ACCRUALS AND FORECASTING

Jim Ohlson and Ken Chu

Hong Kong Polytechnic University

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ABSTRACT

Sloan (1996), Richardson et al. (2005, 2006) examine how firms' accruals relate to subsequent financial performance. They identify a negative correlation and attribute it to accruals lack of reliability. This paper considers the issue from a different starting point: we forecast sales and expenses separately and argue on prior grounds that accruals are generally informative about the changes/growth in the income statement items. Two accruals variables serve as the primary predictors, year-to-year changes in operating assets and operating liabilities. This framework thus implies 2 forecasting equations and where the RHS of each includes the 2 accrual variables, plus controlling variables. Traditional accounting concepts can be applied to gauge the expected magnitudes of the 2x2 load-factors. Moreover, this framework leads to the hypothesis that the 2 accrual variables have a negative effect on the ROA and earnings forecasts, consistent with the literature. However, a closer look at the estimated load-factors shows some subtleties. First, liability accruals are markedly more informative than asset accruals. Second, while both accrual variables forecast ROA robustly, a shift to earnings weakens the results. Third, the 2 accrual variables are more informative about future performance in case of smaller firms. The empirics also highlight the ways in which financial assets and liabilities influence the forecasting and how their effects differ from those of the (operating) accruals.

1. Background and Overview

This paper concerns the predictive content of accruals in forecasting. The forecasts refer to next-year financial outcomes: sales, expenses, both dollar amounts, the ratios return on assets (ROA), profit margin (PM), and, most important, dollar amount earnings. Two accrual variables, related to assets and liabilities, respectively, are of primary interest, that is, it concern their load factors in the various forecasting models. The broad takeaways bear on the distinct conceptual and empirical differences in asset versus liability accruals, the stage-setting centrality of sales and expenses forecasting, and how ratio vs. dollar amounts forecasting affects load factors.

Certain attributes (definitions) of "accruals" frame and motivate the current research. First, accruals relate directly only to operating activities. That is, changes in operating assets and liabilities identify the accruals whereas in contrast financial activities are based on cash accounting. Per text-books this operating activity perspective leads to a summary net balance sheet accrual, operating assets (OA) net of operating liabilities (OL), i.e., net operating assets NOA (= OA – OL, as in Penman, 2009; Easton et al., 2009 and many other textbooks). The change in NOA thus defines the total net accrual. Second, because NOA measures the investment supporting the business, an increase in a period's net accrual (NOA's change) signals business growth. Income statements a year later should accordingly show greater sales and (operating) expenses, on average. These subsequent-years income statement effects on growth should be expected due to matching (or allocation) precepts, with their built-in predictability; e.g., PPE leads to not only sales but also future Depreciation, Inventory leads to CGS, and Deferred Revenues leads to Revenues. Third, accruals potentially "get corrected via reversals" to the extent over- or under-accruing occurred in prior periods. These observations prompt a central FSA question, posited by Sloan (1996) in his well-known paper: do relatively large current accruals increase, on average, current earnings to the detriment of future earnings? This in-expectation trade-off hypothesis will be referred to as the "accrual hypothesis".[1,2,3]

To motivate the accrual hypothesis, Richardson et al. (2005, 2006) (RSST1 and RSST2 henceforth) point to various complexities inherent in accrual accounting. Specifically, the immediate proximate cause of the hypothesis pertains to the greater persistence of cash flows as compared to accruals. The extent of persistence of an accrual's component of earnings, in turn, depends on accruals potential for temporary distortions. Broadly speaking, the distortions are tied to the lack of reliability in the accounting for accruals. And these aspects associate with typically hard-to-observe reversals (which require a control for firms' intrinsic growth). These papers' empirical analyses identify various specific accruals and proceed to connect accrual attributes to the accrual hypothesis. The papers seemingly conclude that low reliability accounting items best explain accruals potential reversals and – ultimately – the accrual hypothesis.[4]

This paper develops the accrual hypothesis without resting the analysis on concepts used in the prior literature, such as accruals relative lack of persistence, lesser reliability, or the pervasiveness of measurement errors due to arcane accounting rules. Instead, our approach effectively assumes that accruals can serve as valid leading indicators of forthcoming income statement changes: earnings are split into sales and expenses to identify growth. Adding some precision to this idea leads to the accrual hypothesis. Thus, our approach provides an alternative, in the sense of being a complement, to traditional concepts and methods to address the accrual hypothesis. In the spirit of the antecedent literature, we expand on the analysis to implement the idea of connecting reversals to the accrual hypothesis.[5]

The forecasting of date t+1 sales and expenses starts naturally from their respective date t realizations. Given these respective anchors, the two forecasting settings focus on changes (increments) in sales and expenses, that is, effectively growth. Useful date t variables should accordingly include leading indicators of forthcoming growth. Specifically, changes in operating assets *and* changes in operating liabilities – both variables taken individually – potentially correlate with the future growth. A reliance on the *net* accrual, the change in NOA, could obscure critical information. To avoid this detriment, we split Ch(NOA) into its components Ch(OA) and Ch(OL), where Ch(.) stands for change over the two balance sheet dates. (To illustrate the relevance of disaggregation, consider two firms, A and B, where for A Ch(OA) = Ch(OL) = $10 million and for B Ch(OA) = Ch(OL) = $100 million, implying Ch(NOA) = 0 both A and B. Since B's growth is 10 times that of A's, the change in NOA by itself hides important information.)[6]

The RHS's of the forecasting models include not only the accruals but also the cash flows measured by financial activities. To motivate our approach, consider as a starting point the balance sheet decomposition Ch(BV) = Ch(OA) + Ch(FA) – Ch(OL) – Ch(FL), where FA and FL refer to financial assets and liabilities respectively. While under idealized circumstances Ch(BV) would suffice to forecast changes in sales and expenses, a more complex world suggests that the forecasting can improve by decomposing Ch(BV) into the 4 Ch(.) variables. In relative terms, however, we hypothesize that the two accrual variables will be more informative than the two financial variables.

The analysis recognizes that the forecasting of dollar amounts (sales, expenses, and earnings) differs from forecasting ROA in two respects: ROA depends on a denominator which is also unknown at the date of forecasting. The empirics accordingly assess the relevance of this denominator aspect on the accrual hypothesis. As Fairfield, Whisenant and Yohn (2003) suggest, a shift to earnings instead of ROA may weaken the accrual hypothesis.

Prior to estimating the full-fledged forecasting models, we evaluate the strength of bivariate growth correlations. First, all 4 Ch(.) variables (in percentage terms) correlate positively with the forthcoming growths in sales and expenses (next year percentage changes). Though these correlations are robust and material, the Ch(FA) and Ch(FL) variables correlate less with growth than the accrual variables. Second, we assess the serial correlations in the Ch(.) variables. These are systematically non-negative, consistent with persistent growth rates. Balance sheets therefore expand in harmony with revenues/expenses trends. But it is also the case that in this regard the two financial variables are generally much weaker than the (operating) accrual variables.

Three classes of settings comprise the multi-variate empirics of forecasting. These are identified by the nature of the variables forecasted: first, (future) dollar sales and expenses; second, ROA and PM; and third, the dollar amount of earnings. The first two forecasting settings set the stage for the third, earnings forecasting, and the extent to which it validates the accrual hypothesis. The second framework juxtaposes our approach and findings to the prior literature on ROA forecasting, an essential step before moving on to explaining the accrual hypothesis in the third setting, (un-deflated) earnings.

Models and findings can be summarized as follows:

…… The two forecast equations focusing on the period t+1 sales and expenses include the 4 Ch(.) variables, date t, on the RHS. In case of sales, the RHS also includes the current value of sales as well as the recent current change; symmetrically, the expenses equation includes current expenses and their recent change. Each forecast equation thereby relies on a total of 6 RHS variables, all dollar amounts like the dependent variables. The load-factors related to Ch(OA) and Ch(OL) are of primary interest. Consistent with our hypothesis based on how accounting data informs in practice, key findings hold robustly: (i) in the *sales* forecasting, both Ch(OA) and Ch(OL) load positively and about the same; (ii) in the *expense* forecasting, Ch(OA) loads positively with the by far largest estimated coefficients; Ch(OL), in sharp contrast, loads positively but only marginally so. The findings suffice to derive the accrual hypothesis; it follows because forecasting revenues minus expenses motivates the expected results when forecasting earnings.

…… Our focus on the profitability measure ROA follows the prior literature (cited above). ROA is deflated using the average of total assets t+1 and t; the RHS variables are deflated using the t and t-1 average. (In the PM setting sales replace assets, of course.) The forecasting equation also controls for current ROA and Ch(ROA), consistent with the structure of the sales/expenses equations. Per prior literature, the (deflated) Ch(OA) variable should load negatively and Ch(OL) positively. Results support this hypothesis. However, results are much stronger for Ch(OL) than Ch(OA), an entirely new finding. (Results for ROA and PM differ little; deflator robustness holds.)

…… Results related to earnings forecasting are similar to the ROA (and PM) settings as one should expect. But overall they are weaker. Again, the Ch(OL) stands out as the most powerful variable. As in the case of ROA forecasting, the two financial variables have no material impact on the forecasting.

…… The paper also tries to develop additional insight regarding the finding that Ch(OL) are more informative than Ch(OA) in explaining the accrual hypothesis. To address this finding, the paper compares the "reversibility" properties of the asset accrual with the liability accruals. As it turns out, the evidence does support that the liability accruals appear to be more likely to reverse.[7]

As an overall takeaway we underscore that the basic accrual hypothesis results follow because the accruals can be viewed as reliable indicators of future growth in sales and expenses. And there are two kinds of accruals, asset accruals and liability accruals asset; the former correlate positively with future growth whereas for the latter the opposite is true. Further, the relative informativeness of asset accruals as compared to liability accruals depends on whether the forecasting pertains to sales or expenses. The related load-factors can be developed in an order of magnitude sense in light of basic concepts of accounting principles, and the empirics is supportive. With these observations in place one can then proceed to address the accrual hypothesis in its two versions, the ratios ROA and PM as opposed to (un-deflated) earnings.

2. Models and Hypotheses

A common structure supports the forecasting equations. Specifically, the dependent variable, Y(t+1), is explained by 6 variables on the RHS:

Y(t), Y(t) – Y(t-1), Ch(OA), Ch(OL), Ch(FA), Ch(FL).

The first variable, Y(t), provides an obvious starting point – it acts as an information anchor in the forecasting; the effective forecasting can be thought of as centering on the expected change in Y. The second variable provides a trend-adjustment (a positive load factor, unless the trend reverts to a long run mean which should be the case if Y is a ratio).

The remaining variables comprise the 4 accounting-based variables: Ch(OA(t)), Ch(OL(t)), Ch(FA(t)), Ch(FL(t)). These variables are deflated when Y has been deflated (i.e. when Y(t+1) and Y(t) are ratios). Depending on the Y(t)-variable, there are three sets of model specifications: (A1, A2), (B1, B2), (C).

A1. Dollar amount of sales, i.e., Y(t+1) = S(t+1). The RHS variables are in dollar amounts too.

A2. Dollar amount of expenses, i.e., Y(t+1) = Exp(t+1). The RHS variables are in dollar amounts too.

B1. Return on Assets (ROA), i.e., Y(t+1) = ROA(t+1) = Earn(t+1)/[Total Assets(t+1) + Total Assets(t)]/2. The RHS variables are similarly deflated by the contemporaneous average total assets though the (t+1, t) average is shifted to a (t, t-1) average. (Thus, ROA(t) = Earn(t)/[Total Assets(t) + Total Assets(t-1)]/2.)

B2. Profit Margin (PM), i.e., Y(t+1) = PM(t+1) = Earn(t+1)/S(t+1). The RHS variables are deflated by the contemporaneous S(t).

C. Earnings, i.e., Y(t+1) = Earn(t+1). The RHS variables are all dollar amounts, like Earn(t+1).

FA comprises cash and marketable securities, and FL comprises short and long-term debt plus preferred stock. OA and OL derive as plugs from the balance sheet equation.

To check for robustness, estimations of the forecasting equations are conditioned on firms' market capitalization. Specifically, each year comprises three equal sized groups where the groups depend on capitalizations. Equation estimations relate to the individual sample year, rather than pooled over the years (to avoid statistical over-fitting). To avoid problems with outliers in the data, estimations apply the Theil-Sen method, as developed in Ohlson and Kim (2015).[8]

Main hypotheses focus on the two load factors related to Ch(OA) and Ch(OL). With respect to the A models:

…… Ch(OA) and Ch(OL) load positively, for both sales and expense forecasting (A1 and A2 respectively).

…… In the expense equation (A2), the OA load factor exceeds the OL load factor.

…… In the sales equation (A1), the two load factors fall in between the extremes in the expense equation.

GAAP's stress on expenditure capitalization and matching rules motivate the hypotheses on relative magnitudes. The non-negativity claims simply pick up on the idea that the two operating Ch(.) variables should correlate with future growth.[9]

Consider next the load factors related to expenses forecasting, A2. Operating assets comprise mainly of Inventory, PPE, and Prepaid Expenses, which to a considerable extent imply expenses in subsequent periods. As a consequence, one should expect that an increase in Ch(OA) leads to an increase in expenses at the next period. Compare such more-or-less-guaranteed increased expensing to the case of Ch(OL). These liabilities tend to provide for expenses incurred in the past, such as Accrued Wages Payable, Pension Obligations, Provision for Warranties, and Taxes Payable. Accordingly, in expense forecasting, we hypothesize that the load-factor related to Ch(OL) should be quite close to zero, in sharp contrast to Ch(OA).[10]

Turning to the sales forecasting, the issue becomes muddier because Ch(OA) and Ch(OL) do not indicate sales as matter of predictable implications of accounting procedures (Deferred Revenues being an exception). The connection to sales occurs due to the inherent characteristics of a business model where expenditures/expenses activities are incurred to generate sales of products and services. But this implication tends to be less than direct. We hypothesize that the informativeness of Ch(OA) and Ch(OL) do not differ materially. In other words, their implied growth rates reflect growth in general and, accordingly, both variables act as a leading indicator of changes in the forthcoming sales. No apparent reasons, as far as we can tell, suggest a distinct difference in the load-factors related to (changes in) operating assets versus liabilities when forecasting sales.

With respect to the financial variables as predictors, we expect positive loads related to Ch(FA)'s, and negative ones for Ch(FL)'s. In other words, the financial policy should align with the planned expansion/contraction of business operations, at least on average. This hypothesis should be the strongest when it comes to expenses forecasting and Ch(FA); that is the financial assets need to build up when the firm plans to increase expenses (which in turn may be related to a planned increase in sales). With respect to sales, this reasoning applies to Ch(FA) and Ch(FL) as well, but it may be less clear-cut insofar sales do not require cash outflows to the same extent as expenditures/expenses.

The above reasoning has non-trite implications because it implies a distinct difference between the two types of liabilities, OL and FL (OL + FL = total liabilities). Per our reasoning, the load factors related to Ch(OL) and Ch(FL) should be of the opposite signs, that is positive and negative; This aspect can be viewed as central in FSA: in forecasting settings, changes in operating and financial liabilities have intrinsically distinct implications.

Next, consider the forecasting of firms' performance per B1 (ROA) and B2 (PM). As noted earlier, the former ties in directly with the literature and the latter checks on robustness.

…… For both the ROA and PM forecasts, Ch(OA) and Ch(OL) load negatively and positively, respectively.

This hypothesis aligns with traditional textbook precepts as well as the prior literature on accruals. However, note the central aspect unique to this paper; *the argument in support of this outcome follows as an extension of the hypotheses related to the A equations*. To elaborate, consider the Ch(OA) variable. If the variable's effect on (increases) in future expenses exceeds its effect on (increases in) sales, then it would seem plausible that the implied accrual due to Ch(OA) has a negative effect on future performance. Similar reasoning applies to Ch(OL), keeping in mind that the negative of Ch(L) determines accrual. This argument in support of the accrual hypothesis makes no reference to many traditional arguments that support the accrual hypothesis, such as reliability, non-recurring items, temporary accounting distortions, etc. While these latter properties related to accruals can also be useful springboards to explain the accrual hypothesis, the setup here does not require them.

The hypothesis on the load-factors for specification B leads to a special case when Ch(NOA) = Ch(OA) – Ch(OL) provides sufficient information in lieu of two separate accruals variables, Ch(OA) and Ch(OL). This outcome, of course, arises when the first load-factor to equal the negative of the second. The empirics examines whether such restriction harms the forecasting effectiveness.

The ROA(t+1) forecasting controls for current ROA(t) and its recent change, Ch(ROA(t)). This aspect opens up the possibility of zero load factors on Ch(OA) and Ch(OL) variables – the focus variables. An acceptance of the null cannot be ruled out, even if the sales/expenses forecasting works as hypothesized. The latter setting (A) accordingly acts as the setup bearing on the signs of the load factors in ROA forecasting, but without guaranteeing the conclusion. (The comments apply to PM no less than ROA.)

Because ROA forecasting does not assign a role for growth as a determining factor in the performance metric, the load factors related to Ch(FA) and Ch(FL) should now be substantially less relevant as compared to the A setting. Though marginal at most, we expect that the signs remain the same, positive for Ch(FA) and negative for Ch(FL), and in addition, the financial effects reduce approximately to the net, Ch(NFA).

The loadings on the financial variables can be viewed as complementing the accrual hypothesis insofar that the net changes in the financial variables correlate with operating cash flows; and in turn, the net of cash flows provides meaningful positive information about future performance. This reasoning conforms to the prior literature (Sloan, 1996). On the other hand, it also conforms to a literature (e.g. Bradshaw et al., 2006; Dechow et al., 2008) suggesting that financing (increase in debt or equity) has a negative effect on future performance (ROA). Thus, a net effect of the financing variables in the forecasting of ROA may end up being close to immaterial.

Next, consider the model that forecasts earnings – that is, ROA prior to its scaling. It is of obvious interest insofar that the forecasting of future earnings is central in investment practice. Our basic hypothesis derives from the A and B settings: as is more or less obvious, it concerns the magnitudes and signs of the load factors attached to the accrual variables, Ch(OA) and *minus* Ch(OL).

…… *The loadings on Ch(OA) and Ch(OL) in the forecasting of earnings remain negative and positive, just like the B setting.*

Again, it is not a foregone conclusion that the last hypothesis holds up even if both the A and B settings hold up. As noted earlier, the literature has suggested that the absence of a deflation can have an adverse effect on the accrual hypothesis (Fairfield et al., 2003). It should also be noted that the conclusion depends on the methodology. We use two approaches. One approach is traditional in the sense that it focuses on the magnitudes of estimated load-factors, and their stability across years and size groups. A second approach is more stringent: it compare the relative forecasting power of various models (RHSs) using relative accuracy scoring (RAS) tests. These tests makes it harder to reject the null that a certain variable on the RHS does not add to the forecasting efficacy. (The prior literature on the accrual hypothesis does not apply such tests.)

3. Data and Variable Definition

The sample includes all Compustat North America (annual) listed firms, from 2000 to 2015, a total of 16 years. We first identify the size breakpoints in each year based on the fiscal year-end market capitalization of all non-financial firms (SIC codes are < 6000 or > 6999) and then put them into one of the size groups running equally from group 1, the smallest firms, to group 3, the largest firms. The original dataset contains 56,450 firm-year records. Definitions of key variables follow standard practice: Earnings (Earns) as Income Before Extraordinary Items (item 18), Expenses (Exp) as Sales (S, item 12) minus Earns, Financial Assets (FA) as Cash and Short-Term Investments (item 1), Financial Liabilities (FL) as sum of Debt in Current Liabilities (item 34) and Long-Term Debt (item 9) and Preferred Stock (item 130), Operating Assets (OA) as Total Assets (TA, item 6) minus FA, Operating Liabilities (OL) = TA minus FL minus Common Equity (item 60) minus Minority Interest (item 38). Table 1 Panel A shows the descriptive statistics of the major variables per size group.

Panel B shows that all the accounting variables, in the balance sheet as well as the income statement, have grown over time. For the smallest size group, rates are slightly negative but this is more than offset by the remaining two groups for all operating variables, and sales and expenses. This is of course what one should expect given the growth in the economy at large. But the financial variables differ insofar that FL grew negatively during the sample period (which the press frequently commented on). Business growth should thus be distinguished from what happens on the financial side.

The correlations in Panel C show that in the cross-section the growth for the individual firms apply across the various accounting items, especially as it relates to the operating activities. The correlations between growth in sales and growth in expenses are the largest for all three size groups, an unsurprising finding. It should further be noted that the growth in OA correlates non-trivially with the growths in sales and expenses, and so does OL though to a lesser extent. The OA and OL correlations are also material, (0.48, 0.54 and 0.64) for the three size groups. As to the growth rates of the financial variable, these show lower correlations with the operating variables, as well as between each other.

The next section considers the correlations when applying a forecasting perspective, rather than the contemporaneous kind. The essence is to evaluate the extent to which (i) the current growth rates in the balance sheet accounts act as leading indicators of growth rates in the income statement, sales and expenses, and (ii) the current growth rates in the balance sheet act as leading indicators of future balance sheet growth rates.

[Insert Table 1 here]

3.1 Preliminary Data Analysis

Bi-variate growth forecasting

The first issue considers the simple forecasting of period t+1 sales and expenses based on the 4 Ch(.) variables at period t, one at a time. Positive correlations are of course expected. More subtly, the results also bear on whether the operating variables are better predictors of sales/expenses than the financial variables. As indicated before, we expect this to be the case. Results are relevant as one anticipates the findings related to the multivariate forecasting. Given that the Ch(OA) and Ch(OL) correlate with the forecasting growth rates materially, and much more so than the Ch(FA) and Ch(FL) variables, there are no reasons to expect negative load-factors in the multivariate setting for the two operating variables. This outcome may not hold for the financial variables; the lowest correlation variable, in particular, might well end up with a negative load-factor in the multivariate setting.

We consider two sets of growth evaluations, starting out with

$$\text{Correlation } \{Ch(X(t))/S(t-1),\ S(t+1)/S(t)\}$$

where X = {OA, OL, FA, FL}. To check for robustness, we also evaluate when expenses replace sales in the correlations.

Three comments clarify the above. First, with respect to OL, as opposed to OA, a correlation between *accruals* (= *minus* Ch(OL)) with t+1 growth is now *negative;* it follows simply because, after having fixed cash flows and Ch(OA), an increase in Ch(OL) lowers income and thus the accrual must be negative. In no way does this aspect negate that one should expect Ch(OL) to correlate positively with growth in (future) sales and expenses. Second, the correlations are predictive, not contemporaneous. While the contemporaneous correlations are positive, they are also materially larger (unsurprisingly, to be sure). We provide evidence to that effect in Table 1, descriptive statistics. Third, the growth correlations related to Ch(FA) and Ch(FL) should differ from those related to Ch(OA) and Ch(OL). Financial assets and liabilities are broadly speaking independent of the operating assets/liabilities since, if nothing else, a firm can change its common shares outstanding and its cash dividends to reconcile operating free cash flows to the financial flows affecting the balance sheet. Financial policy irrelevance (MM in its extreme version) thus suggests that the correlation future sales/expenses growth with Ch(FA), Ch(FL) growth can in principle be quite low and even wholly absent.

Table 2, Panel A, shows the growth correlations, for each of the three size groups. The t+1 sales and expenses growth rates correlate positively with Ch(OA(t)) and Ch(OL(t)), both scaled with sales or expenses (to check for robustness). Moreover, these correlations exceed similar correlations related to Ch(FA(t)), Ch(FL(t)), again scaled. A comparison yields robust findings. For the operating variables the correlations are in the 23% to 40% range; for the financials in the 3% to 16% range.

For future reference, it is worthwhile to compare the difference when sales growth is replaced by expense growth. In case of sales growth, the two operating variables, Ch(OA), Ch(OL) work about the same. In case of expense growth, in contrast, the correlations with Ch(OA) dominate those with Ch(OL), and materially so. The findings do not surprise considering points made in Section 2. A positive Ch(OA) tends to reflect increases in PPE, Inventory and Prepaid Expenses, and the accounting allocation/matching pretty much guarantees increases in next-period expenses (debit expense, credit OA). Ch(OL) differs because it generally rules out OL accounts that increase subsequently due to accounting allocations (that is, transactions like debit expenses and credit OL do not generally occur due to prior periods' transactions). Thus, the correlation between {Ch(OA(t)/Exp(t-1)}, Exp(t+1)/Exp(t)} exceeds all others. The correlations range from 37% to 40% for the three size groups. Replacing OA with OL leads to a lower range, 22% to 34%.

A complementary analysis of the simple forecasting correlations evaluates whether sales/expenses growth correlates with the Ch(.) variables (scaled) in a monotonic fashion. The lack of such a regularity would potentially cause complications in the multivariate forecasting settings. To evaluate the monotonicity property, we apply a Bayesian approach focusing on how the distribution of the "signal" – the Ch(.) variables at period t – depends on the "outcome" – the growth rate at period t+1. There are two steps. First, place the sales growth at the end of period t+1 in an ascending order of 5 equally sized groups. The data is pooled across the years. Then for each growth group, calculate the medians of the 4 Ch(.) variables end at period t normalized by period t sales. This calculation can be repeated by replacing sales with expenses.

Results reported on in Panel B show that the medians of Ch(OA) and Ch(OL), whether normalized by sales or expenses, increase monotonically as sales or expense growths increase. Exceptions do not occur. The monotonicity patterns accordingly demonstrate that, on average, sales and expenses growths tend to be preceded by growth in the operating activities' balance sheet growth in a robust manner. More subtly, the sensitivity of the changes in the operating Ch(.) variables are much greater than for the financial variables – consistent with the notion that operating variables are more informative about future growth. In fact, Ch(FL) appears to be the least informative regarding future growth because their medians are zero. This outcome simply reflects that, overall, about 16% of all balance sheets show zero financial debt, beginning and ending periods.

[Insert Table 2 here]

Serial correlations, the Ch(.) variables

Given that the Ch(.) variables correlate with growth and growth tends to persist over time, positive serial correlations should be expected. That is, firms with large balance sheet growth in period t are likely to show much the same in the next period, t+1. Moreover, as argued previously, these positive serial correlations should be most apparent for the operating variables. Financial variables might well show less of a positive serial correlation since the growth in operating activities can be handled with great financial flexibility (that is, firms can transact with owners in addition to borrowing and lending). This hypothesis aligns with the financial policy irrelevance. It is also consistent with the previously reported relative low correlations in the Ch(.) financial variables and growth in sales and expenses.

The first serial correlation test is non-parametric. Consider the up- and down-ticks of the four Ch(.) variables for two adjacent periods, t and t+1, resulting in 2-by-2 matrices and the implied correlations (denoted Phi). Table 3 Panel A shows that the serial correlation related to Ch(OA) is distinctly the largest out of the 4 Ch(.) variables, across all size groups. The serial correlations of Ch(OL) and Ch(FL) are roughly the same. Serial correlation of Ch(FA) is by far the smallest, actually slightly negative overall.

The second serial correlation test calculates the standard rank correlations of the Ch(.) variables across adjacent years, scaled by sales or expenses. Table 3 Panel B provides results. It appears that, overall, conclusions are effectively the same as those in the previous table.

One can ask the question why Ch(OL)'s correlation is relatively small compared to Ch(OA). One possibility is to pick up on the literature which suggests that the serial correlation depends on *both* "true growth" and as well the potential of accruals that have reversed due to over- or under-accruing in prior periods (per jargon, "accrual reversals" have make their presence felt). Thus, one can hypothesize that OL embeds more of reversals at least as compared to OA. The issue with Ch(FL), which also has a low correlation, is entirely different because as noted, there are reasons suggesting that Ch(FL) could be effectively uncorrelated with revenues and (pre-interest) expenses growth. In addition, on prior grounds it seems less likely that FL are sensitive to over- and under-accruing since financial liabilities tend to be pretty “hard” numbers.

[Insert Table 3 here]

To summarize this section, two conclusions stand out. First, the evidence supports that the operating Ch(.) variables act as leading indicators of subsequent growth in sales or expenses. And these correlations related to operating activities are more material as compared to the two variables related to financial activities, i.e. Ch(FA) and Ch(FL). Second, with respect to the serial correlations, these are non-negative and Ch(OA) stands out as having by far the most positive serial correlation. This suggests that OL embeds the potential of accrual reversals more so than OA does. We further examine this aspect later.

4. Results: The Multivariate Forecasting Models.

4.1 Forecasting Sales and Expenses – model specifications A1 and A2

This section reports on the estimations of specifications A1 (forecasting sales) and A2 (expenses) and the three related hypotheses, developed in in Section 2. Table 4 Panel A and B show the results separately for each size group. In all six cases the estimations pertain to 16 years of data. Details for individual years are shown only for large firms. It saves on space and recognizes that large firms are often viewed as being of greater interest than the smaller ones. In any event, detailed result for the group of large firms also serves as a reasonable indication of the variation across years for the two groups of smaller firms.

Consider first sales forecasting (specification A1) and the hypothesized positive signs related to the estimated load-factors of Ch(OA) and Ch(OL), i.e., k(3) and k(4). Positive load-factors receive strong support: Table 4 Panel A shows that for Ch(OA), k(3) are positive in *all* 48 cases (3 size groups and 16 years). For Ch(OL), k(4) are positive in all but 3 out of 48 cases. Thus, results for both variables are statistically unambiguous.

Consider next the expenses forecasting (specification A2). Table 4 Panel B shows that, like the sales case, the load-factors for Ch(OA), k(3), are again always positive (that is, 48/48). However, results related to Ch(OL) differ dramatically. As a fraction, positive signs hold: 9/16, (large firms), 13/16 (mid-size), 9/16 (small) – a net of 31/48. Though the null of a pooled median of 50-50 can be rejected at the 5% level, it is not so for 1% level.[11]

To summarize the results for sales and expense forecasting: Ch(OA) loads positively without a hitch, both sales and expenses; by contrast, though Ch(OL) overall loads positively for the sales case, for expenses the variable is at best marginal.

[Insert Table 4 here]

The 4 load-factors' relative order of magnitudes are instructive. Specifically, the load on Ch(OA) in the expenses setting is the greatest, and the load on Ch(OL) in this setting is the smallest. For sales forecasting, the load-factors on Ch(OA) and Ch(OL) are roughly the same and the their magnitudes fall in between the two load-factors in expenses forecasting. These findings are robust across years and align with the FM-statistics. The 4 load-factors are in crude order of magnitudes about 0.5 for Ch(OA) in the expenses setting, 0.2 for both load-factors in the sales setting, and the smallest about 0.1 related to Ch(OL) for the expenses setting. *This strong result captures the overwhelming importance of operating assets' growth in expenses forecasting and that operating assets and liabilities increments are roughly of equal importance in sales forecasting.* The finding takes on a central role in the next section which addresses ROA (and PM) forecasting.

To evaluate the informativeness of the Ch(.) variables, more stringent tests go beyond Fama-McBeth and related t-statistics. These tests focus on the extent to which (sets of) variables contribute to the explanation of the dependent variable. Specifically, we apply relative accuracy scores (RAS) to compare the forecasting accuracy of one model versus another. RAS calculates the percentage of times that one model gives a more accurate forecast than a competing model as determined by the comparison of the two forecast errors' absolute magnitudes.

In the sales/expense forecasting settings, we compare the full model (six variables on the RHS) against the full model without Ch(OA) and Ch(OL), the two main variables of interest. In a second model comparison, we also eliminate Ch(FA) and Ch(FL), i.e., the RHS includes only the two basic variables, S(t) and Ch(S(t)), for the sales case and Exp(t) and Ch(Exp(t)) for the expenses case.

Table 4 Panel C evaluates the relative forecasting accuracy of the various models. It shows that the 6-variable (full) sales and expenses models "win" against their competitor models comprising 4 variables (the full model without the operating variables) or 2 variables (without operating and financial variables). The dominance of the full model holds for both sales and expenses forecasting, but the effectiveness of the full model is more apparent in the expenses forecasting. Results hold up for all three size groups too. The typical win ratio, full model versus 4-variable model is on average 53% for both sales and expenses forecasting. (P-values are always less than 0.01 – N is large enough.) As to a test of the full model versus the 2-variable models, there are no surprises: the dominance is even stronger. Finally, one can compare the 4 variables model (no accrual variables) to the 2-variable model to note that the Ch(.) financial variables can contribute in the forecasting of sales and expenses growth.

Before proceeding to the ROA forecasting, the role of the Ch(FA) and Ch(FL) variables deserve a few comments. Most strikingly, Ch(FL) loads with a negative sign – in sharp contrast to the positive load factor related to second liability account, Ch(OL).[12] It is also noteworthy that the negative load-factor related to Ch(FL) is consistent with the positive one related to Ch(FA) – borrowing is the opposite of lending, as should be. Intuitive as the result is, the claim nonetheless requires that the RHS of the forecasting models includes additional variables. Finally, the FM-statistics show that these results are significant at the 1% level, almost all years and size groups.

The above robust findings reassure that "accounting works the way it is supposed to do" – the accruals can thus be viewed as reliable. That said, the ultimate focus in practical FSA tends to be firms' future economic performance and, above all, the forecasting of earnings. The following section accordingly focuses on ROA and PM which can be viewed as an intermediate step before turning to earnings forecasting.

4.2 Forecasting ROA and PM – model specifications B1 and B2

Results reported on motivate the ROA and PM forecasting hypotheses. Recall the key finding in the sales/expenses forecasting that the load-factors related to the operating variables are all positive and satisfy the inequalities:

Exp Model		S model		Exp Model
Load-factor of Ch(OL), k(4)	<	Load-factor of Ch(OA), k(3); Load-factor of Ch(OL), k(4)	<	Load-factor of Ch(OA), k(3)

It follows that sales minus expenses – the numerator in ROA and PM – most likely shows negative and positive load-factors for Ch(OA) and Ch(OL) as well. Because Ch(OL) maps into a negative accrual, the inequalities lead to the hypothesis that the greater the accruals, the more downward pressure on the performance scores, ROA and PM.

The hypothesized finding should not be viewed as a foregone conclusion. In estimating the ROA and PM models, the RHS relies on the six variables; and obviously the load-factors for the accrual variables depend on the totality of correlations. It should further be noted that the scaling of variables may have an effect such that the estimated load-factors end up differing from what has been hypothesized.

Table 5 Panel A and B provide results related to the two specifications of interest, ROA and PM. Consider first ROA. In this case the accrual hypothesis holds up, without any apparent ambiguities. Ch(OA) loads negatively for all size groups; the FM t-statistics are always significant (p-values < 0.01). In fact, the sign of the load-factor is negative in all but one of the 48 cases (as always, 48 = 3 size groups*16 years). Results related to Ch(OL) are even stronger: the signs of the estimated load-factors are now *always* positive; and the FM t-statistics always reject the null hypothesis (p-values < 0.01). A comparison of the two load -factors related to Ch(OA) and Ch(OL), k(3) and k(4), shows that the FM-statistics related to Ch(OL) always exceed those of Ch(OA). The same holds in a comparison of the absolute magnitudes: -k(4) > k(3). On a separate note, results also show that there is a size effect, that is, the results are the strongest for small firms.

With respect to the financial variable, Table 5 shows that the FM-statistics related to Ch(FA) and Ch(OL) are much smaller compared to Ch(OA) and CH(OL); signs often change, and the related FM-stats frequently lack in significance. Thus, as a first-cut, the results related to the informativeness of Ch(FA) and Ch(FL) suggest that these variables lack reliable coefficients in the

ROA forecasting (which would seem to be a necessary condition for informativeness). The finding appeals to economic common sense: it broadly implies financial policy irrelevance.

[Insert Table 5 here]

Shifting the focus to PM instead of ROA does not change conclusions. First, the accrual hypothesis holds up. Second, Ch(OL) remains more informative than Ch(OA) in terms of FM-statistics and load-factor magnitudes. Third, the financial variables remain approximately irrelevant. Fourth, the informativeness of the accruals decreases with firm size. The results impress because it suggests that while *some kind of scaling* of earnings may be important in the forecasting equation, this is not claim that the dependent variable must connect with practice or "applied economics". Thus, as will be discussed shortly, forecasting of earnings should not be confused with the forecasting of earnings deflated by some "reasonable" variable.

To complete the analysis, we also consider RAS tests which evaluate whether Ch(OA) and Ch(OL) add to the forecasting of ROA and PM beyond the remaining 4 variables, Ch(FA), Ch(FL), {ROA(t), PM(t)}, and beyond the two basic starting point variables, {Ch(ROA(t)), Ch(PM(t))}. Table 5 Panel C provides the results. The answer is similarly affirmative: the RAS win rates comparing the full model against both 4-variable ROA and PM models (i.e. without the two accruals variables) are significantly more than 50% (p-values < 0.01) for all three size groups. The same holds against the 2-variable models (i.e. without all 4 Ch(.) variables). In sum, the evidence strongly suggests that the accrual variables are informative in the forecasting of ROA and PM.

4.3 Forecasting Earnings – Model Specification C

The current section reports on the earnings forecasting model C, a dollar amount rather than a ratio setting. As noted earlier, Fairfield et al. (2003) argues that the lack of a deflator is of interest because in the ROA setting the deflator can potentially correlate with the accrual variables (also deflated). This correlation may influence the estimation of the RHS load-factors. Thus it should be underscored that while the ROA (and PM) setting supports the accrual hypothesis, this finding does not necessarily extend to the earnings forecasting setting.[13]

Table 6 Panel A provides the load-factor estimates. It shows that Ch(OL) yields the strongest and most consistent results: for *all* years and size groups, 48 cases, the sign of the load factor, k(4), is positive. The minimum FM statistics across the three size groups equals 9.3, which is impressive insofar N equals only 16. This striking result is effectively the same as in the ROA and PM settings.

Consider next the load-factor of Ch(OA), estimates of k(3). Now results differ materially from the ROA and PM settings. Though the load-factors generally show negative signs, the statistical significance falls short for the group of large firms: the FM statistic equals an insignificant -0.58. For small and mid-size firms the FM-statistics are significant and equal -4.64 and -14.31. But these are less than those in the ROA and PM settings.

The results make it clear that the size effect remains as in the ROA and PM settings. Small firms provide the most compelling and consistent evidence supporting the accrual hypothesis. For both accrual variables, without exceptions the FM statistics decrease as the size group increases.

[Insert Table 6 here]

As to the financial variables, the results differ little from the B setting. That is, as a first cut, Ch(FA) and Ch(FL) are nowhere near as relevant as the accrual variables, except for the group of small firms. For the two groups of larger firms the estimated load factors are at most marginally statistically significant. Accordingly, only three load-factors show statistically significance for all size groups and with consistent signs: positive for the anchor Earns(t); negative for Ch(Earns(t)), and positive for Ch(OL(t)) (the same as negative for operating liability accruals).

The use of FM-statistics is not without limitations since such significance does not per se ensure the forecasting relevance of the variables. To corroborate, we consider RAS tests. Consider a comparison of the full model (6 RHS variables) versus the full model excluding the two accrual variables (i.e. the 4-variable model). Table 6 Panel B shows that going from groups of small to the group of large firms, the win ratio for the full model equals 53.2%, 52.1% and 52.2% respectively (large enough N's ensure p-values less than 0.01). For the full model versus the 2-variable models, the win ratio for the full model equals 53.5%, 51.4% and 51.8%. Thus, the financial variables make no substantive difference. As before, the accrual variables are the most effective in the group of small firms. Overall, the RAS test leads to the same conclusion as compared to the one obtained from the FM-statistics reported on earlier.[14]

Given that both of the accrual variables load with correct signs, one can ask whether the RHS can be effectively simplified via the use of Ch(NOA) in lieu of using its two components, Ch(OA) and Ch(OL). RAS tests can be applied to assess the relevance of keeping the Ch(OA) and CH(OL) variables separate. The issue is important insofar the results reported on so far suggests that Ch(OL) is of particular relevance in the forecasting. Table 7 Panel A compares the 6-variable (full) model to the 5-variable model which uses Ch(NOA(t)) in lieu of Ch(OA(t)) and Ch(OL(t))). Results show that the full model wins with the two largest groups win with p-values less than 0.01. For small firms the win ratio for the full model equals an insignificant 50.5%. The reason for this outcome illustrates the workings of the basic model C as estimated. Ch(NOA) provides sufficient information when Ch(OA) and Ch(OL) have sufficiently similar load-factors (aside from the difference in signs), and this condition seems like a plausible approximation for the group of small firms. Results concerning the general lack of sufficiency for Ch(NOA) remain in the cases of ROA or PM as the dependent variables.

Another way of assessing the validity of Ch(NOA)-sufficiency considers the direct estimation of a model with Ch(NOA) as the only accounting variable on the RHS. This issue in effect raises the possibility of assessing the extent to which the Sloan (1996) model holds up. Consider the estimation of the simplest possible two-variable model, namely, when current earnings and change in NOA are the only independent variables in the earnings forecasting. Table

7 Panel B shows the estimation results for the three size groups. The load-factors of Earns(t), k(1), are close to 1 and always highly significant for all groups, which reaffirms the literature's use of current earnings as the natural starting point. As to Ch(NOA(t)), though its load factor, k(2), is generally negative as should be per the accrual hypothesis, for large firms the variable is insignificant (FM-statistic equals only -1.55); while for the small and mid-size groups, the load-factors are highly significant (FM-statistics equal -10.45 and -4.15 respectively). Again, the result is consistent with the findings in Table 6 that the differences (sign-adjusted) in the load factors for Ch(OA) and Ch(OL) differ much more for larger (groups 2 and 3) firms – aggregation is thus unlikely to work as a starting point. (Additional results (not included in the Table) show that these results change only modestly if the RHS also includes the two financial or the Ch(Earns(t)) variables.) Overall, the mixed results suggest that the Sloan-type model picks up on the accrual hypothesis only partially.

[Insert Table 7 here]

4.4 Ch(OA) and Ch(OL): The Potential for Reversals

While the formal ideas developed in previous sections provide support for the accrual hypothesis, it is less clear why, if at all, one should expect the liability accruals to be so much more informative (larger load-factor in absolute sense) in the estimation of the forecasting models, B and C. It raises the question whether the findings can be aligned with traditional arguments supporting the accrual hypothesis. To address this issue we consider the possibility of accrual reversals in the broad sense that over-accruing in one period leads to (in expectation) to under-accruing in the subsequent period. Thus, we try to provide some empirical evidence that Ch(OL) is a more likely candidate than Ch(OA) to reflect reversals. But it is of course difficult to devise a methodology that can effectively assess reversal. It can be addressed only if one makes assumptions that potentially may be viewed as less than compelling; this caveat must be recognized at the outset.[15]

A generalization of the above benchmark becomes equivocal since it must allow for growth in operating activities which can change over time. If the firm's "intrinsic" growth in some period is non-zero and accruals work perfectly, then so should be the asset and liability accruals: in principle, under ideal circumstances, the accruals should pick up on growth properly. But this "intrinsic" growth is of course unobservable. To the extent the accounting for accruals embed intricate measurement issues, the accruals may be misleading and there is no way this can be readily determined. At best, the data analysis can look for traces in the time-series behavior of accruals to suggest that some of the dynamics embed reversals.

Our approach to assessing accrual reversals is in the same vein as Allen et al. (2013). Two elements underpin this approach. First, we hypothesize that positive intrinsic growth anticipates positive Ch(OA) and Ch(OL) in the absence of any accounting issues. Second, we pick up on potential reversals by identifying negative correlations in accruals *after having controlled for an estimate of intrinsic growth.*[16] It leads to a general model where

$$Ch(X(t+1)) = k*Ch(X(t)) + IG(t) + noise(t+1)$$

where IG(t) equals a linear combination of the variables that potentially capture the effect due to intrinsic growth. There are two cases dependent on the accrual variable, X = {OA, OL}. If X = OA then IG = {Ch(OL), Ch(S), Ch(Exp), Ch(FA), Ch(FL)}, excluding Ch(OL). If X = OL then IG = {Ch(OA), Ch(S), Ch(Exp), Ch(FA), Ch(FL)}, excluding Ch(OA).

Because of the way in which IG(t) depends on the case, OA vs. OL, the RHS, in its *totality,* remains the same (though of course the load-factors may change). Thus, the two cases can be expressed as

M1. Ch(OA(t+1)) = k(1)*Ch(OA(t)) + k(2)*Ch(OL(t)) + k(3)*Ch(S(t)) + k(4)*Ch(Exp(t)) + k(5)*Ch(FA(t)) + k(6)*Ch(FL(t)) + U(t+1)

M2. Ch(OL(t+1)) = k(1)*Ch(OA(t)) + k(2)*Ch(OL(t)) + k(3)*Ch(S(t)) + k(4)*Ch(Exp(t)) + k(5)*Ch(FA(t)) + k(6)*Ch(FL(t)) + U(t+1)

In the first equation, the last five variables combine to identify IG(t); in the second equation, IG is identified by the combination of variables 1, 3, 4, 5, 6 (in other words, without 2). There are thus two models, labeled M1 and M2, each with its own measure of "intrinsic" growth and distinct attentions, k(1) in M1 and k(2) in M2 respectively.

The empirics focus on the possibility of accrual reversals, that is, whether k(1), equation M1, and k(2), equation M2, are negative or not. Thus the "detectability" of reversals hinges on the possibility that practical FSA can forecast accruals. It can do so in different ways, depending on the absence/presence of reversals (on average). The benchmarks with positive k(.)'s simply recognize that the measure of IG can be complemented by the related accrual. A negative k(.), however, identifies a case where, on average, there is "dubious quality accrual accounting" and the forecasting accordingly reflects this property.

We examine results not only in terms of the signs of the load factors related to the accruals, but also their relative magnitudes, that is, the sign of [k(1) in M1] minus [k(2) in M2]. Such focus gauges which of the two accruals seems to be the better candidate for the accrual reversal hypothesis. On the basis of findings so far, it goes almost without saying that one should expect the sign to be positive. But this dominance may of course get rejected because of too crude modelling and a related lack of testing power.

Table 8 provides estimation results. Panel A bears on M1. It shows that the load-factors of Ch(OA), k(1), are significantly positive for all three size groups. In other words, there is no evidence that Ch(OA) reverses after having controlled for the information picking up on IG. Consider next Panel B, the case of M2. It shows that the load-factors related to Ch(OL), k(2), are negative and statistically significant in the two smallest size groups (out of three). For the group of large firms k(2) essentially equals zero, so the reversal property is absent (i.e. the null hypothesis of zero cannot be rejected). In sum, per evidence the reversal hypotheses for Ch(OL) seems reasonable whereas in contrast not so for Ch(OA). That said, it is nonetheless clear that Ch(OL) is much more likely candidate for reversals than Ch(OA).

[Insert Table 8 here]

A second more straightforward and non-parametric test also evaluates the extent of reversals in Ch(OA) and Ch(OL). The IG control is now set a priori and in the spirit of practical FSA. Text-books generally refer to firms' "growth" either in terms total assets or growth in sales.[17] This observation suggests that one can control for IG using a simple average of the two growth measures and put the sample firms into one of five equally-partitioned bins based on the firms' relative IG scores, from the lowest to the highest. The procedure can thus be applied for each of the three size groups and for each year. Given this control procedure, the serial correlations in Ch(OA) and Ch(OL) are obtained by calculating the serial correlation (Phi) between up- and down-ticks of the Ch(.) variables over consecutive periods, t and t+1. Thus, the procedures yield 2 by 2 matrices, where each matrix controls for the IG measure, the average growth in total assets and sales.

Results are unambiguous with respect to Ch(OA). Panel C shows that the serial correlation is small but positive in all 15 (3*5) cases, and these correlations always dominate those pertaining to Ch(OL), shown in Panel D. As to the latter variable, its serial correlations are, for all 5 cases of IG-controls, negative for small firms, on average zero for mid-sized firms, and always positive for large firms. In sum, these additional analyses are similar to the findings reported on in the previous paragraph. But results are now weaker because only the group of small firms pick up on the purported reversibility property of Ch(OL). That said, again results clearly show that to the extent there is any reversibility in the two accrual variables, Ch(OL) is the by far the better candidate. And this finding is, yet again, entirely consistent with those reported on in the previous sections.

5. Summary Remarks

The findings of this paper support Sloan's (1996) longstanding hypothesis that accruals act as a negative indicator of future performance. But it does so by putting forward a different argument which avoids notions that accruals are unreliable. The approach here accordingly also allows for a broader perspective on the empirics related to the accrual hypothesis. These deserve a summary-review because it highlight the importance of concepts as one tries to explain certain findings.[18]

First, to a remarkable degree, the role of Ch(OL) has some unique features and distinct information. As a forecasting matter, the usefulness of Ch(OL) in the performance forecasting derives from its role as a predictor of sales as opposed to expenses. This aspect, taken by itself, makes it unsurprising that liability accruals, negative changes in OL, have a negative effect on future performance.

Second, Ch(OL) seems to be more informative than Ch(OA) to validate the accrual hypothesis. The strength of this finding seems to be novel. And interestingly enough, our analysis of the Ch(OL)-reversals appear to be more discernable as compared to the Ch(OA)-reversals (which seem to be absent). In striking contrast, the Ch(OA) accruals is highly informative regarding future expenses.

Third, shifting the forecasting to earnings rather than ROA weakens the accrual hypothesis. Thus, the elimination of the ROA scaler/denominator is relevant, which supports the hypothesis of Fairfield et al. (2003). To the extent the real-world forecasting does not center on ROA, as opposed to earnings, the importance of the accrual's hypothesis would seem to be less noteworthy.

Fourth, the financial variables illustrate the difference between financial and operating activities: in a way, the financial variables have served a useful role as pseudo-placebos insofar that "what is true for accruals should not be true for financial flows". In sales and expense forecasting settings, the role of Ch(FL) with its in general negative load factor stands in sharp contrast to Ch(OL) – an aggregation Ch(FL) + Ch(OL) = Ch(TL) makes no sense from the forecasting perspective. And in the performance forecasting, the financial variables were much less informative than the operating variables. In this regard, the paper reinforces basic aspects of FSA and the prior literature.

Endnotes

[1] The word "accrual" has no generally agreed upon definition. In this paper, the word refers to operating accounts as opposed to financial accounts. This convention does not rule out that all accounts (including cash, with some imagination) can build in something that involves an "accrual" characteristic. (By way of illustration, consider a pure discount bond. This balance sheet account must be credited each period and credited a non-cash interest expense, arguably an accrual no less than, say, depreciation expense.)

[2] The word "accrual" does not have a generally agreed on definition or how they should be (best) measured. As the recent review paper by LSW makes clear, the flexibility is close to unbounded (only cash, for sure, does not involve accrual accounting.) Our definition would seem to be reasonable in light of the literature (especially FSA text-books), but, that said, we do not wish to imply that in some sense ours is the "right" approach. We only argue that it is an easy and intuitively appealing starting point. Our definition of accruals comes close to accounting practice if one considers the concept of so-called applying Modified Cash Accounting (MCA), often used by small privately held firms Now the definition satisfies Net Accrual = GAAP-earnings minus MCA-earnings, where Net Accrual = Ch(OA) – change in AR and similar assets – [Ch(OL) – change in AP and similar liabilities]. See Ohlson and Aier (2009) for a discussion of this accrual concept. We also applied this approach, (i.e., reclassifications of AR and AP), to the measurement of OA, OL, FA, FL. Overall, results were similar to those reported on.

[3] To motivate a core idea which this paper relies on, we refer to Sunder (1980). This paper shows that relatively large capital expenditures (Dr. PPE) depress earnings in the short run – a clear version of the accrual hypothesis. It further provides evidence that this outcome is independent

of ownership structure and, arguably, incentives to manipulate earnings. (Given the paper's lack of recognition, the phrase "being ahead of its time" comes to mind.)

[4] The literature on the properties of accruals that give rise to the accrual hypothesis has many subtleties and aspects, as espoused by Sloan (1996), Richardson et al. (2005, 2006) and Allen, Larson and Sloan (2013). One argument that seems important runs as follows. As a consequence of (lack of) reliability, or temporary accounting distortions, accruals end up being less persistent than cash flows or, alternatively the lack of reliability gives rise to "bad" accruals as opposed to "good" accrual, where the latter (as should be) pick up on growth. That said, the papers also recognize that the accrual hypothesis may arise due to growth-based explanations, including arguments in the spirit of classical economics like marginal decrease in returns on investment. (For the record, this footnote is our interpretation of the literature and it may not have adequately appreciated the cited papers.)

[5] This paper makes no references to earnings management effects on accruals. The argument here, at its core, presumes (GAAP) accruals are reliable and relevant, though of course accrual earnings management may occur. Empirical evidence supports accrual management at least in certain contexts, as shown in Marquardt and Weidman (2004).

[6] The presumption that operating liabilities can be viewed as the negative of operating assets – to end up with NOA – goes back to Feltham and Ohlson (1995), at least. In some contexts it must be viewed as a conceptual error insofar that liability accruals do not correlate positively with concepts of growth (sales growth, expense growth, asset growth, etc.). In this regard, the so-called Jones Model serve as a prime illustration. Generously speaking, the model is less than an ideal specification, quite aside from the aberration that the regression residual should be labeled "discretionary accruals".

[7] The reasons why this finding should be expected are unclear to us.

[8] Theil-Sen (TS) estimation, as opposed to OLS, avoids the undue influence of outliers. (Ohlson and Kim, 2015). This issue is relevant here because of the prominent status give to "non-articulating accruals" (which relate to mergers and acquisitions; see Hribar and Collins, 2002, and Casey et al., 2017), and "conditionally conservative accruals" (which relate to write-offs; see Larson et.al. (2018)). Also, Dechow and Ge (2006) emphasizes the material effects of special items (typically accruals) as reducing the persistence of accrued earnings components. All of the cited papers on accruals apply OLS and winsorizes the data (or do something similar like trimming and truncation). These popular techniques are not, however, as effective as seems to be commonly believed. Serious issues related to the robustness of conclusions remain, as evidenced by Leone et al. (2017). This paper states, in its abstract, that "We find that winsorization and truncation are largely ineffective in mitigating the effect of influential observations".

[9] No forecasting model reflects us taking a stab at optimizing the RHS via inclusion of variables that may work for whatever reason. This self-imposed limit conforms to the cited literature on the accrual hypothesis; with the possible exception of Sloan (1996), none of these papers seek to develop "ingenious" forecasting schemes; the focus on accruals is for its own sake. (For such

papers see, for example, Amir et al. (2013). Thus, the focus in this paper is squarely on the informativeness of 2 accrual variables plus 4 basic controls.

[10] It should be noted that the negative correlation, liability accrual and sales growth, has not been generally appreciated by the literature. It is often suggested that accruals and sales growth are positively correlated (Richardson et al., 2005), without any recognition of the subtleties involved: though asset accruals and sales growth correlate positively, this correlation by no means clearly dominates the liability accrual. As the tables in this paper show, this holds whether the correlation concerns a forecast or is contemporaneous.

[11] The results related to the forecasting of expenses can be explained by accounting conservatism, in its traditional meaning. Positive increments in operating assets must be conservative, and similarly they must be expensed relatively quickly, which means, in relative terms, an "excess" expensing in the near term. As to growth in operating liabilities – an expression of current period conservative accounting, the opposite has to be true, a "deficit" of future expense. This reasoning aligns with Penman and Zhang (2006). Also, many years ago, Sunder (1980) showed that firms with relatively high capital expenditure incur relatively depressed profits in the subsequent near-term due to an "excess" of depreciation.

[12] In a different context, Nissin and Penman (2003) underscore the need to distinguish between operating as opposed to financial liabilities: it informs differentially on future profitability and it influences the book-to-price ratio.

[13] The accruals literature cited deflate the dependent variable with (average) total assets. Yet, in the discussion of results this aspect never takes on any serious mention, which seems to be a noteworthy omission. To illustrate this point, write, say, ROA(t+1) = X(t+1)*Y(t+1) where X = numerator and Y equals the inverse of the denominator (average total assets). Given this set up, it involves an element of wishful thinking to (implicitly) suggest that the regression focuses (or explains) the X-variable as opposed to the Y-variable. Fairfield et al. (2003) is the only paper that recognizes this point; the paper actually claims that the evidence supports that Y is the more relevant aspect in explaining the accrual hypothesis.

[14] For completeness, we also run RAS tests for the ROA and PM settings. The last two columns of Panel B show the results. Again, the 6-variable (full) models beat the 5-variable models for the two groups of larger firms. The results are expected because only in the case of small firms does the (average) Ch(OA) load factor achieve a (positive) magnitude of adequate materiality. In the cases of larger firms they are percentage wise too small as compared to the statistically significant load factor related to Ch(OL) – which holds strongly for all size groups. Overall, the results thereby reinforce the power of Ch(OL) in contrast to Ch(OA) in the forecasting of ROA and PM.

[15] Conceptualizing reversals poses challenges because it depends on making assumptions that cannot be directly validated. The classical benchmark postulates that "properly measured" earnings are constant over time (a so-called steady state model of operating activities) which implies that "error-free" accruals equal zero. If the accruals are positive in some periods, then they must be negative in some others thereby reversing the error. That is, there must be reversals to ensure that in the long run the average accrual equals zero.

[16] Our approach is arguable even more in the spirit of Amir et al. (2011) and Amir et al. (2015). These papers develop the idea of "conditioning" when one studies the role of a variables serial correlation. Thus the papers distinguish between unconditional and conditional serial correlations, much like in our analysis.

[17] Complementary tests replace total assets with total liabilities. Results end up being somewhat weaker, but otherwise overall the same.

[18] To appreciate accruals' reliability properties, it helps to illustrate their forecasting power. Consider the case when cash earnings replace earnings in the C setting (per definition, cash earnings = earnings – Ch(NOA)). Table 9 provides the results. These show that all of the asset accruals load positively – and unambiguously so – in addition to the liability accruals. And the distinction between accruals and financial variables is sharp indeed since the loads on Ch(FA) are the opposite of Ch(OA), no less than Ch(FL) and Ch(OL). Though accruals of course can be less than totally reliable, it supplies interesting evidence in support of the financial-operating dichotomy taught in standard FSA.

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Table 1. Descriptive Statistics

Panel A. Descriptive statistics of major variables

	Size Group											
	1 = small (N = 18590)				2 (N = 18600)				3 = big (N = 19175)			
	Mean	25%	Median	75%	Mean	25%	Median	75%	Mean	25%	Median	75%
TA	120	21	49	112	561	136	293	638	9456	988	2492	7052
MV	57	17	38	81	413	193	322	522	9795	1312	2624	6819
S	134	14	45	125	571	85	259	644	7315	778	2040	5660
Earns	-14	-12	-2	2	-11	-16	7	23	438	31	108	318
Exp	148	22	52	133	582	95	263	636	6876	723	1921	5330
OA	103	12	33	92	485	77	224	559	8510	780	2150	6311
OL	39	5	12	31	170	27	70	174	3284	231	687	2223
FA	17	2	7	19	76	14	44	97	946	72	215	607
FL	46	0	4	20	183	0	24	168	2807	97	573	2022

Panel B. Growth rates of the major variables: sales, expenses, OA, OL, FA and FL

	Size Group								
	1 = small (N = 16189)			2 (N = 16309)			3 = big (N = 18032)		
	25%	Median	75%	25%	Median	75%	25%	Median	75%
S(t+1)/S(t)	0.88	1.02	1.16	0.97	1.08	1.23	1.01	1.09	1.20
Exp(t+1)/Exp(t)	0.89	1.03	1.17	0.97	1.08	1.22	1.00	1.08	1.20
OA(t+1)/OA(t)	0.84	0.98	1.11	0.95	1.05	1.21	0.99	1.06	1.19
OL(t+1)/OL(t)	0.84	1.01	1.21	0.94	1.07	1.25	0.99	1.08	1.22
FA(t+1)/FA(t)	0.59	0.93	1.38	0.75	1.05	1.51	0.80	1.12	1.57
FL(t+1)/FL(t)	0.03	0.84	1.09	0.13	0.89	1.09	0.81	0.99	1.16

Panel C. Spearman rank correlations among the growth rates of the major variables

Size Group = 1	S(t+1)/S(t)	Exp(t+1)/Exp(t)	OA(t+1)/OA(t)	OL(t+1)/OL(t)	FA(t+1)/FA(t)	FL(t+1)/FL(t)
S(t+1)/S(t)	1.00	0.63	0.48	0.33	0.09	0.15
Exp(t+1)/Exp(t)		1.00	0.37	0.35	0.03	0.20
OA(t+1)/OA(t)			1.00	0.48	0.03	0.24
OL(t+1)/OL(t)				1.00	0.10	0.13
FA(t+1)/FA(t)					1.00	-0.02
FL(t+1)/FL(t)						1

Size Group = 2	S(t+1)/S(t)	Exp(t+1)/Exp(t)	OA(t+1)/OA(t)	OL(t+1)/OL(t)	FA(t+1)/FA(t)	FL(t+1)/FL(t)
S(t+1)/S(t)	1.00	0.71	0.51	0.41	0.07	0.08
Exp(t+1)/Exp(t)		1.00	0.45	0.41	0.00	0.13
OA(t+1)/OA(t)			1.00	0.54	-0.06	0.22
OL(t+1)/OL(t)				1.00	0.10	0.09
FA(t+1)/FA(t)					1.00	-0.04
FL(t+1)/FL(t)						1.00

Size Group = 3	S(t+1)/S(t)	Exp(t+1)/Exp(t)	OA(t+1)/OA(t)	OL(t+1)/OL(t)	FA(t+1)/FA(t)	FL(t+1)/FL(t)
S(t+1)/S(t)	1.00	0.83	0.56	0.51	0.08	0.08
Exp(t+1)/Exp(t)		1.00	0.51	0.48	0.04	0.11
OA(t+1)/OA(t)			1.00	0.64	-0.05	0.28
OL(t+1)/OL(t)				1.00	0.12	0.12
FA(t+1)/FA(t)					1.00	0.00
FL(t+1)/FL(t)						1.00

Panel A. Summary statistics for all (pooled) sample firm-years from 2000 to 2015. Size breakpoints are defined in each year based on the fiscal year-end market capitalization of all non-financial firms (SIC codes are <6000 or >6999), and then firms are put into one of the size groups running equally from size group 1, the smallest firms, to size group 3, the largest firms. The original dataset contains 56,450 firm-year records. Panel B. Growth rates of the major variables: sales, expenses, OA, OL, FA and FL. If both nominator and denominator of the variable are zero, the growth rate is set to zero. Panel C. Their (Spearman) rank correlations. All non-zero correlation coefficients are significant at 1% level. Definitions of key variables follow standard practice: Earnings (Earns) as Income Before Extraordinary Items (item 18), Expenses (Exp) as Sales (S, item 12) minus Earns, Financial Assets (FA) as Cash and Short-Term Investments (item 1), Financial Liabilities (FL) as sum of Debt in Current Liabilities (item 34) and Long-Term Debt (item 9) and Preferred Stock (item 130), Operating Assets (OA) as Total Assets (TA, item 6) minus FA, Operating Liabilities (OL) = TA minus FL minus Common Equity (item 60) minus Minority Interest (item 38). All figures are in Million.

Table 2. Bi-variate Growth Tests

Panel A. Spearman rank correlations between growth in sales (expenses) and the four Ch(.) variables in all years (pooled)

Size Group	**S(t+1)/S(t) vs. Ch(OA(t))/S(t-1)**	**S(t+1)/S(t) vs. Ch(OL(t))/S(t-1)**	**S(t+1)/S(t) vs. Ch(FA(t))/S(t-1)**	**S(t+1)/S(t) vs. Ch(FL(t))/S(t-1)**
1 = small	0.23	0.23	0.03	0.08
2	0.31	0.30	0.03	0.11
3 = big	0.34	0.33	0.14	0.11

Size Group	**Exp(t+1)/Exp(t) vs. Ch(OA(t))/Exp(t-1)**	**Exp(t+1)/Exp(t) vs. Ch(OL(t))/Exp(t-1)**	**Exp(t+1)/Exp(t) vs. Ch(FA(t))/Exp(t-1)**	**Exp(t+1)/Exp(t) vs. Ch(FL(t))/Exp(t-1)**
1 = small	0.37	0.22	0.11	0.12
2	0.40	0.30	0.11	0.13
3 = big	0.40	0.34	0.16	0.13

Panel B. Expanded analysis on the monotonicity between growth in sales (expenses) and the four Ch(.) variables in all years (pooled)

S(t+1)/S(t)	**Ch(OA(t))/S(t-1)**	**Ch(OL(t))/S(t-1)**	**Ch(FA(t))/S(t-1)**	**Ch(FL(t))/S(t-1)**
1 = low	-0.019	-0.006	-0.001	0.000
2	0.009	0.007	0.001	0.000
3	0.035	0.016	0.002	0.000
4	0.071	0.029	0.004	0.000
5 = high	0.165	0.065	0.008	0.000

Exp(t+1)/Exp(t)	**Ch(OA(t))/Exp(t-1)**	**Ch(OL(t))/Exp(t-1)**	**Ch(FA(t))/Exp(t-1)**	**Ch(FL(t))/Exp(t-1)**
1 = low	-0.038	-0.004	-0.003	0.000
2	0.007	0.007	0.001	0.000
3	0.038	0.017	0.002	0.000
4	0.078	0.029	0.004	0.000
5 = high	0.173	0.060	0.016	0.000

Panel A. The correlations between growth in sales (expenses) and the 4 Ch(.) variable: Ch(OA(t)), Ch(OL(t)), Ch(FA(t)) and Ch(FL(t)) in all years (pooled). As usual practice, the 4 Ch(.) variables are scaled by either S(t-1) or Exp(t-1) depending on whether they are correlated with the sales or expenses growth. All correlation coefficients are significant at 1% level. Panel B. Median values of the four scaled variables in all years (pooled) are put into five sales (expenses) growth groups running equally from 1 to 5. Ch(.) variable as of year t, Ch(X(t)), is defined as X(t) – X(t-1).

Table 3. Serial Correlation Tests

Panel A. Percentages of up-ticks (+ve) and down-ticks (-ve) across two adjacent years for the 4 Ch(.) variables in all years (pooled)

Size Group			Ch(OA(t+1)) +ve	Ch(OA(t+1)) -ve	Phi			Ch(OL(t+1)) +ve	Ch(OL(t+1)) -ve	Phi
1 = small	Ch(OA(t))	+ve	26.0	24.0	0.16	Ch(OL(t))	+ve	28.6	26.1	0.00
		-ve	17.8	32.1			-ve	23.5	21.8	
2		+ve	44.3	20.1	0.19		+ve	42.4	22.8	0.04
		-ve	17.8	17.9			-ve	21.3	13.5	
3 = big		+ve	56.6	16.5	0.20		+ve	54.6	19.1	0.08
		-ve	15.3	11.6			-ve	17.4	8.9	

Size Group			Ch(FA(t+1)) +ve	Ch(FA(t+1)) -ve	Phi			Ch(FL(t+1)) +ve	Ch(FL(t+1)) -ve	Phi
1 = small	Ch(FA(t))	+ve	18.9	27.0	-0.06	Ch(FL(t))	+ve	20.9	25.6	0.08
		-ve	25.5	28.7			-ve	19.8	33.7	
2		+ve	27.6	26.8	-0.08		+ve	23.3	24.0	0.12
		-ve	27.0	18.7			-ve	19.6	33.1	
3 = big		+ve	33.9	26.8	-0.10		+ve	29.6	23.0	0.12
		-ve	25.7	13.5			-ve	21.2	26.3	

Panel B. Spearman rank correlations across two adjacent years for the 4 Ch(.) variables in all years (pooled)

Size Group	Ch(OA(t+1))/S(t) vs. Ch(OA(t))/S(t-1)	Ch(OL(t+1))/S(t) vs. Ch(OL(t))/S(t-1)	Ch(FA(t+1))/S(t) vs. Ch(FA(t))/S(t-1)	Ch(FL(t+1))/S(t) vs. Ch(FL(t))/S(t-1)
1 = small	0.18	-0.00	-0.01	0.06
2	0.21	0.06	-0.07	0.11
3 = big	0.27	0.15	-0.07	0.10

Size Group	Ch(OA(t+1))/Exp(t) vs. Ch(OA(t))/Exp(t-1)	Ch(OL(t+1))/Exp(t) vs. Ch(OL(t))/Exp(t-1)	Ch(FA(t+1))/Exp(t) vs. Ch(FA(t))/Exp(t-1)	Ch(FL(t+1))/Exp(t) vs. Ch(FL(t))/Exp(t-1)
1 = small	0.17	-0.01	-0.02	0.06
2	0.22	0.06	-0.07	0.11
3 = big	0.28	0.15	-0.06	0.10

Panel A. The 2x2 matrix of the upticks (+ve) and downticks (-ve) by the 4 Ch(.) variables in consecutive years in all years (pooled). Standard Phi coefficients measure the serial correlations. Panel B. The standard rank correlations by the 4 Ch(.) variables in consecutive years in all years (pooled). As usual practice, the 4 Ch(.) variables are scaled by either S(t-1) or Exp(t-1). All correlation coefficients (except for -0.00 and -0.01) are significant at 1% level. Ch(.) variable as of year t, Ch(X(t)), is defined as X(t) – X(t-1).

Table 4. Estimation Coefficients for the Model Specifications A1 and A2

Panel A. Estimated coefficients for the 6-variable (full) forecasting model for sales

*S(t+1) = k(1)*S(t) + k(2)*Ch(S(t)) + k(3)*Ch(OA(t)) + k(4)*Ch(OL(t)) + k(5)*Ch(FA(t)) + k(6)*Ch(FL(t))*						
Size Group	**k(1)**	**k(2)**	**k(3)**	**k(4)**	**k(5)**	**k(6)**
1 = small	1.00	0.06	0.17	0.27	-0.01	-0.01
	(93.36; 16)	(3.12; 13)	(12.74; 16)	(9.84; 16)	(-1.76; 6)	(-0.89; 6)
2	1.03	0.18	0.18	0.34	0.02	-0.04
	(104.59; 16)	(5.15; 15)	(8.24; 16)	(10.45; 16)	(1.68; 9)	(-2.07; 4)
3 = big	1.03	0.25	0.19	0.20	0.16	-0.11
	(108.48; 16)	(5.25; 15)	(12.33; 16)	(4.73; 13)	(6.18; 16)	(-5.79; 2)
Year	**k(1)**	**k(2)**	**k(3)**	**k(4)**	**k(5)**	**k(6)**
2000	1.08	0.22	0.31	0.40	0.18	-0.26
2001	1.01	0.15	0.07	0.39	0.09	0.03
2002	1.02	0.08	0.11	0.43	0.08	-0.13
2003	1.06	0.12	0.16	0.20	0.10	-0.05
2004	1.08	0.50	0.11	-0.07	0.19	0.01
2005	1.04	0.38	0.26	0.37	0.05	-0.10
2006	1.05	0.33	0.22	-0.03	0.28	-0.18
2007	1.04	0.33	0.18	0.26	0.17	-0.11
2008	1.03	0.33	0.24	0.25	0.13	-0.15
2009	0.92	0.09	0.16	0.21	0.04	-0.20
2010	1.04	-0.26	0.19	0.37	0.47	-0.11
2011	1.06	0.42	0.16	0.23	0.19	-0.11
2012	1.02	0.18	0.19	0.06	0.15	-0.07
2013	1.02	0.33	0.20	0.12	0.07	-0.04
2014	1.03	0.36	0.22	0.22	0.21	-0.12
2015	0.99	0.50	0.19	-0.12	0.21	-0.12

Panel B. Estimated coefficients for the 6-variable (full) forecasting model for expenses

*Exp(t+1) = k(1)*Exp(t) + k(2)*Ch(Exp(t)) + k(3)*Ch(OA(t)) + k(4)*Ch(OL(t)) + k(5)*Ch(FA(t)) + k(6)*Ch(FL(t))*						
Size Group	**k(1)**	**k(2)**	**k(3)**	**k(4)**	**k(5)**	**k(6)**
1 = small	1.02	-0.03	0.64	0.00	0.19	-0.22
	(113.41; 16)	(-2.21; 2)	(30.86; 16)	(-0.09; 9)	(12.29; 16)	(-7.84; 1)
2	1.03	0.05	0.55	0.08	0.21	-0.24
	(120.76; 16)	(2.30; 13)	(24.94; 16)	(2.63; 13)	(10.57; 16)	(-9.47; 0)
3 = big	1.03	0.13	0.40	0.02	0.28	-0.21
	(121.84; 16)	(3.22; 13)	(38.68; 16)	(0.37; 9)	(13.07; 16)	(-11.88; 0)
Year	**k(1)**	**k(2)**	**k(3)**	**k(4)**	**k(5)**	**k(6)**
2000	1.08	0.08	0.48	0.19	0.26	-0.29
2001	1.02	0.00	0.42	0.20	0.22	-0.13
2002	1.01	-0.02	0.42	0.17	0.24	-0.27
2003	1.06	0.06	0.41	-0.01	0.28	-0.24
2004	1.08	0.27	0.34	-0.26	0.29	-0.04
2005	1.05	0.25	0.38	0.14	0.16	-0.11
2006	1.05	0.21	0.39	-0.16	0.39	-0.24
2007	1.05	0.18	0.30	0.24	0.21	-0.20
2008	1.05	0.20	0.39	0.16	0.16	-0.26
2009	0.94	-0.19	0.41	0.04	0.18	-0.30
2010	1.03	-0.18	0.45	0.13	0.45	-0.19
2011	1.06	0.28	0.41	-0.09	0.31	-0.27
2012	1.03	0.13	0.39	-0.23	0.27	-0.19
2013	1.01	0.21	0.39	-0.12	0.25	-0.16
2014	1.03	0.21	0.38	0.11	0.35	-0.23
2015	0.99	0.36	0.38	-0.26	0.39	-0.26

Panel C. RAS for the 6-variable (full) models against the 4- and 2-variable models for forecasting sales and expenses

	versus 4-variable S and Exp models		***versus 2-variable S and Exp models***	
	S	**Exp**	**S**	**Exp**
Size Group	**6-variable model wins**	**6-variable model wins**	**6-variable model win**	**6-variable model win**
1 = small	52.3	52.3	53.5	52.2
	(0.00)	(0.00)	(0.00)	(0.00)
2	53.0	53.0	54.3	54.7
	(0.00)	(0.00)	(0.00)	(0.00)
3 = big	53.6	53.6	52.8	52.2
	(0.00)	(0.00)	(0.00)	(0.00)

Panel A. Estimated coefficients for the 6-variable (full) forecasting model for sales. Panel B. Estimated coefficients for the 6-variable (full) forecasting model for Exp(t+1) = S(t+1) – Earns(t+1). Theil–Sen method is used to estimate the load factors in each year. The upper half of each panel presents the (16 years) time-series means of the load factors. Fama-Macbeth (FM) statistics and the number of positive load factors within 16 years are LHS and RHS inside the parenthesis underneath. Panel C. Binomial test is performed for null = 50. Two-tail p-values are inside the parenthesis underneath. 2-variable model: *X(t+1) = k(1)*X(t) + k(2)*Ch(X(t))*, 4-variable model: *X(t+1) = k(1)*X(t) + k(2)*Ch(X(t))+Ch(FA(t)) + Ch(FL(t)), where X = {S, Exp}.*

Table 5. Estimation Coefficients for the Model Specifications B1 and B2

Panel A. Estimated coefficients for the 6-variable (full) forecasting model for returns on assets (ROA)

*ROA(t+1) = k(1)*ROA((t)) + k(2)*Ch(ROA(t)) + k(3)*Ch(OA(t))/ATA(t) + k(4)*Ch(OL(t))/ATA(t) + k(5)*Ch(FA(t))/ATA(t) + k(6)*Ch(FL(t))/ATA(t), where ATA(t) = [TA(t)+TA(t-1)]/2*

Size Group	**k(1)**	**k(2)**	**k(3)**	**k(4)**	**k(5)**	**k(6)**
1 = small	0.96	-0.06	-0.23	0.30	-0.06	0.16
	(40.20; 16)	(-6.56; 2)	(-10.28; 0)	(12.55; 16)	(-2.96; 3)	(7.65; 16)
2	0.83	-0.05	-0.09	0.17	-0.02	-0.01
	(56.10; 16)	(-4.11; 3)	(-6.10; 1)	(8.97; 16)	(-1.16; 6)	(-0.60; 6)
3 = big	0.93	-0.10	-0.05	0.13	-0.01	-0.02
	(57.15; 16)	(-6.43; 0)	(-5.67; 2)	(11.59; 16)	(-0.45; 7)	(-1.87; 5)
Year	**k(1)**	**k(2)**	**k(3)**	**k(4)**	**k(5)**	**k(6)**
2000	0.93	-0.09	-0.03	0.17	0.01	-0.05
2001	0.79	-0.06	-0.09	0.14	-0.05	0.04
2002	0.94	-0.16	-0.10	0.15	-0.03	-0.02
2003	0.92	-0.07	-0.03	0.16	0.02	-0.02
2004	0.94	0.00	0.02	0.08	0.09	-0.10
2005	0.92	-0.03	0.00	0.12	0.05	-0.06
2006	1.00	-0.08	-0.06	0.13	-0.05	-0.02
2007	0.95	-0.08	-0.02	0.05	0.03	-0.03
2008	0.91	-0.05	-0.05	0.15	0.00	0.01
2009	0.77	-0.17	-0.07	0.13	-0.04	0.00
2010	0.95	-0.20	-0.10	0.11	0.11	-0.08
2011	0.99	-0.04	-0.04	0.16	0.01	-0.02
2012	0.95	-0.08	-0.10	0.18	-0.08	0.02
2013	1.00	-0.20	-0.08	0.16	-0.09	0.00
2014	0.98	-0.18	-0.02	0.03	-0.02	0.00
2015	0.94	-0.10	-0.07	0.10	-0.06	0.03

Panel B. Estimated coefficients for the 6-variable (full) forecasting model for profit margin (PM)

*PM(t+1) = k(1)*PM(t) + k(2)*Ch(PM(t)) + k(3)*Ch(OA(t))/S(t-1) + k(4)*Ch(OL(t))/S(t-1) + k(5)*Ch(FA(t))/S(t-1) + k(6)*Ch(FL(t))/S(t-1)*

Size Group	**k(1)**	**k(2)**	**k(3)**	**k(4)**	**k(5)**	**k(6)**
1 = small	0.89	-0.05	-0.22	0.30	-0.09	0.13
	(33.81; 16)	(-5.66; 0)	(-10.74; 0)	(11.44; 16)	(-5.33; 2)	(6.91; 15)
2	0.81	-0.05	-0.07	0.16	-0.01	-0.01
	(43.64; 16)	(-3.99; 4)	(-5.83; 0)	(8.29; 16)	(-0.88; 5)	(-0.84; 8)
3 = big	0.95	-0.12	-0.03	0.09	0.01	-0.02
	(74.09; 16)	(-6.55; 0)	(-4.33; 2)	(9.06; 16)	(-0.95; 8)	(-2.07; 5)

Year	**k(1)**	**k(2)**	**k(3)**	**k(4)**	**k(5)**	**k(6)**
2000	0.96	-0.15	-0.01	0.12	0.02	-0.05
2001	0.83	-0.07	-0.07	0.10	-0.02	0.02
2002	0.99	-0.18	-0.09	0.14	-0.02	0.00
2003	0.93	-0.07	-0.01	0.12	0.04	-0.03
2004	0.96	-0.01	0.01	0.05	0.09	-0.07
2005	0.92	-0.05	0.02	0.07	0.06	-0.05
2006	0.98	-0.10	-0.03	0.10	-0.02	-0.02
2007	0.95	-0.09	0.00	0.02	0.05	-0.03
2008	0.90	-0.05	-0.03	0.09	0.01	0.01
2009	0.85	-0.19	-0.05	0.11	-0.01	0.00
2010	0.96	-0.24	-0.05	0.05	0.13	-0.10
2011	0.99	-0.04	-0.02	0.12	0.02	-0.02
2012	0.97	-0.12	-0.07	0.16	-0.05	0.01
2013	1.01	-0.24	-0.05	0.13	-0.05	0.00
2014	0.99	-0.19	-0.02	0.02	0.00	0.01
2015	0.97	-0.10	-0.05	0.09	-0.05	0.03

Panel C. RAS for the 6-variable (full) models against the 4- and 2-variable models without the accruals variables

	versus 4-variable ROA and PM models		***versus 2-variable ROA and PM models***	
Size Group	**ROA 6-variable model win**	**PM 6-variable model win**	**ROA 6-variable model win**	**PM 6-variable model win**
1 = small	52.1	51.2	52.8	51.5
	(0.00)	(0.00)	(0.00)	(0.00)
2	52.7	51.2	51.7	50.5
	(0.00)	(0.00)	(0.00)	(0.24)
3 = big	52.7	51.1	51.6	50.8
	(0.00)	(0.00)	(0.00)	(0.03)

Panel A. Estimated coefficients for the 6-variable (full) forecasting model for ROA(t+1) = Earns(t+1)/[TA(t+1) + TA(t)]/2. Panel B. Estimated coefficients for the 6-variable (full) forecasting model for PM(t+1) = Earns(t+1)/S(t+1). Theil–Sen method is used to estimate the load factors in each year. The upper half of each panel presents the (16 years) time-series means of the load factors. Fama-Macbeth (FM) statistics and the number of positive load factors within 16 years are LHS and RHS inside the parenthesis underneath. Panel C. Binomial test is performed for null = 50. Two-tail p-values are inside the parenthesis underneath. 2-variable model: *X(t+1) = k(1)*X(t) + k(2)*Ch(X(t))*, 4-variable model: *X(t) = k(1)*X(t-1) + k(2)*Ch(X, t-1) + Ch(FA, t-1) + Ch(FL, t-1), and X = {ROA, PM}.*

Table 6. Estimation Coefficients for the Model Specification C

Panel A. Estimated coefficients for the 6-variable (full) forecasting model for earnings

*Earns(t+1) = k(1)*Earns(t) + k(2)*Ch(Earns(t)) + k(3)*Ch(OA(t)) + k(4)*Ch(OL(t)) + k(5)*Ch(FA(t)) + k(6)*Ch(FL(t))*

Size Group	k(1)	k(2)	k(3)	k(4)	k(5)	k(6)
1 = small	0.93	-0.05	-0.27	0.31	-0.13	0.16
	(35.03; 16)	(-5.90; 2)	(-14.31; 0)	(15.32; 16)	(-8.05; 0)	(9.61; 16)
2	0.91	-0.04	-0.09	0.20	-0.03	0.00
	(46.18; 16)	(-3.01; 5)	(-4.64; 2)	(9.77; 16)	(-1.93; 5)	(-0.06; 8)
3 = big	1.00	-0.09	-0.01	0.11	0.04	-0.04
	(62.45; 16)	(-4.70; 2)	(-0.58; 8)	(9.30; 16)	(2.60; 11)	(-3.76; 2)
Year	**k(1)**	**k(2)**	**k(3)**	**k(4)**	**k(5)**	**k(6)**
2000	1.05	-0.10	0.02	0.17	0.06	-0.09
2001	0.89	-0.05	-0.12	0.19	-0.05	0.05
2002	1.01	-0.20	-0.06	0.16	0.03	-0.05
2003	0.99	-0.03	0.02	0.14	0.08	-0.05
2004	1.03	0.04	0.07	0.04	0.16	-0.12
2005	0.97	0.00	0.06	0.10	0.11	-0.08
2006	1.07	-0.07	0.00	0.11	0.02	-0.06
2007	1.01	-0.10	0.04	0.04	0.09	-0.06
2008	0.95	-0.02	0.00	0.13	0.04	-0.01
2009	0.83	-0.20	-0.05	0.12	0.00	-0.02
2010	1.02	-0.18	-0.05	0.09	0.17	-0.09
2011	1.05	-0.04	0.03	0.13	0.07	-0.06
2012	1.01	-0.10	-0.05	0.16	-0.02	0.00
2013	1.06	-0.21	-0.02	0.14	-0.04	-0.02
2014	1.04	-0.20	0.03	0.03	0.03	-0.02
2015	0.99	-0.06	-0.03	0.07	-0.04	0.01

Panel B. RAS for the 6-variable (full) models against the 4- and 2-variable models without the accruals variables

	versus 4-variable earnings model	***versus 2-variable earnings model***
Size Group	**6-variable wins**	**6-variable wins**
1 = small	53.2	53.5
	(0.00)	(0.00)
2	52.1	51.4
	(0.00)	(0.00)
3 = big	52.2	51.8
	(0.00)	(0.00)

Panel A. Estimated coefficients for the 6-variable (full) forecasting model for Earns(t+1). Theil–Sen method is used to estimate the load factors in each year. The upper half of each panel presents the (16 years) time-series means of the load factors. Fama-Macbeth (FM) statistics and the number of positive load factors within 16 years are LHS and RHS inside the parenthesis underneath. Panel B. Binomial test is performed for null = 50. Two-tail p-values are inside the parenthesis underneath. 2-variable model: *X(t+1) = k(1)*X(t) + k(2)*Ch(X(t))*, 4-variable model: *X(t+1) = k(1)*X(t) + k(2)*Ch(X(t)) + k(3)*Ch(FA(t)) + k(4)*Ch(FL(t)), and X = {Earns}.*

Table 7. Estimation Coefficients for the Model Specification using Ch(NOA)

Panel A. RAS for the 6-variable (full) models against other models that use Ch(NOA) for forecasting

Size Group	*versus 5-variable earnings model* 6-variable model wins	*versus 5-variable RAO model* 6-variable model wins	*versus 5-variable PM model* 6-variable model wins
1 = small	50.5	50.4	50.5
	(0.19)	(0.30)	(0.19)
2	51.8	52.2	51.8
	(0.00)	(0.00)	(0.00)
3 = big	52.4	51.2	51.3
	(0.00)	(0.00)	(0.00)

Panel B. Estimated coefficients for the 2-variable forecasting model for earnings

*Earns(t+1) = k(1)*Earns(t) + k(2)*Ch(NOA(t))*		
Size Group	**k(1)**	**k(2)**
1 = small	0.85	-0.12
	(32.55; 16)	(-10.46; 0)
2	0.93	-0.05
	(38.85; 16)	(-4.15; 1)
3 = big	1.06	-0.02
	(48.14; 16)	(-1.55; 6)
2000	1.12	0.00
2001	0.91	-0.04
2002	1.07	-0.06
2003	1.06	-0.01
2004	1.17	0.00
2005	1.12	0.02
2006	1.12	0.00
2007	1.06	0.01
2008	1.02	0.01
2009	0.83	-0.02
2010	1.12	-0.17
2011	1.13	-0.01
2012	1.04	-0.01
2013	1.07	-0.01
2014	1.04	0.02
2015	1.01	-0.01

Panel A. Binomial test is performed for null = 50. Two-tail p-values are inside the parenthesis underneath. Panel B. Estimated coefficients for the 2-variable forecasting model for earnings, defined as income before extraordinary items. Theil–Sen method is used to estimate the load factors in each year. The upper half of each panel presents the (16 years) time-series means of the load factors. Fama-Macbeth (FM) statistics and the number of positive load factors within 16 years are LHS and RHS inside the parenthesis underneath. *5-variable model: X(t+1) = k(1)*X(t) + k(2)*Ch(X(t)) + k(3)*Ch(NOA(t)) + k(4)*Ch(FA(t)) + k(5)*Ch(FL(t)) and X = {Earns}. Ch(NOA) = Ch(OA) – Ch(OL); ROA(t) = Earns(t)/[TA(t) + TA(t-1)]/2; PM(t) = Earns(t)/S(t)*

Table 8. Reversibility Tests

Panel A. Estimated coefficients for the forecasting model (specification M1) for Ch(OA(t+1))

*Ch(OA(t+1)) = k(1)*Ch(OA(t)) + k(2)*Ch(OL(t)) + k(3)*Ch(S(t)) + k(4)*Ch(Exp(t)) + k(5)*Ch(FA(t)) + k(6)*Ch(FL(t))*

Size Group	k(1)	k(2)	k(3)	k(4)	k(5)	k(6)
1 = small	0.27	-0.11	0.10	-0.04	0.16	-0.21
	(15.04; 16)	(-4.38; 2)	(5.82; 14)	(-1.72; 6)	(13.15; 16)	(-8.51; 0)
2	0.39	-0.06	0.16	-0.02	0.29	-0.30
	(8.09; 16)	(-1.92; 5)	(5.60; 14)	(-0.78; 6)	(8.22; 16)	(-10.00; 0)
3 = big	0.52	-0.11	0.30	-0.12	0.49	-0.31
	(11.79; 16)	(-1.84; 4)	(4.86; 15)	(-2.67; 3)	(11.73; 16)	(-7.26; 1)
2000	0.71	0.31	0.27	-0.12	0.61	-0.37
2001	0.31	-0.01	0.63	-0.49	0.31	-0.23
2002	0.48	-0.42	0.17	-0.06	0.64	-0.32
2003	0.54	0.31	0.10	-0.10	0.49	-0.50
2004	0.62	-0.16	0.43	-0.15	0.64	-0.40
2005	0.57	0.03	0.30	-0.12	0.36	-0.26
2006	0.50	-0.29	0.41	-0.08	0.55	-0.47
2007	0.62	-0.25	0.61	-0.27	0.33	-0.41
2008	0.45	-0.18	0.49	-0.28	0.39	-0.19
2009	0.06	-0.05	0.52	-0.43	0.16	0.03
2010	0.58	-0.34	-0.39	0.21	0.83	-0.51
2011	0.76	0.00	0.20	-0.03	0.60	-0.63
2012	0.45	0.14	0.32	-0.14	0.41	-0.11
2013	0.55	-0.16	0.26	-0.03	0.43	-0.21
2014	0.79	-0.52	0.22	0.10	0.63	-0.29
2015	0.41	-0.16	0.18	0.06	0.47	-0.14

Panel B. Estimated coefficients for the forecasting model (specification M2) for Ch(OL(t+1))

*Ch(OL(t+1)) = k(1)*Ch(OA(t)) + k(2)*Ch(OL(t)) + k(3)*Ch(S(t)) + k(4)*Ch(Exp(t)) + k(5)*Ch(FA(t)) + k(6)*Ch(FL(t))*						
Size Group	**k(1)**	**k(2)**	**k(3)**	**k(4)**	**k(5)**	**k(6)**
1 = small	0.05	-0.11	0.01	0.02	0.02	-0.04
	(8.63; 16)	(-7.15; 0)	(0.78; 9)	(3.32; 14)	(5.55; 14)	(-3.00; 3)
2	0.10	-0.05	0.00	0.05	0.07	-0.09
	(7.30; 16)	(-2.41; 5)	(0.30; 8)	(4.05; 11)	(5.19; 15)	(-6.20; 0)
3 = big	0.14	0.00	0.04	0.03	0.15	-0.11
	(7.70; 16)	(-0.05; 8)	(1.67; 13)	(1.89; 10)	(7.90; 16)	(-5.62; 1)
2000	0.16	0.16	0.03	0.03	0.14	-0.06
2001	0.06	-0.08	0.08	-0.02	0.06	-0.03
2002	0.17	-0.25	-0.17	0.20	0.26	-0.19
2003	0.16	0.27	0.01	-0.03	0.19	-0.19
2004	0.16	0.08	0.14	0.00	0.21	-0.17
2005	0.14	0.21	0.06	0.02	0.12	-0.15
2006	0.10	-0.14	0.13	0.03	0.16	-0.15
2007	0.11	0.10	0.16	-0.02	0.07	-0.07
2008	0.20	-0.22	0.12	-0.02	0.08	-0.10
2009	0.01	-0.16	0.11	-0.04	0.03	0.02
2010	0.17	-0.04	-0.20	0.11	0.31	-0.22
2011	0.22	0.18	0.04	0.03	0.20	-0.24
2012	0.06	0.19	0.10	-0.04	0.10	-0.01
2013	0.07	0.01	0.05	0.06	0.12	-0.03
2014	0.29	-0.33	0.06	0.08	0.19	-0.15
2015	0.09	-0.02	-0.04	0.12	0.15	-0.05

Panel C. Percentages of up-ticks (+ve) and down-ticks (-ve) by consecutive-period changes in OA per individual size group in all years (pooled)

				Size Group						
		1 = small			**2**			**3 = big**		
		Ch(OA, t+1)			**Ch(OA, t+1)**			**Ch(OA, t+1)**		
IG Group	**Ch(OA, t)**	+ve	-ve	**Phi**	+ve	-ve	**Phi**	+ve	-ve	**Phi**
1 = low	+ve	6.6	10.4	0.08	10.6	9.2	0.09	12.7	7.2	0.12
	-ve	24.3	58.7		33.7	46.4		39.0	41.1	
2	+ve	19.8	21.6	0.08	27.6	18.1	0.10	34.4	16.2	0.14
	-ve	23.4	35.1		27.5	26.7		26.8	22.6	
3	+ve	37.5	29.1	0.09	49.8	22.9	0.11	62.1	17.5	0.12
	-ve	15.8	17.7		15.6	11.7		13.4	7.0	
4	+ve	45.4	34.3	0.07	62.3	22.4	0.10	73.5	16.9	0.07
	-ve	9.7	10.6		9.3	5.9		6.9	2.7	
5 = high	+ve	43.0	39.2	0.06	63.8	25.9	0.07	74.4	19.9	0.06
	-ve	8.0	9.8		6.2	4.2		3.9	1.9	

Panel D. Percentages of up-ticks (+ve) and down-ticks (-ve) by consecutive-period changes in OL per individual size group in all years (pooled)

		Size Group								
		1 = small			2			3 = big		
		Ch(OL, t+1)			Ch(OL, t+1)			Ch(OL, t+1)		
IG Group	Ch(OL, t)	+ve	-ve	**Phi**	+ve	-ve	**Phi**	+ve	-ve	**Phi**
1 = low	+ve	14.7	18.1	-0.01	18.0	14.6	0.01	17.3	12.8	0.01
	-ve	31.1	36.0		36.1	31.2		39.7	30.3	
2	+ve	25.9	22.7	-0.03	31.4	19.7	-0.01	40.0	17.8	0.03
	-ve	28.8	22.5		30.7	18.2		28.1	14.1	
3	+ve	37.8	27.0	-0.03	47.1	22.9	0.02	58.3	18.6	0.04
	-ve	21.5	13.7		19.7	10.3		16.6	6.5	
4	+ve	39.8	34.1	-0.02	54.4	25.7	-0.01	67.0	19.9	0.03
	-ve	14.8	11.3		13.7	6.2		9.6	3.5	
5 = high	+ve	40.4	36.9	-0.01	55.9	29.1	0.01	69.2	23.3	0.01
	-ve	12.2	10.4		9.8	5.3		5.5	2.0	

Panel A. Estimated coefficients for the forecasting model (specification M1) for Ch(OA(t+1)). Panel B. Estimated coefficients for the forecasting model (specification M2) for Ch(OL(t+1)). Theil–Sen method is used to estimate the load factors (coefficients) in each year. The upper half of each panel presents the (16 years) time-series means of the load factors. Fama-Macbeth (FM) statistics and the number of positive load factors within 16 years are LHS and RHS inside the parenthesis underneath. Panel C. The 2x2 matrix of the upticks (+ve) and downticks (-ve) by Ch(OA) in consecutive years in all years (pooled). Panel D. The 2x2 matrix of the upticks (+ve) and downticks (-ve) by Ch(OA) in consecutive years in all years (pooled). IG(t+1) is defined as the average of growth in total assets and growth in sales = 0.5*[TA(t+1)/TA(t) + S(t+1)/S(t)]. Sample firms are put into one of five equally-partitioned bins based the firms' IG measures in each year. The same procedure is applied to the individual size groups.

Table 9. Estimation Coefficients for the Cash Earnings Model

Estimated coefficients for the 6-variable (full) forecasting model for cash earnings

*C_Earns(t+1) = k(1)*C_Earns(t) + k(2)*Ch(C_Earns(t)) + k(3)*Ch(OA(t)) + k(4)*Ch(OL(t)) + k(5)*Ch(FA(t)) + k(6)*Ch(FL(t))*

Size Group	**k(1)**	**k(2)**	**k(3)**	**k(4)**	**k(5)**	**k(6)**
1 = small	0.79	-0.04	0.16	-0.36	-0.34	0.34
	(23.16; 16)	(-3.01; 6)	(8.07; 16)	(-18.20; 0)	(-15.73; 0)	(12.06; 16)
2	0.79	-0.05	0.16	-0.38	-0.34	0.28
	(35.15; 16)	(-4.48; 2)	(6.77; 15)	(-9.87; 0)	(-14.16; 0)	(8.83; 16)
3 = big	0.77	-0.08	0.21	-0.36	-0.27	0.16
	(31.56; 16)	(-6.42; 1)	(10.15; 16)	(-11.47; 0)	(-12.34; 0)	(6.26; 15)
Year	**k(1)**	**k(2)**	**k(3)**	**k(4)**	**k(5)**	**k(6)**
0.69	-0.04	0.17	-0.63	-0.36	0.17	0.69
0.61	0.00	0.06	-0.32	-0.38	0.42	0.61
0.79	-0.04	0.22	-0.30	-0.28	0.14	0.79
0.67	-0.02	0.25	-0.41	-0.18	0.15	0.67
0.77	-0.09	0.20	-0.23	-0.22	0.14	0.77
0.77	-0.13	0.24	-0.20	-0.08	-0.06	0.77
0.71	-0.17	0.15	-0.28	-0.26	0.10	0.71
0.64	-0.07	0.06	-0.21	-0.22	0.28	0.64
0.85	-0.08	0.31	-0.42	-0.28	0.15	0.85
0.76	-0.02	0.33	-0.38	-0.27	0.23	0.76
0.83	-0.09	0.26	-0.39	-0.20	0.10	0.83
0.84	-0.12	0.17	-0.34	-0.25	0.26	0.84
0.79	-0.17	0.14	-0.28	-0.25	0.08	0.79
0.74	-0.07	0.21	-0.27	-0.29	0.13	0.74
0.98	-0.11	0.25	-0.56	-0.39	0.18	0.98
0.91	-0.13	0.34	-0.51	-0.43	0.16	0.91

Estimated coefficients for the 6-variable (full) forecasting model for cash earnings, C_Earns(t+1) = Earns(t+1) – Ch(NOA(t+1)). Theil–Sen method is used to estimate the load factors in each year. The upper half of each panel presents the (16 years) time-series means of the load factors. Fama-Macbeth (FM) statistics and the number of positive load factors within 16 years are LHS and RHS inside the parenthesis underneath.