Why do accruals predict earnings?

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Abstract

We argue that competition in product markets, rather than measurement error in accruals or diminishing marginal returns from investment, explains why accruals are less persistent than cash flows. High accruals predict a long-lasting drop in profits and profitability—arising from disproportionate growth in both cost of goods sold and selling, general, and administrative expense—that is consistent with the hypothesis that accruals correlate with changes in input prices, demand, or competition. While accruals contain a transitory component, this component is far too small to explain, quantitatively, the observed decline in profits. In addition, the small transitory component of accruals comes from changes in current operating liabilities, not from reversals in accounts receivable or inventory.

1. Introduction

A large empirical literature finds that accruals are less persistent than cash flows, i.e., conditional on earnings today, firms with higher accruals tend to be less profitable in the future. This finding is important for valuation and a wide range of issues in accounting: Do firms use accruals to manage earnings? Do large positive or negative accruals reflect the economic conditions of the firm or signal information about the firm's earnings quality? Do accrual reversals explain the negative relation between accruals and subsequent stock returns first documented by Sloan (1996)?

The literature considers two main explanations for the low persistence of accruals. The first is that accruals contain transitory measurement error that inflates today's earnings at the expense of future profits (Sloan 1996; Xie 2001; Dechow and Dichev 2002; Richardson et al. 2005, 2006; Chan et al. 2006; Dechow et al. 2012; Allen, Larson, and Sloan 2013). The second is that accruals are closely linked to investment and predict lower future profitability because of diminishing marginal returns, adjustment costs associated with investment, or conservatism in accounting (Fairfield, Whisenant, and Yohn 2003a,b; Zhang 2007; Dechow, Richardson, and Sloan 2008; Wu, Zhang, and Zhang 2010).

Our paper provides new evidence on the predictive power of accruals that challenges both explanations above. We argue that product market effects—changes in the demand for a firm's products or its production costs—can explain the link between accruals and subsequent profitability better than either the measurement error or investment hypotheses.

A central theme of the paper is that a variety of economic forces could explain the predictive power of accruals and that we cannot measure what accruals 'should' be, or assess the implications of accrual errors, without a careful analysis of the firm's economic environment. More to the point, we offer several new economic-based explanations for the link between accruals and subsequent profits: (i) Accruals might respond to changes in a firm's production costs before the changes have a significant impact on earnings; for example, a jump in input prices could show up as higher inventory costs on the balance sheet before fully hitting cost of goods sold

(COGS) and earnings in the following year (the 'cost shock' hypothesis). (ii) High accruals might predict low earnings in the short run if investment takes time to pay off, raising costs more quickly than revenues (the 'time-to-build' hypothesis). (iii) A firm that earns high profits today is likely to grow, have high accruals, and attract new competition from other firms, the latter of which could lead to lower subsequent profits (the 'market pressure' hypothesis). In short, the predictive power of accruals is potentially consistent with a range of economic phenomena.

To distinguish among the different hypotheses, we carefully lay out what each implies not only about the relation between accruals and next year's earnings—the typical focus of the literature—but also about the behavior of subsequent sales, expenses (COGS, SG&A, etc.), and accruals, over both short and long horizons. We argue that, while the theories predict a similar relation between accruals and next year's profitability, they predict different patterns in long-run earnings and the evolution of future sales, expenses, and accruals. The behavior of those variables provides a powerful way to discriminate among the different hypotheses and a rich picture of the economics underlying the predictive power of accruals.

Our empirical tests yield several key insights. First, we show that the negative relation between accruals and subsequent profitability is driven by an actual drop in profits, not just an increase in assets, contrary to one of the central predictions of the investment hypothesis (and the results of FWY 2003b). Moreover, the decline in profits following high accruals appears to be permanent, in the sense that the relation between accruals and subsequent profits is as strong in years t+2 through t+7 as in year t+1. Thus, we find no evidence that transitory measurement error leads to a temporary drop in profits or that transitory investment effects associated with accruals are followed by longer-term growth in profits.

Second, we show that high accruals predict rapid sales growth and even faster growth in expenses. Controlling for current earnings, a dollar of working-capital accruals is associated with \$0.59 of additional sales and \$0.74 of additional expenses in the following year (the spread between the two numbers, -\$0.14, is the slope on accruals in an earnings predictability regression). The disproportionate growth in expenses is driven equally by disproportionate growth in both COGS and SG&A. Our results suggest that high accruals are *not* indicative of struggling firms—indeed, sales growth of high-accrual firms is nearly as high in year t+1 as it is in year t—and that a general increase is costs, rather than a spike in a particular component of expenses (e.g., inventory write-downs) explains why accruals are negatively associated with subsequent profits. The results also imply that next year's sales growth explains significant variation in current accruals, a factor generally omitted from models of nondiscretionary accruals (e.g., Jones 1991; Dechow, Sloan, and Sweeney 1995).

Third, we find that, while accruals do contain a transitory component, this component is far too small to explain the negative relation between accruals and subsequent earnings. In addition, the transitory component of accruals does not come from reversals in accounts receivable (AR) or inventory but from two effects that do not seem to be attributable to measurement error: (i) High accruals today predict a significant increase in current operating liabilities next year; and (ii) accounts payable, typically regarded as one of the most reliable types of accruals, contains a large transitory component. Our tests show that accruals predict subsequent growth in AR and inventory that almost exactly matches, quantitatively, what we would expect given the behavior of sales, again contrary to the argument that reversals associated with either AR or inventory explain the subsequent drop in profits.

Overall, our results provide a detailed picture of why accruals are negatively related to a firm's subsequent profits and profitability. The long-term drop in earnings, despite growth in sales and commensurate growth in accruals, suggests that production costs rise or output prices decline following high accruals. The evidence is hard to reconcile with the measurement error or investment hypotheses but is consistent with the idea that profits and accruals are jointly driven by the dynamics of supply and/or demand.[1]

The remainder of the paper is organized as follows: Section 2 reviews the literature and summarizes different explanations for the low persistence of accruals; Section 3 describes our tests; Section 4 describes the data and Section 5 presents our main empirical results; Section 6 concludes.

[1] To be clear, our paper does not say that accrual measurement errors and diminishing marginal returns do not exist; our point is only that neither explains the predictive power of accruals observed in the data.

2. Background and hypotheses

The literature proposes several explanations for the low persistence of accruals, focusing primarily on the role of measurement error and investment. We review the literature below and offer several new hypotheses. We discuss what each theory implies about the relation between accruals and subsequent sales, expenses, and accruals, emphasizing how their predictions overlap and differ.

2.1. Measurement error

In his seminal study, Sloan (1996) argues that accruals might contain transitory measurement error that reduces the persistence of accruals relative to cash flows. Richardson et al. (2005) formalize this idea in the context of the persistence regressions popular in the literature, but the basic logic is simple: If accruals contain transitory measurement error, high accruals are a sign that earnings are inflated and will likely drop in the future. Building on this intuition, Xie (2001) and Richardson et al. (2005, 2006) find that discretionary, less reliable, and non-growth accruals are the least persistent components of accruals, while Dechow and Dichev (2002) and Allen, Larson, and Sloan (2013) argue that accrual estimation errors and reversals are significant empirically (see also Moehrle 2002; Chan et al. 2006; Baber, Kang, and Li 2011; Dechow et al. 2012). A similar idea motivates the large and growing literature on earnings management and earnings quality (e.g., Dechow, Ge, and Schrand 2010).

An important but largely untested prediction of the measurement-error hypothesis is that the relation between accruals and future earnings should be closely tied, quantitatively, to accrual reversals. For example, if high accruals signal that inventory is temporarily inflated, we should find that (i) high accruals predict a subsequent reversal in inventory accruals, and (ii) these reversals should be large enough to explain a spike in COGS and the observed decline in earnings.

The measurement-error hypothesis also implies that accruals should predict earnings more strongly in the short run than in the long run. High accruals signal not only that today's earnings are overstated but also that future earnings will be temporarily *understated* when measurement error reverses, after which earnings should partially bounce back. For example, suppose a firm's true economic earnings will be $100 per year in perpetuity. If the firm overstates accruals and earnings by $10 this year at the expense of next year's profits, today's reported earnings will be $110, next year's reported earnings will be $90, and earnings thereafter are expected to be $100 (in the absence of subsequent mischief). This pattern—a strong short-run drop in earnings followed by a partial rebound—should be observable by looking at the long-term behavior of earnings. Since measurement error could be persistent and take more than one year to reverse, we study horizons out to seven years to give the rebound effect a fair chance of showing up in earnings. Also, many of our tests focus on working-capital accruals that should reverse quickly.

2.2. Investment

Fairfield, Whisenant, and Yohn (FWY 2003a) observe that accruals are closely linked to growth and might correlate negatively with subsequent profitability because of diminishing marginal returns from investment or conservatism in accounting. Wu, Zhang, and Zhang (2010) show that adjustment costs related to investment could also induce a negative relation between accruals and subsequent profitability.

The investment hypothesis differs from the measurement-error hypothesis in a number of ways. As noted by FWY (2003b), if investment drives the predictive power of accruals, high accruals should predict a drop in profitability but not in profits. Put differently, accruals should be negatively associated with future ROA—the dependent variable typically used in the literature—because they are associated with an increase in the denominator rather than a decrease in the numerator. This prediction requires only the weak assumption that profits are increasing in total capital (e.g., Wu, Zhang, and Zhang 2010).

Of course, investment could reduce profits in the short run if projects take time to pay off, an idea we label the 'time-to-build' hypothesis. For example, a new factory might have negative margins for a few years even if it is expected to be profitable in the long run. If this effect explains the predictive power of accruals, the negative relation between accruals and earnings should weaken and eventually reverse when we study the long-run behavior of earnings. Again, we look at forecast horizons of up to seven years to give any temporary investment effects a reasonable chance of being observable.

2.3. Cost shocks

A third potential explanation for the predictive power of accruals is that accruals could reflect changes in production costs before the changes hit COGS and profits, an idea we label the 'cost shock' or 'canary-in-the-coal-mine' hypothesis. For example, suppose production costs rise toward the end of the year because of a jump in input prices. The increase could quickly affect inventory costs, resulting in high working-capital accruals, but would not significantly affect profits until the following year.

The cost-shock hypothesis makes different empirical predictions than the measurement-error or investment hypotheses: If cost shocks are important, high accruals would simultaneously predict higher revenues but lower profits, assuming that cost shocks are only partially passed on to customers (consistent with downward-sloping demand curves). In addition, if cost shocks are permanent, high accruals should predict a long-lasting decline in profits and a permanent increase in inventory. In this case, high accruals should have little, or even positive, predictive power for future accruals, in contrast to the reversals expected under the measurement-error hypothesis.

2.4. Market pressure

Product market competition might also explain why accruals negatively predict profits. One possibility is that firms sell differentiated products and can earn temporary abnormal profits because of product innovation or an increase in demand. When this happens, the firm should grow—sales, working capital, and long-term assets would all increase—but will also attract new competition that would be expected to reduce subsequent profit margins. It follows that high accruals today might predict a profit decline in the future as margins are driven down by new competition.

Even in perfectly competitive markets, an increase in demand can lead to abnormal profits in the short run but would induce growth, entry, and a return to normal profits in the long run. Again, this suggests that high accruals might predict high sales growth but lower profitability and profits. Like the cost-shock hypothesis, the market-pressure hypothesis suggests that high accruals should have little or even positive predictive power for future accruals.

2.5. Demand shocks

A related explanation, suggested by Thomas and Zhang (2002), is that unexpected demand shocks can induce short-run changes in inventory that precede changes in profits (see also Dechow, Kothari, and Watts 1998). The idea is that a spike in demand toward the end of the year should reduce inventory but might not show up fully in profits until the subsequent year.

This hypothesis, like our earlier cost-shock hypothesis, is predicated on the idea that inventory reacts quickly to fundamentals. An important difference, however, is that inventory changes caused by unexpected demand shocks should reverse rapidly as the firm adjusts production to meet demand, while the cost-shock hypothesis predicts a long-lasting change. The demand-shock story also suggests that inventory accruals should be negatively associated with subsequent sales growth.

3. Empirical design

Our tests are designed to distinguish among the hypotheses above. We exploit the fact that, while all of the hypotheses imply that accruals are negatively related to a firm's subsequent profitability, they make different predictions about the long-run behavior of profits and the evolution of future sales, expenses, and accruals. We describe our tests in this section.

Our analysis builds on the persistence regressions that are standard in the literature:

$$ROA_{t+1} = b_0 + b_1\, ROA_t + b_2\, ACC_t + e, \tag{1}$$

where ROA_t and ACC_t are earnings and accruals, respectively, divided by average total assets in year t. This regression simply asks whether accruals help to predict subsequent profitability after controlling for current profitability. As noted in the literature (e.g., FWY 2003a), an equivalent regression could be estimated using cash flow (CF_t) as an independent variable in place of ROA_t:

$$ROA_{t+1} = c_0 + c_1\, CF_t + c_2\, ACC_t + e. \tag{2}$$

Because $CF_t = ROA_t - ACC_t$, the slope on ROA_t in eq. (1) is the same as the slope on CF_t in eq. (2), while the slope on ACC_t in eq. (1) equals $c_2 - c_1$. Thus, in the first regression, b_1 captures the persistence of cash flow and b_2 captures the differential persistence of accruals.

The hypotheses in Section 2 all imply that accruals are less persistent than cash flows ($b_2 < 0$) but make distinct predictions about the long-run behavior of profits, sales, expenses, and accruals. We test these predictions by extending the persistence regression in several ways:

Profits vs. profitability. Our first extension is to replace the dependent variable in eq. (1) with earnings in year t+1 divided by average total assets in year t, NI_{t+1}/TA_t, that is, we scale all variables on both sides of the regression by the same asset value:

$$NI_{t+1}/TA_t = d_0 + d_1\, ROA_t + d_2\, ACC_t + e. \tag{3}$$

Deflating all variables by a common scalar removes the impact of asset growth on the dependent variable and, as noted by FWY (2003b), implies that eq. (3) tells us about the predictive power of accruals for future *profits* rather than future *profitability*. This specification can also be interpreted as testing whether accruals predict changes in profits. Specifically, suppose we instead measure the dependent variable as the year-to-year change in earnings, $dNI_{t+1} = NI_{t+1} - NI_t$, divided by TA_t:

$$dNI_{t+1}/TA_t = e_0 + e_1\, ROA_t + e_2\, ACC_t + e. \tag{4}$$

This regression is equivalent to eq. (3) except that the slope on ROA_t drops by one ($e_1 = d_1 - 1$ and $e_2 = d_2$). Thus, the slope on ACC_t in either eq. (3) or (4) tells us whether accruals predict a change in profits controlling for today's earnings. The investment hypothesis predicts this slope will be positive, while the other hypotheses are all consistent with a negative slope.

Long horizons. Our second extension is to expand the forecast horizon for up to seven years, replacing the dependent variable with ROA_{t+k}, NI_{t+k}/TA_t, or dNI_{t+k}/TA_t, for k = 1, 2, …, 7. The goal, as discussed in Section 2, is to test whether the relation between accruals and subsequent earnings reverses over long horizons. (The specification using earnings changes is especially useful because it provides a detailed view of the year-to-year evolution of earnings.) The measurement error, time-to-build, and demand shock hypotheses imply that the predictive power of accruals should weaken or reverse over long horizons, while the cost shock and market pressure hypotheses are consistent with a permanent drop in profits and profitability.

Earnings components. Our third extension is to break future earnings (the dependent variable) into sales, COGS, SG&A, and other expenses in order to explore the behavior of sales and to test whether a particular type of expense drives profits. Because $NI_{t+k} = Sales_{t+k} - COGS_{t+k} - SGA_{t+k} - OthExp_{t+k}$, the slopes when the four variables on the right are regressed on ROA_t and ACC_t mechanically sum to the slope when earnings is regressed on ROA_t and ACC_t. We focus on specifications using changes in the variables (e.g., $dSales_{t+k}/TA_t$) to test whether accruals predict growth in sales and expenses. This choice also side-steps issues related to the high persistence in the levels of sales, COGS, and SG&A.

These regressions do not provide an explicit test of the hypotheses in Section 2, but they shed light on whether accruals' predictive power can be traced to a particular component of expenses. For example, inventory is sometimes viewed as a key source of measurement error, in which case we would expect accruals to predict a significant jump in COGS.

An important complication is that accruals are positively related to future sales, so it should not be surprising that accruals also predict higher expenses. The interesting question is whether expenses grow *abnormally* fast, given the growth in sales. One way to answer this question is to use profit margins as a benchmark for the growth in expenses. For example, if sales grow by \$100 and COGS-to-sales is typically 0.70, we would expect COGS to grow by \$70 unless accruals are associated with an abnormal increase in COGS. A second way to test whether expenses grow abnormally fast is to control directly for future sales growth in the expense regressions. For example, to analyze changes in COGS, we can estimate the regression

$$dCOGS_{t+k}/TA_t = f_0 + f_1\, ROA_t + f_2\, ACC_t + f_3\, (dSales_{t+k}/TA_t) + e. \quad (5)$$

The slope on ACC_t in this regression directly measures whether accruals predict abnormal growth in COGS controlling for future sales growth (and current profitability).

Future accruals. Our fourth extension is to use future accruals in place of future earnings as the dependent variable (scaled by either TA_{t+k} or TA_t):

$$ACC_{t+k} = g_0 + g_1 ROA_t + g_2 ACC_t + e. \tag{6}$$

The basic goal here is to test whether accruals reverse ($g_2 < 0$). Moreover, by keeping the regression specification the same as the persistence regression, we can *quantitatively* assess whether accrual reversals are sufficient to explain earnings predictability: Is the slope on accruals in eq. (6) large enough to explain the slope on accruals in eq. (1)? Note, however, that the same complication discussed above with respect to expenses arises here: Given that ACC_t is positively related to subsequent sales growth, it should also be positively related to subsequent accruals in the absence of any transitory measurement error. The interesting question is whether the behavior of accruals is abnormal, conditional on sales growth. We address this issue in the same way described above for expenses, either using the average accrual-to-sales ratio as a benchmark or controlling directly for sales growth in the regressions. The measurement error and demand-shock hypotheses imply that the slope on ACC_t should be negative and, in the case of measurement error, comparable to the slope on accruals in the persistence regression.

Accrual components. Our final extension is to break working capital into current operating assets and current operating liabilities or, more finely, into AR, inventory, AP, and other current assets and liabilities. The goal is to understand (i) which components have predictive power (used as independent variables), and (ii) which components exhibit reversals (used as dependent variables). The combination of the two allows us to test in a very detailed way whether the behavior of accruals matches the predictions of the measurement-error hypothesis. For example, we can test whether inventory accruals not only predict subsequent earnings but also whether they predict inventory reversals and a spike in COGS.

4. Data

Our primary source of data is the Compustat annual file. The sample incudes all nonfinancial firms that have data for net income, total accruals, sales, COGS, SG&A expense, and average total assets (nonfinancial firms are identified using historical SIC codes from the Center for Research in Security Prices (CRSP)). In addition, we require firms to have beginning-of-year market value on CRSP to ensure that all firms are publicly traded.

Our tests start in 1970, the first year that more than 1,000 firms have data for all of the variables we consider, including the components of accruals. The final sample has an average of 3,458 firms per year from 1970–2012, for a total sample of 148,686 firm-years.

Our tests require data on a firm's earnings, sales, expenses, and accruals. The variables are defined as follows:

NI	= net income,
Sales	= net revenue,
COGS	= cost of goods sold,
SGA	= selling, general, and administrative expense,
OthExp	= other expenses (Sales – COGS – SGA – NI),
COA	= current operating assets (current assets – cash),
COL	= current operating liabilities (current liabilities – short-term debt)
NWC	= net working capital (COA – COL),
LTNOA	= long-term net operating assets (total assets – current assets – nondebt long-term liabilities),
AR	= accounts receivable,
Invent	= inventory,
AP	= accounts payable.

Year-to-year changes in the variables are labeled with a lowercase 'd'. Thus, dNWC measures working-capital accruals and dLTNOA measures long-term operating accruals.

Following the convention in the literature, we deflate all income and accrual variables by average total assets during the year (defined as the average of starting and ending asset value). The only exception is that, as described earlier, the dependent variable in some regressions is scaled by average total assets from the year the predictor variables are measured (e.g., NI_{t+k}/TA_t) rather than the contemporaneous value of average total assets (e.g., NI_{t+k}/TA_{t+k}). The scaled variables are then winsorized annually at their 1st and 99th percentiles to reduce the impact of outliers.

Table 1 reports descriptive statistics for the sample. Sales for the average firm are about a third greater than assets while bottom-line ROA is slightly negative (-2%). COGS averages 93% of assets (69% of sales), SGA averages 34% of assets (25% of sales), and other expenses average 10% of assets (8% of sales). Net working capital is typically positive (19% of assets) because current operating assets (40% of assets) are roughly twice as large as current operating liabilities (21% of assets). AR and inventory make up the bulk of COA, while AP is roughly half of COL. Firm growth is reflected in working-capital accruals (dNWC) that average 1% of assets and long-term accruals (dLTNOA) that average 3% of assets. Both types of accruals are highly variable, with cross-sectional standard deviations of 10% and 16%, respectively.

Table 2 shows that annual changes in most income statement and balance sheet accounts are positively correlated with each other. dSales is especially highly correlated with dCOGS (0.91), dSGA (0.55), and dCOA (0.58) but only weakly correlated with dNI (0.15). dCOA and dCOL also move up and down together, with a correlation of 0.56. As a result, dNWC is less volatile than dCOA by itself (see Table 1) and only slightly negatively correlated with dCOL. Long-term accruals have a relatively weak correlation with dNWC (0.11) but a somewhat stronger correlation (0.23–0.27) with the individual components of working-capital accruals (dAR, dInvent, and dAP).

5. Results

Our tests proceed along the lines described in Section 3. We extend the persistence regressions common in the literature to study the link between accruals and subsequent sales, expenses, and accruals, over both short and long horizons. The goal is to understand better the economics underlying the predictive power of accruals and to distinguish between the hypotheses laid out in Section 2.

Our analysis focuses on slopes from annual Fama-MacBeth (1973) cross-sectional regressions; t-statistics are based on the time-series variability of the estimates, incorporating a Newey-West correction with three lags to account for possible autocorrelation in the slopes.

5.1. Predicting profits and profitability

To begin, Table 3 reports standard persistence regressions, with two key twists: (i) We extend the forecast horizon out to five years to test for both short-term and long-term predictability in earnings, and (ii) we test whether accruals predict both profitability and profits.

The first column of Panel A, using ROA_{t+1} as the dependent variable, confirms the results in prior studies:

ROA is highly persistent but, controlling for current ROA, working-capital and long-term accruals are both strongly negatively related to subsequent ROA. At the one-year horizon, the slopes on dNWC (-0.12) and dLTNOA (-0.11) are nearly identical and more than nine standard errors below zero. The results imply that accruals are significantly less persistent than cash flows.

The slopes remain highly significant over longer horizons and, in the case of working-capital accruals, actually become more negative as the horizon grows (out to t+3), despite the fact that the persistence slope on ROA_t itself drops in magnitude (the slope declines from 0.73 at the one-year horizon to 0.45 at the five-year horizon). In short, controlling for current profitability, higher accruals predict lower subsequent profitability for many years into the future.

In Panel B, we deflate the dependent variable, NI_{t+k}, by assets in year t (rather than t+k) in order to remove the impact of asset growth on the dependent variable, i.e., we test whether accruals predict not only profitability but also profits. In fact, accruals strongly predict profits: Controlling for current earnings, a dollar of working-capital accruals is associated with $0.14 lower profits next year and even lower profits in each of the subsequent four years, peaking at a decline of $0.18 by year t+3. (In untabulated tests, the slopes for years t+6 and t+7 are also significant and slightly larger in magnitude than the slope for year t+5.) The predictive slopes on dLTNOA are similar, starting at -0.16 for one-year-ahead profits and ranging from -0.14 to -0.17 in years t+2 through t+5. Thus, short-term and long-term accruals are both associated with an immediate and long-lasting decline in profits.[2]

Economically, the evidence in Table 3 is hard to reconcile with either the measurement error or investment hypothesis popular in the literature. Perhaps most obviously, the strong (and long-lasting) negative relation

[2] These results contrast with those of FWY (2003b), who find that working-capital accruals predict profitability but not profits. The source of the discrepancy is hard to pin down precisely because our tests differ in many ways. For example, FWY use net operating assets (NOA) at the beginning of year t as the scaling variable rather than average total assets; they drop NASDAQ firms and firms with NOA less than $1 million from the sample; and their tests end in 1993 (their sample has 35,083 firm-years compared with 148,686 firm-years in our paper). We have not replicated FWY's tests exactly, but we do note that our findings are quite robust. For example, the slope on dNWC in the first column of Panel B (-0.14) remains significantly negative if our sample ends in 1993 (-0.13); if we drop NASDAQ stocks (-0.08); if we exclude dLTNOA from the regressions (-0.15); if we use operaring earnings in place of net income (-0.11); or if we scale the variables by average NOA in year t (-0.19) or NOA at the start of year t (-0.21).

between accruals and subsequent profits in Panel B directly contradicts a central prediction of the investment hypothesis, that the decline in ROA following high accruals reflects diminishing marginal returns from asset growth (an increase in the denominator of ROA_{t+k}) rather than an actual drop in profits (see FWY 2003a,b; Wu, Zhang, and Zhang 2010). The slopes for profits in Panel B are, in fact, larger in magnitude than the slopes for profitability in Panel A.

The results also present a challenge to the measurement-error hypothesis. As discussed earlier, if measurement error explains the predictive power of accruals, accruals should predict a short-run decline in profits followed by a partial rebound once measurement error works its way through earnings (i.e., earnings in the short run should be temporarily understated as accruals reverse). Panel B shows, however, that the decline in profits following high accruals is actually stronger in years t+2 through t+5 than in year t+1, with no evidence of a significant rebound at any horizon (including in years t+6 and t+7). This long-lasting decline seems hard to reconcile with measurement error but is broadly consistent with the idea that accruals capture the impact of changes in demand or supply on a firm's profitability and profits.

5.2. Predicting sales and expenses

To further explore the dynamics driving profits and accruals, Table 4 studies the link between accruals and subsequent sales and expenses. The tests maintain the structure of persistence regressions but break the dependent variable into sales, COGS, SG&A, and other expenses. Because $NI_{t+k} = Sales_{t+k} - COGS_{t+k} - SGA_{t+k} - OthExp_{t+k}$, the slopes when $Sales_{t+k}$, $COGS_{t+k}$, etc. are regressed on lagged earnings and accruals sum to the slope when NI_{t+k} is regressed on lagged earnings and accruals. (The relation does not hold exactly in the data because we winsorize the variables, but the deviations are small.) We focus on regressions using changes in sales and expenses scaled by assets in year t in order to test whether accruals predict growth in the variables. This specification also avoids complications caused by persistence in the levels of sales, COGS, etc. For brevity, we report results only for horizons out to year t+3. The regressions for earnings changes from Table 3 are also reproduced for reference.

The results in the top panel of Table 4 reveal several interesting patterns. First, firms that are more profitable today tend to have high sales growth over the subsequent three years, consistent with the intuition that changes in demand and/or supply drive both profits and sales. However, high profits also predict that expenses will grow faster than sales in years t+1 and t+2, leading to a significant drop in profits (far-right columns), i.e., a portion of today's profits is transitory and mean reverting.

Second, controlling for ROA_t, working-capital and long-term accruals are positively related to sales and expense growth in each of the next three years. A dollar of $dNWC_t$ is associated with additional sales growth of $0.58 in year t+1, $0.30 in year t+2, and $0.27 in year t+3, effects that are all highly statistically significant. Similarly, a dollar of $dLTNOA_t$ predicts additional sales growth of $0.47 in year t+1, $0.25 in year t+2, and $0.26 in year t+3. These results show that investments in working capital and long-term assets precede higher sales and contradict the idea that high accruals are, in general, a signal of earnings management by firms struggling with slow sales growth.

At the same time, high accruals predict that expenses will grow faster than sales. The jump in total expenses is, of course, just a restatement of the fact that accruals are negatively related to subsequent profits; the more interesting issue is how different types of expenses contribute to the overall increase. To interpret the results, recall from Table 1 that COGS averages 69% of sales, SG&A averages 25% of sales, and other expenses average 8% of sales. Given that a dollar of working-capital accruals is associated with $0.58 of sales growth in year t+1, we would expect COGS to increase by $0.40 (0.58×0.69), SG&A to increase by $0.15 (0.58×0.25), and other expenses to increase by $0.05 (0.58×0.08) if accruals were associated with 'normal' changes in expenses. Empirically, $1 of dNWC actually predicts a $0.49 increase in $dCOGS_{t+1}$ and a $0.19 increase in $dSGA_{t+1}$, both substantially higher than normal (the increase in $OthExp_{t+1}$, $0.05, matches normal growth). Put differently, a dollar of working-capital accruals predicts a significant $0.14 drop in next year's earnings, of which roughly $0.09 comes from a disproportionate increase in $COGS_{t+1}$ and $0.04 comes from a disproportionate increase in SGA_{t+1}.

Turning to long-term accruals, a $1 increase in $dLTNOA_t$ would be expected to predict $0.32 of additional $COGS_{t+1}$, $0.12 of additional SGA_{t+1}, and $0.04 of additional $OthExp_{t+1}$ if long-term accruals were associated with normal expense growth, given the observed relation between $dLTNOA_t$ and $dSales_{t+1}$ ($0.47). The actual increases in $COGS_{t+1}$ and SGA_{t+1} match this prediction exactly, while the $0.18 increase in other expenses is substantially higher than expected. Thus, long-term accruals predict lower profits because they are associated with an abnormal jump in other expenses. In supplemental tests, we find that the increase in $OthExp_{t+1}$ comes from a combination of sources, including a significant increase in both depreciation ($0.05) and interest expense ($0.04) and a significant decrease in special items (-$0.05).

Panel B provides an alternative and, in some sense, more rigorous way to test whether accruals are associated with a disproportionate increase in expenses given the behavior of sales. In particular, we include $dSales_{t+k}$ (contemporaneous with the dependent variable) as an explanatory variable in the regressions in order to control directly for subsequent growth in sales. The slope on accruals in these regressions provides a direct estimate of whether accruals predict earnings and expenses after controlling for the association between accruals and future sales growth.

Focusing first on earnings (the far-right columns), Panel B shows that controlling for sales growth accentuates the negative relation between accruals and subsequent earnings, i.e., the earnings decline following high accruals is actually stronger than standard persistence regressions suggest because, all else equal, earnings would be expected to increase given the growth in sales (we implicitly control for this expected increase by adding $dSales_{t+k}$ to the regression). The slopes on dNWC and dLTNOA both drop to -0.20, stronger and more significant than the slopes in Panel A (-0.14 and -0.16, respectively).

The remaining panels largely confirm our inferences above. $dNWC_t$ has significant predictive power for both $dCOGS_{t+1}$ (0.09) and $dSGA_{t+1}$ (0.10), implying that the decline in profits following high working-capital accruals comes almost equally from disproportionate growth in COGS and SG&A (working-capital accruals also have some predictive power for $dOthExp_{t+1}$, with a slope of 0.02). Thus, the predictive power of dNWC is not tied to abnormal growth in just one component of expenses. An implication is that measurement error in inventory—a common focus of the literature—cannot explain a significant portion of the accrual effect (indeed, our later tests suggest that inventory reversals play no role at all). Over longer horizons, growth in

COGS becomes normal, or even slightly below average, after year t+1, while growth in SG&A stays elevated in years t+2 and t+3.

The predictive power of long-term accruals comes from very different sources: Controlling for sales growth, $dLTNOA_t$ has no predictive power for $dCOGS_{t+1}$ (slope of 0.00), modest predictive power for $dSGA_{t+1}$ (slope of 0.05), and strong predictive power for $dOthExp_{t+1}$ (slope of 0.16). Growth in other expenses drops after t+1 but remains somewhat elevated in years t+2 and t+3. These results show that the profit drop following high long-term accruals comes largely from an increase in depreciation, interest expense, and losses associated with special items, all of which are included in other expenses (the first two items, depreciation and interest expense, remain high in years t+2 and t+3).

5.3. Predicting accruals

The evidence above suggests that neither measurement error nor investment effects explain the low persistence of accruals. The case against the measurement-error hypothesis is the more circumstantial of the two, built on two observations: (i) we find no evidence of the rebound in profits that would be expected if transitory measurement error explains the drop in earnings; and (ii) COGS and SG&A contribute approximately equally to the jump in expenses following high working-capital accruals, contrary to the specific argument that inventory reversals explain the bulk of the accrual anomaly (e.g., Thomas and Zhang 2002; Allen, Larson, and Sloan 2013). In this section, we look more closely at whether measurement error in working capital might explain the behavior of earnings.

To begin, Table 5 studies two questions: First, do working-capital accruals overall exhibit reversals? Second, do working-capital accruals predict changes in specific components of working capital, in particular, current operating assets (COA) and current operating liabilities (COL), or, more finely, accounts receivable (AR), inventory (Invent), and accounts payable (AP)?

The tests take the same form as our earlier regressions—using lagged earnings and accruals as predictors—allowing us to directly compare the slopes with those from earnings persistence regressions. The goal is to test whether the behavior of accruals can explain, *quantitatively*, changes in earnings: Are accrual reversals large enough to explain the slope on accruals in the earnings persistence regression? An important complication again comes from the fact that dNWC is positively related to subsequent sales growth, so we would expect high dNWC today to predict high dNWC next year in the absence of measurement error (Allen, Larson, and Sloan 2013 make a similar point). Thus, following our approach in Table 4, we report both simple predictive regressions, using only lagged earnings and accruals as predictors, as well as regressions that add future sales growth as a control variable. The second specification provides a powerful and straightforward way to test whether accruals exhibit reversals controlling for the behavior of sales.

The left-most columns in Table 5 test whether total working-capital accruals exhibit reversals. Panel A shows that, in simple predictive regressions, $dNWC_t$ is actually positively related to $dNWC_{t+k}$ in each of the subsequent three years, with a predictive slope of 0.02 at a one-year horizon growing to 0.07 at a three-year horizon (the results for t+1 are consistent with the small positive autocorrelation reported by Allen, Larson, and Sloan 2013). However, when sales growth is added to the regressions, Panel B shows that dNWC is less persistent at the one-year horizon than it should be given the behavior of sales, i.e., given that $dNWC_t$ predicts $dSales_{t+1}$ (Table 4), we would expect $dNWC_t$ to be more positively associated with $dNWC_{t+1}$ than it truly is. The slope on $dNWC_t$ in Panel B implies that a $1 increase in working capital today predicts a $0.04 below-average change next year. If this entire effect is attributed to measurement error in accruals, the results suggest that measurement error can explain at most a small fraction of the accrual effect, roughly $0.04 of the $0.20 drop in NI_{t+1} observed in Table 4.

The remaining tests in Table 5 provide even stronger evidence against the measurement-error hypothesis. In particular, focusing on the results in Panel B, $dNWC_t$ is weakly negatively related to $dNWC_{t+1}$ not because it predicts a drop in $dCOA_{t+1}$ but because it predicts an increase in $dCOL_{t+1}$ (slope of 0.03 with a t-statistic of 4.93). The problem for the measurement-error hypothesis is that reversals in COA, not COL, are typically blamed for the low persistence of accruals (e.g., Richardson et al. 2005). In truth, high dNWC predicts a normal increase in COA next year, exactly matching what would be expected given the growth in $Sales_{t+1}$. The other columns show that $dNWC_t$ predicts a slightly below-average increase in dAR_{t+1} (slope of -0.02 with a t-statistic of -4.00) offset by a slightly above-average increase in $dInvent_{t+1}$ (slope of 0.03 with a t-statistic of 3.95). The slopes are small relative to the slope on $dNWC_t$ in our earnings persistence regressions, providing additional evidence that accrual reversals are too small to explain the behavior of profits.

Tables 6 and 7 look in more detail at dCOA and dCOL, specifically, whether the two components themselves help to predict changes in earnings, sales, expenses, and future accruals. In essence, we mimic the tests in Tables 3, 4, and 5 but now decompose the *independent* variable into dCOA vs. dCOL in order to study more carefully how the two components behave.

Table 6 shows predictive regressions for sales, expenses, and earnings. Like total working-capital accruals, dCOA and dCOL are both strongly related to future sales growth, with a slope of 0.73 on dCOA and 0.88 on dCOL at the one-year horizon (t-statistics of 15.19 and 11.85, respectively). Thus, an increase in either current operating assets or current operating liabilities anticipates higher growth in sales. A key difference, however, is that dCOA predicts a big increase in expenses and a drop in earnings, while dCOL predicts a more modest increase in expenses and a jump in earnings. Panel B, with sales growth added as a control variable, shows that high dCOA predicts a disproportionate increase in COGS (0.09) and SG&A (0.12), while high dCOL predicts a below-normal increase in COGS (-0.08) and other expenses (-0.09), effects that are all highly significant. dCOA and dCOL both appear to contribute to the predictive power of working-capital accruals, though in different ways.

Table 7 tests whether dCOA and dCOL predict subsequent accruals. The goal is understand whether either variable behaves in a way that indicates the presence of transitory measurement error. In truth, $dCOA_t$ is actually *positively* related to subsequent $dCOA_{t+1}$ (slope of 0.16 in Panel A), an effect that closely matches what would be expected given the behavior of sales (as indicated by the near-zero slope in Panel B). The results provide no evidence that reversals in AR or inventory—the typical focus of the measurement-error literature—explain the drop in earnings following high accruals. In contrast, dCOL does exhibit reversals, with a one-year slope of -0.08 in the predictive regressions in Panel A and -0.19 when we control for sales growth in Panel B. Reversals in dCOL are consistent with the existence of transitory measurement error but, given the relatively high reliability of short-term liabilities (Richardson et al. 2005), seem more likely to be explained by temporary changes in payments to suppliers or taxes payable that do not directly affect earnings or indicate earnings management.

5.4. Interpretation

The results in Tables 3 through 7 provide a detailed picture of the link between accruals and subsequent earnings, sales, expenses, and accruals. Collectively, the evidence provides significant new insights into dynamics of earnings and accruals:

(i) High accruals predict not just a drop in ROA but also a large, essentially permanent, drop in the actual level of profits. The long-lasting drop in profits is consistent with the argument that accruals correlate with changes in demand or supply but is hard to reconcile with either the measurement error or investment hypothesis (the former predicts a partial rebound in profits after measurement error reverses, while the latter predicts a drop in profitability but not a permanent drop in profits).

(ii) Accruals predict sales and expense growth up to five years in the future. The behavior of sales suggests that accruals either reflect investments that drive growth or correlate with underlying demand or supply shocks that drive growth. The evidence contradicts one version of the demand hypothesis—that unexpected changes in demand near the end of the year have an opposite impact on inventory levels—but is consistent with the idea that an increase in demand leads to high investment and temporarily high profits, subsequently driven down by competition. Alternatively, high accruals might reflect an increase in production costs that shows up with a lag in sales, expenses, and earnings (assuming higher costs are partially passed onto customers). The results for sales and expenses do not, by themselves, contradict the measurement-error hypothesis. However, the increase in both COGS and SG&A suggests that, if measurement error does drive earnings, it must not be isolated to inventory or any other specific component of accruals.

(iii) Accrual reversals do not seem to explain the behavior of earnings. High working-capital accruals tend to predict higher, not lower, working-capital accruals in the future, though the strength of the relation in year t+1 is somewhat weaker than expected given the link between accruals and $dSales_{t+1}$. The small discrepancy—weaker-than-expected growth in $dNWC_{t+1}$ of $0.04 per dollar of current $dNWC_t$—suggests that accruals contain a transitory component, but the magnitude is too small to explain the predictive power of accruals for subsequent earnings (a drop of about $0.20 per dollar of current $dNWC_t$ when we control for $dSales_{t+1}$). Moreover, the transitory component of dNWC seems to be attributable to the behavior of current operating liabilities not to reversals in AR or inventory.

6. Conclusion

The link between accruals and future profitability is well-documented in the accounting literature but remains the subject of much debate. Prior studies typically argue that accruals' predictive power comes from either measurement error in accruals or the negative impact of investment on future profitability that, in turn, can be traced to diminishing marginal returns or conservatism in accounting.

Our paper contributes to the literature in two main ways. First, we argue that the link between accruals and subsequent profitability is, at face value, consistent with a wide range of economic phenomena. Accruals are likely to be correlated with changes in a firm's production costs, product-market demand, and competitive environment, all of which could explain why profitability drops following high accruals. Second, we extend the persistence regressions that are popular in the literature to provide a detailed analysis of the link between accruals and subsequent earnings, sales, expenses, and accruals over both short and long horizons. This analysis helps to discriminate between the different hypotheses and provides a rich picture of the dynamics underlying the predictive power of accruals.[3]

Our results present a significant challenge to the measurement error and investment hypotheses. We show that accruals predict a long-lasting drop in profits, not just profitability, contrary to one of the central predictions of the investment hypothesis. We also find no evidence that profits rebound once transitory measurement error

[3] The methodology we develop here to measure accrual reversals and to tie them quantitatively to earnings should be useful in other contexts as well; for example, the same method can be used to assess models of discretionary accruals and earnings management (Lewellen and Resutek 2014).

has worked its way through earnings or that accrual reversals are large enough to explain the drop in earnings, contrary to the measurement-error hypothesis. Moreover, the small accrual reversals we do find come from predictability in current operating liabilities, not current operating assets, opposite to what most studies on measurement error have generally predicted.

Our evidence is consistent with the idea that accruals capture the impact of changes in demand, supply, and competition on firm's profits, sales, and expenses. One story that seems to fit the data well is that firms with high profits today—whether from product innovation or just an increase in demand—have high sales growth and high accruals but, because profits attract new competition and entry, subsequent profits are driven down by competitive price pressure. The predictions work in reverse for firms that are unprofitable, which should induce restructuring, exit, and an increase in subsequent profits.

We certainly do not claim that the story above is the only possible explanation or the one that holds in all situations. All of the different hypotheses in Section 2 are plausible and might contribute to the predictive power of accruals in some situations. Our point is simply that product-market dynamics can explain the drop in profits following high accruals, and many of the other patterns we find, better than the two most popular hypotheses from the literature.

Our results have implications for a variety of topics in accounting. For example, large literatures have developed to explore the determinants of earnings management and 'discretionary' accruals, how earnings quality affects managerial behavior and varies across firms, and why accruals help to predict future stock returns. A common theme in many of these studies is that accrual errors—intentional or not—are pervasive. Our paper suggests, however, that measurement error may be less important than commonly perceived and that product market effects, rather than measurement error, should be considered as an alternative explanation for some results in the literature.

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Table 1
Descriptive statistics, 1970–2012

This table reports the time-series average of the annual cross-sectional mean, median (Med), standard deviation (Std), 1st percentile (Min), 99th percentile (Max), and sample size (N) for the variables listed. Flow and change variables are scaled by average total assets for the year, while ending balance sheet variables are scaled by ending total assets. All variables are winsorized annually at their 1st and 99th percentiles. The sample includes all nonfinancial firms on Compustat that have data for average total assets, net income, net operating assets, selling, general, and administrative expense, and beginning-of-year market value (from CRSP).

Variable	Description	Mean	Med	Std	Min	Max	N
Sales	Revenue	1.357	1.207	0.885	0.055	5.057	3,458
COGS	Cost of goods sold	0.930	0.763	0.753	0.014	4.293	3,458
SGA	Selling, general, and admin.	0.338	0.275	0.267	0.016	1.397	3,458
OthExp	Other expenses[a]	0.104	0.094	0.094	-0.161	0.529	3,458
NI	Net income	-0.016	0.037	0.198	-1.000	0.285	3,458
dSales	Change in Sales	0.109	0.092	0.321	-1.076	1.231	3,452
dCOGS	Change in COGS	0.068	0.054	0.250	-0.942	0.983	3,452
dSGA	Change in SGA	0.022	0.018	0.099	-0.433	0.350	3,421
dOthExp	Change in OthExp	0.005	0.010	0.121	-0.600	0.432	3,421
dNI	Change in NI	0.011	0.007	0.175	-0.578	0.873	3,452
NWC	Net working capital[b]	0.188	0.185	0.197	-0.395	0.659	3,457
LTNOA	Long-term net operating assets[c]	0.401	0.381	0.217	-0.050	0.908	3,457
COA	Current operating assets[d]	0.399	0.401	0.209	0.020	0.866	3,457
COL	Current operating liabilities[e]	0.211	0.185	0.130	0.026	0.783	3,457
AR	Accounts receivable	0.186	0.173	0.122	0.003	0.600	3,448
Invent	Inventory	0.183	0.162	0.149	0.000	0.641	3,442
AP	Accounts payable	0.100	0.077	0.084	0.006	0.474	3,457
dNWC	Change in NWC	0.011	0.011	0.101	-0.368	0.333	3,458
dLTNOA	Change in LTNOA	0.034	0.017	0.156	-0.520	0.638	3,458
dCOA	Change in COA	0.030	0.024	0.119	-0.396	0.431	3,458
dCOL	Change in COL	0.019	0.014	0.076	-0.253	0.304	3,458
dAR	Change in AR	0.015	0.011	0.070	-0.234	0.263	3,446
dInvent	Change in Invent	0.013	0.006	0.063	-0.217	0.244	3,440
dAP	Change in AP	0.008	0.005	0.047	-0.161	0.191	3,456

[a] OthExp = Sales – COGS – SGA – NI
[b] NWC = Current assets – cash – non-debt current liabilities
[c] LTNOA = Total assets – current assets – non-debt long-term liabilities
[d] COA = Current assets – cash
[e] COL = Current liabilities – short-term debt

Table 2
Correlations, 1970–2012

This table reports the average annual cross-sectional correlation between each pair of variables. The variables are scaled by average total assets and winsorized annually at their 1st and 99th percentiles. The sample includes all nonfinancial firms on Compustat with data for average total assets, net income, net operating assets, selling, general, and administrative expenses, and beginning-of-year market value from CRSP. Variables are defined in Table 1.

	dSales	dCOGS	dSGA	dOthExp	dNI	dNWC	dLTNOA	dCOA	dCOL	dAR	dInvent	dAP
dSales	-	0.91	0.55	0.20	0.15	0.34	0.29	0.58	0.45	0.52	0.45	0.40
dCOGS	0.91	-	0.46	0.16	-0.01	0.28	0.24	0.51	0.41	0.45	0.40	0.40
dSGA	0.55	0.46	-	0.16	-0.25	0.21	0.26	0.43	0.37	0.34	0.35	0.30
dOthExp	0.20	0.16	0.16	-	-0.58	-0.03	0.02	0.11	0.20	0.09	0.07	0.10
dNI	0.15	-0.01	-0.25	-0.58	-	0.14	0.05	0.07	-0.05	0.10	0.05	-0.05
dNWC	0.34	0.28	0.21	-0.03	0.14	-	0.11	0.73	-0.11	0.56	0.59	0.06
dLTNOA	0.29	0.24	0.26	0.02	0.05	0.11	-	0.29	0.29	0.26	0.23	0.27
dCOA	0.58	0.51	0.43	0.11	0.07	0.73	0.29	-	0.56	0.80	0.75	0.52
dCOL	0.45	0.41	0.37	0.20	-0.05	-0.11	0.29	0.56	-	0.48	0.39	0.74
dAR	0.52	0.45	0.34	0.09	0.10	0.56	0.26	0.80	0.48	-	0.33	0.45
dInvent	0.45	0.40	0.35	0.07	0.05	0.59	0.23	0.75	0.39	0.33	-	0.42
dAP	0.40	0.40	0.30	0.10	-0.05	0.06	0.27	0.52	0.74	0.45	0.42	-

Table 3
Predicting earnings, 1970–2012
This table reports average slopes and R^2s from annual cross-sectional regressions (intercepts are included in all regressions but omitted from the table). t-statistics, reported below the slope estimates, are based on the time-series variability of the estimates, incorporating a Newey-West correction with three lags to account for possible autocorrelation in the estimates. In panel A, the dependent variables, NI_{t+k} and dNI_{t+k}, are scaled by average total assets in year t+k; in panel B, the dependent variables are scaled by average total assets in year t. The sample includes all nonfinancial firms on Compustat with data for net income, net operating assets, selling, general, and administrative expenses, and market value on CRSP (as well as data required for the regression). Variables are defined in Table 1. The average sample size is 3,410 firms in the t+1 regressions dropping to 2,569 firms in the t+5 regressions.

	Predicting profits					Predicting changes in profits				
	NI_{t+1}	NI_{t+2}	NI_{t+3}	NI_{t+4}	NI_{t+5}	dNI_{t+1}	dNI_{t+2}	dNI_{t+3}	dNI_{t+4}	dNI_{t+5}
Panel A: NI_{t+k} and dNI_{t+k} scaled by assets in year t+k										
NI_t	0.73	0.60	0.52	0.48	0.45	-0.29	-0.15	-0.09	-0.06	-0.04
t	62.54	26.33	19.25	18.28	18.33	-9.15	-6.14	-4.38	-2.65	-1.92
$dNWC_t$	-0.12	-0.14	-0.13	-0.11	-0.10	-0.14	0.00	0.00	0.02	0.02
t	-15.15	-10.28	-11.45	-6.79	-8.37	-9.14	0.08	0.20	2.19	1.77
$dLTNOA_t$	-0.11	-0.11	-0.09	-0.09	-0.08	-0.19	0.00	0.03	0.02	0.01
t	-9.59	-9.58	-8.12	-6.98	-5.01	-5.16	0.19	1.59	2.00	1.95
R^2	0.456	0.297	0.220	0.176	0.150	0.191	0.029	0.015	0.010	0.008
Panel B: NI_{t+k} and dNI_{t+k} scaled by assets in year t										
NI_t	0.76	0.70	0.69	0.70	0.74	-0.20	-0.04	0.01	0.03	0.06
t	44.33	22.99	18.53	14.70	12.41	-12.14	-2.73	0.71	1.50	2.23
$dNWC_t$	-0.14	-0.16	-0.18	-0.17	-0.15	-0.14	-0.02	-0.02	-0.01	0.02
t	-8.62	-6.58	-6.78	-4.29	-4.62	-9.81	-1.60	-1.37	-0.53	0.95
$dLTNOA_t$	-0.16	-0.17	-0.16	-0.15	-0.14	-0.16	-0.02	0.00	0.00	-0.01
t	-5.95	-5.48	-4.86	-3.79	-2.98	-6.13	-1.39	-0.21	-0.04	-0.65
R^2	0.454	0.279	0.197	0.151	0.124	0.142	0.014	0.010	0.010	0.009

Table 4
Predicting sales and expenses, 1970–2012
This table reports average slopes and R^2s from annual cross-sectional regressions (intercepts are included in all regressions but omitted from the table). t-statistics, reported below the slope estimates, are based on the time-series variability of the estimates, incorporating a Newey-West correction with three lags to account for possible autocorrelation in the estimates. All variables are scaled by average total assets in year t. The sample includes all nonfinancial firms on Compustat with net income, net operating assets, selling, general, and administrative expenses, and beginning-of-year market value from CRSP (as well as data required for the regression). Variables are defined in Table 1. The average sample size is 3,410 firms in the t+1 regressions dropping to 2,961 firms in the t+3 regressions.

Panel A: Standard predictive regressions

	$dSales_{t+k}$			$dCOGS_{t+k}$			$dSGA_{t+k}$			$dOthExp_{t+k}$			dNI_{t+k}		
	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3
NI_t	0.20	0.20	0.21	0.18	0.16	0.14	0.09	0.07	0.04	0.11	0.01	0.00	-0.20	-0.04	0.01
t	2.22	2.01	1.69	2.83	2.27	1.82	3.26	2.15	1.08	14.16	0.52	0.31	-12.14	-2.73	0.71
$dNWC_t$	0.58	0.30	0.27	0.49	0.21	0.16	0.19	0.10	0.10	0.05	0.03	0.03	-0.14	-0.02	-0.02
t	11.00	4.79	4.36	13.37	4.24	3.47	8.15	5.71	6.42	5.28	3.54	4.27	-9.81	-1.60	-1.37
$dLTNOA_t$	0.47	0.25	0.26	0.32	0.15	0.17	0.12	0.05	0.04	0.18	0.07	0.06	-0.16	-0.02	0.00
t	12.49	7.43	6.30	11.03	6.12	6.08	9.35	6.15	4.75	11.40	6.17	3.69	-6.13	-1.39	-0.21
R^2	0.075	0.020	0.017	0.081	0.018	0.013	0.125	0.036	0.022	0.138	0.016	0.012	0.142	0.014	0.010

Panel B: Controlling for $dSales_{t+k}$

	$dCOGS_{t+k}$			$dSGA_{t+k}$			$dOthExp_{t+k}$			dNI_{t+k}		
	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3
NI_t	0.03	0.01	-0.01	0.06	0.04	0.01	0.10	-0.01	-0.01	-0.22	-0.06	0.00
t	3.95	1.25	-0.78	3.51	2.17	0.62	11.26	-0.92	-1.22	-12.79	-2.99	-0.19
$dNWC_t$	0.09	0.00	-0.02	0.10	0.05	0.06	0.02	0.01	0.01	-0.20	-0.03	-0.03
t	10.92	0.08	-2.51	7.91	5.43	6.81	2.36	1.01	0.67	-11.77	-3.17	-2.64
$dLTNOA_t$	0.00	-0.02	-0.01	0.05	0.01	0.00	0.16	0.05	0.04	-0.20	-0.03	-0.02
t	0.08	-4.77	-1.29	7.88	1.54	-0.03	9.62	5.54	2.84	-7.90	-2.67	-1.24
$dSales_{t+k}$	0.68	0.68	0.68	0.15	0.17	0.16	0.05	0.07	0.08	0.11	0.07	0.06
t	65.87	56.29	57.91	16.69	16.58	18.73	16.66	18.78	17.69	12.28	8.77	8.64
R^2	0.870	0.870	0.869	0.410	0.416	0.423	0.183	0.110	0.116	0.233	0.069	0.066

Table 5
Predicting working capital, 1970–2012

This table reports average slopes and R^2s from annual cross-sectional regressions (intercepts are included in all regressions but omitted from the table). t-statistics, reported below the slope estimates, are based on the time-series variability of the estimates, incorporating a Newey-West correction with three lags to account for possible autocorrelation in the estimates. All variables are scaled by average total assets in year t. The sample includes all nonfinancial firms on Compustat with net income, net operating assets, selling, general, and administrative expenses, and beginning-of-year market value from CRSP (as well as data required for the regression). Variables are defined in Table 1. The average sample size is 3,410 firms in the t+1 regressions dropping to 2,971 firms in the t+3 regressions.

Panel A: Standard predictive regressions

	$dNWC_{t+k}$			$dCOA_{t+k}$			$dCOL_{t+k}$			dAR_{t+k}			$dInvent_{t+k}$			dAP_{t+k}		
	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3
NI_t	0.13	0.09	0.06	0.14	0.09	0.08	0.00	0.00	0.01	0.05	0.03	0.03	0.08	0.05	0.04	0.01	0.01	0.00
t	3.26	2.89	2.57	2.72	2.31	1.86	0.21	-0.10	0.31	2.45	1.94	1.68	2.67	2.43	2.05	1.31	0.85	0.46
$dNWC_t$	0.02	0.06	0.07	0.14	0.12	0.13	0.10	0.07	0.06	0.06	0.06	0.06	0.09	0.06	0.06	0.05	0.03	0.03
t	1.49	3.56	4.08	5.80	5.16	5.80	8.46	6.75	8.09	4.95	5.14	6.05	6.93	5.16	5.82	5.72	4.08	4.94
$dLTNOA_t$	0.03	0.00	-0.01	0.09	0.05	0.04	0.06	0.05	0.05	0.05	0.03	0.03	0.02	0.00	0.01	0.03	0.02	0.02
t	5.85	-0.67	-1.35	7.77	5.37	4.11	8.21	7.54	6.59	8.66	6.70	4.40	3.57	0.58	1.46	6.12	4.84	4.88
R^2	0.038	0.015	0.010	0.050	0.019	0.014	0.028	0.013	0.010	0.028	0.014	0.010	0.042	0.016	0.011	0.021	0.008	0.007

Panel B: Controlling for $dSales_{t+k}$

	$dNWC_{t+k}$			$dCOA_{t+k}$			$dCOL_{t+k}$			dAR_{t+k}			$dInvent_{t+k}$			dAP_{t+k}		
	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3
NI_t	0.12	0.07	0.04	0.10	0.05	0.03	-0.02	-0.02	-0.02	0.03	0.01	0.01	0.06	0.03	0.02	0.00	-0.01	-0.01
t	3.49	3.18	3.06	2.97	2.37	1.81	-3.28	-5.50	-2.93	2.60	1.50	1.39	2.84	2.54	2.02	0.24	-2.53	-2.83
$dNWC_t$	-0.04	0.02	0.04	0.00	0.05	0.06	0.03	0.03	0.02	-0.02	0.02	0.03	0.03	0.03	0.03	0.01	0.00	0.01
t	-3.29	2.01	3.25	-0.16	3.50	5.29	4.93	4.14	4.53	-4.00	2.93	5.18	3.95	4.23	4.95	1.45	1.48	2.36
$dLTNOA_t$	-0.02	-0.03	-0.03	-0.02	-0.01	-0.02	0.00	0.02	0.02	-0.01	0.00	-0.01	-0.03	-0.02	-0.02	-0.01	0.00	0.01
t	-3.53	-4.80	-5.26	-3.50	-1.85	-3.10	-1.07	4.81	5.46	-1.51	0.25	-2.61	-6.99	-3.71	-3.49	-1.96	0.72	2.58
$dSales_{t+k}$	0.11	0.10	0.10	0.23	0.23	0.23	0.13	0.12	0.13	0.13	0.12	0.12	0.09	0.09	0.09	0.07	0.06	0.06
t	13.30	13.01	12.61	21.53	25.68	24.41	25.00	26.70	27.10	16.79	19.16	19.75	15.11	13.82	12.61	21.12	26.47	26.85
R^2	0.166	0.154	0.147	0.413	0.409	0.414	0.285	0.295	0.302	0.333	0.336	0.343	0.254	0.245	0.245	0.225	0.229	0.234

Table 6
Predicting earnings with the components of working-capital accruals, 1970–2012

This table reports average slopes and R^2s from annual cross-sectional regressions (intercepts are included in all regressions but omitted from the table). t-statistics, reported below the slope estimates, are based on the time-series variability of the estimates, incorporating a Newey-West correction with three lags to account for possible autocorrelation in the estimates. All variables are scaled by average total assets in year t. The sample includes all nonfinancial firms on Compustat with net income, net operating assets, selling, general, and administrative expenses, and beginning-of-year market value from CRSP (as well as data required for the regression). Variables are defined in Table 1. The average sample size is 3,410 firms in the t+1 regressions dropping to 2,961 firms in the t+3 regressions.

Panel A: Standard predictive regressions

	$dSales_{t+k}$			$dCOGS_{t+k}$			$dSGA_{t+k}$			$dOthExp_{t+k}$			dNI_{t+k}		
	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3
NI_t	0.16	0.19	0.19	0.14	0.15	0.13	0.08	0.06	0.03	0.11	0.01	0.00	-0.20	-0.04	0.01
t	2.59	2.12	1.73	3.53	2.41	1.88	3.65	2.26	1.05	13.66	0.60	0.35	-12.42	-2.78	0.76
$dCOA_t$	0.73	0.35	0.31	0.59	0.23	0.18	0.23	0.12	0.12	0.04	0.03	0.03	-0.13	-0.02	-0.01
t	15.19	5.11	4.59	17.77	4.47	3.60	10.48	6.30	6.66	4.67	4.58	4.06	-7.69	-1.73	-1.01
$dCOL_t$	0.88	0.30	0.33	0.53	0.22	0.25	0.12	0.10	0.07	-0.04	0.03	0.02	0.27	-0.06	-0.02
t	11.85	6.12	4.85	8.68	4.74	5.50	11.32	8.38	5.66	-1.84	2.10	1.49	14.21	-3.80	-1.15
$dLTNOA_t$	0.22	0.15	0.17	0.15	0.08	0.11	0.07	0.02	0.02	0.18	0.06	0.05	-0.18	0.00	0.00
t	9.69	6.67	4.52	7.90	5.11	4.45	8.27	3.22	2.38	10.63	5.36	3.29	-6.92	-0.36	0.07
R^2	0.158	0.031	0.025	0.152	0.027	0.021	0.176	0.051	0.031	0.140	0.018	0.013	0.148	0.016	0.011

Panel B: Controlling for $dSales_{t+k}$

	$dCOGS_{t+k}$			$dSGA_{t+k}$			$dOthExp_{t+k}$			dNI_{t+k}		
	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3
NI_t	0.03	0.01	-0.01	0.06	0.04	0.01	0.10	-0.01	-0.01	-0.21	-0.06	0.00
t	3.73	1.12	-0.82	3.62	2.21	0.53	11.35	-0.75	-1.05	-12.85	-3.08	-0.11
$dCOA_t$	0.09	0.00	-0.03	0.12	0.06	0.06	0.01	0.01	0.01	-0.21	-0.04	-0.03
t	11.31	-0.22	-2.84	10.93	7.04	7.65	0.64	1.16	0.54	-11.51	-3.75	-2.23
$dCOL_t$	-0.08	0.01	0.03	-0.01	0.05	0.01	-0.09	0.01	-0.01	0.18	-0.08	-0.04
t	-10.69	0.42	2.47	-0.51	6.57	2.01	-4.64	0.53	-0.94	8.29	-5.04	-2.92
$dLTNOA_t$	0.00	-0.02	-0.01	0.03	-0.01	-0.01	0.17	0.05	0.04	-0.20	-0.01	-0.01
t	-0.08	-4.36	-1.35	6.46	-1.84	-1.82	9.68	4.89	2.86	-7.83	-1.23	-0.70
$dSales_{t+k}$	0.68	0.68	0.68	0.15	0.16	0.16	0.05	0.07	0.08	0.11	0.07	0.06
t	65.11	56.35	57.93	16.31	16.60	18.69	19.05	18.63	17.63	12.52	8.87	8.70
R^2	0.870	0.870	0.869	0.415	0.420	0.425	0.186	0.111	0.117	0.235	0.072	0.068

Table 7

Predicting working capital with the components of working-capital accruals, 1970–2012

This table reports average slopes and R^2s from annual cross-sectional regressions (intercepts are included in all regressions but omitted from the table). t-statistics, reported below the slope estimates, are based on the time-series variability of the estimates, incorporating a Newey-West correction with three lags to account for possible autocorrelation in the estimates. All variables are scaled by average total assets in year t. The sample includes all nonfinancial firms on Compustat with net income, net operating assets, selling, general, and administrative expenses, and beginning-of-year market value from CRSP (as well as data required for the regression). Variables are defined in Table 1. The average sample size is 3,410 firms in the t+1 regressions dropping to 2,971 firms in the t+3 regressions.

Panel A: Standard predictive regressions

	$dNWC_{t+k}$			$dCOA_{t+k}$			$dCOL_{t+k}$			dAR_{t+k}			$dInvent_{t+k}$			dAP_{t+k}		
	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3
NI_t	0.13	0.08	0.06	0.14	0.09	0.07	0.00	0.00	0.00	0.05	0.03	0.03	0.08	0.05	0.04	0.01	0.01	0.00
t	3.52	3.05	2.66	2.86	2.42	1.89	0.31	-0.13	0.19	2.57	2.04	1.71	2.78	2.51	2.07	1.32	0.89	0.34
$dCOA_t$	0.04	0.06	0.06	0.16	0.14	0.14	0.11	0.08	0.07	0.06	0.07	0.07	0.10	0.06	0.06	0.05	0.03	0.03
t	2.67	3.92	3.66	6.56	5.67	5.89	8.29	7.05	7.83	5.30	5.49	5.82	7.89	5.49	6.00	5.55	4.22	5.10
$dCOL_t$	0.22	0.08	0.01	0.12	0.10	0.06	-0.08	0.03	0.05	0.06	0.04	0.03	0.04	0.03	0.01	-0.04	0.01	0.02
t	8.56	5.23	0.69	5.04	6.82	2.76	-5.69	1.94	3.06	5.87	4.25	2.38	2.10	3.37	0.89	-6.65	2.94	2.10
$dLTNOA_t$	-0.01	-0.03	-0.02	0.05	0.01	0.01	0.05	0.03	0.04	0.03	0.01	0.01	-0.01	-0.01	-0.01	0.03	0.01	0.02
t	-1.89	-4.23	-3.19	5.73	2.02	1.54	8.23	6.30	5.15	7.94	4.49	2.21	-1.41	-2.60	-1.28	5.95	3.53	3.67
R^2	0.064	0.021	0.012	0.069	0.030	0.020	0.033	0.018	0.017	0.041	0.021	0.015	0.057	0.022	0.015	0.025	0.012	0.011

Panel B: Controlling for $dSales_{t+k}$

	$dNWC_{t+k}$			$dCOA_{t+k}$			$dCOL_{t+k}$			dAR_{t+k}			$dInvent_{t+k}$			dAP_{t+k}		
	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3
NI_t	0.11	0.06	0.04	0.11	0.05	0.03	-0.01	-0.02	-0.02	0.03	0.01	0.01	0.06	0.03	0.02	0.00	-0.01	-0.01
t	3.61	3.31	3.12	2.88	2.41	1.73	-1.80	-5.37	-3.21	2.45	1.51	1.29	2.81	2.56	1.95	0.50	-2.36	-2.86
$dCOA_t$	-0.04	0.02	0.03	-0.02	0.06	0.06	0.01	0.03	0.03	-0.04	0.02	0.03	0.03	0.03	0.03	-0.01	0.00	0.01
t	-3.07	2.21	2.56	-1.66	4.09	5.08	1.02	5.26	5.35	-5.38	3.16	4.48	3.41	4.46	5.05	-1.68	1.31	3.05
$dCOL_t$	0.13	0.05	-0.02	-0.09	0.03	-0.02	-0.19	-0.01	0.01	-0.05	0.01	-0.02	-0.05	0.00	-0.02	-0.11	-0.01	-0.01
t	6.44	3.84	-1.48	-5.52	3.56	-1.77	-13.90	-0.70	0.82	-6.50	1.22	-2.14	-4.52	0.64	-2.44	-11.31	-1.37	-1.15
$dLTNOA_t$	-0.03	-0.04	-0.04	-0.01	-0.02	-0.03	0.02	0.02	0.02	0.00	0.00	-0.01	-0.03	-0.02	-0.02	0.01	0.00	0.01
t	-5.88	-5.42	-4.53	-1.50	-3.84	-3.53	5.22	3.74	4.36	1.09	-1.14	-2.98	-5.98	-4.42	-3.65	3.21	0.75	2.41
$dSales_{t+k}$	0.10	0.10	0.10	0.24	0.23	0.23	0.14	0.12	0.13	0.13	0.12	0.12	0.09	0.09	0.09	0.07	0.06	0.06
t	12.85	13.11	12.75	21.43	25.78	24.38	27.69	27.20	27.03	16.73	19.25	19.62	15.44	13.89	12.65	22.61	26.67	26.79
R^2	0.171	0.156	0.148	0.418	0.411	0.415	0.306	0.296	0.304	0.341	0.337	0.344	0.255	0.247	0.246	0.246	0.230	0.235