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Why do accruals predict earnings?☆

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ABSTRACT

Higher accruals are associated with lower subsequent earnings. We show this phenomenon can be explained by the way sales, profits, and working capital respond to changes in a firm's product markets. Empirically, high accruals predict high subsequent sales growth but a long-lasting drop in both profits and profitability. Accruals also predict an increase in future competition, suggesting that accruals are correlated with abnormally high—and, in equilibrium, transitory—true profitability that attracts new entrants to the industry. Overall, the predictive power of accruals is better explained by product-market effects than by measurement error in accruals or diminishing returns from investment.

1. Introduction

It is well-established that, given two firms with the same earnings today, the one that reports higher accruals tends to be less profitable going forward. This link between accruals and future profitability, often summarized by saying that accruals are 'less persistent' than cash flows, is important for firm valuation, financial statement analysis, 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 explores two main explanations for the low persistence of accruals. The first is that subjectivity and 'distortions' in financial reporting lead to transitory measurement error in accruals and earnings (Sloan 1996; Xie 2001; Dechow and Dichev 2002; Richardson et al. 2005, 2006; Chan et al. 2006; Dechow et al. 2012; Allen et al. 2013). The second is that accruals are closely linked to investment and predict lower future profitability because of decreasing returns to scale, adjustment costs associated with investment, or conservatism in accounting (Fairfield et al. 2003a,b; Zhang 2007; Dechow et al. 2008; Wu et al. 2010).

In this paper, we propose a third explanation for the predictive power of accruals based on the way firms' profits and working capital respond to demand and supply shocks in product markets. In addition, we provide new evidence on the dynamics of sales, profits, accruals, and competition that allows us to discriminate our model from the measurement error and investment hypotheses.

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Our explanation for the low persistence of accruals centers on the role of product markets. We develop a simple dynamic model of accruals for a value-maximizing firm that reacts to changes in input and output prices. The model is intentionally simple—it certainly does not capture all of the forces driving accruals—but serves to illustrate (i) how accruals depend on the endogenous production and sales decisions of the firm, and (ii) that a link between accruals and future profits can arise naturally in equilibrium even if accruals are perfectly measured and the scale of the firm is fixed. In our model, high accruals correlate with transitory changes in profit margins—and predict lower subsequent profits—for two reasons: (i) An increase in input prices raises the firm's production and inventory costs today but lowers future profits when the inventory is sold. (ii) An increase in demand leads to a temporary rise in profits and working capital, followed by mean reversion in the variables as competition drives prices and profitability back to their long-term equilibrium levels; as a result, accruals are positively associated with current profits but, controlling for this relation, negatively associated with subsequent profits. In short, the low persistence of accruals arises because of the way production, sales, and profits respond to changes in the firm's product markets.

A key contribution of our paper is to compare theoretically the measurement error, investment, and product market hypotheses. All three hypotheses imply that accruals should be negatively related to next year's profitability—the typical focus of the empirical literature—but they make different predictions about the long-run behavior of profits, profitability, sales, and expenses. For example, the measurement error hypothesis implies that accruals should predict earnings less strongly in the long run than in the short run, while the investment hypothesis implies that accruals should be negatively related to future *profitability* but positively related to the level of future *profits* (with some caveats). Neither prediction is shared by our product market hypothesis, providing a way to distinguish among the theories.

Our second contribution is to study empirically the joint dynamics of accruals, earnings, sales, costs of goods sold (COGS), selling, general, and administrative expense (SG&A), and industry competition. The link between accruals and the other variables, over short and long horizons, provides a rich picture of the forces driving accruals and a test of the different hypotheses.

Our tests yield several 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 and profitability is as strong in years t+2 through t+7 as in year t+1. As we discuss in Section 2, this pattern contradicts a key prediction of the measurement error hypothesis—that the predictive slope on accruals should revert to zero—as well as the idea that a transitory profit decline associated with new investment is followed by longer-term growth in profits.

Second, we show that high accruals predict rapid sales growth but even faster growth in expenses. Controlling for current earnings, a dollar of working-capital accruals is associated with \$0.56 of additional sales and \$0.69 of additional expenses in the following year (the spread between the two, -\$0.13, represents the predicted drop in earnings). The growth in expenses is driven, approximately equally, by an increase in COGS and SG&A relative to sales, not from asset write-downs or other expenses included in special items. Our results suggest that high accruals are *not* indicative of struggling firms—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 in costs relative to sales, rather than a spike in a particular type of expense (e.g., inventory write-downs), explains why accruals are negatively associated with subsequent profits. These results are consistent with our product-market hypothesis and imply that accruals are linked to expected sales growth, a factor generally omitted from models of nondiscretionary accruals (e.g., Jones 1991; Dechow et al. 1995).

Third, firms that report high accruals face significantly higher competition in the future, measured as either new firms entering the industry or a reduction in the industry's Herfindahl index. The patterns suggest that high accruals are associated with abnormally high *true* profitability that attracts new entry and competition, which in turn drive down subsequent profits. Further, industry accruals predict industry profits and sales growth over both short and long horizons, similar to our firm-level results. Accruals appear to be correlated with industry-wide demand and supply shocks that can help explain the behavior of profits, again consistent with our product market hypothesis.

Finally, our evidence shows that accruals do contain a small transitory component, consistent with the presence of negatively autocorrelated measurement error, but this component does not come from reversals in accounts receivable (AR) or inventory but from predictable changes in current operating liabilities, which are often regarded as one of the most reliable types of accruals. Accruals predict changes in current operating assets that match what we would expect given the behavior of sales, contrary to the argument that measurement error reversals in 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 decline in future earnings, along with higher sales and an increase in industry competition, suggests that high accruals are linked to temporarily high *true* earnings and changes in a firm's product markets. At the same time, our paper does not say that measurement error and diminishing marginal returns from investment do not exist or are unimportant in all situations. Our results only show that neither explains the low persistence of accruals or other patterns we observe in the data.

The remainder of the paper is organized as follows: Section 2 develops the formal hypotheses; Section 3 describes our empirical methodology; Sections 4 and 5 summarize the data and present our main empirical results; Section 6 concludes.

2. Accrual models

Accruals are a key output of the financial reporting system, encompassing everything that drives a wedge between earnings and cash flow. They reflect a large variety of corporate decisions, including a firm's sales, production, investment, accounting, and cash management choices. In this section, we study how these factors can induce a link between accruals and future earnings, focusing on three key issues: measurement error in accruals, investment effects, and production and sales decisions.

At the outset, it might be useful to clarify some terminology. The accrual literature often considers so-called 'persistence' regressions of the form

$$NI_{t+1} = a_0 + a_1 CF_t + a_2 ACC_t + e_{t+1}, \tag{1}$$

where NI_t is a measure of earnings in year t (typically scaled by total assets), ACC_t is either working-capital accruals or total accruals, and CF_t is either operating cash flow or free cash flow (depending on the definition of accruals), given by $CF_t = NI_t - ACC_t$. In this context, 'persistence' refers to the slopes in Eq. (1), not to the autocorrelation of the variables, and the 'low persistence' of accruals refers to the empirical observation that $a_2 < a_1$, i.e., accruals and cash flows are positively related to future earnings but the predictive slope on accruals is lower. Further, as noted by FWY (2003a), an equivalent regression can be estimated substituting earnings for cash flow on the right-hand side of this equation:

$$NI_{t+1} = b_0 + b_1 NI_t + b_2 ACC_t + e_{t+1}. \tag{2}$$

The difference, compared with Eq. (1), is that the slope on accruals in Eq. (2) equals the *differential* persistence of accruals and cash flow, $b_2 = a_2 - a_1$ (the other parameters are identical in the two regressions). Thus, the low persistence of accruals relative to cash flow ($a_2 < a_1$) implies that accruals are negatively related to future earnings controlling for current earnings ($b_2 < 0$). Measurement error, investment, and product market effects provide three different explanations for that result.

2.1. Hypothesis 1: measurement error

In his seminal study, Sloan (1996) argues that subjectivity and distortions in financial reporting—what we call measurement error—will tend to reduce the persistence of accruals. We model this idea formally below, but the intuition is simple: measurement error in accruals adds a transitory component to earnings that tends to reverse. Building on this logic, Xie (2001) and Richardson et al. (RSST 2005, 2006) show that discretionary, low-reliability, and non-growth accruals are the least persistent components of accruals, while Dechow and Dichev (2002) and Allen et al. (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; Gerakos and Kovrijnykh 2013).

Formally, following RSST (2005), we interpret Sloan's (1996) subjectivity hypothesis as the idea that reported earnings and accruals differ from correctly-measured earnings and accruals because valuation errors creep into AR, inventory, etc. (possibly due to intentional earnings management). To be specific, RSST hypothesize that the slope on accruals in Eq. (2) would be zero in the absence of measurement error, implying that 'true' earnings, NI_t^*, follow a simple AR(1) process:

$$NI_{t+1}^* = c + \rho NI_t^* + e_{t+1}. \tag{3}$$

True accruals are the difference between NI_t^* and cash flow, $ACC_t^* = NI_t^* - CF_t$. However, reported accruals may contain error η_t, implying $ACC_t = ACC_t^* + \eta_t$ and $NI_t = NI_t^* + \eta_t$. We allow η_t to be serially correlated but, for simplicity, assume it is not related to true earnings or cash flow (we discuss the time-series properties of η_t below).[1] This measurement error makes reported earnings predictably related to past accruals. In particular, the Appendix shows that the slope on accruals in Eq. (2) equals:

$$b_2 = -\sigma_\eta^2(\rho - \lambda)\frac{\sigma_{NI,CF}}{\sigma_{ACC}^2\sigma_{CF}^2[1 - \rho_{ACC,CF}^2]}, \tag{4}$$

where ρ is the autocorrelation of true earnings, λ is the autocorrelation of measurement error, and $\sigma^2{}_{(\cdot)}$, $\sigma_{(\cdot)}$, and $\rho_{(\cdot)}$ denote the variance, covariance, and correlation of the variables indicated. Measurement error leads to a negative slope on accruals as long as earnings and cash flows are positively related (Dechow 1994) and measurement error has a lower autocorrelation than true earnings.[2]

The time-series properties of measurement error are important. RSST assume that $\lambda = 0$, but, as they and others discuss, accrual errors should reverse in practice. For example, suppose that ACC_t represents working-capital accruals. Error in the level of working capital might be positively autocorrelated if valuation mistakes tend to repeat, intentionally or otherwise,

[1] The assumption that η_t is unrelated to true earnings simplifies the algebra but is not critical for the results. For example, in simulations calibrated to the data, the slope on accruals in this model only changes slightly (from −0.14 to −0.12) as the correlation between η_t and NI_t^* varies from −0.50 to 0.50.

[2] Eq. (4) generalizes RSST's results and, in the special case that $\lambda = 0$, corrects a minor error in their formulas (b_2 can be found from Eqs. 7 and 8 in their paper). One difference is that the sign of b_2 in Eq. (4) depends on the correlation between earnings and cash flow, whereas RSST's results suggest that b_2 is unambiguously negative.

but should be temporary since any misvaluation of, say, AR and inventory reverses as receivables are collected and inventory is sold. If so, we might expect error in the *level* of working capital to follow a mean-reverting process, e.g., $z_{t+1} = \rho_z z_t + \varepsilon_{t+1}$, with $\rho_z \geq 0$. Measurement error in *accruals* would then be negatively autocorrelated because accruals equal the year-over-year change in working capital, i.e., $\eta_t = z_t - z_{t-1}$ with autocorrelation $\lambda = -(1-\rho_z)/2$. In other words, if earnings are overstated one year ($\eta_t > 0$), future earnings will tend to be understated ($\eta_{t+1} < 0$) as valuation errors are corrected. Such reversals amplify the negative slope on accruals in Eq. (4).

A key prediction of the model is 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* as measurement error reverses, after which earnings should partially bounce back. For example, suppose a firm's true 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 error). This pattern—a strong short-run drop in earnings followed by a partial rebound—should be observable by looking at long-horizon persistence regressions, replacing next year's earnings in Eq. (2) with 2-year-ahead, 3-year-ahead, etc., earnings. Specifically, with NI_{t+k} as the dependent variable, the slope on accruals (see the Appendix) is

$$b_{2k} = -\sigma_\eta^2\left(\rho^k - \lambda_k\right)\frac{\sigma_{NI,CF}}{\sigma_{ACC}^2\sigma_{CF}^2[1-\rho_{ACC,CF}^2]}, \tag{5}$$

which matches Eq. (4) except that kth-order autocorrelations of true earnings and measurement error, ρ^k and λ_k, replace ρ and λ. The 'rebound' effect discussed above will be reflected in a decline in the magnitude of the 2-year slope relative to the 1-year slope, followed by additional decay over longer horizons.[3] Our tests look for evidence of such a pattern in the data.

Another implication of the model is that slope on accruals depends on three parameters that cannot be estimated directly: the persistence of true earnings (ρ) and the volatility and autocorrelation of measurement error (σ_η and λ). The Appendix shows that we can actually infer ρ from observable statistics, test whether true earnings follow an AR(1) process, and make joint inferences about σ_η and λ. We discuss these tests later but, for now, summarize the predictions of the measurement-error hypothesis as follows:

Hypothesis 1. Measurement Error: *If true earnings follow an AR(1) process but reported earnings and accruals contain transitory measurement error, then, controlling for current earnings: (i) accruals in year t will be negatively related to subsequent earnings NI_{t+1}, as given by Eq. (4); (ii) the slope on accruals for predicting longer term earnings will decay toward zero, as given by Eq. (5), with an especially large rebound at short horizons if measurement error reverses quickly; and (iii) the persistence of true earnings can be estimated and the hypothesis that true earnings follow an AR(1) process can be tested using the slope coefficients for t+1, t+2, etc., as described in the Appendix.*

2.2. Hypothesis 2: investment

FWY (2003a) observe that accruals are a component not only of earnings, as emphasized by Sloan (1996), but also of growth in net operating assets. This link between accruals and growth suggests that high accruals might predict lower future profitability because of decreasing returns to scale, accounting conservatism, or adjustment costs associated with investment (see Wu et al. 2010).

As noted by FWY (2003b) and Zhang (2007), the investment hypothesis implies that high accruals should predict a decline in *profitability* (earnings scaled by assets) but an increase in the actual *level of 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. The argument is quite general: Suppose profits are a function of beginning-of-year capital, $NI_{t+1} = f(K_t)$, with $f(0) = 0$, $f' > 0$, and $f'' < 0$, where the last inequality captures decreasing returns to scale. If the firm chooses investment optimally and the cost of capital is r, the first-order condition for value-maximization is simply $f'(K_t^*) = r$, which implies that investment goes up when r falls ($dK_t^*/dr < 0$). Thus, if we interpret accruals as part of investment (FWY 2003a; Wu et al. 2010), a drop in r leads to higher accruals and profits (since f is increasing in capital) but lower profitability because profits increase less than capital.[4] It follows that, with decreasing returns to scale, accruals should be positively related to future profits but negatively related to future profitability.

A potential caveat is that new investment may not become productive immediately. High investment could lead to lower profits in the short run if projects take time to pay off, an idea we call the 'time-to-build' hypothesis. For example, a new factory might have negative margins for a few years even if it generates profits in the long run. If this effect is important empirically, we might see a negative relation between accruals and profits in the short run that weakens, and eventually

[3] To illustrate, suppose that true earnings have a first-order autocorrelation of $\rho = 0.80$ and measurement error in the level of working capital is completely transitory, $\rho_z = 0$, implying that $\lambda = -0.5$ and $\lambda_2 = \lambda_3 = \ldots = 0$. The 2-year-ahead slope on accruals is roughly half the 1-year-ahead slope ($\rho^2 - \lambda_2 = 0.64$ compared with $\rho - \lambda = 1.30$), and slopes for longer horizons then decay at a rate of 0.80 toward zero.

[4] The easiest way to see this is to note that profits increase less than proportionally with investment, i.e., $f(cK) < c\,f(K)$ for any $c > 1$ (Varian 1992). Dividing both sides of the inequality by cK, it follows that $f(cK)/(cK) < f(K)/K$. The implication is that profitability at any $cK > K$ is lower than profitability at K.

reverses, when we study the long-run behavior of profits. Our tests examine forecast horizons of up to seven years to give any long-run investment effects a reasonable chance of being observable.

Hypothesis 2. Investment: *If investment effects such as diminishing marginal returns or adjustment costs explain the low persistence of accruals, then, controlling for earnings in year t, accruals in year t will be negatively related to subsequent profitability but positively related to subsequent profits. A caveat is that, if investment takes time to pay off, the slope on accruals for predicting profits might be negative in the short run but should turn positive in the long run (after any transitory investment effects have 'worn off'). The long-run positive effects should more than offset the short-run negative effects.*

2.3. Hypothesis 3: product markets

In this section, we show that a firm's response to demand and supply shocks provides a third explanation for the low persistence of accruals. While a variety of product-market effects could be important, our analysis focuses on two possibilities: First, an increase in input prices (or production costs more generally) could raise inventory costs today and reduce future profits later, when the inventory is sold. Second, demand shocks for a firm's products can induce transitory changes in sales, profits, and accruals. For example, an increase in demand should lead to a rise in output, profits, and inventory, followed by mean reversion in these variables as competition drives prices back to long-term competitive levels. This pattern implies that higher accruals today will be associated with lower subsequent profits—even if accruals are perfectly measured and the scale of the firm is fixed.[5]

To develop these ideas formally, consider a long-lived value-maximizing firm in a competitive industry, producing output y from a single variable input x using a standard Cobb-Douglas production technology (Varian 1992): $y_t = x_t^{\alpha}$ in year t, with $0 < \alpha < 1$. The firm has an exogenous fixed amount of capital K and nonproduction fixed costs F_t that do not vary with output or sales. As explained below, the firm also has working capital but, to study profitability, we divide earnings only by the fixed capital K to avoid the 'denominator effect' discussed above for the investment hypothesis. Input prices, output prices, and fixed costs can all vary through time.

We assume output is sold in the year after production. Thus, the firm chooses input x_t at the beginning of year t based on forecasts of this year's input price, c_t, and next year's sales price, p_{t+1}. Variable production costs in year t, $C_t = c_t\ x_t$, lead to sales in year t+1 of $R_{t+1} = p_{t+1}\ x_t^{\alpha}$. The delay between production and sales gives rise to inventory, carried on the balance sheet at cost. In the simplest version of the model, sales are collected and production costs are paid immediately, so inventory is the only component of working capital. In this case, profits and cash flow in year t+1 equal

$$NI_{t+1} = p_{t+1}x_t^{\alpha} - c_t x_t - F_{t+1}, \tag{6}$$

$$CF_{t+1} = p_{t+1}x_t^{\alpha} - c_{t+1}x_{t+1} - F_{t+1} = NI_{t+1} - (c_{t+1}x_{t+1} - c_t x_t). \tag{7}$$

Notice that profits in year t+1 depend on lagged production costs ($c_t x_t$) but cash flow depends on current production costs ($c_{t+1}x_{t+1}$). The parenthetical term in Eq. (7) is the change in inventory, implying that CF_{t+1} differs from NI_{t+1} only because of inventory accruals. As discussed later, the model is easily adapted to include accounts receivable and payable or to add measurement error to accruals, but we focus initially on the model with only inventory accruals.

For simplicity, suppose discount rates are zero. The firm chooses production in year t to maximize expected profits in year t+1 given the information available, implying:

$$x_t^* = (\alpha E_{t-1}[p_{t+1}]/E_{t-1}[c_t])^{1/(1-\alpha)}. \tag{8}$$

Intuitively, the firm raises production when the expected sales price goes up or the expected input price goes down. Expected production costs in year t are

$$E_{t-1}[c_t x_t^*] = (\alpha E_{t-1}[p_{t+1}])^{1/(1-\alpha)}/E_{t-1}[c_t]^{\alpha/(1-\alpha)}, \tag{9}$$

while expected revenues in t+1 are

$$E_{t-1}\left[p_{t+1}(x_t^*)^{\alpha}\right] = E_{t-1}[p_{t+1}]^{1/(1-\alpha)}(\alpha/E_{t-1}[c_t])^{\alpha/(1-\alpha)}. \tag{10}$$

Comparing Eqs. (9) and (10), variable costs are expected to be α times revenue, so the firm's expected gross margin is simply $1-\alpha$. Naturally, production, revenues, and earnings are all positively related to the expected output price and negatively related to the expected input price.

Changes in prices and costs induce straightforward dynamics. An unexpected increase in c_t leads to higher inventory costs in year t and lower profits in year t+1, followed by a decline in production, as the firm adjusts to higher costs, and

[5] These effects by no means exhaust the possible product-market explanations for the low persistence of accruals. A third possibility, for example, is that receivables reflect the financial strength of a firm's customers: an increase in AR might signal that customers are struggling and need longer to pay, which presages a drop in future sales and profits. A fourth possibility is that an unexpected demand shock might induce short-run changes in inventory of the opposite sign (Dechow et al. 1998; Thomas and Zhang 2002). For example, a surge in orders at the end of the year might lead to a temporary drop in inventory—low accruals this year—followed by higher sales and profits in the subsequent year. The common element of these stories is that accruals predict subsequent profits because they reflect underlying product-market forces rather than measurement error or investment.

Table 1
Earnings, cash flow, and accrual dynamics in the model. This table reports descriptive statistics for earnings (NI), accruals (ACC), and cash flow (CF) in the model, along with predictive slopes from regressions of future earnings and sales (S) on lagged earnings and accruals. The estimates come from simulations of 200,000 years of data, given the parameter assumptions for each scenario described in the text.

Scenario	Var	Univariate statistics			Correlations				$Y = b_0 + b_1\ NI_t + b_2\ ACC_t + e$			
		Avg	Std	Auto	NI	ACC	CF		$Y = NI_{t+1}$	$Y = NI_{t+2}$	$Y = NI_{t+3}$	$Y = S_{t+1}$
1:	NI	0.07	0.09	0.89	1	0.03	0.95	b_1	0.89	0.80	0.71	0.00
F_t varies	ACC	0.00	0.03	−0.49	0.03	1	−0.29	b_2	0.00	0.00	0.00	0.00
	CF	0.07	0.10	0.77	0.95	−0.29	1					
2:	NI	0.07	0.12	0.78	1	0.29	0.74	b_1	0.79	0.65	0.54	0.55
F_t, p_t vary	ACC	0.00	0.09	−0.14	0.29	1	−0.42	b_2	−0.07	−0.11	−0.12	0.44
	CF	0.07	0.12	0.67	0.74	−0.42	1					
3:	NI	0.07	0.10	0.86	1	0.18	0.79	b_1	0.89	0.78	0.68	0.12
F_t, c_t vary	ACC	0.00	0.07	−0.42	0.18	1	−0.46	b_2	−0.21	−0.18	−0.16	0.39
	CF	0.07	0.11	0.57	0.79	−0.46	1					
4:	NI	0.07	0.12	0.77	1	0.32	0.66	b_1	0.80	0.64	0.53	0.61
F_t, p_t, c_t vary	ACC	0.00	0.11	−0.23	0.32	1	−0.50	b_2	−0.12	−0.13	−0.13	0.40
	CF	0.07	0.13	0.55	0.66	−0.50	1					
5:	NI	0.07	0.09	0.87	1	0.07	0.94	b_1	0.88	0.79	0.70	0.00
F_t varies +	ACC	0.00	0.03	−0.49	0.06	1	−0.28	b_2	−0.14	−0.08	−0.07	0.00
error	CF	0.07	0.10	0.77	0.94	−0.28	1					

a (partial) rebound in profits. In contrast, an unexpected increase in output price, p_{t+1}, leads to higher revenue and profits in year t+1, followed by an increase in production, revenues, and profits in future years. The exact effects would depend on the nature of competition in the industry. For example, an increase in demand should lead to higher profits in the short run, along with industry growth and entry that drive prices and profits back to normal. Similarly, an increase in costs would lead to exit, a decrease in supply, and an eventual return to normal profitability. To capture these effects in reduced form, we assume that prices and costs follow lognormal AR(1) processes, e.g., $\log(c_t) = a + \rho\ \log(c_{t-1}) + e$. We model the dynamics in logs to guarantee that the variables all stay positive, while mean reversion of the variables captures the intuition that prices and profits eventually return to normal levels.

Given the structure above, all quantities in the model can be solved in closed form, but we do not have simple expressions for persistence regression slopes due to the model's nonlinearities. Therefore, we use simulations to illustrate how the model's simple dynamics induce a link between accruals and future profits under a variety of different assumptions about parameters:

Scenario 1: We start with a benchmark case in which only fixed costs F_t vary through time, which neutralizes all product-market effects (production and sales are constant). This provides a convenient baseline because profits follow a simple AR(1) process. To make the model more realistic, we introduce AR and AP by assuming that a fraction π_t^{ar} of sales remains to be collected at year-end and a fraction π_t^{ap} of fixed costs remains to be paid (π_t^{ar} and π_t^{ap} are assumed lognormal and IID for simplicity). Variation in AR_t and AP_t generates randomness in accruals but does not affect production decisions.[6]

Scenario 2: The parameters are the same as Scenario 1 except that output price p_t varies over time, leading to endogenous variation in production and inventory. $\text{Log}(p_t)$ is assumed to have an autocorrelation of 0.60 and conditional standard deviation of 0.06. As discussed above, the mean reversion of p_t captures the intuition that the price effects of demand shocks are competed away as industry growth pushes profits back to normal. The autocorrelation of 0.60 implies that 'abnormal' prices last for several years, with the first-year price shock reverting 40% in the second year and roughly 80% by the fourth year. The standard deviation of p_t is chosen to generate reasonable variation in sales and profits.

Scenario 3: The parameters are the same as Scenario 1 except that input price c_t now varies over time. $\text{Log}(c_t)$ has an autocorrelation of 0.60 and conditional standard deviation of 0.04. The persistence of c_t captures the intuition that production cost are persistent but mean reverting (or that firms adapt over several years to changes in costs, mitigating the initial impact). The standard deviation of c_t is again chosen to generate reasonable variation in sales and profits.

Simulation results for the three scenarios are reported in Table 1. At the top, Scenario 1 shows that variation in fixed costs alone, without changes in production or sales, does not generate differential persistence of accruals (as indicated by the regressions in the far-right columns). Profits and profitability follow AR(1) processes, and accruals just offset cash-flow timing effects caused by fluctuations in AR_t and AP_t, leading to a persistence slope on accruals that is indistinguishable from zero.

[6] We choose parameters so that fixed costs are roughly 25% of sales and variable costs are 65% of sales, close to the empirical values we report later for SG&A and COGS. $\text{Log}(F_t)$ has a mean of log(0.25), autocorrelation of 0.90, and conditional standard deviation of 0.15. The autocorrelation captures the intuition that fixed costs change slowly. The parameter α is 0.65; input price (c_t) and capital (K) are normalized to one; and the output price (p_t) is set to 1.30, which makes sales roughly on par with assets. Average AR is assumed to be 15% of sales and average AP is assumed to be 10% of fixed costs, both with a standard deviation of 15% in logs.

Table 2
Empirical predictions. This table summarizes the predictions of the measurement error, investment, and product-market hypotheses. The entries show the predicted sign, if any, of the relation between accruals in year t and the variables listed in the first column, with the strength of the relation indicated by the number of '+'s or '–'s.

Relation[a] between ACC_t and future …	Measurement error hypothesis	Investment hypothesis	Product-market hypothesis
Profitability			
Short run (t+1)	– –	– –	– –
Long run (t+k)	–[b]	–	– –
Profits			
Short run (t+1)	– –	+[c]	– –
Long run (t+k)	–	++	– –
Sales		++	++
Expenses		+	+++
Competition			++

[a] Controlling for current earnings.
[b] The slope should rebound toward zero at t+2 (if measurement error reverses quickly) and then decay toward zero.
[c] The slope could be negative if time-to-build effects are important.

The results change when the firm's production and sales respond, endogenously, to changes in output prices (Scenario 2), input prices (Scenario 3), or both (Scenario 4 combines the effects). Not surprisingly, profits, accruals, and cash flow are more volatile in these scenarios. More importantly, accruals become positively related to contemporaneous profits and, controlling for this relation, negatively related to future profits, closely mirroring the empirical results in the literature. It is useful to note that accruals *by themselves* are positively correlated with future profits when prices fluctuate; the slope in the predictive regression is negative only because the regression controls for current profits.

The results are fairly intuitive. Consider first Scenario 3, with only variation in input costs. A positive shock to the input price raises production costs and inventory in year t but does not reduce profits until year t+1, when the inventory is sold. Thus, high accruals in year t predict lower profits in year t+1. In subsequent years, the firm responds to higher costs by cutting production, inducing reversals in inventory. Profits increase from their depressed level both because the firm adjusts to higher costs (production declines) and because costs revert back to normal levels.

The economics are more subtle when output prices change through time (Scenario 2). Here, a high expected sales price in year t+1 is associated with higher inventory in year t, since the firm ramps up production in anticipation of higher prices. This effect makes accruals positively correlated with future sales and future profits. At the same time, profits themselves are persistent, and the key issue is how accruals relate to future profits controlling for current profits. Intuitively, if accruals today are high, it is a sign that p_t is elevated and profits will decline in the future as competition drives prices back to normal levels. The result is that accruals are negatively related to future profits conditional on current profits.

The bottom panel of Table 1 (Scenario 5) adds measurement error to accruals, illustrating the effects discussed in Section 2.1. In particular, we start with Scenario 1 but assume that a portion of nonproduction fixed costs is erroneously capitalized into inventory each year. Error in the level of inventory is assumed to be IID through time with a standard deviation of 0.75%, which induces a persistence slope on accruals that roughly matches empirical estimates. The simulations illustrate the bounce-back discussed earlier: the accrual slope predicting 2-year-ahead earnings is roughly half the slope predicting 1-year-ahead earnings, reflecting the fact that high accruals in year t signal not just that current earnings are overstated but that earnings in year t+1 will be temporarily understated as the valuation error reverses. Thus, with measurement error, accruals predict an especially strong drop in short-run earnings and smaller drops in long-run earnings.

We do not see a similar rebound effect in Scenarios 2, 3, and 4—indeed, in absolute value, the long-horizon slopes on accruals in Scenarios 2 and 4 actually increase relative to the 1-year-ahead slope (and only decay slowly in Scenario 3). Moreover, the right-most column in Table 1 shows that high accruals predict not only lower earnings but also higher sales as firms respond to input and output prices (inventory accruals lead sales). The measurement error hypothesis does not predict this relation, at least in the simple version discussed here in which measurement error is unrelated to the firm's underlying performance. These patterns suggest a way to distinguish the product market and measurement error hypotheses.

Hypothesis 3. Product Markets: *If input costs and output prices change over time, then, controlling for earnings in year t: (i) accruals should be negatively related to subsequent earnings (profits and profitability) but positively related to subsequent sales; (ii) the relation between accruals and subsequent earnings should be long-lasting, with no particular rebound in slopes at short horizons (indeed, the slopes may increase with the horizon); and (iii) the drop in profits should be linked to industry-wide demand and supply shocks that show up in industry growth, profits, and competition.*

2.4. Summary

Measurement error, investment effects, and demand and supply dynamics can all induce a link between accruals and future earnings. Importantly, as summarized in Table 2, the models make different predictions about (i) the behavior of profits vs. profitability; (ii) the link between accruals and earnings in the short run vs. the long run; (iii) the link between accruals and sales; and (iv) industry dynamics. The different predictions provide a way to discriminate between the hypotheses

empirically, recognizing that the theories do not make crisp predictions about all variables. For example, the measurement error hypothesis does not clearly state whether accruals should predict profits or just profitability, but it seems reasonable to think accruals will be negatively related to both if measurement error is important. The time-to-build version of the investment hypothesis does not clearly delineate 'short run' versus 'long run,' so any empirical test will require judgment about how many years in the future to look. These issues make it difficult to distinguish between the theories, a challenge we take up in the next section.

3. Empirical design

Our tests explore the link between accruals and subsequent earnings, sales, expenses, and competition, over short and long horizons, to distinguish among the hypotheses above. The starting point for our analysis is the persistence regression in Eq. (2), restated here for reference:

$$NI_{t+1}/TA_{t+1} = b_0 + b_1 NI_t/TA_t + b_2 ACC_t/TA_t + e, \tag{11}$$

where NI_t is a measure of earnings, ACC_t is a measure of accruals, and TA_t is a measure of assets used to scale the variables (typically defined as average total assets for the year). Notice that earnings in t+1 is scaled by contemporaneous assets, TA_{t+1}, so Eq. (11) essentially regresses profitability on lagged profitability and scaled accruals. This regression is the form most often used in the empirical literature. The hypotheses in Section 2 all imply that accruals are less persistent than cash flows ($b_2 < 0$) but make different predictions about the long-run behavior of profits, sales, expenses, and accruals. We test these predictions by extending the persistence regression in several ways.

3.1. Profits vs. profitability

Our first extension is to re-scale earnings on the left-hand side of Eq. (11) with assets from year t, so all variables have the same denominator:

$$NI_{t+1}/TA_t = c_0 + c_1 NI_t/TA_t + c_2 ACC_t/TA_t + e. \tag{12}$$

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. (12) tells us about the predictive power of accruals for future *profits* rather than future *profitability*. The investment hypothesis implies that the slope on accruals in this regression should be positive, even though accruals are negatively related to profitability in Eq. (11). In contrast, the measurement error and product market hypotheses imply the slope will be negative regardless of whether TA_t or TA_{t+1} is used to scale the dependent variable.

3.2. Long horizons

Our second extension is to expand the forecast horizon up to seven years, replacing NI_{t+1} with NI_{t+2}, ..., NI_{t+7}. The goal, as discussed in Section 2, is to explore the long-run predictive power of accruals. The measurement error and time-to-build hypotheses imply that accruals' predictive power should weaken or reverse over long horizons, while the product-market hypothesis is consistent with a long-term drop in profits and profitability. We are especially interested in whether the slopes reveal any 'rebound' effect associated with transitory measurement error.

3.3. Sales and expenses

Our third extension is to test whether accruals predict future sales and expenses. Because $NI_{t+k} = Sales_{t+k} - COGS_{t+k} - SGA_{t+k} - OthExp_{t+k}$, the slopes when the four right-hand side variables are regressed on NI_t and ACC_t mechanically sum to the slopes in the earnings regression Eq. (11) or (12). We focus on specifications using changes in sales and expenses to test whether accruals predict growth in the variables. The investment and product-market hypotheses imply that accruals should have a positive slope in these regressions, while the measurement error hypothesis does not make an explicit prediction here without additional assumptions. For example, in the sales regression, the slope on accruals would be zero if sales follow a random walk—even if accruals are measured with error—but we would expect a negative slope if positive accrual errors are more prevalent among distressed, slow-growth firms. The expense regressions are interesting because they shed light on whether accruals' predictive power is tied to a specific type of expense. An important complication is that accruals turn out to be positively related to future sales, and the interesting question is whether expenses grow *abnormally* fast, given the growth in sales. As described later, we test this either using average margins as a benchmark for normal expense growth or by controlling directly for sales growth in the expense regressions.

3.4. Industry dynamics

Our fourth extension is to explore how accruals correlate with industry-wide sales, profits, and competition. The motivation here is twofold. First, the product-market hypothesis suggests that the predictive power of accruals should extend to industry profits because demand and supply shocks will affect many firms in the industry at the same time (as we explain

later, the measurement error hypothesis does not make the same prediction). Second, the product-market hypothesis says that high accruals are linked to abnormal *true* profitability that should attract new entry and competition, which in turn contributes to the subsequent decline in profit margins. We study both issues empirically but defer a detailed description of the tests until later.

3.5. Future accruals

Our final extension is to use future accruals as the dependent variable:

$$ACC_{t+1}/TA_{t+1} = f_0 + f_1 NI_t/TA_t + f_2 ACC_t/TA_t + e. \tag{13}$$

The basic goal here is to test whether accruals exhibit time-series reversals ($f_2 < 0$). An important complication arises, however, from the link between accruals and subsequent sales growth. This link suggests that accruals could have a persistent component in the absence of measurement error (see also Allen et al. 2013), and the interesting question is whether accruals exhibit abnormal reversals, given the growth in sales. We address this issue in the same way described above for expenses, controlling for sales growth in the regressions.

4. Data

Our main data source is the Compustat annual file. The sample includes all nonfinancial firms that have data for earnings, accruals, sales, COGS, SG&A, and average total assets (financial firms are identified using historical SIC codes from the Center for Research in Security Prices (CRSP); in order to guard against any look-ahead bias, we require a firm to have data available on CRSP at the beginning of the financial year, as indicated by a nonmissing stock price). Our tests start in 1970, the first year that more than 1000 firms have data for all variables we consider. The final sample has an average of 3432 firms per year from 1970–2015, for a total sample of 157,850 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).

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 income, expenses, and accruals by average total assets during the year. The only exception is that the dependent variable is sometimes scaled by assets from the year the predictor variables are measured (NI_{t+k}/TA_t) rather than the contemporaneous value of assets (NI_{t+k}/TA_{t+k}). The scaled variables are winsorized annually at their 1st and 99th percentiles to reduce the impact of outliers.

Table 3 reports descriptive statistics for the sample. Sales for the average firm are about a third greater than assets while bottom-line earnings are slightly negative (-1.8%). COGS average 91% of assets (68% of sales), SGA averages 34% of assets (25% of sales), and other expenses average 10% of assets (8% of sales). Working capital is typically positive (18% of assets) because current operating assets (39% of assets) are roughly double current operating liabilities (21% of assets). 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 4 shows that annual changes in most income statement and balance sheet accounts are positively correlated with each other and with contemporaneous earnings. dSales is especially highly correlated with dCOGS (0.90), dSGA (0.54), and dCOA (0.58) but only weakly correlated with dNI (0.14). 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 3) and only slightly negatively correlated with dCOL. Long-term accruals have a relatively weak correlation with dNWC (0.11) but a somewhat stronger correlation (0.29) with the components of working-capital accruals (dCOA and dCOL).

5. Empirical results

The 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, profits, and competition 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

Table 3
Descriptive statistics, 1970–2015. 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 each variable. Flow and change variables are scaled by average total assets for the year, while end-of-year 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, and SG&A expense. Financial firms are identified using historical SIC codes from CRSP.

Variable	Description	Mean	Med	Std	Min	Max	N
Sales	Revenue	1.331	1.180	0.876	0.050	4.967	3432
COGS	Cost of goods sold	0.910	0.743	0.744	0.013	4.216	3432
SGA	Selling, general, and admin.	0.335	0.270	0.267	0.015	1.395	3432
OthExp	Other expenses[a]	0.103	0.093	0.094	−0.163	0.527	3432
NI	Net income	−0.018	0.036	0.200	−1.013	0.284	3432
dSales	Change in Sales	0.103	0.087	0.313	−1.059	1.194	3426
dCOGS	Change in COGS	0.064	0.052	0.244	−0.931	0.955	3426
dSGA	Change in SGA	0.021	0.017	0.097	−0.426	0.348	3395
dOthExp	Change in OthExp	0.005	0.010	0.120	−0.593	0.431	3395
dNI	Change in NI	0.009	0.006	0.174	−0.582	0.854	3426
NWC	Net working capital[b]	0.181	0.177	0.196	−0.400	0.656	3431
LTNOA	Long-term net operating assets[c]	0.403	0.384	0.219	−0.054	0.909	3431
COA	Current operating assets[d]	0.392	0.391	0.209	0.019	0.863	3431
COL	Current operating liabilities[e]	0.211	0.183	0.131	0.025	0.784	3431
dNWC	Change in NWC	0.010	0.010	0.099	−0.360	0.325	3432
dLTNOA	Change in LTNOA	0.033	0.016	0.157	−0.525	0.641	3432
dCOA	Change in COA	0.028	0.023	0.116	−0.388	0.419	3432
dCOL	Change in COL	0.018	0.014	0.075	−0.250	0.300	3432

[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 4
Correlations, 1970–2015. This table reports the average annual cross-sectional correlation between the 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, and SG&A expense. Financial firms are identified using historical SIC codes from CRSP. Variables are defined in Table 3.

	NI	dNI	dSales	dCOGS	dSGA	dOthExp	dNWC	dLTNOA	dCOA	dCOL
NI	–	0.36	0.28	0.21	0.15	−0.16	0.29	0.28	0.27	0.05
dNI	0.36	–	0.14	−0.02	−0.25	−0.58	0.14	0.06	0.07	−0.05
dSales	0.28	0.14	–	0.90	0.54	0.20	0.33	0.29	0.58	0.45
dCOGS	0.21	−0.02	0.90	–	0.45	0.15	0.28	0.24	0.50	0.40
dSGA	0.15	−0.25	0.54	0.45	–	0.16	0.20	0.26	0.42	0.37
dOthExp	−0.16	−0.58	0.20	0.15	0.16	–	−0.03	0.02	0.11	0.20
dNWC	0.29	0.14	0.33	0.28	0.20	−0.03	–	0.11	0.72	−0.12
dLTNOA	0.28	0.06	0.29	0.24	0.26	0.02	0.11	–	0.29	0.29
dCOA	0.27	0.07	0.58	0.50	0.42	0.11	0.72	0.29	–	0.56
dCOL	0.05	−0.05	0.45	0.40	0.37	0.20	−0.12	0.29	0.56	–

autocorrelation in the slopes. We find qualitatively and quantitatively similar results from panel regressions that include year fixed effects and standard errors clustered by firm and year—the slopes are close to those reported below and the standard errors are typically smaller—but prefer Fama-MacBeth regressions because of their simplicity, flexibility, and robustness.

5.1. Predicting profitability

To begin, Table 5 reports standard persistence regressions—profitability regressed on prior-year profitability and accruals—along with tests that extend the forecast horizon out to seven years. The predictability of earnings over long horizons is interesting in its own right, but the central question for our purposes is whether the slope on accruals rebounds and decays toward zero, as predicted by the measurement error hypothesis. Our main focus is on the predictive power of working-capital accruals, but we include dLTNOA in the regressions following FWY (2003a) and others. (The results are very similar if dLTNOA is omitted since dNWC and dLTNOA are only weakly correlated; see Table 4.)

The first column, using $ROA_{t+1} \equiv NI_{t+1}/TA_{t+1}$ as the dependent variable, confirms the results in prior studies: Profitability is highly persistent but, controlling for current earnings, working-capital and long-term accruals are strongly negatively related to subsequent ROA_{t+1}. At the one-year horizon, the slopes on dNWC (−0.12) and dLTNOA (−0.11) are nearly identical

Table 5
Predicting profitability, 1970–2015. This table reports average slopes and R^2s from annual cross-sectional regressions of profitability on lagged profitability and accruals: $NI_{t+k}/TA_{t+k} = b_0 + b_1\ NI_t/TA_t + b_2\ dNWC_t/TA_t + b_3\ dLTNOA_t/TA_t + e$. 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. The sample includes all nonfinancial firms on Compustat with data for net income, net operating assets, selling, general, and administrative expenses, and market value (from CRSP). Variables are defined in Table 3.

Regressor	Dependent variable: NI_{t+k}/TA_{t+k}						
	t+1	t+2	t+3	t+4	t+5	t+6	t+7
NI_t	0.74	0.62	0.54	0.50	0.46	0.43	0.40
t	58.36	25.68	18.44	17.94	17.69	15.89	15.33
$dNWC_t$	−0.12	−0.14	−0.13	−0.12	−0.11	−0.11	−0.10
t	−15.53	−9.75	−10.80	−7.25	−7.77	−7.03	−6.84
$dLTNOA_t$	−0.11	−0.11	−0.09	−0.09	−0.09	−0.07	−0.06
t	−10.06	−10.45	−8.59	−7.22	−5.52	−5.90	−5.28
R^2	0.467	0.313	0.238	0.196	0.165	0.140	0.117

and more than ten standard errors below zero. The results imply that accruals are significantly less persistent than cash flows.

The slopes remain highly significant for longer horizons and, in the case of working-capital accruals, actually become more negative for horizons out to t+3, despite the fact that the slope on lagged ROA_t declines (from 0.74 at the 1-year horizon to 0.54 at the 3-year horizon). Even after seven years, the slope on $dNWC_t$ remains nearly as large (−0.10) as the 1-year slope (−0.12). (The slope for t+7 is highly significant and statistically indistinguishable from the 1-year-ahead slope.) Thus, controlling for current profitability, higher accruals predict lower profitability for many years into the future.[7]

These results are inconsistent with the measurement-error hypothesis. As discussed earlier, if measurement error explains the low persistence of accruals, we expect accruals to predict a relatively large drop in short-run profitability followed by a partial rebound once measurement-error reversals have worked their way through earnings (with additional decay as the horizon is lengthened). The rebound should occur relatively quickly for working-capital accruals since any error in, say, AR and inventory automatically reverses as receivables are collected and inventory is sold. Table 5 shows, however, that the drop in profitability following high dNWC is actually stronger in years t+2 and t+3 than in year t+1, with no evidence of a significant rebound at any horizon. The initial strengthening of the slope and the long-term predictive power of accruals is hard to reconcile with the measurement error hypothesis, but both are consistent with our analysis of how demand and supply shocks can affect accruals and profitability.

More formally, we can interpret the slopes using the measurement error model in Section 2. If accruals predict earnings because of measurement error, Section 2.1 shows that the k-year-ahead slope on accruals equals

$$b_{2k} = -\sigma_\eta^2\left(\rho^k - \lambda_k\right)\frac{\sigma_{NI,CF}}{\sigma_{ACC}^2\sigma_{CF}^2[1-\rho_{ACC,CF}^2]}, \tag{14}$$

where ρ^k and λ_k are the kth-order autocorrelations of true earnings and measurement error, respectively, and $\sigma^2{}_{(\cdot)}$, $\sigma_{(\cdot)}$, and $\rho_{(\cdot)}$ denote the variance, covariance, and correlation of the variables indicated. The ratio in Eq. (14) depends only on observables and is close to 100 in the data.[8] The term in parentheses is a difference between two autocorrelations and, while we cannot estimate it explicitly, we would expect it to be around 1.0 for relatively short horizons given the high persistence of ROA and the expectation that measurement error exhibits reversals (i.e., ρ should be close to one and λ should be a small negative number). Thus:

$$b_{2k} \approx -\sigma_\eta^2 \times 100. \tag{15}$$

It follows that, to explain a slope of −0.12 for $k = 1$ in Table 5, the standard deviation of measurement error would need to be around 0.035 (3.5% of assets), implying a variance of 0.0012. This suggests that errors would have to be implausibly large, with earnings and accruals often misstated by more than 4% or 5% of assets.[9] This result adds to the bigger problem

[7] Our results here are robust to the way we deal with extreme observations. We find very similar patterns in Table 5 if we drop extreme values rather than winsorize; if we winsorize at the 5th and 95th percentiles rather than at the 1st and 99th percentiles; if we drop observations in which dNWC is below its 10th percentile or above its 90th percentile or outside the range −10% to + 10% of assets; or if we drop microcap stocks from the regressions (defined as stocks below the NYSE 20th percentile based on market cap). In all cases, the slopes for all horizons are statistically negative and the slope for t+7 is similar to (and sometimes even bigger than) the slope for t+1.

[8] The ratio can be estimated in two ways. If we estimate each of the inputs annually, average the results, and then calculate the ratio, we get an estimate of 96.0 ($\sigma_{NI,CF} = 0.038$; $\sigma_{CF} = 0.210$; $\sigma_{ACC} = 0.099$; $\rho_{ACC,CF} = -0.290$). Alternatively, we can estimate the ratio itself every year and then average, giving an estimate of 112.0. Our back-of-the-envelope calculation above is similar using either value.

[9] For perspective, Chief Financial Officers surveyed by Dichev et al. (2013) believe that 20% of firms intentionally manage earnings in a given year and, for such firms, earnings management represents perhaps 10% of earnings, a number that would typically translate into less than 1% of assets.

Table 6
Predicting profits, 1970–2015. This table reports average slopes and R^2s from annual cross-sectional regressions of profits, NI_{t+k}, on lagged profits and accruals, NI_t and ACC_t, all scaled by average total assets in year t: $NI_{t+k}/TA_t = b_0 + b_1\ NI_t/TA_t + b_2\ dNWC_t/TA_t + b_3\ dLTNOA_t/TA_t + e$. 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. The sample includes all nonfinancial firms on Compustat with data for net income, net operating assets, SG&A expense, and market value (from CRSP). Variables are defined in Table 3.

Regressor	Dependent variable: NI_{t+k}/TA_t						
	t+1	t+2	t+3	t+4	t+5	t+6	t+7
NI_t	0.77	0.72	0.72	0.75	0.78	0.81	0.84
t	41.66	23.72	19.66	16.50	14.18	12.92	12.13
$dNWC_t$	−0.14	−0.15	−0.18	−0.18	−0.16	−0.17	−0.15
t	−8.92	−6.78	−6.82	−4.96	−5.40	−4.65	−3.94
$dLTNOA_t$	−0.16	−0.17	−0.16	−0.15	−0.14	−0.10	−0.06
t	−6.48	−5.94	−5.30	−4.08	−3.11	−2.15	−1.32
R^2	0.468	0.299	0.219	0.175	0.143	0.120	0.102

for the measurement error hypothesis, that the slope does not rebound or significantly decay for up to seven years, contrary to the model's predictions.

An interesting feature of the measurement-error model is that, if it *is* well-specified, we can infer the autocorrelation of true earnings from the estimates in Table 5. In particular, the Appendix shows that ρ is linked directly to the slopes on lagged earnings (b_1) and accruals (b_2):

$$\rho = b_1 + (\sigma_{ACC,CF}/\sigma_{NI,CF})b_2. \tag{16}$$

The term in parentheses is −0.39 in the data, implying that $\rho = 0.777$ (standard error = 0.01). This parameter suggests that the slope on accruals in year 7 should decay to roughly 22% (i.e., 0.777^6) of the 1-year slope, again contrary to what we observe in the data.

A formal specification test of the measurement-error model comes from the observation that we can directly estimate higher-order autocorrelations of earnings from the k-year-ahead persistence regressions and test whether they decay toward zero at the rate predicted by the model. For example, using the formula in Eq. (16) and the regression slopes for k = 7 ($b_{1,7} = 0.40$ and $b_{2,7} = -0.10$), the 7th-order autocorrelation of true earnings is 0.43 (standard error of 0.02). However, the first-order autocorrelation estimated above implies a 7th-order autocorrelation of $0.777^7 = 0.17$. This inconsistency—a direct estimate of 0.43 vs. an implied value of 0.17—allows us to formally reject that the persistence slopes in Table 5 decay at the rate predicted by the measurement error model.

5.2. Predicting profits

The tests above focus on the link between accruals and profitability (i.e., NI_{t+k} scaled by assets in year t+k). As discussed in Section 2, the investment hypothesis predicts that the drop in ROA following high accruals comes from an increase in the denominator, and profits themselves should be positively related to lagged accruals. The easiest way to test this prediction is to scale future NI_{t+k} in the regressions by TA_t rather than TA_{t+k}, removing the impact of asset growth on the dependent variable. Put differently, scaling variables on both sides of the regression by the same deflator allows us to study the predictive power of accruals for future *profits* rather than future *profitability*.

Regressions with NI_{t+k}/TA_t replacing NI_{t+k}/TA_{t+k} as the dependent variable are reported in Table 6. In fact, accruals are strongly negatively related to future 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 six years, peaking at a decline of \$0.18 in years t+3 and t+4. 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 before dropping off in years t+6 and t+7. Thus, high short-term and long-term accruals predict an immediate and long-lasting decline in profits.[10]

The evidence in Table 6 is hard to reconcile with the investment hypothesis. The strong, long-lasting negative relation between accruals and subsequent profits directly contradicts a central prediction of the investment hypothesis, that the drop

[10] Our 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 157,850 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 Table 6 (−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 operating earnings in place of net income (−0.10); or if we scale the variables by average NOA in year t (−0.18) or NOA at the start of year t (−0.20).

Table 7
Predicting sales and expense growth, 1970–2015. This table reports average slopes and R^2s from annual cross-sectional regressions of changes in sales, expenses, and earnings ($dSales_{t+k}$, $dCOGS_{t+k}$, $dSGA_{t+k}$, $dOthExp_{t+k}$, and dNI_{t+k}) on lagged earnings and accruals (NI_t, $dNWC_t$, and $dLTNOA_t$). In panel B, sales growth in year t+k, $dSales_{t+k}$, is included as a control variable. All variables are scaled by average total assets in year t. 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. The sample includes all nonfinancial firms on Compustat with net income, net operating assets, SG&A expenses, and beginning-of-year market value (from CRSP). Variables are defined in Table 3.

	$dSales_{t+k}$			$dCOGS_{t+k}$			$dSGA_{t+k}$			$dOthExp_{t+k}$			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
Panel A: Simple predictive regressions															
NI_t	0.19	0.21	0.23	0.17	0.17	0.15	0.08	0.06	0.04	0.11	0.01	0.01	−0.19	−0.04	0.02
t	2.18	2.07	1.91	2.84	2.36	2.06	2.82	1.98	1.11	14.62	0.56	0.55	−11.02	−2.56	1.06
$dNWC_t$	0.56	0.28	0.25	0.47	0.19	0.15	0.18	0.10	0.10	0.04	0.03	0.02	−0.13	−0.02	−0.02
t	10.27	4.39	4.49	12.89	4.02	3.75	7.43	5.54	6.74	5.18	3.54	3.49	−9.43	−1.82	−1.47
$dLTNOA_t$	0.45	0.24	0.25	0.31	0.15	0.16	0.12	0.05	0.04	0.18	0.07	0.05	−0.16	−0.02	−0.01
t	12.07	7.85	6.23	11.05	6.49	6.12	9.90	6.78	4.94	11.82	6.63	3.97	−6.64	−1.76	−0.55
R^2	0.073	0.020	0.017	0.080	0.018	0.013	0.120	0.037	0.025	0.135	0.016	0.011	0.136	0.014	0.010
Panel B: Controlling for $dSales_{t+k}$															
NI_t				0.03	0.01	−0.02	0.05	0.04	0.01	0.10	−0.01	−0.01	−0.21	−0.05	0.00
t				4.43	1.47	−1.02	2.85	1.84	0.53	12.03	−0.90	−0.80	−11.29	−2.83	0.03
$dNWC_t$				0.09	0.00	−0.02	0.09	0.05	0.06	0.02	0.01	0.00	−0.19	−0.04	−0.03
t				10.94	0.31	−2.14	6.53	5.59	7.54	2.22	1.03	0.40	−11.11	−3.26	−2.76
$dLTNOA_t$				0.00	−0.02	−0.01	0.05	0.01	0.00	0.16	0.05	0.03	−0.21	−0.03	−0.02
t				0.54	−3.91	−1.10	8.53	1.92	0.35	9.98	5.95	3.14	−8.48	−3.08	−1.56
$dSales_{t+k}$				0.68	0.68	0.68	0.16	0.17	0.17	0.05	0.07	0.08	0.11	0.07	0.06
t				61.82	50.15	51.65	17.24	17.43	19.05	16.28	17.38	15.62	12.81	9.52	9.67
R^2				0.859	0.859	0.858	0.400	0.411	0.423	0.179	0.107	0.112	0.223	0.068	0.064

in ROA following high accruals reflects diminishing marginal returns—an increase in the denominator of ROA_{t+k}—rather than an actual drop in profits (see FWY 2003a,b; Zhang 2007; Wu et al. 2010). Interestingly, the slopes for profits in Table 6 are larger in magnitude than the slopes for profitability in Table 5, implying that asset growth from t to t+k masks, rather than causes, the negative slope on accruals when ROA_{t+k} is the dependent variable. The magnitudes also seem too large to be explained by a temporary drop in profits caused by time-to-build effects: the slopes are negative at least to t+7 and, if we sum the slopes across horizons, a \$1 increase in accruals is associated with about a \$1 cumulative drop in profits over the next seven years (the cumulative slope is −1.14 for dNWC and −0.95 for dLTNOA). This suggests that, if time-to-build effects explain the patterns, the entire payoff would have to occur after the investment has effectively been written off over the first seven years.

5.3. Predicting sales and expenses

Tables 5 and 6 show that the link between accruals and future earnings is too strong and too long-lasting to be explained by measurement error or investment effects. The patterns are consistent with our product-market model but do not directly establish that demand and supply effects explain the results. Our goal in the following sections is to explore the role of product markets in more detail.

As a first step, Table 7 studies the link between accruals and subsequent sales and expenses. The tests maintain the structure of persistence regressions but, in effect, break the dependent variable into its components. Because $NI_{t+k} = Sales_{t+k} - COGS_{t+k} - SGA_{t+k} - OthExp_{t+k}$, the slopes (appropriately signed) when the four variables on the right-hand side of this equality are regressed on lagged earnings and accruals sum to the slopes in the earnings persistence regressions above. (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. For brevity, we report results only for horizons out to year t+3.

The results, in the top panel of Table 7, reveal several interesting patterns. First, firms that are more profitable tend to have higher sales growth over the subsequent three years, consistent with the idea that demand and supply drive both profits and sales. However, expenses for high-profit firms grow even more rapidly than sales in years t+1 and t+2, leading to a drop in bottom-line earnings (far-right columns). Thus, a portion of today's profits is transitory because future margins deteriorate, despite growth in revenue.

Accruals also have strong predictive power. A dollar of $dNWC_t$ is associated with sales growth of \$0.56 in year t+1, \$0.28 in year t+2, and \$0.25 in year t+3, while a dollar of $dLTNOA_t$ is associated with sales growth of \$0.45 in year t+1, \$0.24 in year t+2, and \$0.25 in year t+3 (all statistically significant). The positive relation between accruals and future sales runs counter to the idea that high accruals are a sign of earnings management by struggling firms. The results are consistent with our product-market model in Section 2.3, in which changes in working capital lead sales.

High accruals also predict rapid growth in expenses. The jump in total expenses is expected, since accruals negatively predict profits, so the interesting issue is how different types of expenses contribute to the increase. To interpret the slopes,

recall that COGS, SGA, and OthExp average 68%, 25%, and 8% of sales, respectively (Section 4). Given that a dollar of dNWC predicts \$0.56 of additional sales in year t+1, we would expect COGS to increase by \$0.38 (0.56 × 0.68), SGA to increase by \$0.14 (0.56 × 0.25), and other expenses to increase by \$0.05 (0.56 × 0.08) if they grew proportionally with sales. Empirically, a dollar of dNWC actually predicts a \$0.47 increase in $dCOGS_{t+1}$ and a \$0.18 increase in $dSGA_{t+1}$, both substantially higher than normal. Put differently, \$1 of working-capital accruals predicts a significant \$0.13 drop in next year's earnings (far-right columns), 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 predict an additional \$0.31 of $COGS_{t+1}$, \$0.11 of SGA_{t+1}, and \$0.04 of $OthExp_{t+1}$ if expenses grow proportionally with $dSales_{t+1}$. The actual slopes for $COGS_{t+1}$ and SGA_{t+1} match the predictions exactly, but the slope for $OthExp_{t+1}$, 0.18, indicates a substantially greater-than-normal increase. (In supplemental tests, we find that the predictable increase in $OthExp_{t+1}$ comes from a combination of sources, including a significant increase in depreciation (\$0.05) and interest expense (\$0.04) and a significant decrease in special items (−\$0.05).) The differential predictive power of dNWC and dLTNOA for the components of expenses implies that current- and long-term accruals forecast lower profits for different reasons, dNWC because of shrinking operating margins and dLTNOA because of an increase in nonoperating expense. This result contradicts the idea that dNWC and dLTNOA are just two components of a generic investment effect (FWY 2003a).

Panel B of Table 7 adds $dSales_{t+k}$ (contemporaneous with the dependent variable) to the regressions as an alternative way to test whether accruals predict an abnormal increase in expenses, controlling for the relation between accruals and future sales.

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 even stronger than persistence regressions indicate because, all else equal, earnings should increase along with sales in t+1. The slopes on dNWC and dLTNOA drop to −0.19 and −0.21, respectively, stronger and more significant than the slopes in Panel A (−0.13 and −0.16, respectively). The larger slopes in these regressions make it even more difficult for measurement error and investment effects to explain the magnitude of the profit decline following high accruals.

The expense regressions confirm our inferences above. $dNWC_t$ has significant predictive power for both $dCOGS_{t+1}$ (0.09) and $dSGA_{t+1}$ (0.09), implying that a disproportionate increase in both variables contributes to the profit decline following high working-capital accruals. In contrast, $dLTNOA_t$ has modest predictive power for $dSGA_{t+1}$ (0.05) and strong predictive power for $dOthExp_{t+1}$ (0.16), indicating that profits decline following high long-term accruals largely because of a disproportionate rise in Other Expenses.

The predictive power of working-capital accruals for sales and expenses is consistent with our product-market hypothesis in Section 2. For example, an increase in demand should induce firms to raise production, leading to high working-capital accruals and high subsequent sales growth. At the same time, expenses will also grow, and subsequent profits decline, as growth, entry, and competition in the industry drive profit margins back to their long-run equilibrium level. (Cost shocks would have similar effects.) As illustrated in Section 2.3, these dynamics can generate patterns in sales, expenses, and profits that closely match the patterns documented in Tables 5–7. [11]

5.4. Industry dynamics

The product market story suggests that industry dynamics should help to explain the low persistence of accruals. For example, higher demand for bicycles should lead to temporarily high profits for bicycle manufacturers, along with an increase in industry-wide production and accruals and a subsequent decline in industry earnings as margins return to normal. These industry effects are not predicted by the measurement error hypothesis if measurement errors are idiosyncratic or, at least, not as highly correlated across firms as true earnings.[12] Thus, we explore industry profits, accruals, and growth as an additional test of the product-market hypothesis. To be specific, we look at two issues: (i) Do industry accruals predict industry profitability, profits, and sales growth? (ii) Do accruals predict changes in industry competition and entry in a way that might contribute to the subsequent decline in profit margins?

Table 8 considers the first issue. The regressions take the same form as our main tests but focus on industry-level profits, sales growth, and accruals. We calculate the industry average of the variables at the three-digit SIC-code level, dropping industries with fewer than 10 firms, to ensure that industries are relatively homogeneous but have enough firms to diversify away any firm-specific measurement error in earnings and accruals. (The main advantage of SIC codes, relative to GICS or

[11] The product-market hypothesis can even generate some of the more subtle patterns in Table 7. For example, the simulations in Section 2.3 indicate that working-capital accruals should predict an increase in both variable and fixed costs, with longer-lasting predictive power for fixed costs, similar to our empirical results for COGS and SGA. We do not want to read too much into these results, given the highly stylized nature of the model, but they do provide additional evidence that product-market effects can explain many features of the data.

[12] To illustrate, we estimate firm- and industry-level persistence regressions using data simulated from the measurement-error model in Section 2.1, assuming true earnings and measurement error contain firm-specific and industry components. As long as the correlation across firms in measurement error is less than the correlation in true earnings, we find that accruals should have less predictive power at the industry level. For example, using parameters calibrated to firm-level data, an accrual slope of -0.13 at the firm level implies a slope of −0.08 at the industry level if the within-industry earnings correlation is 0.40 but the within-industry measurement error correlation is 0.20 (50 industries of 40 firms). If measurement error is completely idiosyncratic, the slope in industry regression is just −0.01.

Table 8
Industry profits, sales, and accruals, 1970–2015. This table reports average slopes and R^2s from annual cross-sectional regressions of industries' earnings and sales growth on lagged earnings and accruals. Industries are based on three-digit SIC codes from CRSP, as described in the text. The dependent variable is the industry average of future profits scaled by future assets in Panel A, future profits scaled by current assets in Panel B, and future changes in sales scaled by current assets in Panel C. 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. Variables are defined in Table 3.

Regressor	Horizon						
	t+1	t+2	t+3	t+4	t+5	t+6	t+7
Panel A: Dependent variable $= NI_{t+k}/TA_{t+k}$							
NI_t	0.87	0.75	0.69	0.65	0.65	0.65	0.63
t	66.59	25.06	20.07	18.42	28.46	23.04	13.77
$dNWC_t$	−0.12	−0.20	−0.25	−0.25	−0.24	−0.26	−0.26
t	−4.37	−5.68	−7.10	−6.83	−5.98	−5.30	−5.05
$dLTNOA_t$	−0.14	−0.16	−0.16	−0.17	−0.19	−0.16	−0.18
t	−7.23	−5.72	−4.15	−4.00	−4.05	−4.27	−4.83
R^2	0.691	0.525	0.446	0.407	0.387	0.370	0.355
Panel B: Dependent variable $= NI_{t+k}/TA_t$							
NI_t	0.90	0.85	0.86	0.93	1.04	1.13	1.10
t	37.13	19.21	15.55	11.36	9.83	8.81	8.00
$dNWC_t$	−0.14	−0.18	−0.24	−0.23	−0.22	−0.30	−0.30
t	−5.14	−4.64	−5.20	−4.19	−2.91	−3.33	−2.62
$dLTNOA_t$	−0.16	−0.21	−0.22	−0.25	−0.32	−0.24	−0.28
t	−5.34	−4.70	−3.31	−2.68	−2.66	−2.20	−2.36
R^2	0.685	0.502	0.410	0.367	0.335	0.290	0.256
Panel C: Dependent variable $= dSales_{t+k}/TA_t$							
NI_t	0.02	−0.26	−0.39	−0.27	−0.31	−0.36	−0.38
t	0.27	−2.36	−2.83	−1.48	−1.62	−1.72	−1.07
$dNWC_t$	1.05	0.66	0.73	0.73	0.81	0.95	1.15
t	7.11	3.19	2.97	2.50	2.74	3.40	3.52
$dLTNOA_t$	0.53	0.33	0.54	0.62	0.70	0.64	0.60
t	5.24	2.43	4.06	3.27	3.06	2.62	2.64
R^2	0.141	0.083	0.083	0.098	0.091	0.083	0.083

NAICS codes, is that they are available for our entire time period whereas the GICS and NAICS classification schemes were not established until the late 1990s.) On average, there are 89 industries in our sample each year with at least 10 firms, and the average industry contains just over 30 firms.

The industry slopes are very similar to our firm-level results. In panel A, industry accruals are strongly negatively related to the industry's future profitability. The slopes on $dNWC_t$ (−0.12) and $dLTNOA_t$ (−0.14) at the one-year horizon are highly significant and closely match the firm-level slopes in Table 5. Moreover, the slopes increase in magnitude as the horizon is lengthened and, like the firm-level slopes, exhibit no evidence of a rebound or decay. The same is true of the slopes in Panel B, which focus on the predictability of future profits rather than future profitability (i.e., future earnings in Panel B are scaled by assets from year t in order to eliminate the impact of asset growth on the dependent variable): The slopes are highly significant, similar to the firm-level slopes in Table 6, and tend to increase in magnitude as the horizon grows. Thus, industry accruals predict a strong and long-lasting decline in industry profits and profitability, suggesting that industry-wide changes help explain the low persistence of accruals.

Panel C shows that industry accruals also predict significantly higher industry sales: $dNWC_t$ and $dLTNOA_t$ are strongly positively related to sales growth ($dSales_{t+k}/TA_t$) in the short run and for up to seven years. Just as we saw at the firm level, high accruals signal high industry sales growth going forward, again suggesting that accruals are correlated with either demand or supply shocks in the industry.

Table 9 explores the connection between accruals and competition. In particular, we return to our firm-level regressions but, rather than test whether accruals predict a firm's profits or sales, we ask whether a firm's accruals predict changes in industry competition measured either as new entry into the industry or as a change in the industry's Herfindahl index. The goal is to explore whether the industry behaves in a way that suggests high accruals signal abnormally high—and, in equilibrium, temporary—*true* profitability. If so, we expect high accruals to attract new competition, which, in turn, would help to explain the drop in subsequent profit margins. Entry and competition are not necessary to explain a drop in margins—existing firms might expand or contract until profits are driven back to long-run equilibrium—but a connection between accruals and entry supports the argument that accruals correlate with industry shocks.

Table 9 shows that accruals do predict a significant increase in competition. We keep the regressors—earnings, working-capital accruals, and long-term accruals—the same as in our main persistence regressions to ensure comparability of the results (i.e., we are interested in whether accruals predict competition controlling for the other two variables, similar to

Table 9
Accruals and competition, 1970–2015. This table reports average slopes and R^2s from annual cross-sectional regressions of new competition in a firm's industry on the firm's lagged profitability and accruals. For each firm, new competition is estimated in three ways: (i) percentage growth in the number of firms on Compustat in the same three-digit SIC code (Entry–Compustat); (ii) percentage growth in the number of all private enterprises in the same three-digit SIC code from the Bureau of Labor Statistics' Quarterly Census of Employment and Wages (Entry–all private); and the percentage change in the Herfindahl index of the three-digit SIC code, based on sales from Compustat (Herfindahl). 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. The sample includes all nonfinancial firms on Compustat with data for net income, net operating assets, selling, general, and administrative expenses, and market value (from CRSP). Variables are defined in Table 2.

	Entry–Compustat			Entry–all private			Herfindahl		
	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3
NI_t	−0.03	−0.01	−0.02	−0.01	−0.01	−0.01	0.00	0.01	0.01
t	−3.96	−2.37	−2.41	−2.69	−2.30	−3.46	−0.15	0.94	1.62
$dNWC_t$	0.05	0.03	0.03	0.01	0.01	0.01	−0.01	−0.03	−0.01
t	3.52	3.31	3.30	3.15	2.89	2.96	−2.09	−2.20	−1.02
$dLTNOA_t$	0.07	0.05	0.04	0.04	0.03	0.02	−0.03	−0.02	−0.01
t	4.44	4.07	3.45	2.63	3.05	2.63	−4.16	−1.94	−1.06
R^2	0.018	0.010	0.008	0.021	0.012	0.009	0.007	0.006	0.006

the way they predict profitability). We report three sets of results: In the first set of columns, the dependent variable is the percentage change in the number of firms in the same three-digit SIC code in our Compustat sample (again restricted to industries with at least 10 firms in year t). In the second set, we instead use total growth in the number of private enterprises in the industry from the U.S. Bureau of Labor Statistics' Quarterly Census of Employment and Wages (QCEW) to capture a much broader sample of firms (annual data by SIC code is available on the BLS's website for 1975–2000). Finally, in the right-most columns, we calculate percentage changes in the industry's Herfindahl index using sales from Compustat, where a decrease in the index is a sign of greater competition.

All three measures indicate that accruals are positively related to competition. Firms with high accruals are in industries that experience significantly greater entry in the subsequent three years, measured using either Compustat firms or all private enterprises from the QCEW. A one-standard-deviation increase in $dNWC_t$ (0.20) predicts a 2.0% increase in the number of Compustat firms and a 0.8% increase in the total number of private enterprises in the industry over the next three years. Similarly, a one-standard-deviation increase in $dLTNOA_t$ (0.16) predicts a 2.6% increase in the number of Compustat firms and a 1.3% increase in the total number of private enterprises. The results using the Herfindahl index are qualitatively similar.[13]

In short, Tables 8 and 9 show that accruals are significantly related to industry profits, growth, and competition. At the industry level, high accruals predict a strong and long-lasting drop in future profits similar to our findings at the firm level, and correlate with sales growth and firm entry in a way that suggests that accruals are correlated with industry-wide demand or supply shocks.

5.5. Predicting accruals

The evidence above suggests that product-market effects can explain the link between accruals and subsequent profits, sales, expenses, and competition better than measurement error or investment effects. Our final tests explore the predictability of accruals themselves to provide additional perspective on whether accruals behave as if they contain measurement error. In particular, our tests focus on two questions: (i) Do working-capital accruals exhibit reversals? (ii) Do working-capital accruals predict changes in current operating assets (COA), current operating liabilities (COL), or both?

One way to interpret the tests is that they ask whether high accruals signal that working capital is currently overstated and likely to drop in the future. The main complication comes from the fact that accruals could be predictable even in the absence of measurement error. For example, AR might increase when customers are slow in making payments and then return to normal in the following year, inducing reversals even in correctly-measured working capital. Conversely, our earlier tests show that dNWC predicts subsequent sales growth, so high $dNWC_t$ this year should be positively related to $dNWC_{t+1}$ if working capital in t+1 grows along with sales (Jones 1991; Dechow et al.1998; Allen et al. 2013). We control, at least partially, for these effects by adding future sales growth to the regressions. Our Appendix shows that, if the predictability of true accruals is captured by $dSales_{t+k}$, the slope on $dNWC_t$ in the second specification will have the same sign as the au-

[13] The negative slopes on NI_t in the 'entry' regressions in Table 9 are somewhat anomalous, suggesting that low profits are associated with higher subsequent competition. A possible explanation is that industries with lower profitability tend to have lower barriers to entry. Alternatively, rapidly growing industries could have temporarily low profits because investments in R&D and intangibles are expensed rather than capitalized. These possibilities are interesting but beyond the scope of the current paper to investigate.

Table 10
Predicting working-capital accruals, 1970–2015. This table reports average slopes and R^2s from annual cross-sectional regressions of working-capital accruals ($dNWC_{t+k}$, $dCOA_{t+k}$, and $dCOL_{t+k}$, all scaled by TA_{t+k}) on lagged profits and accruals (NI_t, $dNWC_t$, and $dLTNOA_t$, all scaled by TA_t). In panel B, sales growth in year t+k, $dSales_{t+k}$, is included as a control variable. 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. The sample includes all nonfinancial firms on Compustat with net income, net operating assets, SG&A expenses, and beginning-of-year market value (from CRSP). Variables are defined in Table 2.

	$dNWC_{t+k}$			$dCOA_{t+k}$			$dCOL_{t+k}$		
	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3
Panel A: Simple predictive regressions									
NI_t	0.13	0.08	0.05	0.15	0.10	0.07	0.02	0.02	0.01
t	3.59	3.67	4.00	3.45	3.76	3.73	1.91	2.86	2.24
$dNWC_t$	−0.02	−0.01	0.00	0.07	0.03	0.01	0.08	0.03	0.02
t	−1.41	−0.69	−0.66	5.15	2.72	2.59	9.49	7.41	4.49
$dLTNOA_t$	0.02	−0.01	−0.01	0.05	0.01	−0.01	0.03	0.01	0.01
t	5.55	−1.34	−1.82	6.93	0.78	−0.88	6.91	4.32	1.98
R^2	0.040	0.014	0.009	0.055	0.018	0.010	0.025	0.008	0.004
Panel B: Controlling for $dSales_{t+k}$									
NI_t	0.11	0.06	0.04	0.11	0.06	0.04	0.00	−0.01	0.00
t	3.58	3.49	4.02	3.48	3.47	3.44	−1.02	−1.57	−1.02
$dNWC_t$	−0.06	−0.01	−0.01	−0.01	0.01	0.01	0.04	0.02	0.01
t	−5.83	−2.08	−1.42	−1.67	0.87	1.14	6.31	6.35	3.20
$dLTNOA_t$	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	0.00	0.01	0.00
t	−2.47	−2.74	−2.63	−2.14	−1.71	−2.32	−0.54	2.19	0.98
$dSales_{t+k}$	0.10	0.10	0.10	0.21	0.21	0.21	0.11	0.10	0.10
t	13.19	13.83	14.33	24.89	26.97	28.12	36.43	35.63	36.78
R^2	0.140	0.119	0.113	0.353	0.337	0.332	0.205	0.194	0.186

tocorrelation of measurement error and should be closely related to (but smaller than) the slope in an earnings persistence regression.

Table 10 reports the results. In simple predictive regressions (Panel A), working-capital accruals exhibit little evidence of reversals: $dNWC_t$ is insignificantly related to $dNWC_{t+k}$ in each of the subsequent three years, with a predictive slope of just −0.02 (t-statistic of −1.41) at the one-year horizon. However, the slope on $dNWC_t$ is lower than we would expect given that $dNWC_t$ is positively related to future sales growth, which suggests it should also be positively related to future accruals. The tests in Panel B control for this effect by adding $dSales_{t+k}$ to the regressions. In fact, controlling for sales growth, high working-capital accruals this year are followed by abnormally low working-capital accruals for up to two years. A $1 increase in working capital today predicts a $0.06 below-average change next year and $0.01 below-average change in years t+2 and t+3. At face value, this evidence is consistent with the presence of negatively autocorrelated measurement error. The problem for the measurement error hypothesis is that the short-lived reversals in Table 10 are not reflected appropriately in the earnings persistence regressions in Table 5; the slopes in those regressions do not bounce back and decay as they should if measurement error is truly negatively autocorrelated (see Section 5.1).

The remaining columns in Table 10 provide additional evidence on whether reversals in working-capital accruals can be attributed to measurement error. In particular, focusing on Panel B, $dNWC_t$ is negatively related to $dNWC_{t+1}$ not because it predicts a drop in $dCOA_{t+1}$ (slope of −0.01 with a t-statistic of −1.67) but because it predicts an *increase* in $dCOL_{t+1}$ (slope of 0.04 with a t-statistic of 6.31). Again, this pattern is hard to reconcile with the measurement-error hypothesis because COA, not COL, is generally thought to be the less reliable component of accruals (e.g., RSST 2005). This suggests that reversals in dNWC are likely driven by something other than measurement error.

6. Interpretation and conclusion

The link between accruals and future profitability is well-documented in the accounting literature. Prior studies suggest that the decline in earnings following high accruals is explained by a combination of measurement error in accruals or investment effects driven by decreasing returns to scale, conservatism in accounting, or adjustment costs.

Our paper contributes to the literature in three main ways. First, we propose a new explanation for the link between accruals and future profitability based on the way firms' sales, accruals, and profits respond to demand and supply shocks in product markets. Our model shows that high accruals correlate with transitory changes in profit margins—in the absence of measurement error or investment effects—because sales, production, and accruals naturally respond to changes in input and output prices. Second, we extend the measurement-error model of RSST (2005) to derive testable new implications of measurement error. Finally, 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, competition, 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.

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 any transitory measurement error has worked its way through earnings—indeed, the predictive slope on accruals in long-run persistence regressions initially grows as the horizon is lengthened and shows essentially no decay out to seven years, contrary to the measurement-error hypothesis. Moreover, the time-series properties of accruals themselves exhibit relatively weak reversals that come from predictability in COL, not COA, opposite to what studies on measurement error generally predict.

The patterns in sales, expenses, and profits we document are consistent with our product-market hypothesis. More directly, we provide evidence that accruals' predictive power shows up reliably at the industry level, consistent with the idea that industry-wide changes in demand and/or supply help explain the link between accruals and future earnings. In addition, firms that report high accruals face significantly higher competition in the future—measured either as new entry into the industry or as a lower Herfindahl index—suggesting that high accruals correlate with abnormally high *true* profitability that attracts new entrants to the industry. This new entry can help explain why high profits are only temporary and provides additional evidence that accruals are linked to industry-wide events.

We certainly do not claim that our product-market hypothesis is the only possible explanation or the one that holds in all situations. Measurement error and investment effects almost certainly play a role. 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, an extensive literature studies 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 studies is that accrual errors—intentional or not—are pervasive. Our paper suggests, however, that product-market effects, rather than accrual measurement error, should be considered as an alternative explanation for some results in the literature.

Appendix

This appendix develops the measurement-error model in Section 2.1. The analysis builds on RSST (2005) but extends their results in several ways, e.g., we allow measurement error to be serially correlated and consider new implications of measurement error.

At a basic level, we are interested in the predictive regression

$$\mathrm{NI}_{t+1} = b_0 + b_1\mathrm{NI}_t + b_2\mathrm{ACC}_t + e_{t+1}, \tag{A1}$$

when 'true' earnings follow an AR(1) process, $\mathrm{NI}_{t+1}{}^* = c + \rho\ \mathrm{NI}_t{}^* + \mu_{t+1}$, but observed earnings and accruals are measured with error, $\mathrm{NI}_t = \mathrm{NI}_t{}^* + \eta_t$ and $\mathrm{ACC}_t = \mathrm{ACC}_t{}^* + \eta_t$. (Here, correctly-measured accruals are defined as true earnings minus cash flow, $\mathrm{ACC}_t{}^* \equiv \mathrm{NI}_t{}^* - \mathrm{CF}_t$.) Our analysis allows measurement error to be serially correlated but, for simplicity, we maintain RSST's assumption that η_t is not related to $\mathrm{NI}_t{}^*$ or $\mathrm{ACC}_t{}^*$. The existence of measurement error means that observed earnings will be predictably related to accruals (b_2 will differ from zero) even though true earnings are AR(1).

Formally, if we stack the slopes in Eq. (A1) into the column vector $b = (b_1, b_2)$ and the regressors into the vector $x_t = (\mathrm{NI}_t, \mathrm{ACC}_t)$, standard regression analysis implies that

$$b = \mathrm{var}^{-1}(x_t)\mathrm{cov}(x_t, \mathrm{NI}_{t+1}). \tag{A2}$$

To evaluate this expression, first note that the variance-covariance matrix of x_t is

$$\mathrm{var}(x_t) = \begin{bmatrix} \sigma^2_{\mathrm{NI}} & \sigma_{\mathrm{NI,ACC}} \\ \sigma_{\mathrm{NI,ACC}} & \sigma^2_{\mathrm{ACC}} \end{bmatrix} = \begin{bmatrix} \sigma^2_{\mathrm{NI}^*} + \sigma^2_\eta & \sigma_{\mathrm{NI}^*,\mathrm{ACC}^*} + \sigma^2_\eta \\ \sigma_{\mathrm{NI}^*,\mathrm{ACC}^*} + \sigma^2_\eta & \sigma^2_{ACC^*} + \sigma^2_\eta \end{bmatrix}, \tag{A3}$$

where $\sigma^2{}_{(\cdot)}$ and $\sigma_{(\cdot)}$ denote the variance or covariance of the variables indicated. The inverse is

$$\mathrm{var}^{-1}(x_t) = \frac{1}{D}\begin{bmatrix} \sigma^2_{\mathrm{ACC}} & -\sigma_{\mathrm{NI,ACC}} \\ -\sigma_{\mathrm{NI,ACC}} & \sigma^2_{\mathrm{NI}} \end{bmatrix}, \tag{A4}$$

with determinant

$$D = \sigma^2_{\mathrm{ACC}}\sigma^2_{\mathrm{NI}} - \sigma^2_{\mathrm{NI,ACC}} = \sigma^2_{\mathrm{ACC}}\sigma^2_{\mathrm{NI}}(1 - \rho^2_{\mathrm{NI,ACC}}) = \sigma^2_{\mathrm{ACC}}\sigma^2_{\mathrm{CF}}(1 - \rho^2_{\mathrm{CF,ACC}}), \tag{A5}$$

where $\rho_{(\cdot,\cdot)}$ denotes a correlation. The last equality in (A5) uses the fact that the residual variance when NI_t is regressed on ACC_t, $\sigma^2_{\mathrm{NI}}(1-\rho^2_{\mathrm{NI,ACC}})$, is the same as the residual variance when CF_t is regressed on ACC_t, $\sigma^2_{\mathrm{CF}}(1 - \rho^2_{\mathrm{CF,ACC}})$, since $\mathrm{NI}_t = \mathrm{ACC}_t + \mathrm{CF}_t$. Returning to Eq. (A2), the covariance between x_t and NI_{t+1} is

$$\mathrm{cov}(x_t, \mathrm{NI}_{t+1}) = \begin{bmatrix} \rho\sigma^2_{\mathrm{NI}^*} + \mathrm{cov}(\eta_t, \eta_{t+1}) \\ \rho\sigma_{\mathrm{NI}^*,\mathrm{ACC}^*} + \mathrm{cov}(\eta_t, \eta_{t+1}) \end{bmatrix} = \begin{bmatrix} \rho\sigma^2_{\mathrm{NI}^*} + \lambda\sigma^2_\eta \\ \rho\sigma_{\mathrm{NI}^*,\mathrm{ACC}^*} + \lambda\sigma^2_\eta \end{bmatrix}, \tag{A6}$$

where λ is the first-order autocorrelation of η_t. Substituting Eqs. (A4) and (A6) into Eq. (A2) gives:

$$\begin{aligned} b &= \frac{1}{D}\begin{bmatrix} \sigma^2_{ACC} & -\sigma_{NI,ACC} \\ -\sigma_{NI,ACC} & \sigma^2_{NI} \end{bmatrix}\begin{bmatrix} \rho\sigma^2_{NI^*} + \lambda\sigma^2_\eta \\ \rho\sigma_{NI^*,ACC^*} + \lambda\sigma^2_\eta \end{bmatrix} \\ &= \frac{1}{D}\begin{bmatrix} \rho\sigma^2_{NI^*}\sigma^2_{ACC} - \rho\sigma_{NI,ACC}\sigma_{NI^*,ACC^*} + \lambda\sigma^2_\eta(\sigma^2_{ACC} - \sigma_{NI,ACC}) \\ -\rho\sigma^2_{NI^*}\sigma_{NI,ACC} + \rho\sigma_{NI^*,ACC^*}\sigma^2_{NI} + \lambda\sigma^2_\eta(\sigma^2_{NI} - \sigma_{NI,ACC}) \end{bmatrix} \end{aligned} \tag{A7}$$

Using the fact that $\sigma^2_{NI^*}=\sigma^2_{NI} - \sigma^2_\eta$ and $\sigma_{NI^*,ACC^*}=\sigma_{NI,ACC} - \sigma^2_\eta$, Eq. (A7) can be rewritten as:

$$\begin{aligned} b &= \frac{1}{D}\begin{bmatrix} \rho\sigma^2_{NI}\sigma^2_{ACC} - \rho\sigma^2_{NI,ACC} - \rho\sigma^2_\eta(\sigma^2_{ACC} - \sigma_{NI,ACC}) + \lambda\sigma^2_\eta(\sigma^2_{ACC} - \sigma_{NI,ACC}) \\ -\rho\sigma^2_{NI}\sigma_{NI,ACC} + \rho\sigma^2_\eta\sigma_{NI,ACC} + \rho\sigma_{NI,ACC}\sigma^2_{NI} - \rho\sigma^2_\eta\sigma^2_{NI} + \lambda\sigma^2_\eta(\sigma^2_{NI} - \sigma_{NI,ACC}) \end{bmatrix} \\ &= \frac{1}{D}\begin{bmatrix} \rho D + (\lambda - \rho)\sigma^2_\eta(\sigma^2_{ACC} - \sigma_{NI,ACC}) \\ (\lambda - \rho)\sigma^2_\eta(\sigma^2_{NI} - \sigma_{NI,ACC}) \end{bmatrix} \end{aligned} \tag{A8}$$

The second equality uses the fact that $D=\sigma^2_{ACC}\sigma^2_{NI} - \sigma^2_{NI,ACC}$ to simplify the top row, and the observation that two terms in the second row cancel. The top row can be simplified further by observing that $\sigma_{NI,ACC}=\sigma_{ACC}{}^2+\sigma_{ACC,CF}$, so the final term in parentheses is $-\sigma_{ACC,CF}$. Similarly, $\sigma^2_{NI}=\sigma_{NI,ACC}+\sigma_{NI,CF}$, so the final term in the second row is just $\sigma_{NI,CF}$. This yields:

$$b = \begin{bmatrix} \rho + \frac{\sigma^2_\eta(\rho-\lambda)\sigma_{ACC,CF}}{D} \\ -\frac{\sigma^2_\eta(\rho-\lambda)\sigma_{NI,CF}}{D} \end{bmatrix}. \tag{A9}$$

The top row gives b_1, the predictive slope on earnings, and the bottom row gives b_2, the predictive slope on accruals. The slopes have the 'correct' values, $b_1=\rho$ and $b_2=0$, in the absence of measurement error but will provide biased estimates of those coefficients if $\sigma_\eta{}^2 > 0$. In particular, we expect $\rho > \lambda$ since earnings should be more highly autocorrelated than measurement error (indeed, we expect λ to be negative if measurement error reverses). This implies that $b_1 < \rho$ as long as cash flow is negatively correlated with accruals, and $b_2 < 0$ as long as cash flow is positively correlated with earnings (see, e.g., Dechow 1994 or the descriptive statistics reported in the text).

An interesting feature of the results is that we can recover the autocorrelation of true earnings given estimates of b_1 and b_2. Specifically, Eq. (A9) implies that:

$$\rho = b_1 + (\sigma_{ACC,CF}/\sigma_{NI,CF})b_2. \tag{A10}$$

where all of the terms on the right-hand side can be estimated from the data. Thus, the slopes b_1 and b_2 allow us to infer what the autocorrelation of earnings would be in the absence of measurement error. Unfortunately, it is not possible to infer $\sigma_\eta{}^2$ or λ without additional assumptions about the time-series properties of measurement error, i.e., we can use b_2 to estimate $\sigma_\eta{}^2$ (ρ – λ), but we cannot separately estimate $\sigma_\eta{}^2$ or λ (in essence, we have one equation with two unknowns).

The analysis above is easily extended to long-horizon regressions:

$$NI_{t+k} = b_{0k} + b_{1k}NI_t + b_{2k}ACC_t + e_{t+k}, \tag{A11}$$

which is identical to Eq. (A1) except that we have substituted NI_{t+k} in place of NI_{t+1} on the left-hand side. The vector of slopes $b_{(k)}=(b_{1k}, b_{2k})$ takes the same form as the 1-year-ahead slopes but involves the covariance with NI_{t+k} rather than NI_{t+1}:

$$b_{(k)} = \mathrm{var}^{-1}(x_t)\mathrm{cov}(x_t, NI_{t+k}). \tag{A12}$$

The covariance between NI_t and NI_{t+k} equals $\rho^k\sigma_{NI^*}{}^2+\lambda_k\sigma_\eta{}^2$ and the covariance between ACC_t and NI_{t+k} equals $\rho^k\sigma_{NI^*,ACC^*}+\lambda_k\sigma_\eta{}^2$, where ρ^k is the kth-order autocorrelation of true earnings and λ_k is the kth-order autocorrelation of η_t (λ_k does not have to equal λ^k since measurement error is not assumed to be AR1). Using the expressions above for var(x_t), it follows that b_k is

$$b_{(k)} = \frac{1}{D}\begin{bmatrix} \sigma^2_{ACC} & -\sigma_{NI,ACC} \\ -\sigma_{NI,ACC} & \sigma^2_{NI} \end{bmatrix}\begin{bmatrix} \rho^k\sigma^2_{NI^*} + \lambda_k\sigma^2_\eta \\ \rho^k\sigma_{NI^*,ACC^*} + \lambda_k\sigma^2_\eta \end{bmatrix}. \tag{A13}$$

This is the same as b in Eq. (A7) except that ρ^k replace ρ and λ_k replaces λ. Thus, $b_{(k)}$ simplifies to

$$b_{(k)} = \begin{bmatrix} \rho^k + \frac{\sigma^2_\eta(\rho^k-\lambda_k)\sigma_{ACC,CF}}{D} \\ -\frac{\sigma^2_\eta(\rho^k-\lambda_k)\sigma_{NI,CF}}{D} \end{bmatrix}, \tag{A14}$$

where the top row gives the predictive slope on earnings, b_{1k}, and the bottom rows gives the k-year-ahead slope on accruals, b_{2k}. Following our earlier logic, we can recover ρ^k from these slopes:

$$\rho^k = b_{1k} + (\sigma_{ACC,CF}/\sigma_{NI,CF})b_{2k}. \tag{A15}$$

In other words, we can estimate ρ from the one-year-ahead predictive regression and ρ^k from the k-year-ahead predictive regression. If the measurement error model is well-specified, the estimates of ρ and ρ^k should be consistent with each other

(i.e., ρ^k should equal ρ raised to the kth power). This prediction provides what, in essence, is an overidentifying restrictions test of the model.

A distinct issue is how measurement error shows up in the time-series properties of accruals themselves. In particular, one of our tests estimates predictive regressions with ACC_{t+1} as the dependent variable:

$$ACC_{t+1} = c_0 + c_1 NI_t + c_2 ACC_t + e_{t+1}. \tag{A16}$$

Transitory measurement error will induce reversals in accruals, which, intuitively, should be reflected in a negative slope c_2. The complication is that c_2 captures not just reversals caused by measurement error but also any predictability of true accruals, and there is no reason to think the latter effect is zero. Specifically, c_2 can be interpreted as the sum of d_2 and f_2 in the following regressions:

$$ACC_{t+1}{}^* = d_0 + d_1 NI_t + d_2 ACC_t + e_{t+1}, \tag{A17}$$

$$\eta_{t+1} = f_0 + f_1 NI_t + f_2 ACC_t + e_{t+1}. \tag{A18}$$

Even if measurement error induces accrual reversals ($f_2 < 0$), c_2 could be positive if *true* accruals are positively related to lagged accruals ($d_2 > 0$). (This is similar to Allen et al's., 2013, argument that accruals have a positively autocorrelated growth component and a negatively autocorrelated error component.) In fact, our tests show that accruals predict sales growth, so we might expect d_2 to be positive if $ACC_{t+1}{}^*$ is linked to $dSales_{t+1}$ (Jones 1991; Dechow et al. 1998). We need to control for this effect if we want to detect reversals caused by measurement error. To do so, suppose that true accruals equal

$$ACC_{t+1}{}^* = \beta\, dSales_{t+1} + a_{t+1}*, \tag{A19}$$

where $a_{t+1}{}^*$ is assumed to be unpredictable and uncorrelated with $dSales_{t+1}$. This implies that true accruals are expected to grow along with sales but also contain an additional random component. Observed accruals, $ACC_{t+1} = \beta\, dSales_{t+1} + a_{t+1}{}^* + \eta_{t+1}$, are made up of three components: a predictable component related to sales ($\beta\, dSales_{t+1}$), an unpredictable component related to randomness in true accruals ($a_{t+1}{}^*$), and measurement error (η_{t+1}). The first component can be eliminated by regressing accruals on sales growth, leaving $a_{t+1} = ACC_{t+1} - \beta\, dSales_{t+1} = a_{t+1}{}^* + \eta_{t+1}$. The predictability of this residual is then entirely due to measurement error, i.e., the slopes in

$$a_{t+1} = f_0 + f_1 NI_t + f_2 ACC_t + e_{t+1}, \tag{A20}$$

are identical to the slopes in Eq. (A18). In essence, if we assume predictability of *true* accruals is driven by the predictability of sales growth, we can isolate accrual reversals caused by measurement error by controlling for sales growth in the tests. Conveniently, (A20) takes the same form as the persistence regression in Eq. (A1), except accruals replace earnings as the dependent variable, so the slopes can be derived with only small changes to our earlier analysis. In particular, the 2×1 vector of slopes in (A20) equal

$$f = \begin{bmatrix} \frac{-\lambda\sigma_\eta^2\sigma_{ACC,CF}}{D} \\ \frac{\lambda\sigma_\eta^2\sigma_{NI,CF}}{D} \end{bmatrix}. \tag{A21}$$

As long as cash flow is positively correlated with earnings ($\sigma_{NI,CF} > 0$), the slope on accruals (f_2, in the bottom row) has the same sign as the autocorrelation of measurement error, λ. Moreover, the slopes in this regression should be closely related to the slopes in the persistence regression (b_2): $f_2 = \lambda/(\lambda - \rho) \times b_2$.

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