#### Why do accruals predict earnings?

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We are grateful to Salman Arif (FARS 2018 discussant), Linda Bamber, John Core, Joseph Gerakos, S.P. Kothari, Chad Larson, Sarah McVay, Richard Sansing, two anonymous referees, and workshop participants at Dartmouth College, University of Georgia, University of North Carolina, Yale School of Management, and the University of Washington for helpful comments and suggestions.

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#### Abstract

Firms with high accruals tend to have lower future earnings. We propose a new explanation for this phenomenon based on the way sales, profits, and working capital respond to changes in a firm's product markets. These effects arise in the absence of measurement error in accruals or investment-related changes in profitability. Empirically, we show that high accruals predict a long-lasting drop in both profits and profitability even though accruals are positively related to sales growth going forward. Accruals also predict a significant increase in future competition, suggesting that high 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 marginal returns from investment.

#### **1. Introduction**

It is now well-established that, given two firms with the same earnings today, the one with higher accruals tends to be less profitable going forward. This link between accruals and future profitability, often characterized 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. One possibility is that accruals contain 'distortions,' or measurement errors, that inflate today's earnings at the expense of future profits (Sloan 1996; Xie 2001; Dechow and Dichev 2002; Richardson et al. 2005, 2006; Chan et al. 2006; Dechow et al. 2012; Allen, Larson, and Sloan 2013). The second is that accruals correlate with investment and predict lower future profitability because of decreasing returns to scale, adjustment costs associated with investment, or conservatism in accounting (Fairfield, Whisenant, and Yohn 2003a,b; Zhang 2007; Dechow, Richardson, and Sloan 2008; Wu, Zhang, and Zhang 2010).

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, expenses, accruals, and competition that offers novel insights into the economic forces that drive accruals.

Our explanation for the low persistence of accruals focuses on the way firms react to changes in product markets. In particular, we develop a simple dynamic model of accruals for a value-maximizing firm that faces shocks to input and output prices. The model is intentionally simple—it is certainly not designed to 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) A shock to input prices raises the firm's production and inventory costs but only affects profits later when inventory is actually sold. (ii) A shock to demand leads to a temporary increase in profits and working capital, followed by mean reversion in the variables as competiton 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, we argue that the low persistence of accruals might arise in equilibrium because production and sales optimally respond to changes in the firm's input and output markets.

A key contribution of our paper is to compare, theoretically, the implications of the product market, measurement error, and investment hypotheses. We present a formal model of each in order to compare and contrast their predictions. We show that, while all three hypotheses predict a negative relation between accruals and next year's profitability—the typical focus of the empirical literature—they make different predictions about long-run behavior of profits, profitability, sales, and expenses. The evolution of those variables therefore provides a way to distinguish among the hypotheses (recognizing, of course, that they do not always make crisp predictions about the behavior of all variables).

Our second contribution is empirical. A central theme of our theoretical analysis is that accruals reflect a variety of economic forces and a broad view of the firm's environment is needed to understand the behavior of accruals. To this end, our tests explore the joint dynamics of accruals, earnings, sales, costs of goods sold (COGS), and selling, general, and administrative expense (SG&A), as well as the behavior of industry profits and competition. The link between accruals and the other variables, over short and long horizons, provides a rich picture of the economic forces driving accruals.

Our empirical tests yield several key insights. First, we show that the negative relation between accruals and subsequent profitability is driven by an actual drop in profits, not just an increase in assets, contrary to one of the central predictions of the investment hypothesis (and the results of FWY 2003b). Moreover, the decline in profits following high accruals appears to be permanent, in the sense that the relation between accruals and

subsequent profits and profitability is as strong in years t+2 through t+7 as in year t+1. 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 expenses such as asset write-downs or losses included in special items. Our results suggest that high accruals are *not* indicative of struggling firms—indeed, sales growth of high-accrual firms is nearly as high in year t+1 as it is in year t—and that a general increase 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. The results also imply that next year's sales growth explains significant variation in current accruals, a factor generally omitted from models of nondiscretionary accruals (e.g., Jones 1991; Dechow, Sloan, and Sweeney 1995).

Third, we show that firms reporting 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, which attracts new entry and competition that, 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, consistent with our product-market hypothesis.

Finally, we show that accruals 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 (COL), which are often

regarded as one of the most reliable types of accruals. Our tests show that accruals predict subsequent growth in current operating assets that matches what we expect given the behavior of sales, contrary to the argument that error in AR or inventory explains the subsequent drop in profits.

Overall, our results provide a detailed picture of why accruals are negatively related to a firm's subsequent profits and profitability. The long-term drop in earnings, along with higher sales and an increase in industry competition, suggests that high accruals are correlated with demand and supply shocks that lead to temporarily high *true* earnings. The evidence is hard to reconcile with the measurement error or investment hypotheses but is consistent with our product-market hypothesis.

To be clear, our paper does not say that measurement error and diminishing marginal returns from investment are absent or unimportant in all situations. Our results only show that neither is large enough to explain the predictive power of accruals or other patterns we observe in the data. Our broader point is that accruals are the endogenous outcome of firms' production, sales, and investment decisions and, as such, are shaped by a large variety of forces. We explore some of these forces but believe more work is needed to understand how the firm's economic environment affects the behavior of accruals.

The remainder of the paper is organized as follows: Section 2 presents our 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. As such, they reflect a large variety of corporate decisions, including a firm's investment, sales, production, 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. Much of the accrual literature considers so-called persistence regressions:

$$NI_{t+1} = a_0 + a_1 CF_t + a_2 ACC_t + e_{t+1},$$
(1)

where NI<sub>t</sub> is some measure of earnings in year t (typically scaled by total assets), ACC<sub>t</sub> is either workingcapital accruals or total accruals, and CF<sub>t</sub> is either operating cash flow or free cash flow (depending on the definition of accruals), given by  $CF_t = NI_t - ACC_t$ . The 'low persistence' of accruals refers to the empirical observation that  $a_2 < a_1$ , i.e., accruals have less predictive power for future earnings than do cash flows. In other words, 'persistence' refers to the slopes in eq. (1) not to the autocorrelation of the variables. Further, as noted in the literature (FWY 2003a), an equivalent regression can be estimated substituting earnings for cash flow on the right-hand side of this equation:

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

The key difference compared with eq. (1) is that the slope on accruals in eq. (2) equals the *differential* persistence of accruals and cashflows,  $b_2 = a_2 - a_1$  (the residuals and other coefficients 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 ( $b_2 < 0$ ). Our main goal is to explore what economic forces, broadly defined, make accruals less persistent than cash flow, or equivalently, why the slope on accruals is negative in eq. (2).

#### 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 develop this hypothesis formally below, but the intuition is simple: if accruals are measured with error, high accruals are a signal that earnings are overstated and will likely be lower in the future. 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, Larson, and Sloan (2013) argue that accrual estimation errors and reversals are significant empirically (see also Moehrle 2002; Chan et al. 2006; Baber, Kang, and Li 2011; Dechow et al. 2012).

Formally, following RSST (2005), we interpret Sloan's (1996) 'subjectivity' hypothesis to be the idea that reported earnings and accruals can differ from true (correctly-measured) earnings and accruals because AR, inventory, etc., might be valued imperfectly (for whatever reason). 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:

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

True accruals represent the difference between NI<sub>t</sub>\* and the firm's cash flow, ACC<sub>t</sub>\* = NI<sub>t</sub>\* – CF<sub>t</sub>. However, reported accruals may contain some error  $\eta_t$ , implying that ACC<sub>t</sub> = ACC<sub>t</sub>\* +  $\eta_t$  and NI<sub>t</sub> = NI<sub>t</sub>\* +  $\eta_t$ . Following RSST, we assume for simplicity that  $\eta_t$  is unrelated to true earnings and cash flow, but, unlike RSST, we allow  $\eta_t$  to be serially correlated (we discuss the time-series properties below).<sup>1</sup> The presence of this measurement error means that ACC<sub>t</sub> will generally help to predict future earnings after controlling for NI<sub>t</sub>. In particular, we show in the Appendix that the slope on accruals in eq. (2) equals:

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

where  $\rho$  is the autocorrelation of true earnings,  $\lambda$  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. Eq. (4) implies that measurement error leads to a negative slope on accruals as long as earnings and cash flows are positively related ( $\sigma_{NLCF} > 0$ ; see Dechow 1994) and the autocorrelation of measurement error is less than the autocorrelation of true earnings ( $\lambda < \rho$ ).<sup>2</sup>

The time-series properties of measurement error are important. RSST assume that  $\lambda = 0$ , but, as they discuss, accrual measurement errors are expected to reverse in practice (see also Allen, Larson, and Sloan 2013). For example, suppose that ACC<sub>t</sub> represents working-capital accruals. Error in the *level* of working capital might

<sup>&</sup>lt;sup>1</sup> The assumption that measurement error is uncorrelated with the firm's true performance is not critical for the analysis (but greatly simplifies the algebra). For example, in simulations calibrated to the data, the slope on accruals changes by only +/-0.01 (from -0.13 to either -0.12 or -0.14) if the correlation between measurement error and true earnings is 0.50 or -0.50 rather than zero (holding all else constant).

<sup>&</sup>lt;sup>2</sup> Eq. (4) generalizes RSST's results to allow  $\lambda \neq 0$  and, in the special case that  $\lambda = 0$ , appears to correct a minor error in their formulas. (RSST do not derive b<sub>2</sub> directly, but it can be found from their eqs. 7 and 8 on p. 442.) One difference is that the sign of b<sub>2</sub> in eq. (4) depends on the correlation between earnings and cash flow, whereas RSST's results suggest that b<sub>2</sub> is unambiguously negative.

be positively autocorrelated if valuation errors tend to repeat, intentionally or otherwise, but should be temporary since misvaluation of, say, AR and inventory is realized as customers make payments and inventory is sold. If so, we might expect measurement error in the *level* of working capital to follow a persistent but mean-reverting process, for example,  $z_{t+1} = \rho_z z_t + v_{t+1}$ , with  $\rho_z \ge 0$ . 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 first-order 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 as measurement error reverses ( $\eta_{t+1} < 0$ ). Such reversals accentuate the negative slope on accruals in eq. (4).

A key insight from this 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 1-year-ahead earnings in eq. (2) with 2-year ahead, 3-year-ahead, etc., earnings. Specifically, with NI<sub>t+k</sub> as the dependent variable, the slope on accruals (see the Appendix) is

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

where  $\rho^k$  and  $\lambda_k$  are the kth-order autocorrelations of true earnings and measurement error, respectively, both of which should diminish as the horizon is lengthened. The 'rebound' effect discussed above will be reflected in a decline in the 2-year slope relative to the 1-year slope, followed by additional decay over longer horizons.<sup>3</sup> Our empirical tests look for evidence of such a pattern in the data.

<sup>&</sup>lt;sup>3</sup> 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  $\lambda_2 = \lambda_3 = ... = 0$ . The 2-year-ahead slope on accruals is roughly half the 1-year-ahead slope ( $\rho - \lambda = 1.30$  compared with  $\rho^2 - \lambda_2 = 0.64$ ), and slopes for longer horizons (k > 2) then decay at a rate of 0.80 toward zero.

Another key implication of the model is that slope on accruals depends on three statistics that cannot be estimated directly: the persistence of true earnings ( $\rho$ ) and the variance and autocorrelation of measurement error ( $\sigma_{\eta}$  and  $\lambda$ ). Interestingly, our Appendix shows that we can infer  $\rho$  from observable statistics, as well as test whether *true* earnings follow an AR(1) process, i.e., we can test the hypothesis that neither accruals nor any other variable has predictive power for *true* earnings controlling for current earnings. While it is not possible to estimate the variance and persistence of measurement error explicitly, we can make joint inferences about the two statistics, including inferences about how much measurement error is needed to explain the slope on accruals. We discuss these tests in more detail in the empirical section but, for now, we summarize the empirical 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 relatively quickly;

(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. The link between accruals and growth suggests that accruals could predict future profitability because of decreasing returns to scale, accounting conservatism, or adjustment costs associated with investment (see Wu, Zhang, and Zhang 2010).

As noted by FWY (2003b) and Zhang (2007), a key implication of this 'investment hypothesis' is that, while high accruals might predict a decline in *profitability* (earnings scaled by assets), they should predict 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. Formally, suppose profits are a function of beginning-ofyear capital,  $NI_{t+1} = f(K_t)$ , with f(0) = 0, f' > 0, and f'' < 0, i.e., profits are increasing in capital but the firm faces decreasing returns to scale. If the firm chooses investment to maximize value and the cost of capital is r, the first-order condition for value-maximation is simply  $f'(K_t^*) = r$ . This equality implies that investment moves inversely with the cost of capital,  $dK_t^*/dr < 0$ . Thus, if we interpret accruals as part of investment (following FWY 2003a, Wu, Zhang, and Zhang 2010, and others), a drop in r leads to higher investment, accruals, and profits (since f is increasing in capital) but lower profitability because the ratio of profits to capital falls.<sup>4</sup> 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 investment is assumed to pay off quickly in the analysis above (in the year after it is made). In reality, 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 predictive slope on accruals in the short run that weakens and eventually reverses when we study the long-run behavior of profits. Our tests explore forecast horizons of up to seven years to give any temporary 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.

<sup>&</sup>lt;sup>4</sup> 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.

#### 2.3. Hypothesis 3: Product markets

Measurement error and investment effects suggest two very different explanations for the negative relation between accruals and future earnings. In this section, we show that a firm's response to demand and supply shocks provides a third explanation, with distinct empirical predictions.

Intuitively, accruals could be linked to profits through a variety of product-market channels. Our analysis focuses on two possibilities. The first is that an increase in input prices (or production costs more generally) shows up in inventory costs quickly but does not affect profits until the inventory is actually sold; thus, a jump in inventory today predicts a decline in subsequent profits. The second is that demand shocks can induce transitory changes in sales, production, 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 competiton drives prices back to long-term competitive levels. We show that this pattern implies that high accruals today will be associated with lower subsequent profits.<sup>5</sup>

To illustrate these ideas, consider the simplest model of a value-maximizing firm in a competitive industry, producing output y from a single variable input x (taking input and output prices as given). The production function takes the standard form  $y = x^{\alpha}$ , with  $0 < \alpha < 1$ , which guarantees a positive but finite amount of production. The firm has an exogenous fixed amount of capital K and (nonproduction) fixed expenses F that do not vary with production or sales. As explained below, the firm also has working capital but, when we calculate profitability, we divide earnings only by the fixed capital K. This choice ensures that the predictive power of accruals in the model comes from a link between accruals and profits rather than the 'denominator effect' discussed above for the investment hypothesis. In the model below, input prices, output prices, and fixed costs all vary through time.

<sup>&</sup>lt;sup>5</sup> 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 induces short-run changes in inventory of the opposite sign (Dechow, Kothari, and Watts 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.

We assume the firm is long-lived and holds inventory because sales take place in the year after production. Specifically, the firm chooses production,  $x_t$ , at the beginning of year t based on forecasts of the input price,  $c_t$ , and the sales price,  $p_{t+1}$ , the firm expects to receive when output is sold the following year. Thus, 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, we assume 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

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

$$CF_{t+1} = p_{t+1} x_t^{\alpha} - c_{t+t} x_{t+t} - F_{t+1} = NI_{t+1} - (c_{t+1}x_{t+1} - c_tx_t).$$
(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 ( $c_{t+1}x_{t+t}$ ). The parenthetical term in eq. (7) equals the change in inventory, implying that  $CF_{t+1}$ differs from NI<sub>t+1</sub> because of inventory accruals. In a richer version of the model, we allow a portion of sales to be made on credit and a portion of fixed costs to be paid in the year after they are incurred, generating both accounts receivable and payable (AR<sub>t</sub> and AP<sub>t</sub>). We can also inject measurement error into the model by assuming that a portion of fixed costs is erroneously classified as production costs and capitalized into end-ofyear inventory. We discuss these generalizations later but, for sake of exposition, focus our initial discussion on the version of 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 information available at the beginning of year t:

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

The first-order condition for profit maximation implies that:

$$\mathbf{x}_{t}^{*} = (\alpha \mathbf{E}_{t-1}[\mathbf{p}_{t+1}] / \mathbf{E}_{t-1}[\mathbf{c}_{t}])^{1/(1-\alpha)}, \tag{9}$$

$$\mathbf{y}_{t+1}^* = (\alpha \mathbf{E}_{t-1}[\mathbf{p}_{t+1}]/\mathbf{E}_{t-1}[\mathbf{c}_t])^{\alpha/(1-\alpha)}.$$
(10)

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

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

while actual costs scale this up or down by  $c_t/E_{t-1}[c_t]$ . Similarly, expected revenues in t+1 are

$$E_{t-1}[p_{t+1}y_{t+1}^*] = E_{t-1}[p_{t+1}]^{1/(1-\alpha)}(\alpha/E_{t-1}[c_t])^{\alpha/(1-\alpha)},$$
(12)

(11)

and actual revenues scale this up or down by  $p_{t+1}/E_{t-1}[p_{t+1}]$ . Comparing eqs. (11) and (12), we see that, in expectation, variable costs are  $\alpha$  times revenue, implying that the firm's expected profit margin is simply 1– $\alpha$ . Quite naturally, costs, revenues, and earnings are all positively related to the expected output price and negatively related to the expected input price.

Shocks to costs and prices lead to intuitive dynamics. At the most basic level, an unexpected increase in  $c_t$  raises production costs in year t, leading to an unexpected increase in inventory costs at the end of year t and a drop in profits in year t+1. An unexpected increase in  $p_{t+1}$  leads to higher revenue in year t+1 and an increase in profits. Moreover, if costs and prices are persistent, these shocks will have long-term effects as the firm adjusts production and sales in subsequent years in response to changes in  $c_t$  and  $p_t$ . For example, an increase in  $c_t$  will lead to higher expected costs going forward, so the short-run spike in production costs is followed by a subsequent drop in production and inventory as the firm adjusts to higher costs. An increase in  $p_t$  will raise expectations of output prices going forward, leading to an increase in future production, inventory, and profits. Thus, inventory accruals covary with current and future profits because of the way production and sales respond to price shocks in the model.

The exact dynamics depend on the time-series properties of prices and, intuitively, should be driven by the nature of competition and entry in the industry. In a more complete model, we could model industry demand and cost curves that vary through time. In the short run, an increase in demand would lead to an increase in output price, production, and profits, followed by long-run growth and entry into the industry that drive prices and profits back to normal. Similarly, an increase in costs would lead to exit, a decrease in supply, and an eventual increase in output prices until normal profitability is restored. To capture these effects in reduced form, we simply assume prices and costs follow mean-reverting processes,  $log(v_t) = a + \rho_v log(v_{t-1}) + e$ , where  $v_t$  is either  $c_t$ ,  $p_t$ , or  $F_t$  and the error terms are normally distributed. The advantange of modeling the dynamics in

logs is that the level of each variable is guaranteed to be positive. The stationarity of the variables captures the intuition that price and cost shocks have transitory effects yet, in the long run, profits eventually mean revert to normal levels. These assumptions are meant to illustrate how simple economic dynamics can induce a link between accruals and future profits.

Given the structure above, we have closed-form formulas for all quantities in the model. However, converting those quantities into regression slopes is a challenge because of the nonlinear nature of the model and the fact that, to keep things positive, prices are assumed to be log-normal rather than just normal. We therefore rely on simulations to illustrate the persistence slopes and other time-series properties of the variables under a variety of different assumptions about parameters:

<u>Scenario 1</u>: We start with a benchmark case in which only fixed costs  $F_t$  vary through time, which neutralizes product-market effects in the model (production and sales are constant). This case provides a convenient baseline because profits, like  $F_t$ , then follow a simple AR(1) process. A minor complication is that inventory is constant in this scenario, so we need other types of accruals to induce some variability in working capital. In particular, we introduce AR and AP by assuming that some fraction  $\pi_t^{ar}$  of sales remains to be collected at year-end and some fraction  $\pi_t^{ap}$  of fixed costs remains to be paid. We assume both  $\pi_t^{ar}$  and  $\pi_t^{ap}$  are lognormally distributed and IID for simplicity. The resulting variation in AR<sub>t</sub> and AP<sub>t</sub> generates randomness in accruals (offsetting cash-flow timing effects) but does not affect production decisions.

To be specific, we choose parameters so that fixed costs average roughly 25% of sales and variable costs are 65% of sales, close to the empirical values we report later for SG&A and COGS. Log( $F_t$ ) has a mean of log(0.25), autocorrelation of 0.90, and conditional standard deviation of 0.15 (the latter is roughly the standard deviation of percentage changes in  $F_t$ ). The autocorrelation captures the intuition that fixed costs change slowly and profitability is highly persistent. The parameter  $\alpha$  is 0.65 (equal to variable costs divided by sales); input price ( $c_t$ ) and capital (K) are normalized to one; and the output price ( $p_t$ ) is set to 1.30, which leads to sales that are roughly on par with assets. Average AR<sub>t</sub> is assumed to be 15% of sales and average AP<sub>t</sub> is

assumed to be 10% of fixed costs, both with a standard deviation of 15% in logs.

<u>Scenario 2</u>: 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. Log( $p_t$ ) has a mean of log(1.30), autocorrelation of 0.60, and conditional standard deviation of 0.06. As discussed above, the mean reversion of  $p_t$  captures the intution 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 by 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.

<u>Scenario 3</u>: The parameters are the same as Scenario 1 except that input price  $c_t$  now varies over time (output price is constant). Again, this leads to variation in sales and inventory as the firm responds to changes in input costs. Log( $c_t$ ) has a mean of zero, autocorrelation of 0.60, and conditional standard deviation of 0.04. The persistence of  $c_t$  captures the intution 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.

<u>Scenario 4</u>: The basic parameters are the same as Scenarios 1, 2, and 3 but now input and output prices both vary over time.

Simulation results for the four scenarios are reported in Table 1. At the top, Scenario 1 shows that variation in fixed costs  $F_t$  leads to fluctuations and persistence in profits but, as expected, no 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<sub>t</sub> and AP<sub>t</sub>. The slope on NI<sub>t</sub> in the persistence regressions, in the far-right columns, reflects the autocorrelation of earnings, and the slope on accruals is indistinguishable from zero.

Scenarios 2, 3, and 4 illustrate how the results change when production, sales, and accruals respond to changes

#### 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.

		Univ	ariate sta	tistics	C	Correlatio	ns		$\mathbf{Y} = \mathbf{I}$	$b_0 + b_1 NI_t$	$+ b_2 ACC_1$	t + e
Scenario	Var	Avg	Std	Auto	NI	ACC	CF		$Y \!\!=\!\! NI_{t+1}$	$Y \!\!=\!\! NI_{t+2}$	$Y{=}NI_{t+3}$	$Y \!\!=\!\! S_{t+1}$
1: Ft varies	NI ACC CF	0.07 0.00 0.07	0.09 0.03 0.10	0.89 -0.49 0.77	1 0.03 0.95	0.03 1 -0.29	0.95 -0.29 1	b1 b2	0.89 0.00	$\begin{array}{c} 0.80\\ 0.00\end{array}$	0.71 0.00	0.00 0.00
2: F <sub>t</sub> , pt vary	NI ACC CF	0.07 0.00 0.07	0.12 0.09 0.12	0.78 -0.14 0.67	1 0.29 0.74	0.29 1 -0.42	0.74 -0.42 1	b <sub>1</sub> b <sub>2</sub>	0.79 -0.07	0.65 -0.11	0.54 -0.12	0.55 0.44
3: F <sub>t</sub> , c <sub>t</sub> vary	NI ACC CF	0.07 0.00 0.07	0.10 0.07 0.11	0.86 -0.42 0.57	1 0.18 0.79	0.18 1 -0.46	0.79 -0.46 1	b1 b2	0.89 -0.21	0.78 -0.18	0.68 -0.16	0.12 0.39
4: F <sub>t</sub> , p <sub>t</sub> , c <sub>t</sub> vary	NI ACC CF	0.07 0.00 0.07	0.12 0.11 0.13	0.77 -0.23 0.55	1 0.32 0.66	0.32 1 -0.50	0.66 -0.50 1	b1 b2	0.80 -0.12	0.64 -0.13	0.53 -0.13	0.61 0.40
5: F <sub>t</sub> varies + error	NI ACC CF	0.07 0.00 0.07	0.09 0.03 0.10	0.88 -0.49 0.77	1 0.06 0.94	0.06 1 -0.28	0.94 -0.28 1	$b_1 \\ b_2$	0.88 -0.13	0.79 -0.07	0.70 -0.07	0.00 0.00

in output prices (Scenario 2), input prices (Scenario 3), or both (Scenario 4). 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 important 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 (or, equivalently, because accruals have a lower predictive slope than cash flows).<sup>6</sup>

The results are fairly intuitive. Consider first Scenario 3, in which input costs vary over time but output prices are constant. A positive shock to the input price is reflected in higher production costs and inventory in year t but does not reduce profits until year t+1, when inventory is sold. Thus, high accruals in year t predict lower

<sup>&</sup>lt;sup>6</sup> In this regard, our analysis is more rigorous than discussions of the investment effect in the literature, which focus on comparative statics rather than actual regressions slopes in their models (e.g., Wu, Zhang, and Zhang 2010). In contrast, our model is fully dynamic and illustrates that product-market effects can generate simple correlations and multiple-regression slopes that match the data.

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 and because costs mean revert back to normal levels. Interestingly, accruals are positively related to contemporaneous profits because the drop in inventory (from t to t+1) as the firm adjusts to high costs is associated with a contemporaneous decline in profits.

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 both future profits and sales. At the same time, profits themselves are persistent, and the key issue is whether accruals have predictive power controlling for current profits. Intuitively, accruals will have incremental predictive power if profits consist of multiple components with different levels of persistence and accruals correlate differently with each. In Scenario 2, profits are driven by changes in output prices and fixed costs, and accruals correlate with the former but not the latter (fixed costs do not affect production). Implicitly, when profits and accruals are both high, it is a sign that pt is high and profits will decline in the future as competition drives prices back to normal levels; if profits are high but accruals are not, it is a sign that fixed costs are low and profits will return more slowly to normal levels. The implication is that accruals become negatively associated with future profits after controlling for current profits.<sup>7</sup>

For completeness, the bottom panel of Table 1 (Scenario 5) shows that measurement error can be added to the model, illustrating the effects discussed in Section 2.1. In particular, we start with Scenario 1, with variation only in nonproduction fixed costs, but assume that a portion of these expenses are erroneously capitalized into inventory each year. This injects measurement error into accruals and earnings but has no effect on cash flow or production. For simplicity, we assume measurement error in the level of inventory is IID through time with

<sup>&</sup>lt;sup>7</sup> The results for Scenario 2 are driven by mean reversion in output prices, but the intuition is more general. Empirically, profitability is driven by many forces—technological innovation, competition, fixed and variable costs, interest rates, accounting policies, etc.—some of which will lead to relatively stable and long-lasting differences in profitability and some of which are more transitory. Accruals, since they reflect *changes* in the firm, should correlate more strongly with variables that vary through time and less strongly with variables that are permanent or long-lasting. If so, accruals might capture transitory movements in profits for many possible reasons.

a mean of zero and a standard deviation of 0.007. Accrual errors are relatively small but induce a negative slope on accruals in the predictive regression for  $NI_{t+1}$  that roughly matches empirical estimates. The regressions illustrate the bounce-back discussed earlier: the 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 understated as measurement error reverses. Thus, with transitory 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. More generally, if measurement error is strategic, we might expect a firm to overstate earnings when it is doing poorly, suggesting that high accruals should predict lower, not higher, future sales. 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 <u>and</u> 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 connected to industry-wide demand and supply shocks that show up in industry growth, profits, and competition.

#### 2.4. Summary

The analysis above shows how measurement error, investment effects, and demand and supply dynamics can all induce a link between accruals and future earnings. Importantly, 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 differential predictions provide a way to distinguish between the hypotheses empirically, recognizing of course that some predictions overlap and the theories do not make crisp predictions about all variables. For example, the measurementerror hypothesis does not clearly state whether accruals should predict profits or just profitability (since it says nothing about the behavior of assets in the denominator of profitability), but it seems reasonable to think accruals will predict 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

The analysis above emphasizes that accruals, as the endogenous result of a firm's investment, production, sales, and accounting decisions, are shaped by a variety of forces. Our tests explore the joint dynamics of earnings, sales, expenses, accruals, and competition in order to better understand these forces. Narrowly, the goal is to distinguish among the hypotheses above, but the empirical patterns also provide a rich picture of the economic forces driving accruals.

The starting point for our analysis is the persistence regression in eq. (2), restated here for reference:

$$NI_{t+1}/TA_{t+1} = b_0 + b_1 NI_t/TA_t + b_2 ACC_t/TA_t + e,$$
(13)

where NI<sub>t</sub> is a measure of earnings, ACC<sub>t</sub> is a measure of accruals, and TA<sub>t</sub> is a measure of assets used to scale the variables (typically defined as the average of beginning and ending total assets). Notice that earnings in t+1 is scaled by contemporaneous assets, TA<sub>t+1</sub>, so eq. (13) essentially regresses profitability in year t+1 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. *Profits vs. profitability*. Our first extension is to re-scale earnings on the left-hand side of eq. (13) with assets from year t, so all variables are scaled by the same asset value:

$$NI_{t+1}/TA_t = c_0 + c_1 NI_t/TA_t + c_2 ACC_t/TA_t + e.$$
(14)

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. (14) 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 because investment and accruals should be positively related to subsequent profitability in eq. 13). In contrast, the measurement error and product market hypotheses imply the slope will be negative regardless of whether TA<sub>t</sub> or TA<sub>t+1</sub> is used to scale the dependent variable.

*Long horizons*. Our second extension is to expand the forecast horizon up to seven years, replacing  $NI_{t+1}$  with  $NI_{t+k}$  for k = 2, ..., 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.

*Earnings components*. Our third extension is to break future earnings into sales, COGS, SG&A, and other expenses in order to explore the behavior of sales and test whether a particular type of expense drives profits. Because  $NI_{t+k} = Sales_{t+k} - COGS_{t+k} - SGA_{t+k} - OthExp_{t+k}$ , the slopes when the four components on the right are regressed on  $NI_t$  and  $ACC_t$  mechanically sum to the slopes in the earnings regression (eq. 13 or 14). We focus on specifications using changes in the variables scaled by lagged assets (e.g.,  $dSales_{t+k}/TA_t$ ) to test whether accruals predict growth in sales and expenses. This choice also side-steps issues related to the high persistence in the levels of sales, COGS, and SG&A. The investment and product-market hypotheses imply that accruals should be positively related to future sales. The measurement-error hypothesis does not make an explicit prediction unless we impose additional structure on the model. For example, if sales follow a random

walk, accruals would be unrelated to future sales regardless of whether accruals are measured with error. On the other hand, if measurement error reflects earnings management by distressed firms struggling with poor sales growth, we might expect accruals to be negatively related to future sales.

The expense regressions shed light on whether accruals' predictive power can be traced to a particular component of expenses. For example, inventory is sometimes viewed as a key source of measurement error, in which case we would expect accruals to predict a significant jump in COGS. A complication is that accruals turn out to be positively related to future sales, so it should not be surprising that accruals are also positively related to expenses. The interesting question is whether expenses grow *abnormally* fast, given the growth in sales. One way to answer this question is to use average profit margins as a benchmark for the normal growth in expenses (for example, if sales grow by \$100 following high accruals and COGS-to-sales is typically 0.70, we would expect COGS to grow by \$70). An alternative approach is to control directly for sales growth, dSales<sub>t+k</sub>, in the expense regressions.

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

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

$$ACC_{t+1}/TA_{t+1} = f_0 + f_1 NI_t/TA_t + f_2 ACC_t/TA_t + e.$$
(15)

The basic goal here is to test whether accruals exhibit time-series reversals ( $f_2 < 0$ ). Moreover, by keeping the regression specification the same as the persistence regression, we can quantitatively compare the slopes in eq. (15) with the slopes in eq. (13). However, the same complication discussed above with respect to expenses

arises here: Given that  $ACC_t$  is positively related to subsequent sales growth, it should also be positively related to subsequent accruals in the absence of measurement error; the interesting question is whether the growth of accruals is abnormal, conditional on sales growth. We address this issue in the same way described above for expenses, controlling directly for dSales<sub>t+k</sub> in the regressions. As we discuss later, the measurementerror hypotheses suggests the slope on  $ACC_t$  in these regressions should be negative and related to the volatility and persistence of measurement error.

#### 4. Data

Our primary 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 1,000 firms have data for all variables we consider. The final sample has an average of 3,432 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, as described earlier, the dependent variable in some regressions is 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

### Table 2Descriptive 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	3,432
COGS	Cost of goods sold	0.910	0.743	0.744	0.013	4.216	3,432
SGA	Selling, general, and admin.	0.335	0.270	0.267	0.015	1.395	3,432
OthExp	Other expenses <sup>a</sup>	0.103	0.093	0.094	-0.163	0.527	3,432
NI	Net income	-0.018	0.036	0.200	-1.013	0.284	3,432
dSales	Change in Sales	0.103	0.087	0.313	-1.059	1.194	3,426
dCOGS	Change in COGS	0.064	0.052	0.244	-0.931	0.955	3,426
dSGA	Change in SGA	0.021	0.017	0.097	-0.426	0.348	3,395
dOthExp	Change in OthExp	0.005	0.010	0.120	-0.593	0.431	3,395
dNI	Change in NI	0.009	0.006	0.174	-0.582	0.854	3,426
NWC	Net working capital <sup>b</sup>	0.181	0.177	0.196	-0.400	0.656	3,431
LTNOA	Long-term net operating assets <sup>c</sup>	0.403	0.384	0.219	-0.054	0.909	3,431
COA	Current operating assets <sup>d</sup>	0.392	0.391	0.209	0.019	0.863	3,431
COL	Current operating liabilities <sup>e</sup>	0.211	0.183	0.131	0.025	0.784	3,431
dNWC	Change in NWC	0.010	0.010	0.099	-0.360	0.325	3,432
dLTNOA	Change in LTNOA	0.033	0.016	0.157	-0.525	0.641	3,432
dCOA	Change in COA	0.028	0.023	0.116	-0.388	0.419	3,432
dCOL	Change in COL	0.018	0.014	0.075	-0.250	0.300	3,432

<sup>a</sup> OthExp = Sales - COGS - SGA - NI

<sup>b</sup> NWC = Current assets  $- \cosh - \text{non-debt current liabilities}$ 

<sup>c</sup>LTNOA = Total assets - current assets - non-debt long-term liabilities

<sup>d</sup>COA = Current assets - cash

<sup>e</sup>COL = Current liabilities – short-term debt

variables are winsorized annually at their 1st and 99th percentiles to reduce the impact of outliers.

Table 2 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 3 Correlations, 1970–2015

Compustat w	ith data for	average t	otal assets,	, net incom	e, net oper	ating assets.	, and SG&	A expense.	Financial	firms are			
identified usin	ng historica	l SIC code	s from CR	SP. Variab	les are defi	ned in Table	e 2.						
	0												
	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	-			

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

Table 3 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 2) 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 workingcapital accruals (dCOA and dCOL).

#### **5.** Empirical results

Our tests proceed along the lines described in Section 3. We extend the persistence regressions common in the literature to study the link between accruals and subsequent sales, expenses, 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 autocorrelation in the slopes. (We get 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 4 reports standard persistence regressions with one simple twist: We extend the forecast horizon out to seven years to explore the long-run behavior of earnings. 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 3.)

The first column, using  $ROA_{t+1} = NI_{t+1}/TA_{t+1}$  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 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 persistence slope on  $ROA_t$  drops in magnitude (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 indistingushable from the 1-year-ahead slope.) Thus, controlling for current profitability, higher accruals predict lower subsequent profitability for many years into the future.

These results pose a challenge to 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

## Table 4Predicting profitability, 1970–2015

This table reports average slopes and R<sup>2</sup>s 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 2.

	Dependent variable: NI <sub>t+k</sub> /TA <sub>t+k</sub>											
Regressor	t+1	t+2	t+3	t+4	t+5	t+6	t+7					
NI <sub>t</sub>	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 <sub>t</sub>	-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					
dLTNOAt	-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 <sup>2</sup>	0.467	0.313	0.238	0.196	0.165	0.140	0.117					

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 4 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

$$b_{2k} = -\sigma_{\eta}^{2}(\rho^{k} - \lambda_{k}) \frac{\sigma_{\text{NI,CF}}}{\sigma_{\text{ACC}}^{2}\sigma_{\text{CF}}^{2}[1 - \rho_{\text{ACC,CF}}^{2}]},$$
(16)

where  $\rho^k$  and  $\lambda_k$  are the kth-order autocorrelations of true earnings and measurement error, respectively, and  $\sigma^2_{(\cdot)}$ ,  $\sigma_{(\cdot,\cdot)}$ , and  $\rho_{(\cdot,\cdot)}$  denote the variance, covariance, and correlation of the variables indicated. The ratio in eq.

(16) is independent of the horizon and close to 100 in the data.<sup>8</sup> Thus:

$$b_{2k} \approx -\sigma_{\eta}^2 \left( \rho^k - \lambda_k \right) \cdot 100. \tag{17}$$

The term in parentheses is a difference between two autocorrelations and, given the high persistence of ROA ( $\rho$ ), might be expected to be around 1.0 for relatively short horizons, depending on the exact value of  $\lambda$  (which we would expect to be a smaller negative number). Thus, to generate a slope of -0.12 in the 1-year persistence regression, the variance of measurement error would need to be around 0.0012, implying a standard deviation of 0.035 (3.5% of assets). This strikes us greater than what might be considered a plausible amount of error. For example, it implies that ROAs are often misstated by more than 4% or 5% of assets in a given year.<sup>9</sup> In any case, the bigger problem for the measurement-error hypothesis is that the slope does not exhibit a short-run rebound or significant decay for up to 7 years, contrary to what we expect given mean reversion in profitability and reversals in measurement error.

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 regressions in Table 4. In particular, the Appendix shows that the slope on lagged earnings,  $b_1$ , is biased downward relative to  $\rho$ :

$$\mathbf{b}_1 = \rho - (\sigma_{\text{ACC,CF}} \sigma_{\text{NI,CF}}) \mathbf{b}_2. \tag{18}$$

The term in parentheses is -0.39 in the data, so the bias in  $b_1$  is somewhat less than half the slope on accruals. Solving for  $\rho$  gives an estimate of  $\rho = 0.777$  (standard error = 0.01). This parameter suggests that, if  $\lambda_k$  is reasonably close to zero, the slope on accruals (eq. 17) should decay to just 22% of the 1-year slope by year 7 (0.777<sup>6</sup>), again contrary to what we observe in the data.

A formal specification test of the measurement-error model (which does not depend on the unknown  $\lambda_k$ ) comes from the observation that we can directly estimate higher-order autocorrelations of earnings from the k-year-

<sup>&</sup>lt;sup>8</sup> The ratio depends on the properties of observed earnings, accruals, and cash flows and can be estimated in two ways. If we estimate 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.

<sup>&</sup>lt;sup>9</sup> 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.

ahead persistence regressions and test whether they decay toward zero at the rate predicted by the model. For example, the persistence slopes for k = 7,  $b_{1,7} = 0.40$  and  $b_{2,7} = -0.10$ , imply that the 7th-order autocorrelation of true earnings is 0.43 (standard error of 0.02) using the formula in eq. (18). However, the autocorrelation parameter estimated above, 0.777, implies a 7th-order autocorrelation of  $0.777^7 = 0.17$ . This inconsistency (0.43 vs. 0.17) allows us to formally reject that the persistence slopes in Table 4 decay at the rate predicted by the measurement error model.

#### 5.2. Predicting profits

The results in Table 4 focus on the behavior of profitability (i.e., earnings in year t+k are 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<sub>t+k</sub> in the regressions by TA<sub>t</sub> rather than TA<sub>t+k</sub>, 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 5. 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, short-term and long-term accruals both predict an immediate and long-lasting decline in profits.<sup>10</sup>

<sup>&</sup>lt;sup>10</sup> These results contrast with those of FWY (2003b), who find that working-capital accruals predict profitability but not profits. The source of the discrepancy is hard to pin down precisely because our tests differ in many ways. For example, FWY use net operating assets (NOA) at the beginning of year t as the scaling variable rather than average total assets; they drop NASDAQ firms and firms with NOA less than \$1 million from the sample; and their tests end in 1993 (their sample has 35,083 firm-years compared with 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 5 (-0.14) remains significantly negative if our sample ends in 1993 (-0.13); if we drop NASDAQ stocks (-0.08); if we exclude dLTNOA from the regressions (-0.15); if we use operaring earnings in place of net income (-0.10); 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 5Predicting 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<sub>t</sub>, 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 2.

		Dependent variable: $NI_{t+k}/TA_t$											
Regressor	t+1	t+2	t+3	t+4	t+5	t+6	t+7						
NI <sub>t</sub>	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 <sub>t</sub>	-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						
dLTNOAt	-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						
$\mathbb{R}^2$	0.468	0.299	0.219	0.175	0.143	0.120	0.102						

Economically, the evidence in Table 5 is hard to reconcile with the investment hypothesis. The strong, longlasting negative relation between accruals and subsequent profits directly contradicts a central prediction of the investment hypothesis, that the drop in ROA following high accruals reflects diminishing marginal returns—an increase in the denominator of ROA<sub>t+k</sub>—rather than an actual drop in profits (see FWY 2003a,b; Zhang 2007; Wu, Zhang, and Zhang 2010). Interestingly, the slopes for profits in Table 5 are larger in magnitude than the slopes for profitability in Table 4, implying that asset growth from t to t+k masks, rather than causes, the profit decline when ROA<sub>t+k</sub> 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 implies 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

The evidence above suggests that measurement error and investment effects cannot explain the low persistence of accruals: The link between accruals and future profits and future profitability is too strong and too long-

lasting to be explained by either model. The patterns are generally consistent with our product-market model, but the tests do not provide direct evidence that demand and supply shocks really drive the results. In this and the following sections, our goal is to explore in more detail the economic dynamics driving profits and accruals.

As a first step, Table 6 studies the link between accruals and subsequent sales and expenses. The tests maintain the structure of our earlier persistence regressions but break future earnings (the dependent variable) into sales, COGS, SG&A, and other expenses. Because  $NI_{t+k} = Sales_{t+k} - COGS_{t+k} - SGA_{t+k} - OthExp_{t+k}$ , the slopes (appropriately signed) when  $Sales_{t+k}$ ,  $COGS_{t+k}$ , etc. are regressed on lagged earnings and accruals sum to the slope when  $NI_{t+k}$  is regressed on lagged earnings and accruals. (The relation does not hold exactly in the data because we winsorize the variables, but the deviations are small.) We focus on regressions using changes in sales and expenses scaled by assets in year t in order to test whether accruals predict growth in the variables. This specification also avoids complications caused by persistence in the levels of sales, COGS, etc. For brevity, we report results only for horizons out to year t+3.

The results, in the top panel of Table 6, reveal several interesting patterns. First, firms that are more profitable today tend to have higher sales growth over the subsequent three years, consistent with the intuition that changes in demand and/or 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 decline in bottom-line earnings (far-right columns). Thus, a portion of today's profits is transitory because future margins deteriorate, despite the fact that top-line revenues grow rapidly.

Second, controlling for earnings, working-capital and long-term accruals also have strong predictive power for sales and expenses. A dollar of dNWC<sub>t</sub> 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<sub>t</sub> 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 (the slopes are all highly statistically significant). These relations imply that high accruals typically signal high future sales growth, contrary to the idea that high accruals are, in general, a sign of earnings management by firms struggling with slow growth. The results are consistent with our

# Table 6Predicting 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<sub>t+k</sub>, dCOGS<sub>t+k</sub>, dSGA<sub>t+k</sub>, dOthExp<sub>t+k</sub>, and dNI<sub>t+k</sub>) on lagged earnings and accruals (NI<sub>t</sub>, dNWC<sub>t</sub>, and dLTNOA<sub>t</sub>). In panel B, sales growth in year t+k, dSales<sub>t+k</sub>, 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 2.

	$dSales_{t+k}$			$dCOGS_{t+k}$			$dSGA_{t+k}$			dOthExpt	+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	e predictive	regression	ıs												
$\mathbf{NI}_{\mathrm{t}}$	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
dNWCt	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	5.49	-9.43	-1.82	-1.4/
dLTNOA <sub>t</sub>	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
$\mathbb{R}^2$	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: Contr	olling for d	$Sales_{t+k}$													
NIt				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 <sub>t</sub>				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 <sub>t</sub>				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 <sub>t+k</sub>				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
$\mathbb{R}^2$				0.859	0.859	0.858	0.400	0.411	0.423	0.179	0.107	0.112	0.223	0.068	0.064

product-market model in Section 2, in which demand and supply shocks induce changes in working-capital accruals that lead sales.

At the same time, Table 6 shows that high accruals predict even faster growth in expenses. The jump in total expenses is, of course, just a restatement of the fact that accruals are negatively related to subsequent profits. The more interesting issue is how different types of expenses contribute to the overall increase. To interpret the results, recall from Table 2 that COGS averages 68% of sales, SGA averages 25% of sales, and other expenses average 8% of sales. Given that a dollar of working-capital accruals is associated with \$0.56 of sales growth in year t+1, we would expect COGS to increase by \$0.38 ( $0.56 \times 0.68$ ), SGA to increase by \$0.14 ( $0.56 \times 0.25$ ), and other expenses to increase by \$0.05 ( $0.56 \times 0.08$ ) if accruals were associated with 'normal' changes in expenses. Empirically, \$1 of dNWC actually predicts a \$0.47 increase in dCOGS<sub>t+1</sub> and a \$0.18 increase in dSGA<sub>t+1</sub>, both substantially higher than normal (the increase in OthExp<sub>t+1</sub>, \$0.04, is close to normal growth). Put differently, a dollar 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<sub>t+1</sub> and \$0.04 comes from a disproportionate increase in SGA<sub>t+1</sub>.

Turning to long-term accruals, a \$1 increase in dLTNOA<sub>t</sub> would predict \$0.31 of additional COGS<sub>t+1</sub>, \$0.11 of additional SGA<sub>t+1</sub>, and \$0.04 of additional OthExp<sub>t+1</sub> if long-term accruals were associated with normal expense growth, given the observed relation between dLTNOA<sub>t</sub> and dSales<sub>t+1</sub> (\$0.45). The actual increases in COGS<sub>t+1</sub> and SGA<sub>t+1</sub> match the predictions exactly, while the \$0.18 increase in other expenses is substantially higher than expected. Thus, long-term accruals are primarily associated with an abnormal jump in other expenses. (In supplemental tests, we find that the predictable increase in OthExp<sub>t+1</sub> 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 are two components of a generic

investment effect (FWY 2003a).

Panel B of Table 6 provides an alternative and, in some sense, more rigorous way to test whether accruals are associated with a disproportionate increase in expenses given the behavior of sales. In particular, we include  $dSales_{t+k}$  (contemporaneous with the dependent variable) as an explanatory variable in the regressions in order to control directly for subsequent growth in sales. The slope on accruals in these regressions provides a direct estimate of whether accruals predict earnings and expenses after controlling for the association between accruals and future sales growth.

Focusing first on earnings (the far-right columns), Panel B shows that controlling for sales growth accentuates the negative relation between accruals and subsequent earnings, i.e., the earnings decline following high accruals is stronger than standard persistence regressions suggest because, all else equal, earnings should actually increase given the growth in sales in t+1 (we control for the expected increase by adding dSales<sub>t+1</sub> to the regression). 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 the measurement error and investment hypotheses 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 the profit decline following high working-capital accruals comes equally from disproportionate growth in COGS and SG&A (with an additional small amount related to predictable changes in  $dOthExp_{t+1}$ ). Thus, the predictive power of  $dNWC_t$  is not tied to abnormal growth in just one component of expenses but, instead, from a general rise in expenses relative to sales. (Growth in COGS becomes normal or even slightly below average after year t+1, while growth in SG&A stays elevated in years t+2 and t+3.) In contrast,  $dLTNOA_t$  has modest predictive power for  $dSGA_{t+1}$  (0.05) and strong predictive power for  $dOthExp_{t+1}$  (0.16), implying 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 (and output price) should induce firms to raise production, leading to high working-capital accruals and high subsequent sales growth. At the same time, subsequent profits should decline as additional 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 4, 5, and 6.

#### 5.4. Industry dynamics

The product-market hypothesis implies that industry dynamics should help to explain the low persistence of accruals. For example, an increase in 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-wide effects are not predicted by the measurement-error hypothesis to the extent that measurement error is idiosyncratic or, at least, not as highly correlated across firms as true earnings. Thus, we explore industry profits, accruals, and growth as an additional way to test whether product-markets effects help to explain the low persistence of accruals. To be specific, we look at two issues: (i) Do industry accruals predict industry profits, profitability, 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 7 considers the first issue. The regressions take the same form as our main tests but the data points now represent the industry average of the firm-level profitability, profit, sales growth, and accrual variables from Tables 4, 5, and 6. We use three-digit SIC codes, 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 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

#### Table 7

#### Industry profits, sales, and accruals, 1970-2015

This table reports average slopes and  $R^2s$  from annual cross-sectional regressions of industries' profits and sales growth on industries' lagged profits and accruals. Industries are based on historical three-digit SIC codes from CRSP. 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. The industries are described further in the text and variables are defined in Table 2.

				Horizon			
Regressor	t+1	t+2	t+3	t+4	t+5	t+6	t+7
Panel A: Dependen	t variable = N	$I_{t+k}/TA_{t+k}$					
NIt	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
dNWCt	-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
dLTNOAt	-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
$\mathbb{R}^2$	0.691	0.525	0.446	0.407	0.387	0.370	0.355
Panel B: Dependen	t variable = N	$I_{t+k}/TA_t$					
NIt	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
dNWCt	-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
dLTNOAt	-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
$\mathbb{R}^2$	0.685	0.502	0.410	0.367	0.335	0.290	0.256
Panel C: Dependen	t variable = d	$Sales_{t+k}/TA_t$					
NIt	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
dNWCt	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
dLTNOAt	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 <sup>2</sup>	0.141	0.083	0.083	0.098	0.091	0.083	0.083

firms, and the average industry contains just over 30 firms.

The table shows that industry results are very similar to our firm-level results. In panel A, industry accruals are strongly negatively related to an industry's subsequent profitability. At the one-year horizon, the slopes on  $dNWC_t$  (-0.12) and  $dLTNOA_t$  (-0.14) are highly significant and closely match the firm-level slopes in Table 4. Moreover, the slopes increase in magnitude as the horizon in lengthened and, like the firm-level slopes, exhibit

no evidence of a rebound or decay at any horizon. 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 5, 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 8 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, helps 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 8 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 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 threedigit SIC code in our Compustat sample (again restricted to industries with at least 10 firms in year t). In the

#### Table 8

#### Accruals and competition, 1970–2015

This table reports average slopes and R<sup>2</sup>s 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 U.S. 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). The unit of observation in a regression is an individual firm. 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 2.

	En	Entry-Compustat			try–all pri	vate		Herfindahl		
	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3	
NI <sub>t</sub>	-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 <sub>t</sub>	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 <sub>t</sub>	0.07	$\begin{array}{c} 0.05 \\ 4.07 \end{array}$	0.04	0.04	0.03	0.02	-0.03	-0.02	-0.01	
t	4.44		3.45	2.63	3.05	2.63	-4.16	-1.94	-1.06	
$\mathbb{R}^2$	0.018	0.010	0.008	0.021	0.012	0.009	0.007	0.006	0.006	

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<sub>t</sub> (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<sub>t</sub> (0.16) predicts a 2.6% increase in the number of Compustat firms and a 1.3% increase in the total number of number of private enterprises. The results using the Herfindahl index are qualitatively similar.

In short, Tables 7 and 8 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. The results line up well with the predictions of our product-market hypothesis.

#### 5.5. Predicting accruals

The evidence above suggests that product-market effects can explain the link between accruals and subsequent profits, sales, and expenses 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 this year should be positively related to dNWC next year if working capital in t+1 grows along with sales (Jones 1991; Dechow, Kothari, and Watts 1998; Allen, Larson, and Sloan 2013). To control at least partially for these effects, we report both simple predictive regressions, using lagged earnings and accruals as predictors, as well as regressions that control for future sales growth. Our Appendix shows that, if the predictability of true accruals is captured by dSales<sub>t+k</sub>, the slope on dNWC<sub>t</sub> in the second specification will have the same sign as the autocorrelation of measurement error and should be closely related to (but smaller than) the slope in an earnings persistence regression.

Table 9 reports the results. The first columns in Panel A show that, in simple predictive regressions, workingcapital accruals exhibit little evidence of reversals:  $dNWC_t$  is insignificantly related to  $dNWC_{t+k}$  in each of the

#### Table 9

#### Predicting working-capital accruals, 1970–2015

This table reports average slopes and  $R^2s$  from annual cross-sectional regressions of working-capital accruals (dNWC<sub>t+k</sub>, dCOA<sub>t+k</sub>, and dCOL<sub>t+k</sub>, all scaled by TA<sub>t+k</sub>) on lagged profits and accruals (NI<sub>t</sub>, dNWC<sub>t</sub>, and dLTNOA<sub>t</sub>, all scaled by TA<sub>t</sub>). In panel B, sales growth in year t+k, dSales<sub>t+k</sub>, 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 <sub>t+k</sub>			dCOA <sub>t+k</sub>			dCOL <sub>t+k</sub>			
	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3		
Panel A: Simple	e predictive r	egressions	7								
NIt	0.13	0.08	0.05	0.13	0.08	0.05	0.02	0.02	0.01		
t	3.59	3.67	4.00	3.59	3.67	4.00	1.91	2.86	2.24		
dNWCt	-0.02	-0.01	0.00	-0.02	-0.01	0.00	0.08	0.03	0.02		
t	-1.41	-0.69	-0.66	-1.41	-0.69	-0.66	9.49	7.41	4.49		
dLTNOAt	0.02	-0.01	-0.01	0.02	-0.01	-0.01	0.03	0.01	0.01		
t	5.55	-1.34	-1.82	5.55	-1.34	-1.82	6.91	4.32	1.98		
R <sup>2</sup>	0.040	0.014	0.009	0.040	0.014	0.009	0.025	0.008	0.004		
Panel B: Contro	olling for dSa	$ales_{t+k}$									
NIt	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		
dNWCt	-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		
dLTNOAt	-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 <sub>t+k</sub>	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		
$\mathbb{R}^2$	0.140	0.119	0.113	0.353	0.337	0.332	0.205	0.194	0.186		

subsequent three years, with a predictive slope of just -0.02 (t-statistic of -1.41) at the one-year horizon. (Earnings and long-term accruals are both positively related to  $dNWC_{t+1}$ .) However, dNWC is less persistent than it 'should be' given the behavior of sales, i.e., given that  $dNWC_t$  predicts high  $dSales_{t+1}$  (Table 6), we might expect that it would also predict high  $dNWC_{t+1}$ . The tests in Panel B control directly for expected growth in dNWC by adding  $dSales_{t+1}$  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 9 are not reflected appropriately, if measurement error really explains the reversals, in the earnings persistence regressions in Table 4 (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 9 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 drop in earnings following high accruals is explained either by measurement error in accruals or the negative impact of investment on future profitability which, in turn, can be traced to diminishing marginal returns or conservatism in accounting.

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 provide a formal analysis of how measurement error will affect persistence regressions, deriving testable new implications of measurement error. Finally, we extend the 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 to 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 diminishing marginal returns from investment almost certainly exist in the data. 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 has

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

#### Appendix

This appendix develops the measurement-error model in Section 2.1. The analysis builds on RSST (2005) but extends their results in a variety of 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

$$NI_{t+1} = b_0 + b_1 NI_t + b_2 ACC_t + e_{t+1},$$
(A1)

when 'true' earnings follow an AR(1) process,  $NI_{t+1}^* = c + \rho NI_t^* + \mu_{t+1}$ , but observed earnings and accruals are measured with error,  $NI_t = NI_t^* + \eta_t$  and  $ACC_t = ACC_t^* + \eta_t$ . (Here, correctly-measured accruals are defined as true earnings minus cash flow,  $ACC_t^* = NI_t^* - CF_t$ .) Our analysis allows measurement error to be positively or negatively autocorrelated but, for simplicity, we maintain RSST's assumption that  $\eta_t$  is not related to  $NI_t^*$  or  $ACC_t^*$ . The existence of measurement error means that, while true earnings are AR(1), observed earnings are predictably related to lagged accruals.

Formally, if we stack the slopes in eq. (A1) into the column vector  $\mathbf{b} = (\mathbf{b}_1, \mathbf{b}_2)$  and the regressors into the vector  $\mathbf{x}_t = (\mathbf{NI}_t, \mathbf{ACC}_t)$ , standard regression analysis implies that

$$\mathbf{b} = \operatorname{var}^{-1}(\mathbf{x}_t) \operatorname{cov}(\mathbf{x}_t, \operatorname{NI}_{t+1}). \tag{A2}$$

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

$$\operatorname{var}(\mathbf{x}_{t}) = \begin{bmatrix} \sigma_{\mathrm{NI}}^{2} & \sigma_{\mathrm{NI,ACC}} \\ \sigma_{\mathrm{NI,ACC}} & \sigma_{\mathrm{ACC}}^{2} \end{bmatrix} = \begin{bmatrix} \sigma_{\mathrm{NI}^{*}}^{2} + \sigma_{\eta}^{2} & \sigma_{\mathrm{NI}^{*},\mathrm{ACC^{*}}} + \sigma_{\eta}^{2} \\ \sigma_{\mathrm{NI}^{*},\mathrm{ACC^{*}}} + \sigma_{\eta}^{2} & \sigma_{\mathrm{ACC^{*}}}^{2} + \sigma_{\eta}^{2} \end{bmatrix},$$
(A3)

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

$$\operatorname{var}^{-1}(\mathbf{x}_{t}) = \frac{1}{D} \begin{bmatrix} \sigma_{ACC}^{2} & -\sigma_{NI,ACC} \\ -\sigma_{NI,ACC} & \sigma_{NI}^{2} \end{bmatrix},$$
(A4)

with determinant

$$D = \sigma_{ACC}^2 \sigma_{NI}^2 - \sigma_{NI,ACC}^2 = \sigma_{ACC}^2 \sigma_{NI}^2 (1 - \rho_{NI,ACC}^2) = \sigma_{ACC}^2 \sigma_{CF}^2 (1 - \rho_{CF,ACC}^2),$$
(A5)

where  $\rho_{(\cdot,\cdot)}$  denotes a correlation. The last equality in (A5) uses the fact that the residual variance when NIt is

regressed on ACC<sub>t</sub>,  $\sigma_{NI}^2 (1 - \rho_{NI,ACC}^2)$ , is the same as the residual variance when CF<sub>t</sub> is regressed on ACC<sub>t</sub>,  $\sigma_{CF}^2 (1 - \rho_{CF,ACC}^2)$ , since NI<sub>t</sub> = ACC<sub>t</sub> + CF<sub>t</sub>. Returning to eq. (A2), the covariance between x<sub>t</sub> and NI<sub>t+1</sub> is

$$\operatorname{cov}(\mathbf{x}_{t}, \operatorname{NI}_{t+1}) = \begin{bmatrix} \rho \, \sigma_{\operatorname{NI}^{*}, \operatorname{cov}(\eta_{t}, \eta_{t+1})} \\ \rho \, \sigma_{\operatorname{NI}^{*}, \operatorname{ACC^{*}}} + \operatorname{cov}(\eta_{t}, \eta_{t+1}) \end{bmatrix} = \begin{bmatrix} \rho \, \sigma_{\operatorname{NI}^{*}, \operatorname{ACC^{*}}}^{2} + \lambda \sigma_{\eta}^{2} \\ \rho \, \sigma_{\operatorname{NI}^{*}, \operatorname{ACC^{*}}} + \lambda \sigma_{\eta}^{2} \end{bmatrix},$$
(A6)

where  $\lambda$  is the first-order autocorrelation of  $\eta_t$ . Substituting eqs. (A4) and (A6) into eq. (A2) gives:

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

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

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

The second equality uses the fact that  $D = \sigma_{ACC}^2 \sigma_{NI}^2 - \sigma_{NI,ACC}^2$  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,  $\sigma_{NI}^2 = \sigma_{NI,ACC} + \sigma_{NI,CF}$ , so the final term in the second row is just  $\sigma_{NI,CF}$ . This yields:

$$\mathbf{b} = \begin{bmatrix} \rho + \frac{\sigma_{\eta}^{2}(\rho - \lambda)\sigma_{\text{ACC,CF}}}{D} \\ -\frac{\sigma_{\eta}^{2}(\rho - \lambda)\sigma_{\text{NI,CF}}}{D} \end{bmatrix}.$$
 (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  $\lambda$  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 actually recover the autocorrelation of true earnings given estimates of  $b_1$  and  $b_2$ . Specifically, eq. (A9) implies that:

$$\rho = \mathbf{b}_1 + (\sigma_{\text{ACC,CF}}/\sigma_{\text{NI,CF}}) \mathbf{b}_2. \tag{A10}$$

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  $\lambda$  without additional assumptions about the time-series properties of measurement error, i.e., we can use  $b_2$  to estimate  $\sigma_{\eta}^2 (\rho - \lambda)$ , but we cannot separately estimate  $\sigma_{\eta}^2$  or  $\lambda$  (in essence, we have one equation with two unknowns).

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

$$NI_{t+k} = b_{0k} + b_{1k}NI_t + b_{2k}ACC_t + e_{t+k},$$
(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  $NI_{t+1}$ :

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

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

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

This is the same as b in eq. (A7) except that  $\rho^k$  replace  $\rho$  and  $\lambda_k$  replaces  $\lambda$ . Thus,  $b_{(k)}$  simplifies to

$$\mathbf{b}_{(k)} = \begin{bmatrix} \rho^{k} + \frac{\sigma_{\eta}^{2}(\rho^{k} - \lambda_{k})\sigma_{\text{ACC,CF}}}{D} \\ -\frac{\sigma_{\eta}^{2}(\rho^{k} - \lambda_{k})\sigma_{\text{NI,CF}}}{D} \end{bmatrix},$$
(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  $\rho^k$  from these slopes:

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

In other words, we can estimate  $\rho$  from the one-year-ahead predictve regression and  $\rho^k$  from the k-year-ahead predictive regression. If the measurement error model is well-specified, the estimates of  $\rho$  and  $\rho^k$  should be consistent with each other (i.e.,  $\rho^k$  should equal  $\rho$  raised to the kth power). This prediction provides what, in essense, 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:

$$ACC_{t+1} = c_0 + c_1 NI_t + c_2 ACC_t + e_{t+1}.$$
(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:

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

$$\eta_{t+1} = f_0 + f_1 N I_t + f_2 A C C_t + e_{t+1}.$$
(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, Larson, and Sloan'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<sub>t+1</sub>\* is linked to dSales<sub>t+1</sub> (Jones 1991; Dechow, Kothari, and Watts 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<sub>t+1</sub>. This implies that true accruals are expected to grow along with sales but also contain an additional random component. It follows that observed accruals, ACC<sub>t+1</sub> =  $\beta$  dSales<sub>t+1</sub> +  $a_{t+1}^*$  +  $\eta_{t+1}$ , are made up of three components: a predictable component related to sales ( $\beta$  dSales<sub>t+1</sub>), an unpredictable component related to random variation in true accruals ( $a_{t+1}^*$ ), and measurement error ( $\eta_{t+1}$ ). The first component can be eliminated by regressing accruals on sales growth, leaving  $a_{t+1} = ACC_{t+1} - \beta$  dSales<sub>t+1</sub> =  $a_{t+1}^* + \eta_{t+1}$ . The predictability of this residual is then entirely due to the predictability of measurement error, i.e., the slopes in

$$a_{t+1} = f_0 + f_1 N I_t + f_2 A C C_t + e_{t+1},$$
(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  $2 \times 1$  vector of slopes slopes in (A20) equal

$$f = \begin{bmatrix} \frac{-\lambda \sigma_{\eta}^2 \sigma_{ACC,CF}}{D} \\ \frac{\lambda \sigma_{\eta}^2 \sigma_{NI,CF}}{D} \end{bmatrix}.$$
 (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,  $\lambda$ . Moreover, the slopes in this regression should be closely related to the slopes in the persistence regression (b<sub>2</sub>):  $f_2 = \lambda/(\lambda - \rho) \times b_2$ .

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