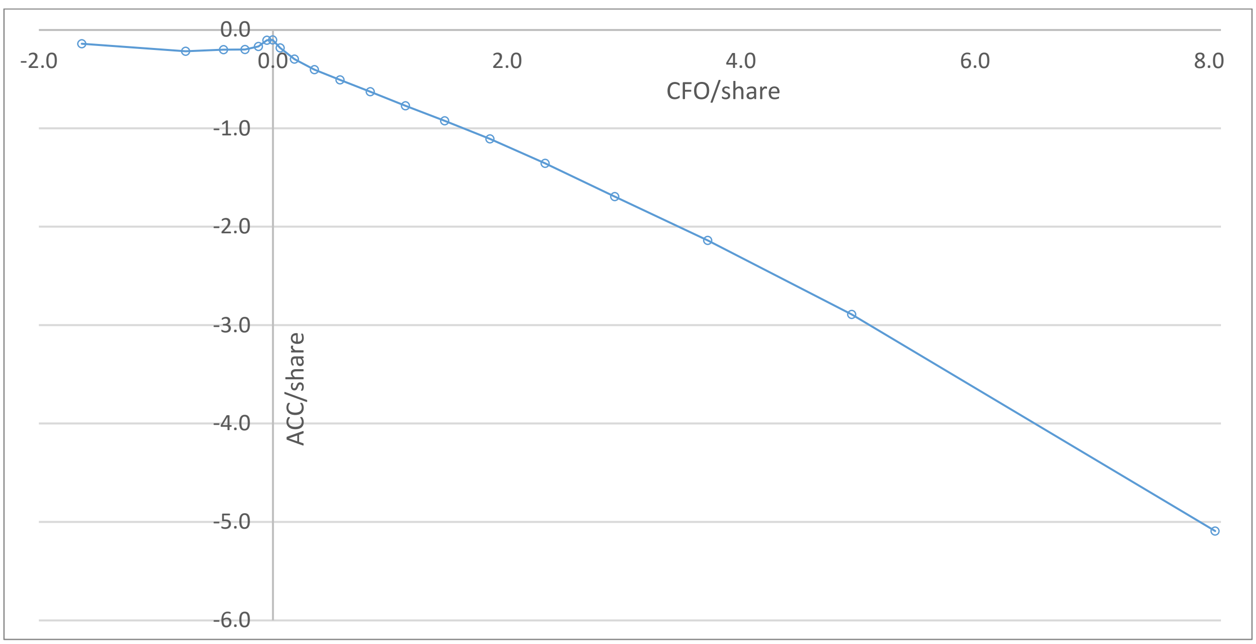
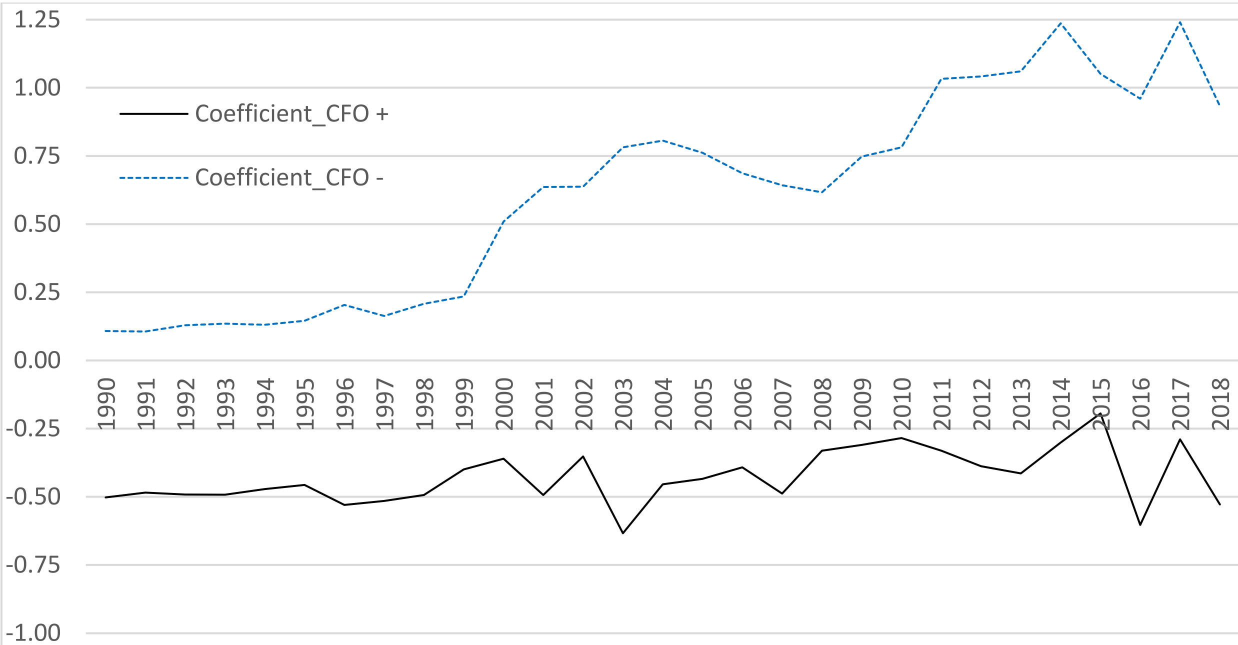


FIGURE 5 Time-series of smoothing coefficients for partitions based on CFO sign

Panel A: Slope from regression of ACC on CFO, both deflated by total assets (AT)



Panel B: Slope from regression of ACC on CFO, both based on per share data

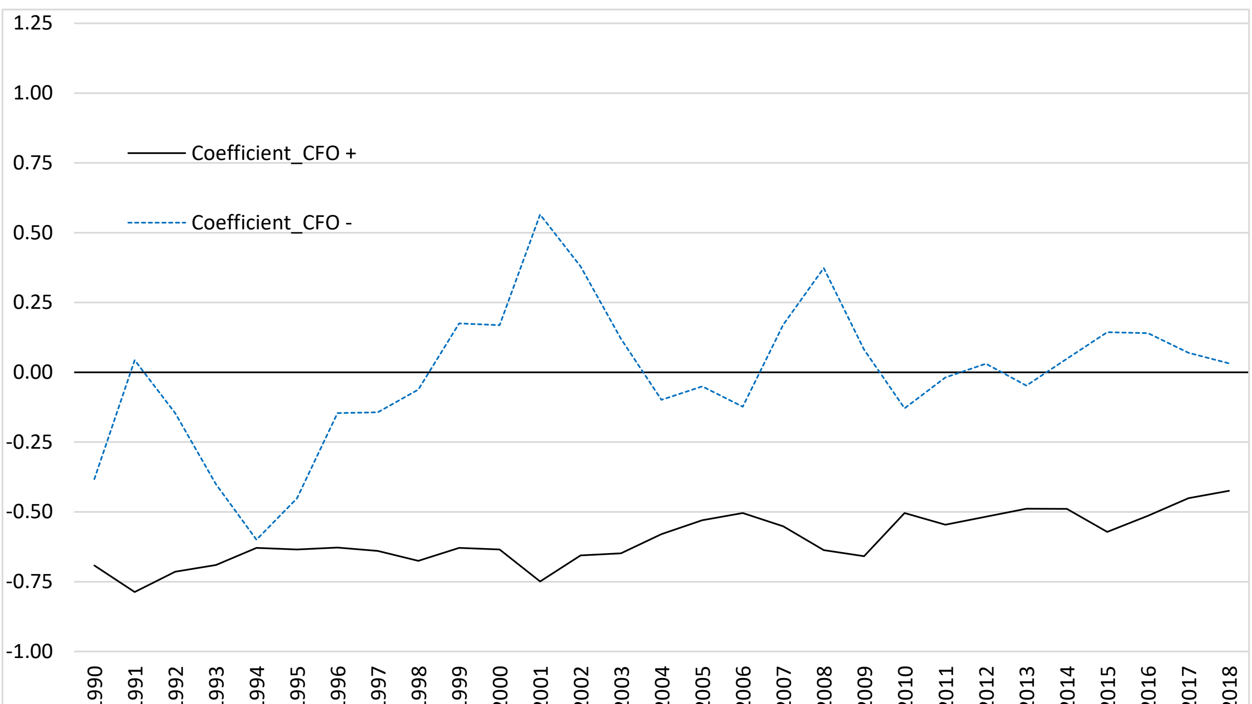
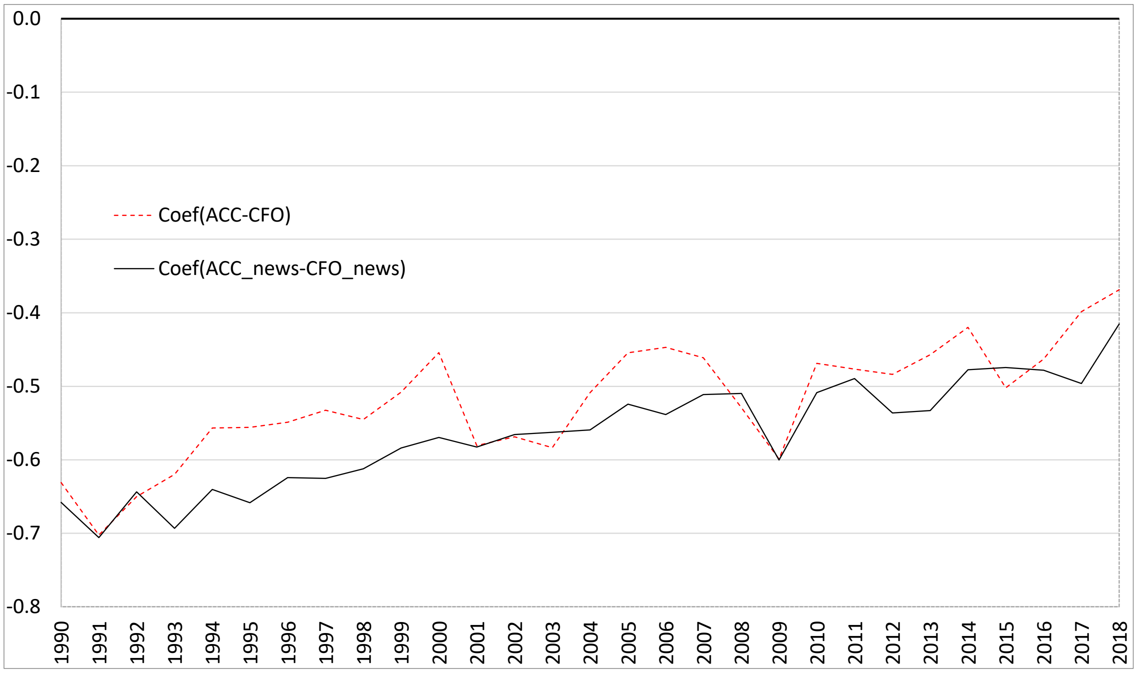


FIGURE 6 Time-series of smoothing coefficients based on unexpected components of ACC and CFO, for overall sample and partitions based on CFO sign (per share data)

News is estimated as the residual from annual cross-sectional regressions of current values on lagged values of that variable, within 2-digit SIC industries, allowing for different slopes for positive and negative values of the lagged variable.

Panel A: Slope from regression of ACC news on CFO news. The slopes from ACC/CFO levels regressions (Fig. 2 Panel B) are included for reference. The slope from a regression of smoothing coefficients based on ACC/CFO news on time is 0.0074.



Panel B: Slope from regression of ACC news on CFO news, for CFO+ and CFO− groups

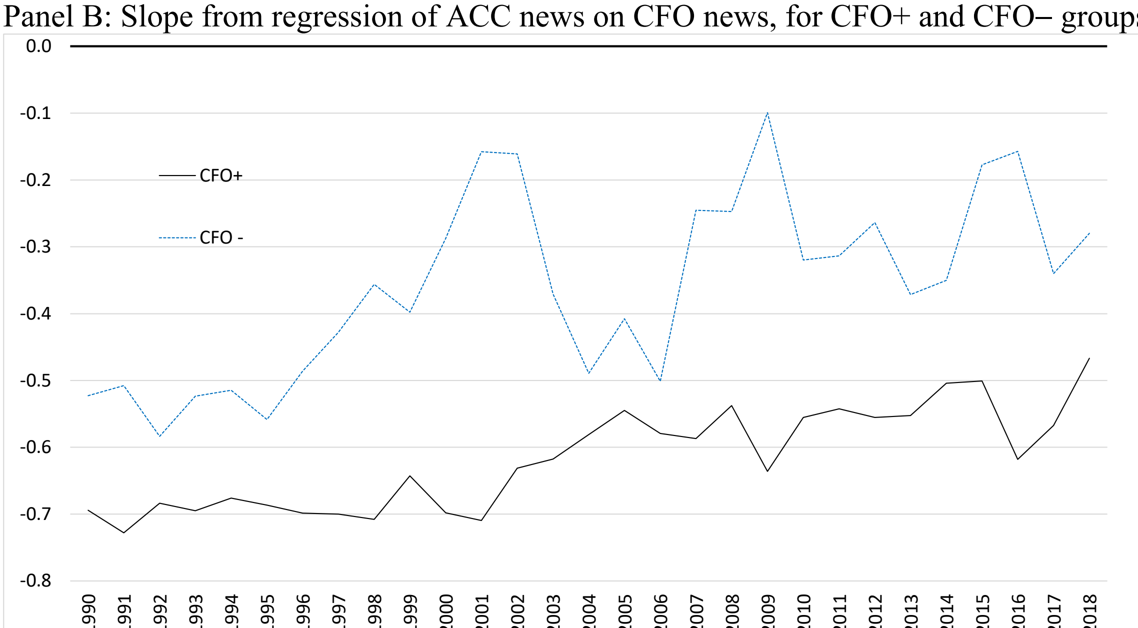
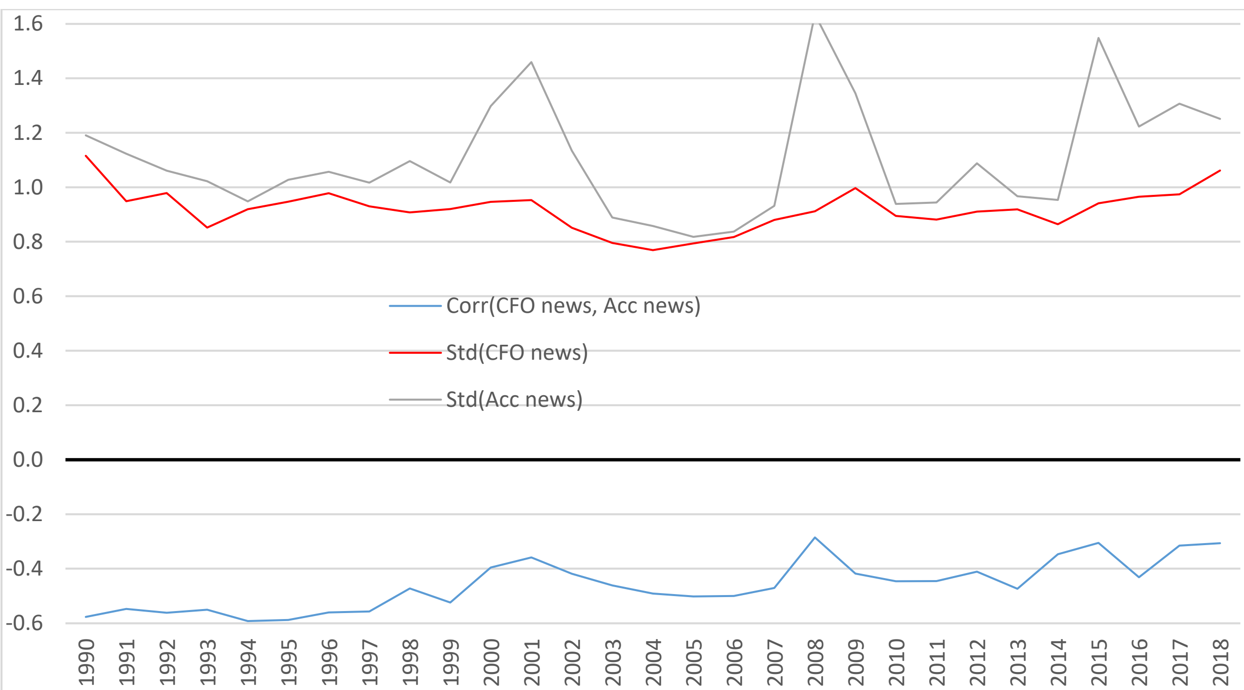


FIGURE 7 Explaining time-series increase (less negative) in annual smoothing coefficients

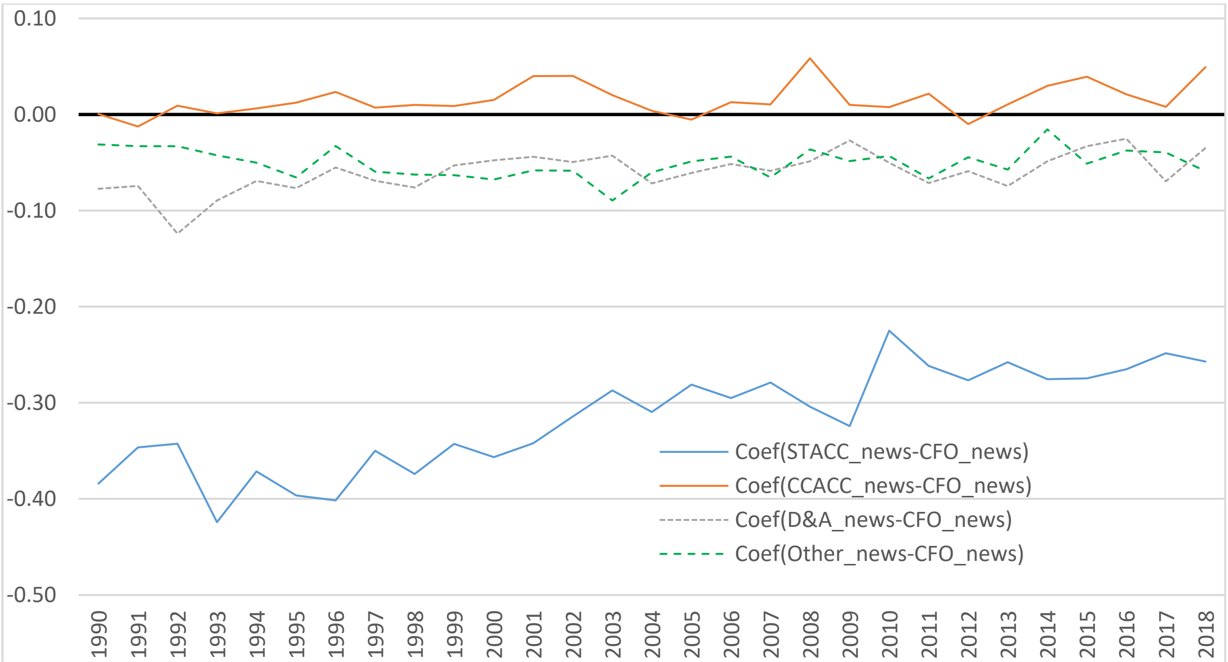
We follow a decomposition process to identify possible explanations for the increasing smoothing coefficient reported for the annual regressions of ACC news on CFO news (Figure 6, Panel A). News is estimated as the residual from annual cross-sectional regressions of current values on lagged values of that variable, within 2-digit SIC industries, allowing for different slopes for positive and negative values of the lagged variable.

Panel A provides trends for the three determinants of smoothing coefficients: the standard deviations of ACC news and CFO news, and their correlation. Panel B provides smoothing coefficients for four components of ACC news: short-term accruals (STACC), one-time items (CCACC), depreciation and amortization (D&A), and other operating accruals (Other). Results suggest that STACC is the component that is most relevant. Panel C reports smoothing coefficients for three of the five components of STACC news that exhibit trends similar to STACC: changes in accounts receivable, inventory, and accounts payable., The other two components exhibit relatively flat trends. Panel D provides trends for the variance of news for those three components as well as the variance of CFO news (the variances of news in the accrual component and CFO determine the smoothing coefficients reported in Panel C.) Panel E provides trends for the median levels of the three STACC components to see if the decline in variance of news in Panel D is due to a reduction in the magnitudes of those STACC components. Requirements for non-missing data reduce sample size relative to the full sample. All analyses are on per share data.

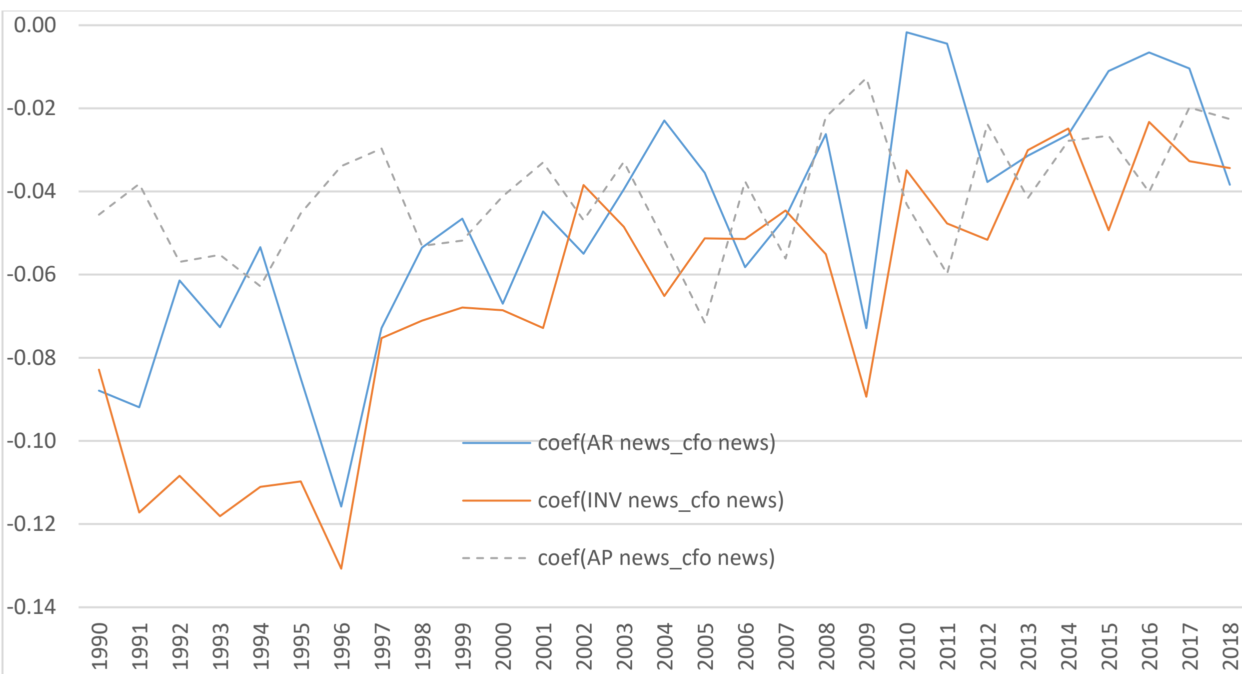
Panel A: Standard deviations and correlations underlying smoothing coefficient in Figure 6, Panel A.



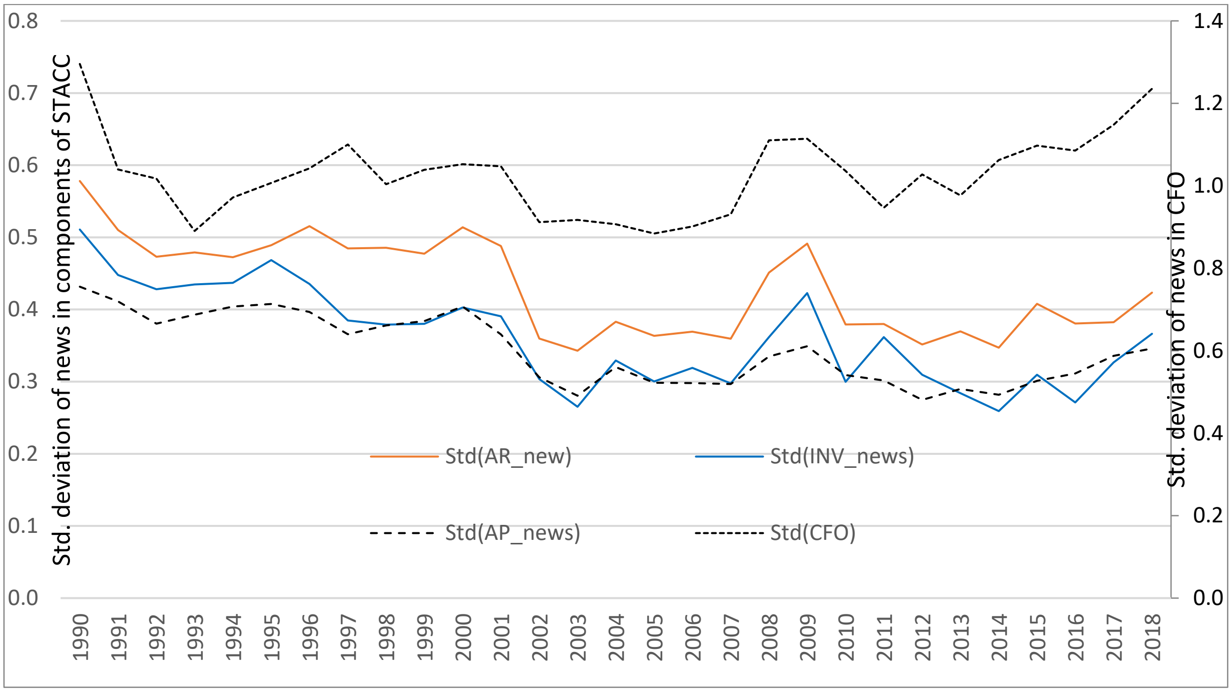
Panel B: Smoothing coefficient from regression of news in four accrual components on CFO news. The slopes from regressions of smoothing coefficients on time for news in STACC, CCACC, D&A, and Other are 0.0054, 0.0008, 0.0014, and 0.0000, respectively.



Panel C: Smoothing coefficient from regression of news in changes in three components of short-term accruals on CFO news (the remaining two components show flat trends). The slopes from regressions of smoothing coefficients on time for news in accounts receivable (AR), inventory (INV), and accounts payable (AP) are 0.0026, 0.0030, and 0.0008, respectively.



Panel D: Std. deviation of CFO news and news in three components of short-term accruals: accounts receivable (AR), inventory (INV), and accounts payable (AP)



Panel E: Median per share levels for three components of short-term accruals: accounts receivable (AR), inventory (INV), and accounts payable (AP).