

Accrual Noise Ratio as a Measure of Accrual  
Reliability

by

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Dissertation submitted in partial fulfillment of the requirements for the degree of  
Doctor of Philosophy in the Department of Business Administration  
in the Graduate School of Duke University

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ABSTRACT  
(Business Administration)

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# Abstract

I develop an empirical model that estimates a firm-specific accrual noise ratio (ANR), an operational and statistically grounded measure of accrual reliability, and test the measure's construct validity. The model allows accrual reliability to vary across firms, which is particularly important because many reliability determinants vary in cross-section. Unlike metrics that measure relative perceived reliability, ANR measures accrual reliability independent of the perceptions of investors, creditors or auditors. I find that ANR relates in expected ways with multiple proxies of accounting reliability, that ANR's relation with the proxies of other accounting constructs is consistent with theory, and that ANR's sensitivity to percentage changes of accrual components is consistent with a subjective ordinal ranking of the components' reliability from prior literature.

This dissertation is dedicated to my loving wife Miriam and our kids Mike, Faith, Paul and Joy.

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# Chapter 1

## Introduction

Reliability is a key attribute that makes accounting information useful for decision making. Previous researchers have pointed to the need for a tractable empirical measure of reliability.<sup>1</sup> However, estimating firm-specific accrual reliability has proven difficult, because it requires an estimate of the variance of unobservable measurement error in small samples. In this paper, I develop an empirical model that estimates a firm-specific accrual noise ratio as a measure of accrual reliability, and I examine the measure's construct validity.

I extend prior research in three ways. First, I develop a model that allows accrual reliability to vary across firms. This is important because many determinants of accrual reliability (e.g., management expertise or the extent to which GAAP accruals capture firms' business models and operating environments) likely vary across firms. Second, estimation of an accrual noise ratio (hereafter ANR) does not require estimating, or making assumptions about, the length of accrual reversal periods. Accordingly, ANR can be used to estimate the reliability of total accruals

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<sup>1</sup> For example, Maines and Wahlen [2006, p. 419] call for archival researchers to pursue research that assesses representational faithfulness by modeling and estimating the relation between accounting data and underlying economic constructs. Schipper [2007, p. 315-316] points out that an approach that estimates reliability without relying on the perceptions of participants in the financial reporting process would be desirable. Richardson, Sloan, Soliman and Tuna [2005, p. 483] call for further refinement of their analysis on the differing degrees of reliability associated with different categories of accruals.

that include noncurrent components.<sup>2</sup> Third, in contrast to research based on market reactions to accounting information that estimates *perceived relative* reliability (e.g., Barth [1991]; Choi, Collins and Johnson [1997]), I estimate ANR without using the reliability perceptions of participants in the financial reporting process (e.g., investors and auditors).

My approach to measuring accruals reliability is based on the well-documented result that measurement error induces attenuation bias on OLS coefficient estimates. Thus, if attenuation bias is estimable, the magnitude of measurement error variance can be inferred. Attenuation bias can be estimated using two methods: (1) the difference between an OLS coefficient estimate and its theoretical coefficient value if the latter is known, or (2) the difference between an OLS coefficient estimate and a coefficient estimate that corrects for attenuation bias. Theoretical coefficient values against which OLS coefficients can be compared are unavailable for accruals. As such, I focus on the second method. Specifically, following Carroll et al. [2004], I use the two stage least squares (TSLS) estimator as a correction-for-attenuation estimator to infer accrual measurement error variance from attenuation bias. Further, since accrual instruments derived from accounting fundamentals have sometimes been found to be weak and endogenous, I draw on Larcker's [2003, p. 93] recommendation and consider Lewbel's [1997] approach to construct accrual instruments from the moments of cash flow and accruals distributions.

Since my research design requires the use of instruments in small samples to estimate accrual noise ratio (hereafter ANR), it has limitations. Specifically, while using a longer time-series can improve instrumental variable estimation, it exacer-

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<sup>2</sup> Some accounting research (e.g., Healy [1985]; Jones [1991]; Sloan [1996]; Dechow, Sloan and Sweeney [1995]) defines accruals as change in non-cash working capital less depreciation, thus omitting many noncurrent operating accruals and deferrals (e.g., deferred taxes, postretirement benefit obligations, long-term receivables). The contribution of noncurrent accruals to the unreliability of total accruals remains an empirical question that I pursue in ANR's construct validity tests.

bates survivorship bias and constrains reliability to be invariant over long horizons. Second, inference based on ANR is a joint test of reliability and the quality of instruments used. Ultimately, I substitute the problem of finding valid instruments for the problem of investor perceptions inherent in prior research for three reasons. First, formal econometric tests can be used to test the null hypothesis of weak or endogenous instruments, thus mitigating concerns about instrument quality. Second, like reliability, perception is latent and therefore difficult to measure. Perception assumptions can be particularly difficult to formally test.<sup>3</sup> Third, perception measures may be unavailable, especially for infrequently traded stocks.

If ANR is a valid measure of accrual reliability, it should capture the extent to which reported accruals meet accounting reliability criteria. Specifically, reliable accruals should remove the timing and matching problems in cash flows, generate an earnings number that captures actual financial performance, be without manipulative or unintentional error, and be predictive of a transaction's future cash flows. My construct validation seeks to assess ANR's ability to capture the extent to which reported accruals meet these criteria. Drawing on theory that links reliability to other accounting constructs, I examine the external, convergent and divergent validity of ANR with respect to persistence, timeliness, informativeness, smoothness, the level of competition in product markets, the volatility of cash flows and accruals, losses, cash flow predictability and accounting discretion. I also examine the extent to which ANR's sensitivity to percentage changes in accrual components matches the subjective reliability ranking of accrual components proposed by Richardson, Sloan, Soliman and Tuna [2005]. Taken together, evidence from these tests suggests that ANR is a valid measure of accrual reliability.

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<sup>3</sup> The extent to which investors process reliability is an empirical question. For example, the accrual and growth anomalies hypothesize that prices behave as if investors do not fully anticipate the implications of accrual reliability, or growth, for future firm performance.

# Chapter 2

## Literature review

### 2.1 Accounting research that extracts reliability from attenuation bias

Barth [1991] and Choi et al. [1997] compare the reliability of alternative metrics of pension and nonpension assets and liabilities as perceived by investors, in a joint test of relevance and reliability. Both studies use a balance sheet valuation framework, under two assumptions. First, markets are efficient. Second, within this valuation framework, the theoretical capitalization coefficient of a perfectly reliable *and* relevant book value is one. In this approach, deviations of OLS coefficient estimates from the theoretical value of one are interpretable as attenuation bias, which is a function of the covariances among measurement errors and book values. While it is difficult to estimate each explanatory variables' measurement error variance, this research uses the Garber and Klepper [1980] approach to infer either *relative* measurement error variance or *relative* noise ratio from the magnitude of the estimated attenuation bias. Effectively this research makes a relative ranking of the reliability of the explanatory variables.

As both Barth, Beaver and Landsman [2001, p. 80-81] and Schipper and Vincent [2003, p. 103-104] explain, this approach does not measure reliability separately

from relevance. In addition, as Barth [1991, footnote 23] points out, this research treats measurement error variance or noise ratio of alternative metrics as cross-sectional constants. Effectively, this research design does not allow the reliability of a given accounting metric to vary across firms. Further, as Choi et al. [1997] explain, their relative noise ratio metric provides inference on the *perceived* differences in the reliability of alternative metrics.

I extend this research along three dimensions. First, while Barth [1991] and Choi et al. [1997] focus on balance sheet items, I focus on accruals. Second, my model allows the noise ratio to vary across firms. Third, from a methodological standpoint, I do not use the theoretical values based on a balance sheet valuation model as a benchmark to infer attenuation bias; instead, I use the two stage least squares (TSLS) coefficient estimator as a benchmark. On one hand, using instruments in small samples is difficult. On the other hand, theoretical coefficient values are restrictive, and tend to be difficult to verify or justify. For example, drawing inference based on market perceptions requires assumptions about investors ability to process reliability; such ability, however, is likely heterogeneous across investors and likely shifts across time for any given investor. Indeed, the extent to which investors perceive the reliability of accruals is an open empirical question.<sup>1</sup> In addition, capitalization coefficients can deviate from the theoretical value of one for other reasons besides measurement error (e.g., omitted variables and nonlinearity). I note that ANR can potentially shed light on the extent to which, and the conditions under which, perception assumptions hold.

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<sup>1</sup> For example, the accrual anomaly literature (e.g., Sloan [1996]; Richardson et al. [2005]) hypothesizes that prices behave as if investors do not fully anticipate the lower persistence of accruals with lower reliability. Ultimately, I substitute the problem of perception assumptions for the problem of instruments.

## 2.2 Accounting research that infers reliability from perceived verifiability

Teoh and Wong [1993] (hereafter TW) consider an analytical model that links the earnings response coefficient (ERC) to the reliability ratio (i.e., one minus noise ratio) of earnings. They test a simplified version of Holthausen and Verrecchia's [1988] analytical model. Using simplifying assumptions, TW consider the simplest setting sufficient for a test of the relation between the market response to an information signal and the precision of the signal. Subramanyam [1996] also considers a similar analytical model. TW use audit quality, as captured by auditor size, to make earnings reliability, as perceived by investors, empirically operational. Effectively, they consider audit quality as a measure of the credibility of accounting information. Specifically, TW (p. 348) posit that audit quality assures investors of the reliability of financial data. Since audit quality, varies across firms, TW's research design allows for cross-sectional heterogeneity in earnings reliability as perceived by investors.

I extend TW along three dimensions. First, while TW focus on reliability from a verifiability perspective (as captured by audit quality), my focus is on the representational faithfulness perspective. TW's analytical model does not, however, distinguish between these perspectives. Both perspectives are useful because accounting reliability is a broad conceptual construct that is difficult to capture in a single proxy. As such, I consider ANR as a complement rather than a substitute of audit quality. Second, the cross-sectional variation in ANR is likely higher than that of auditor size. Effectively, ANR can vary across firms that share the same auditor. Third, ANR's estimation is independent of investors' perceptions, while in TW's setting, earnings reliability derives from investors' perception of the credibility of accounting information based on auditor size. In addition, I focus on accruals while TW focus on aggregate earnings.

## 2.3 Accrual models based on direct estimation approaches

Previous earnings management and accrual quality literatures directly estimate the abnormal component of accruals based on the residuals of a regression of accruals (e.g., total accruals or working capital accruals) on accounting fundamentals (e.g., sales, cash flows or fixed assets). The fitted value from this regression is interpretable as the estimated benchmark, against which reported accruals are compared. The abnormal accruals component serves as an inverse measure of earnings quality. This strand of research includes Jones [1991], Dechow, Sloan and Sweeney [1995], Dechow and Dichev [2002] and Francis, LaFond, Olsson and Schipper [2004, 2005]. The direct estimation approach does not, in general, require making perception assumptions. In addition, as Schipper and Vincent [2003, p. 103] explain, to the extent that the abnormal accruals component derived from the direct estimation approaches captures measurement errors that move reported earnings away from economic income, then this metric is consistent with representational faithfulness. The implicit assumption is that the fitted benchmark is indicative of the extent to which accounting earnings faithfully represent economic income.

However, Schipper [2007] explains that drawing meaningful inference on accrual reliability based on evidence from the direct estimation approach can be problematic and requires using strong assumptions. For example, it requires the assumption that the fitted benchmark is itself not mismeasured; however, assessing the extent a benchmark is mismeasured is difficult in this setting. It also requires a specific and formal statistical link between reliable accruals and accounting fundamentals, based on which the unreliability of accruals can be estimated. In addition, such inference requires fundamentals that represent a benchmark.

My study extends this research in two ways. First, from an instrumental variables perspective, I view the accounting fundamentals that serve as predictors in direct estimation models as external instrumental variables in a first stage regres-

sion. The problem of selecting predictors therefore translates into the problem of instrument selection. Since obtaining such instruments in accounting settings is difficult, I draw on Larcker [2003] and use the Lewbel [1997] approach to construct internal instruments. Unlike the direct estimation approach, however, I do not infer accrual reliability based on the first stage regression's residuals. Instead, I use a second stage regression and obtain the TSLS estimator. Following Carroll et al [2004] the TSLS estimator serves as a correction-for-attenuation estimator that can be used to estimate the attenuation bias in a naive OLS estimator. This attenuation provides a statistical relation between the two estimators, based on which I extract the accrual measurement error variance. An empirical strength in my research design is that the Lewbel approach generates a huge set of usable instruments. In addition, because the finite sample properties of the resultant TSLS estimator are well known, it is possible to empirically assess instrument validity.

Second, in contrast to Dechow and Dichev [2002] and Francis et al. [2004, 2006], I consider the reliability of total accruals that include noncurrent accruals that reverse over long, and difficult to identify periods. Thus, my research design does not require the identification of the accrual reversal period.

## **2.4 Ordinal ranking of accrual reliability**

Richardson et al. [2005] develop an analytical model that links accrual reliability to earnings persistence. This theoretical model uses perfect foresight accruals as a benchmark against which reported accruals are measured. In particular, the authors propose accrual noise ratio as a natural measure of accrual reliability. Subject to the model's assumptions, Richardson et al. [2005] analytically show that the lower persistence of reported accruals, relative to that of the cash flow component of reported earnings, decreases with the accrual noise ratio. However, Richardson et al. [2005] do not empirically estimate ANR; they comprehensively categorize accruals, and conduct an ordinal ranking of the reliability of different accrual categories based the level of subjectivity involved in estimating each accrual category, as perceived



by the researchers. Effectively, this research design substitutes investor perceptions with researcher perceptions. The authors call on future research to both corroborate and further refine the analysis of the differing degrees of reliability associated with different accrual categories.

Like Barth [1991] and Choi et al. [1997], Richardson et al. [2005] use a research design that treats the reliability of a specific accounting metric as homogeneous across firms. Specifically, it is infeasible to use this ordinal ranking to compare the reliability of a specific accrual category across numerous firms, or across time. In contrast, I draw on Lewbel [1997], Carroll Ruppert, Stefanski, and Crainiceanu [2004] and Erickson and Whited [2006] to develop an empirical model that estimates firm-specific ANR independent of researcher perceptions. As a cardinal measure, ANR complements the ordinal accrual reliability ranking by Richardson et al. [2005].

Whether the persistence of accruals is lower than that of the cash flow component of earnings is controversial. Francis and Smith [2005] show that inclusion of non-current-period transactions in the accounting definition of accruals leads to a downward bias of the persistence of accruals relative to that of cash flows. One interpretation of this result is that accounting accruals contain a predictable *non-random* measurement error component, that time-specific accruals purge. Further, the authors show that if time-specific accruals are used instead, the persistence difference between the two components largely disappears. However, Francis and Smith [2005, p. 427] explain that based on this model, it is difficult to predict the effect of the *random* measurement error component on the relative magnitude of persistence coefficient estimates. My model explicitly incorporates both random and nonrandom measurement error components. However, while I find that the random measurement error component reduces the persistence of aggregate earnings, my focus in this study is not to compare the persistence of cash flows to that of accounting accruals. In particular, my model and its predictions are not predicated on the relative magnitudes of persistence coefficient estimates. While ANR

can be useful in such a comparison, that is a separate question that I defer to future research.

## 2.5 Statistics literature on estimation of linear measurement error models

A measurement error model seeks to estimate the effect of a latent variable, that is measured with error, on a dependent variable. In an ordinary least squares model, this effect as captured by the naive OLS coefficient estimate, is inconsistent and attenuated toward zero. The traditional method of addressing this problem is the instrumental variable approach. An instrument is defined as a variable that is correlated with the latent variable, but uncorrelated with either the observable variable's measurement error or the regression error. In this literature, an instrument that is not included in the initial regression is referred to as an external instrument. In many settings, however, obtaining an external instrument that is strongly correlated with the latent variable but uncorrelated with the observable variables' measurement error is very difficult.

Over the last three decades, numerous statistics and econometrics studies have examined the problem of model estimation given weak or endogenous external instruments. As such, the literature on the estimation of linear and nonlinear measurement error models is extremely broad and involves numerous methods.<sup>2</sup> My brief review of this literature draws on Carroll et al. [2006], who classify measurement error models based on two major defining characteristics. First, the structure of the error model relating the true but unobservable variable to its observable counterpart that is measured with error. Second, the type and amount of additional data available to assess the important features of this error model. This literature typically assumes that the true variable is serially uncorrelated, uncorrelated with

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<sup>2</sup> Several books are either entirely dedicated to this topic (see, Fuller [1987]; Carroll et al. [1995]; Cheng and van Ness [1999]; Wansbeek and Meijer [2000]; Dunn [2004]) or include at least a chapter on the topic (e.g., Kendall and Stuart [1979]; Judge, Griffiths, Carter and Lee [1980]; Seber and Wild [1989]; Casella and Berger [2001]). This is in addition to numerous papers on this topic.

the measurement error, and its first and second moments exist.

In this literature, given a sample, the calculability of the population variances of both the measurement error and the latent variable, as well as the true (population) regression coefficients, is referred to as the identifiability problem. Solving the identifiability problem requires making assumptions about: (1) order of moments available; (2) prior knowledge of a subset of the parameters; (3) covariance structure between measurement error and regression error; (5) serial correlation in the measurement error; (6) distribution of the latent variable, measurement error, observed variable and dependent variable; and (7) and whether the model is linear or nonlinear.

Cheng and van Ness [1999] and Casella and Berger [2001] describe this identifiability problem in a simple classical measurement error model. When only the first two moments are used, the result is five moment conditions with six unknown parameters, resulting in a difficult identifiability problem. Additional assumptions are therefore necessary to derive unique solutions. Several approaches are used in this regard. First, a restriction can be imposed by assuming prior knowledge of the parameters. If, in addition, normality is imposed, the resultant method of moment estimators are equivalent to the maximum likelihood estimators. This prior knowledge can be with respect to the model intercept, the variance of measurement error, the variance of the true variable, the ratio of regression error variance to measurement error variances etc. (see Kendall and Stuart [1979]; Cheng and van Ness [1999]; Casella and Berger [2001]). As a practical matter, however, in the absence of external data, this *ex ante* parameter knowledge assumption is a very strong assumption and is both problematic and controversial (see, for example, Carroll, and Ruppert [1996]; Huang and Huwang [2001]; Dunn [2004]). In particular, since focus in on estimating measurement error variance in an accounting setting, such prior knowledge is typically infeasible. As such, I do not pursue this approach.

Second, high order moments (orders three and higher), if they exist, can be used to identify model parameters, including measurement error variance without

using any external data (e.g., Geary [1942]; Pal [1980], van Monfort, Mooijaart, and Leeuw [1987]; Cragg [1997]; Erickson and Whited [2000,2002,2006]). This approach can either allow the regression and measurement errors to be correlated if normality is imposed, or allow arbitrary distributions but assume the regression and measurement errors are uncorrelated. However, the high order moments approach requires use of large samples. For example, Erickson and Whited [2006] use a cross-section of about 700 manufacturing firms, and treat the reliability of a specific measure of Tobin's  $q$  as a cross-sectional constant. In this setting, a sample size of even two hundred firm-year observations is considered too small to allow the GMM estimators to pass the prerequisite identification test (see Erickson and Whited [2006, p. 20]). Accordingly this approach is inapplicable in firm-specific settings, but could be suitable in examining whether an industry's accrual reliability has declined over time.<sup>3</sup>

Third, distribution assumptions and nonlinearity can be used to identify model parameters without additional parameter restrictions or any additional external data. For example, Fuller [1987] shows that if the true regressor is *not* normally distributed, model parameters, including measurement error variance are identifiable. Huang and Huwang [2001] show that under normality, a polynomial measurement error model can be identified. However, as Carroll et al. [2006] (p. 184) explain, such estimation is very sensitive to violations of the distribution assumptions.<sup>4</sup> This approach is particularly problematic in firm-specific settings involving small samples with unknown distributions. For this reason, I do not use this approach.

Finally, additional external data in the form of validation, replication or instrumental variables, can be used to estimate measurement error variance. Unlike in survey and experimental studies (see, Chen, Hong and Tamer [2005]; Carroll et

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<sup>3</sup> This is a separate working paper in progress.

<sup>4</sup> For example, Carroll, Spiegelman, Lan, Bailey and Abbott [1984] show that for binary regression models, the probit model is not identified. However, as Carroll et al. [2006] explain, the difference between the logistic and probit models is so slight that there is really no useful information about the parameters in the absence of external data.

al. [2006] ), in accounting studies, validation and replication data are typically unavailable.<sup>5</sup> In the absence of validation or replication data, previous econometrics research has used the instrumental variable approach to estimate measurement error variance (see Lewbel [1997]; Carroll et al. [2004]).

A valid instrument is a variable that is: (1) correlated with the unobservable underlying construct; (2) uncorrelated with measurement error; and (3) redundant given the underlying construct. All instruments measure the underlying construct with error; however, for an instrument to be valid, any such error must be uncorrelated with measurement error. In this literature, there are two types of instruments: (1) *internal* instruments constructed from functions of the specified model's data and (2) *external* instruments obtained from additional data outside this model. The instrumental variable approach can use valid internal or valid external instruments to obtain consistent TSLS coefficient estimates in measurement error models.

Carroll et al. [2004] show how an TSLS estimator, derived from an external instrument, can be interpreted as a correction-for-attenuation estimator, and used to estimate measurement error variance. In accounting settings, however, such external instruments are typically difficult to find. Specifically, external instruments tend to be weak, resulting in a first-stage regression that has very low  $R^2$ , or related with measurement error, resulting in endogenous instruments. A weak or endogenous instruments combined with a small firm-specific sample pose insurmountable econometric problems to the identification of measurement error variance.

However, within this literature, one approach is particularly well suited for an accounting setting. Specifically, Lewbel [1997] addresses the issue of weak or endogenous instruments and shows how to use functions of a measurement error model's data to construct valid internal instruments. Lewbel [1997] shows that given a linear regression model with measurement errors in variables, simple functions of the model data can be used as instruments for two staged least squares

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<sup>5</sup> For example, the true values, that are measured by accounting values, are never directly observed, meaning validation data are unavailable. Likewise, repeated measurements of the true value are typically unreported, meaning replicate data are also unavailable.

(TSLS) estimation, exploiting the skewness of the data.

Lewbel's approach does not impose any distributional assumptions; for example, normality is neither required nor assumed. Instead, identification is derived from the skewness of the unobservable true variable, such that the greater the skewness the greater the quality of instruments. Lewbel [1997] explains that unless measurement error is substantially skewed in the opposite direction as the true variable, the proposed instruments will work best when the observed mismeasured variable is strongly skewed. I find that reported accruals are typically skewed, either to the left or to the right, indicating that high quality Lewbel instruments are feasible. The use of Lewbel's approach to construct internal instruments has been proposed in accounting research, in settings where external instruments are either weak or endogenous. Larcker [2003] (p. 93) notes that since the choice of external instruments is generally very difficult, other approaches for selecting instruments should be considered. In particular, he suggests that it would be useful to examine the suitability of higher-order moments, as in Lewbel [1997].

While numerous instruments can be constructed using the Lewbel approach, my firm-specific research design restricts sample size, and limits use of multiple instruments (see Hausman [2001]; Hahn and Hausman [2002]). Accordingly, I choose two Lewbel instruments, on the basis of which I obtain a two stage least squares (TSLS) estimator; as do Lewbel [1997] and Carroll et al. [2004], I treat this TSLS estimator as a correction-for-attenuation estimator, and extract the measurement error variance.

A simple (univariate) classical measurement error model assumes that measurement error is uncorrelated with regression error. In this case, the OLS coefficient estimate is attenuated toward zero, and is the lower bound of the true slope parameter. In addition, the inverse of the reverse OLS regression's coefficient estimate is biased upwards, forming the upper bound. These two bounds form the Gini bound (see Gini [1921]; Erickson [1993]; Hausman [2001]). A limitation of the instrumental variable approach is that in finite samples, there is no guarantee that the TSLS es-

timator will lie between these two bounds (see Lewbel [1997] (p.1209); Dunn [2004] (p.83-86); Carroll et al. [2004] (p.738)). Consequently, when the absolute value of the IV is below the lower bound, estimated measurement error variance can be negative; alternatively, when it is above the upper bound, estimated measurement error variance can be greater than accrual variance. To address this concern, Carroll et al. [2004] suggest imposing a lower bound to measurement error variance. Dunn [2004] conducts simulations that show that negative measurement error variance is a signal of weak instruments, model misspecification, outliers, small samples, or low variance of the true variable.

Econometrics research documents that the bias in IV estimators is a function of the number of instruments used, the sample size, the correlation between measurement error and regression error, and the proportion of the mismeasured metric's variance that is explained by instruments (first stage  $R^2$ ) (e.g., Hausman [2001]; Hahn and Hausman [2002]; Hahn and Hausman [2003]). Further, this literature finds that the first stage  $R^2$  is not a sufficient test for the presence of weak instruments. Stock and Yogo [2002] derive a formal table of critical values of the first stage F-statistic in a null test that the instruments used are weak against the alternative that they are not weak. This study formalizes a a rule of thumb, from Staiger and Stock [1997], that proposes that if the first-stage F-statistic is below 10, then the instruments should be deemed weak. I examine the weakness of my Lewbel instruments based on this test. The next section develops a general accrual measurement error model and discusses the model's limitations as well as envisioned refinements.

# Chapter 3

## Accrual measurement error model

In this section, I specify the conceptual benchmark that I use to define accrual reliability and accrual measurement error. In addition, I present the accrual measurement error model and discuss related literature.

### 3.1 Accrual reliability

The estimation of accrual reliability requires a benchmark in the form of an underlying economic construct which the accruals purport to measure (Maines and Wahlen [2006]). My benchmark is economic income, defined as change in net economic assets other than from transactions with owners (Hicks [1946]). As a construct, economic income is interpretable as the true underlying, but unobservable, firm performance. I argue that economic income, as I define it, is inconceivable without adjustments to cash flow realizations for two reasons. First, economic assets and liabilities are not restricted to cash. Second, cash receipts or disbursements can precede or follow changes in noncash economic assets or liabilities.

I define perfect accruals as the adjustments required to obtain economic income given cash flow realizations, so that true performance equals cash flows plus perfect accruals. Perfect accruals capture the adjustments that anticipate or delay the



recognition of cash flows and eliminate all timing and matching problems without generating error. The notion of perfect accruals as a benchmark for reported accruals has been used in previous accounting literature (e.g., Richardson et al. [2005, p. 442]).<sup>1</sup> I define accrual measurement error as the deviation between reported accruals and perfect accruals. Accordingly, I conceptually view accrual reliability as the extent to which reported accruals faithfully represent perfect accruals.<sup>2</sup>

### 3.2 The model

The basic idea is that since measurement error induces attenuation bias on OLS coefficient estimates, if this attenuation bias is estimable, the magnitude of measurement error variance can be inferred. Attenuation bias can be inferred from the difference between an OLS coefficient estimate and a coefficient estimate that corrects for attenuation bias. Following Carroll et al. [2004] and Lewbel [1997] the usual TSLS estimator can be used as a correction-for-attenuation estimator to infer accrual measurement error variance from attenuation bias. Based on this theory, I develop a measurement error model for an individual firm.

A measurement error model focuses on measuring the partial effect of a latent regressor on an observable dependent variable, holding constant the effect of exogenous observable regressors. An accrual measurement error model requires a

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<sup>1</sup> The use of unobservable benchmarks to assess the reliability of observable measures is well documented in numerous fields. For example, in the psychology literature or in the economics of education literature, ability and education are never observable. However, the reliability of reported years of schooling in measuring education is estimable (e.g., Griliches [1977]; Lam and Schoeni [1993]; Neumark [1999]). Likewise, the reliability of aptitude test scores in measuring ability is estimable.

<sup>2</sup> I focus on representational faithfulness, which concerns the precision of measurement. Following Maines and Wahlen [2006, footnote 4], this focus is justifiable if: (1) verifiability is viewed as a characteristic that describes the extent to which the reliability of an accounting metric can be assessed by auditors and other external parties, rather than as a component of reliability; and (2) neutrality is viewed as a characteristic of the nature of the accounting standards and the standard-setting process.

correctly specified model, in which the accrual whose ANR is to be calculated is a regressor. I begin by developing a general accrual model and then show its application in estimating the reliability of different types of accruals. This general accrual model draws on Erickson and Whited [2006], who use a classical measurement error model.<sup>3</sup>

Consider a multivariate model that seeks to estimate the partial effect of perfect accruals,  $X$ , on a dependent variable  $Y$ , holding constant the effect of a vector of exogenous observable regressors  $\mathbf{Z}$ . However, since perfect accruals is a conceptual benchmark,  $X$  is unobservable; instead, we only observe reported accruals,  $W$  that measure  $X$  subject to additive error,  $\gamma + \varepsilon_t$ . That is:

$$Y_t = \mathbf{Z}_t\boldsymbol{\beta}_z + X_t\beta_x + u_t \quad (3.1)$$

$$W_t = \gamma + X_t + \varepsilon_t \quad (3.2)$$

In this model  $\gamma$  is the systematic bias component with nonzero mean, while  $\varepsilon_t$  is the mean zero, random component of measurement error.

The model makes three classical assumptions: (1)  $\varepsilon$ , the random component of accrual measurement error, is independently and identically distributed (*i.i.d.*); (2)  $\varepsilon$  and  $u$ , the regression error term, are mutually independent and also independent of both  $\mathbf{Z}$  and  $X$ ; and (3) if measurement error is present in  $Y$ , it is uncorrelated with  $\varepsilon$ ; further if measurement error is present in  $\mathbf{Z}$ , it is uncorrelated with  $\varepsilon$  or  $u$ .

In my setting, focus is on the noise ratio, which heuristically corresponds to one minus the  $R^2$  of Equation (3.2).<sup>4</sup> The support of the noise ratio is zero to one,

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<sup>3</sup> Erickson and Whited [2006] focus on comparing the reliability of alternative measures of Tobin's  $q$  used in finance, while in my setting numerous firms use the same financial performance metric under GAAP, but there is heterogeneity in the reliability of an input to that metric, namely firm-specific accruals.

<sup>4</sup> To see this, note that in the statistics literature, the reliability ratio is defined as variance of

where a value of zero implies measurement error is absent, and that of one implies pure noise. Thus, the noise ratio is an inverse measure of reliability.

In the measurement error model described by Equations (3.1) and (3.2), focus is on estimating  $\beta$ , the partial effect  $X$  on  $Y$ , holding constant the effect of  $\mathbf{Z}$ . By definition, the partial effect in a multivariate regression involves netting out the effect of exogenous regressors on the endogenous regressor of interest and the dependent variable. In the econometrics literature, this netting out procedure is referred to as ‘partialing out’ and it is based on the well-documented Frisch-Waugh-Lovell theorem (see Greene [2004, p. 27]).<sup>5</sup> Since this model assumes  $\mathbf{Z}$  is exogenous (i.e., uncorrelated either the regression error term or measurement error) the first step is to ‘partial out’  $Z$  from the model. Thus, I regress  $Y$  on  $\mathbf{Z}$  and use the OLS residuals as the dependent variable. Likewise, I regress  $W$  on  $\mathbf{Z}$  and use the OLS residuals as the regressor. Formally, I proceed as follows:

$$Y_t = \mathbf{Z}_t \boldsymbol{\theta}_y + v_t \quad (3.3)$$

$$W_t = \mathbf{Z}_t \boldsymbol{\theta}_w + e_t. \quad (3.4)$$

Let  $\hat{\boldsymbol{\theta}}_y$  and  $\hat{\boldsymbol{\theta}}_w$  be the OLS slope coefficient estimates in Equations (3.3) and (3.4).

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the true underlying construct divided by variance of the observed variable (i.e.,  $\frac{\text{var}(X)}{\text{var}(W)}$ ) See, for example, Crocker et al. [1989, p. 115]; Fuller [1987, p. 3]; Greene [2003, p. 89]; Carroll, et al. [2006, p. 43]). Since noise ratio equals one minus reliability ratio, it follows that:  $\frac{\text{var}(\varepsilon)}{\text{var}(W)}$ . Since  $1 - R^2 = \frac{RSS}{TSS} \approx \frac{\text{var}(\varepsilon)}{\text{var}(W)}$  where  $RSS$  is residual sum of squares and  $TSS$  is the total sum of squares, it follows that  $1 - R^2$  approximates the noise ratio.

<sup>5</sup> ‘Partialing out’ exogenous regressors from a measurement error model in order to focus on the partial effect of the regressor measured with error is a standard procedure in this literature (e.g., Hausman [2001, footnote 2; Hahn and Hausman [2002]; and Erickson and Whited [2000, 2002, 2006]). This procedure simplifies estimation by eliminating complex covariances.

Further, define:

$$y_t = Y_t - \mathbf{Z}_t \hat{\boldsymbol{\theta}}_y$$

$$w_t = W_t - \mathbf{Z}_t \hat{\boldsymbol{\theta}}_w$$

$$x_t = X_t - \mathbf{Z}_t \hat{\boldsymbol{\theta}}_w,$$

where the lower-case variables  $y_t$ ,  $w_t$  and  $x_t$  are, respectively, the residuals from OLS estimation of the regressions of  $Y_t$ ,  $W_t$  and  $X_t$  on  $\mathbf{Z}_t$ . Equations (3.1) and (3.2) can now be rewritten in univariate form as:

$$y_t = \alpha + x_t \beta + u_t \tag{3.5}$$

$$w_t = x_t + \varepsilon_t. \tag{3.6}$$

Suppose valid instruments are available for  $w_t$ . The second step is the instrumental variable estimation of  $\beta$  in the univariate measurement model specified by Equations (3.5) and (3.6). Let  $\mathbf{S}_t = \{IV_1, IV_2, \dots, IV_K\}$  be a vector of instrumental variables; where each instrument,  $IV_k$  is correlated with the true but unobservable variable,  $x_t$ , but independent of either measurement error,  $\varepsilon_t$ , or the regression error,  $u_t$ . Further, let  $\beta_{TSLs}$  be the usual TSLs estimator of  $\beta$  derived from using  $\mathbf{S}_t$  as instruments; that is:

$$\beta_{TSLs} = \frac{y' \mathbf{P}_s w}{w' \mathbf{P}_s w} \tag{3.7}$$

where  $\mathbf{P}_s = \mathbf{S}(\mathbf{S}'\mathbf{S})^{-1}\mathbf{S}'$  is the projection matrix that projects any vector onto the linear space spanned by the columns of  $\mathbf{S}$ . It can be shown (see Appendix B) that the firm-specific noise ratio is estimable as:

$$ANR = \frac{\beta_{TSLs} var(w_t) - cov(y_t, w_t)}{\beta_{TSLs} [\hat{\boldsymbol{\theta}}_w' var(\mathbf{Z}) \hat{\boldsymbol{\theta}}_w + var(w)]}. \tag{3.8}$$

Based on equation (3.8), reliability inference based on the noise ratio is a joint test of reliability and the quality of instruments used. In Carroll et al. [2004],  $\mathbf{S}$

consists of an external instrument. In most accounting settings, however, obtaining a valid external instruments is difficult. Lewbel [1997] shows how to construct internal instruments based on the moments of the observable data in a measurement error model (i.e.,  $y$  and  $w$  in the model described by Equations (3.5) and (3.6)).

Let  $\bar{r}$  denote the sample mean  $\bar{r} = \frac{1}{T} \sum_{t=1}^T r_t$ ; Lewbel [1997] shows that two stage least squares is consistent using internal instruments,  $IV$ , of the form:

$$IV_{L,M,t} = (w_t - \bar{w})^L (y_t - \bar{y})^M \quad (3.9)$$

where  $L + M > 1$  and  $L$  and  $M$  are nonnegative integers.<sup>6</sup> As Lewbel explains, identification is achieved primarily through the skewness of  $x$ , the unobservable underlying construct, such that the greater the skewness, the better the quality of these internal instruments. He also notes that relative to low order moment instruments, higher order moment instruments will require larger sample sizes to estimate.

Hausman [2001] explains that in finite samples, using too many instruments can overfit the model, increasing the TSLS estimator bias. In addition, based on Equations (3.5) and (3.6) above, Hahn and Hausman [2003] show that the bias of  $\beta_{TSLS}$  is given by:

$$E[\beta_{TSLS}] - \beta \approx \frac{\text{corr}(u, v) K (1 - R^2)}{TR^2} \quad (3.10)$$

Effectively, endogeneity as captured by the correlation between measurement error and regression error,  $\text{corr}(u, v)$ ; using numerous instrumental variables,  $K$ ; using a small sample size,  $T$ ; or using weak instruments as captured by the first stage  $R^2$

<sup>6</sup> For example, the following are potentially feasible instruments:  $IV_{1,1,t} = (w_t - \bar{w})(y_t - \bar{y})$ ;  $IV_{2,0,t} = (w_t - \bar{w})^2$ ;  $IV_{0,2,t} = (y_t - \bar{y})^2$ ;  $IV_{2,1,t} = (w_t - \bar{w})^2 (y_t - \bar{y})$ ;  $IV_{1,2,t} = (w_t - \bar{w})(y_t - \bar{y})^2$  etc.

(i.e. the proportion of the mismeasured accrual's variance that is explained by the instrumental variables in stage one of the two stage least squares estimation) will increase the bias of  $\beta_{TSLs}$ , the TSLs estimator of  $\beta$ . Since firm-specific settings rely on small samples, using numerous or weak instruments in such settings is particularly problematic.

In addition to examining the determinants of its bias, it is useful to specify the upper and lower bounds of  $\beta_{TSLs}$  as described in Hausman [2001]. To do this, consider the following two equations:

$$y_t = \alpha + w_t\beta + u_t \tag{3.11}$$

$$w_t = \phi + y_t\delta + v_t \tag{3.12}$$

where Equation (3.12) is a reverse regression of Equation (3.11). Recall that  $w_t$  is measured with error as described in Equation (3.6). Define  $b$  and  $d$  as the OLS slope coefficient estimates of Equations (3.11) and (3.12) respectively. Under the assumption that measurement error is uncorrelated with regression error, the absolute value of the OLS estimator,  $|b|$ , is attenuated toward zero and is the lower bound of  $|\beta|$ , the absolute value of the true estimator, while  $\left|\frac{1}{d}\right|$  is its upper bound.<sup>7</sup>

This is the Gini [1921] bound that is:  $|b| \leq |\beta| \leq \left|\frac{1}{d}\right|$  (see, for example, Erickson [1993]; Hausman [2001]).

As Lewbel [1997], Dunn [2004] and Carroll et al. [2004] explain, in finite samples there is no guarantee that  $|b| \leq |\beta_{TSLs}| \leq \left|\frac{1}{d}\right|$ , implying there is no guarantee that estimated measurement error variance (9) is nonnegative and less than the sample

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<sup>7</sup> Erickson [1993] shows that if the assumption that measurement error is uncorrelated with regression error is violated, then this Gini bound does not hold.

variance of  $w$ ; that is, there is no guarantee that  $0 \leq \text{var}(\hat{\varepsilon}) \leq \text{var}(w)$ . This is the unavoidable cost of a firm-specific research design; for a proportion of the firms, the estimated measurement error variance will be inadmissible. As long as finite samples are used, this proportion may be reduced but is unlikely to be eliminated. Increasing sample size can mitigate this problem but this involves a trade-off with survivorship bias and restricting reliability to be constant over long horizons. However, as I will show, this concern can greatly be mitigated by using accounting knowledge to correctly specify the measurement error model.

# Chapter 4

## Model applications

This section shows how the general model developed above can be applied to estimate the ANR of total accruals. Following Dechow, Kothari and Watts [1998] and Barth, Cram and Nelson [2001], who explicitly model the accrual process and examine the role of accruals in predicting future cash flows, I consider the following firm-specific accrual measurement error model:

$$CFO_{t+1} = \alpha_0 + \alpha_1 CFO_t + \beta TAC_t^* + u_t \quad (4.1)$$

$$TAC_t = TAC_t^* + \gamma + \varepsilon_t, \quad (4.2)$$

where  $CFO$  is cash flows from operations and  $TAC^*$  is unobservable *perfect* total accruals. We observe reported accruals,  $TAC$ , that captures  $TAC^*$  subject to additive measurement error,  $\gamma + \varepsilon_t$ , as Equation (4.2) describes. In Equation (4.2),  $\gamma$ , is interpretable as the systematic bias component of accrual measurement error with nonzero mean, while  $\varepsilon$  captures the mean zero, random component of the measurement error.<sup>1</sup> My focus is estimation of the firm-specific noise ratio of reported accruals, ANR, defined as:

$$ANR = \frac{\widehat{var}(\varepsilon)}{var(TAC)}. \quad (4.3)$$

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<sup>1</sup> Both  $\varepsilon$  and  $\gamma$  may, for example, arise from neutral application of imperfect GAAP rules on recognition and measurement, or from systematic manipulation.



Heuristically, ANR corresponds with the  $1 - R^2$  of Equation (4.2).

The model makes three classical assumptions: (1)  $\varepsilon$ , the random component of accrual measurement error, is independently and identically distributed (*i.i.d.*); (2)  $\varepsilon$  and  $u$  are mutually independent and also independent of both  $CFO$  and  $TAC^{*2}$ ; and (3) if measurement error is present in  $CFO$ ,<sup>3</sup> it is small (relative to accrual measurement error) and uncorrelated with either accrual measurement error ( $\varepsilon$ ), or the regression error ( $u$ ). To the extent that the accrual process violates these classical measurement error assumptions, my research design may not accurately capture the reliability implications of some accounting choices. A richer model that accommodates covariances among measurement error, accruals and cash flows is feasible but difficult to estimate in firm-specific settings.

The model described by Equations (4.1) and (4.2) is distinct from direct estimation approaches (e.g., Jones [1991] and Dechow and Dichev [2002]). Direct estimation approaches regress reported accruals on accounting fundamentals and interpret the residuals as the discretionary accrual component. The accounting fundamentals (e.g., leads and lags of operating cash flows, change in sales and property plant and equipment) are assumed to be uncorrelated with accrual measurement error but correlated with reliable accruals and can therefore be viewed as instruments. Thus, a direct estimation regression is interpretable as a first-stage regression in TSLS estimation. My approach differs from direct estimation approaches in that instead of using the variance of residuals from the first-stage regression to estimate the variance of accrual measurement error, I proceed to the

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<sup>2</sup> That is, the random component of accrual measurement errors and the unexplained portion of next-period  $CFO$  conditional on current-period  $CFO$  and reported accruals (i.e., the true error term in Equation (13)) are mutually independent and also independent of both  $CFO$  and perfect accruals.

<sup>3</sup> For example, the timing of cash flows can be manipulated (Rowchowdhury [2006]). The classification of cash flows into operating, investing and financing activities is also prone to misclassification error.

second stage and estimate the TSLS coefficient estimate. I use the TSLS estimator as a correction-for-attenuation estimator and exploit its relation with the OLS estimator to extract the variance of accrual measurement error variance. In addition, I use Lewbel instruments constructed from functions of the model data instead of using accounting fundamentals obtained outside the model. I formally test the validity of these Lewbel instruments.

ANR is a ratio between zero and one, where the denominator is accrual variance. Higher ANR implies lower accrual reliability. Since the denominator of ANR is accrual variance, ANR is consistent with McNichols' [2002] call for accrual quality measures that control for cross-sectional differences in accrual volatility. *Ceteris paribus*, if two firms have the same level of accrual variance, ANR will rank the firm with smaller measurement error variance as having more reliable accruals. However, if two firms have the same level of measurement error variance, ANR will rank the firm with a bigger accrual variance as having more reliable accruals. In cross-section, the mapping between ANR and accrual variance is not one-to-one, meaning that firms with similar levels of accrual variance could have different levels of reliability.

Since the model described by Equations (4.1) and (4.2) assumes cash flows are exogenous (i.e., uncorrelated with accrual measurement error) my first step is to 'partial out'  $CFO_t$  from the model. Thus, I regress  $CFO_{t+1}$  on  $CFO_t$  and use the OLS residuals as the dependent variable. Likewise, I regress  $TAC_t$  on  $CFO_t$  and use the OLS residuals as the regressor. Formally, I proceed as follows:

$$CFO_{t+1} = \delta + \theta_{cfo}CFO_t + v_{t+1} \quad (4.4)$$

$$TAC_t = \kappa + \theta_{tac}CFO_t + e_t. \quad (4.5)$$

Let  $\hat{\delta}$ ,  $\hat{\theta}_{cfo}$ ,  $\hat{\kappa}$ ,  $\hat{\theta}_{tac}$  and  $\hat{v}_{t+1}$  be the OLS coefficient estimates in Equations (4.4) and

(4.5). Further, define:

$$cfo_{t+1} = CFO_{t+1} - \hat{\delta} - \hat{\theta}_{cfo}CFO_t$$

$$tac_t = TAC_t - \hat{\kappa} - \hat{\theta}_{tac}CFO_t$$

$$tac_t^* = TAC_t^* - \hat{\kappa} - \hat{\theta}_{tac}CFO_t,$$

where the lower-case variables  $cfo_{t+1}$ ,  $tac_t$  and  $tac_t^*$  are, respectively, the residuals from OLS estimation of the regressions of  $CFO_{t+1}$ ,  $TAC_t$  and  $TAC_t^*$  on  $CFO_t$ . Equations (4.1) and (4.2) can now be rewritten in univariate form as:

$$cfo_{t+1} = \alpha_0 + tac_t^*\beta + u_t \quad (4.6)$$

$$tac_t = tac_t^* + \varepsilon_t. \quad (4.7)$$

Suppose valid instruments are available for  $tac_t$ . The second step is the instrumental variable estimation of  $\beta$  in the univariate measurement model specified by Equations (4.6) and (4.7). Specifically, let  $\beta_{TSLs}$  be the usual TSLs estimator of  $\beta$  in Equation (4.6) given valid instruments. It can be shown (see Appendix B) that the firm-specific ANR is estimable as:

$$ANR = \frac{\beta_{TSLs}var(tac_t) - cov(cfo_{t+1}, tac_t)}{\beta_{TSLs}[\hat{\theta}'_{tac}var(CFO_t)\hat{\theta}_{tac} + var(tac_t)]}. \quad (4.8)$$

Recall that  $\hat{\theta}_{tac}$  is the OLS coefficient estimate in a univariate regression of current-period total accruals on current-period cash flows as specified in Equation (4.5). It is well-documented that these two variables are negatively correlated (see Barth et al. [2001]; Dechow and Dichev [2002]). Thus, as  $\hat{\theta}_{tac}$  approaches negative one (i.e., as  $\hat{\theta}_{tac} \rightarrow -1$ ), a change in cash flows is offset by an equal and opposite change in accruals, implying accruals will dampen negative cash flow autocorrelations, generating an earnings series that is smoother than the cash flow series.  $\hat{\theta}_{tac}$  is therefore

indicative of earnings smoothness, implying the denominator in Equation (4.8) weights cash flow variance by the square of earnings smoothness. ANR therefore predicts that, *ceteris paribus*, reliability increases with earnings smoothness.

Based on Equations (4.4) and (4.5) above,  $cov(cfo_{t+1}, tac_t)$  is the covariance between current-period accruals and next-period cash flows, holding constant (i.e., after netting out) the effect of current-period cash flows. Thus, this covariance is indicative of current-period accruals' ability to predict next-period cash flows. Based on Equation (4.8), ANR therefore predicts that, *ceteris paribus*, reliability increases with accruals' ability to predict next-period cash flows, holding the effect of current-period cash flows constant.

## 4.1 Lewbel instruments

The previous discussion assumes that valid instruments are available to estimate  $\beta_{TOLS}$ . However, external instruments derived from accounting fundamentals data (e.g., the levels, changes or lags of cash, sales, and property, plant and equipment) tend to either have low explanatory power with respect to accruals or to be predictably correlated with accrual measurement error. Weak or endogenous instruments combined with a small sample pose insurmountable econometric problems to the estimation of measurement error variance.

Following Lewbel [1997], instruments constructed from moments of the model data can be used to obtain a consistent TOLS estimator. When skewness is nonzero, the third moments of the joint distribution of the latent variable (perfect accruals in my setting) and the regression's observable variables ensure that Lewbel instruments are strongly correlated with the latent variable. I find that  $tac_t$  is skewed for my sample firms, meaning the conditional skewness of accruals given cash flows is nonzero. Specifically, the mean (median) firm has accruals with a conditional

skewness of -0.979 (-0.854), while the 10<sup>th</sup> (90<sup>th</sup>) firm has accruals with a conditional skewness of -4.143 (1.034), suggesting that high-quality Lewbel instruments are, in principle, feasible.

I consider the following set of Lewbel instruments:

$$IV_{L,M,t} = (cfo_{t+1} - \overline{cfo})^L (tac_t - \overline{tac})^M, \quad (4.9)$$

where  $\overline{cfo}$  and  $\overline{tac}$  are, respectively, the firm-specific sample means of  $cfo_{t+1}$  and  $tac_t$ , and  $L$  and  $M$  are nonnegative integers where  $2 \leq L + M \leq 4$  (i.e., I limit my search from the second to the fourth own and cross moments).<sup>4</sup>

The  $k^{th}$  central sample moment of random variable  $x$ , is defined as:  $\mu_n = \frac{1}{T} \sum_{t=1}^T (x_t - \bar{x})^k$ , where  $T$  is the sample size and  $\bar{x}$  is the sample mean. Thus, based on Equations (4.4) and (4.5), the elements in the set of Lewbel instruments specified in Equation (4.9) are derived from own and cross moments of unexpected next-period cash flows and unexpected current-period cash accruals, conditional on current-period cash flows (i.e., own and cross moments of the conditional residuals of next-period cash flows and of current-period accruals).

I empirically search within the set of Lewbel instruments described in Equation (4.9) for the instrument that works best across my sample firms based on the

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<sup>4</sup> I do not consider first-moment-based instruments, that is:  $IV_{1,0,t} = (cfo_{t+1} - \overline{cfo})^1$  or  $(tac_t - \overline{tac})^1$ , because both are linear functions of the the model's variables. Instead I consider instruments derived from second to fourth moments. For example, the second moment-based instruments are:

$$(1) IV_{1,1,t} = (cfo_{t+1} - \overline{cfo})^1 (tac_t - \overline{tac})^1; \quad (2) IV_{2,0,t} = (cfo_{t+1} - \overline{cfo})^2; \quad \text{and} \quad (3) IV_{0,2,t} = (tac_t - \overline{tac})^2.$$

The third moment-based instruments are:

$$(1) IV_{2,1,t} = (cfo_{t+1} - \overline{cfo})^2 (tac_t - \overline{tac})^1; \quad (2) IV_{1,2,t} = (cfo_{t+1} - \overline{cfo})^1 (tac_t - \overline{tac})^2; \\ (3) IV_{3,0,t} = (cfo_{t+1} - \overline{cfo})^3; \quad \text{and} \quad (4) IV_{0,3,t} = (tac_t - \overline{tac})^3.$$

following four criteria: (1) the F-test of the first stage regression (Stock and Yogo [2002]); (2) the small sample bias of the TSLS estimator.<sup>5</sup>; (3) the Hausman [1978] test<sup>6</sup>; and (4) the number of violations of the lower and upper TSLS bounds. With respect to criterion (4), the OLS estimator is the lower bound for admissible TSLS values, while the reciprocal of the reverse OLS estimator is the upper bound. This is the Gini [1921] bound for a TSLS estimator. Each of these criteria identifies the following instrument as best-performing:

$$IV_{1,2,t} = (cfo_{t+1} - \overline{cfo})^1 (tac_t - \overline{tac})^2. \quad (4.10)$$

This instrument is the ‘de-meaned’ unexpected next-period cash flows multiplied by the square of ‘de-meaned’ unexpected current-period cash flows, conditional on current-period cash flows.<sup>7</sup> While this instrument per se might not be intuitive, its functional form has desirable characteristics. First, its product form ensures a univariate association with both variables used in the model (i.e.,  $cfo_{t+1}$  and  $tac_t$ ).

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<sup>5</sup> Hahn and Hausman [2003] show that the small sample bias of  $\beta_{TSLS}$ , the TSLS estimator, is estimable as:

$$E[\beta_{TSLS}] - \beta \approx \frac{corr(u, \varepsilon) K (1 - R^2)}{TR^2}.$$

Effectively, the bias of  $\beta_{TSLS}$  increases with endogeneity,  $corr(u, \varepsilon)$ ; using numerous instrumental variables,  $K$ ; using a small sample size,  $T$ ; or using weak instruments as captured by the first stage  $R^2$

<sup>6</sup> I use the regression-based Hausman [1978, 1982] test (see Wooldridge [2002 p.118-119]). Specifically, I estimate the first-stage regression:

$$tac_t = \alpha_0 + \alpha_1 \mathbf{S}_t + \xi_t.$$

I obtain,  $\hat{\xi}$ , the OLS residuals from this first stage regression, and use them in the following regression:

$$cfo_{t+1} = \alpha_0 + \beta tac_t + \rho \hat{\xi}_t + v_t.$$

If  $\rho$  is significant (based on the standard t-test), the TSLS estimator is consistent while the OLS estimator is not, thus rejecting Hausman’s null hypothesis that the OLS and TSLS estimators differ only by sampling error.

<sup>7</sup> The term ‘de-meaned’ refers to subtracting a variable’s sample mean from the variable (see Wooldridge [2002])

Second, the instrument is nonlinear in accruals, and is derived from a joint distribution, implying the instrument's correlation with measurement error is unlikely.

## 4.2 Using the operating cycle to refine the model

Thus far, the measurement error model has used  $cf_{o_{t+1}}$  as the dependent variable. However, there is no reason to restrict accruals' predictive ability to  $cf_{o_{t+1}}$ . Accruals are also predictive with respect to  $cf_{o_{t+2}}$ ,  $cf_{o_{t+3}}$ ,  $cf_{o_{t+4}}$ , etc. In particular, for firms with longer operating cycles, accruals predict cash flows over longer horizons. Indeed, Barth, Cram and Nelson [2001] show that accruals have the ability to predict cash flows up to four years ahead. More important, varying the horizon of future cash flows is a simple technique to identify the firm-specific setting in which a given Lewbel instrument works best.

To illustrate, consider a firm-specific regression of  $cf_{o_{t+1}}$  on  $cf_{o_t}$  and  $tac_t$  as described in Equation (4.6). Suppose the Hausman [1978] test fails to reject the null that OLS and TSLS estimators differ only by sampling error. A possible explanation is that even without measurement error, this firm's  $tac_t$  is uncorrelated with  $cf_{o_{t+1}}$ , possibly because the firm has a long operating cycle. In this case, the Lewbel instrument is not the problem; the problem is using the wrong model specification for this firm. Thus, changing the dependent variable to, for example,  $cf_{o_{t+4}}$  has the potential to mitigate this problem. Effectively, using the Lewbel instrument in the setting in which it works best for a specific firm can refine the model.

Accordingly, for each firm, I examine  $cf_{o_{t+1}}$ ,  $cf_{o_{t+2}}$ ,  $cf_{o_{t+3}}$ ,  $cf_{o_{t+4}}$  and  $\sum_{s=1}^S cf_{o_{t+s}}$  for  $S = 2, 3, 4, 8, 12$  as candidate dependent variables. I select the best specification based on the following four criteria: (1)  $tac_t$  loads significantly and the null under

the Hausman [1978] test is most strongly rejected, indicating that measurement error is detectable; (2) the first stage F-test is highest; (3) the TSLS small sample bias is smallest; and (4) the Gini bound is not violated.

### 4.3 Sample Selection

To be included in the sample, I require firms to have Compustat quarterly data on cash flows from operations from the statement of cash flows (# 108).<sup>8</sup> This requirement constrains my sample period to be 19 years from 1988 - 2007. To calculate ANR, I use an 8-year rolling window, within which I require each firm to have at least 29 consecutive firm-quarters of data on  $TAC_t$ ,  $CFO_t$ , and  $CFO_{t+1}$  between quarters  $t - 31$  and  $t$ . I roll the window annually, thus, ANR for 1995 is estimated using the 8-year window from 1988 to 1995, ANR for 1996 is estimated using the 8-year window from 1989 to 1996, etc. I eliminate financial institutions (SIC 6000-6999) because it is difficult to distinguish operating, investing and financing cash flows for these firms. I also eliminate regulated utilities (SIC 4900-4999). These selection criteria yield a sample of 5,026 distinct firms (about 40% of all distinct Compustat firms over the sample period), with 29,180 firm-years of estimated ANR.

Table 4.1 describes the sample. Because I require at least 29 quarters of non-missing quarterly data, my sample consists of large, profitable firms. The median sample firm has a market value of equity of \$216.18 million, \$227.02 million in total assets, \$244.81 million in sales and a market-to-book ratio of 2.032. The median sample firm is larger and more profitable than the median Compustat firm, but smaller and less profitable than the 75<sup>th</sup> percentile Compustat firm. The reported standard deviations of size and profitability are substantial, suggesting that cross-sectional homogeneity is highly unlikely to be a concern. My sample is similar to

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<sup>8</sup> # denotes data items from the Compustat quarterly database unless indicated otherwise



that of Dechow and Dichev [2002], who require firms to have at least eight years of data.

Variable	SAMPLE						COMPUSTAT				
	Mean	Std. Dev	10%	25%	Median	75%	90%	Mean	25%	Median	75%
ANR	0.250	0.228	0.025	0.066	0.174	0.377	0.600				
CFO	0.0540	0.1903	-0.1009	0.0172	0.0824	0.1417	0.2039	0.0199	-0.0182	0.0645	0.1260
ACC	-0.0447	0.1042	-0.1448	-0.0858	-0.0423	-0.0012	0.0532	-0.0438	-0.0896	-0.0405	0.0050
TAC	-0.3850	33.2267	-0.1740	-0.1008	-0.0532	-0.0118	0.0419	-4.4673	-0.1257	-0.0540	-0.0017
Assets	2,275.52	9,658.96	14.01	46.30	227.02	1,063.99	4,077.10	1,509.52	17.55	98.47	545.43
Sales	2,267.94	10,520.73	11.23	45.26	244.81	1,125.22	4,134.50	1,509.52	17.55	98.47	545.43
BVE	931.47	4193.68	6.53	23.20	110.84	467.55	1,635.28	678.35	10.96	52.31	247.09
MVE	3,231.16	1,5251.75	10.36	40.13	216.18	1,163.81	4,870.19	1,930.06	21.75	106.47	599.74
MTB	4.375	42.487	0.729	1.216	2.032	3.514	6.368	7.619	1.198	2.042	3.757
ROA	0.034	0.223	-0.151	0.005	0.074	0.132	0.195	-0.006	-0.037	0.061	0.119
LEV	0.203	0.181	0.000	0.027	0.179	0.324	0.458	0.211	0.023	0.179	0.345

Table 4.1: Sample descriptive statistics relative to Compustat firms

*Continued on next page*

Table 4.1

**Notes**

The sample is based on 5,026 distinct firms with 29,180 firm-years of estimated ANR. MVE is market value of equity, computed as (#199)\*(#25). Assets and SALES are #6 and #12 respectively. ROA is return on assets, computed as (#18)/(#6). BVE is book value of equity (#60), MTB is the market-to-book ratio, calculated as MVE divided by BVE. LEV is leverage (#34 + #9)/ #6. CFO is cash flows from operations (#308 - #124), TAC is total accruals (#308 - CFO). Operating accruals, ACC, is estimated as  $\Delta(\#40 - \#36) - \Delta(\#9 - \#45) - (\#5)$  based on the balance sheet approach. CFO, TAC and ACC are deflated by average total assets. For this table only, # refers to the data item on Compustat industrial annual file.

## 4.4 Performance comparison between Lewbel and external instruments

Using the four instrument selection criteria above, I compare the performance of the Lewbel's instrument derived above,  $IV_{1,2,t}$ , to that of external accrual instruments based on accounting fundamentals. Specifically, I compare the performance of the following six instruments based on the accrual measurement model specified in equations (4.1) and (4.2):  $IV_{1,2,t} = (CFO_{t+1} - \overline{CFO_{t+1}})^1 (TAC_t - \overline{TAC_t})^2$ ,  $\Delta SALES_t$ ,  $SALES_t$ ,  $PPE_t$  and  $CFO_{t-1}$ .<sup>9</sup>

As Table 4.2 reports, the Lewbel instrument outperforms the external instruments on all four criteria. The external instruments yield a mean (median) first stage  $R^2$  below 10% (5%), relative to 31.7% (28%) for the Lewbel instrument. The Lewbel instrument yields a first stage F-statistic of 26.87 (11.401), well above the 9.08 critical value.<sup>10</sup> In comparison, the external instruments yield a mean (median) first-stage F-statistic of 4.56 (1.51) or lower. Further, the small sample bias of the TSLS estimator when using the Lewbel instrument is 0.05 (0.002), which is smaller than that of any of the external instruments.

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<sup>9</sup> As an empirical matter, using sales changes as an instrument imposes a restriction on the coefficients on sales and lagged sales to be identical. While I examine both sales and lagged sales, I report results on sales because results on lagged sales are virtually identical results.

<sup>10</sup> Stock and Yogo [2002] document that a high first stage  $R^2$  is not a sufficient criterion to reject the null hypothesis of a weak instrument. They provide formal tables of the first stage F-statistic critical values. The tables report the first stage F-statistic critical values for the null hypothesis that the bias in a TSLS estimator is greater than 10% of the bias in the OLS estimator (at the 5% level of significance). For a single instrument and a single endogenous regressor, this critical value is 9.08. If the first stage F-statistic exceeds 9.08, the null that the instrument is weak can be rejected at the 5% level.

Instrument for $TAC_t$	Criteria	Mean	Std. Dev.	10%	25%	Median	75%	90%	Violations
$\Delta SALES_t$ Jones [1991]; Dechow et al. [1995; 2003]; Francis et al. [2004, 2005]	Stage1 $R^2$	0.104	0.134	0.002	0.011	0.049	0.144	0.295	7,452 (25.5%)
	F-test	4.56	8.096	0.061	0.332	1.51	4.913	12.248	
	TSLS bias	0.060	0.115	0.003	0.008	0.022	0.055	0.142	
	Hausman test	1.216	1.005	0.1748	0.443	0.956	1.717	2.654	
$SALES_t$	Stage1 $R^2$	0.083	0.106	0.002	0.009	0.040	0.114	0.228	6,184 (21.2%)
	F-test	3.242	5.323	0.053	0.280	1.200	3.770	8.688	
	TSLS bias	0.059	0.102	0.004	0.011	0.026	0.059	0.137	
	Hausman test	1.482	1.144	0.226	0.572	1.233	2.129	3.127	
$PPE_t$ Jones [1991]; Dechow et al. [1995; 2003]; Francis et al. [2004, 2005]	Stage1 $R^2$	0.100	0.131	0.002	0.011	0.047	0.135	0.283	7,599 (26.0%)
	F-test	2.806	4.64	0.051	0.251	1.062	3.22	7.603	
	TSLS bias	0.232	0.886	0.005	0.014	0.033	0.091	0.354	
	Hausman test	1.242	0.986	0.179	0.466	1.006	1.795	2.650	
$CFO_{t-1}$ Dechow and Dichev [2002]; McNichols [2002]; Francis et al. [2004, 2005]	Stage1 $R^2$	0.069	0.090	0.001	0.008	0.032	0.094	0.193	7,965 (27.3%)
	F-test	2.557	4.044	0.004	0.215	0.939	2.953	6.83	
	TSLS bias	0.079	0.160	0.004	0.0109	0.0276	0.072	0.184	
	Hausman test	1.197	0.951	0.181	0.451	0.973	1.702	2.555	
LEWBEL's $IV_{1,2,t}$	Stage1 $R^2$	0.317	0.249	0.02	0.091	0.280	0.502	0.681	5,482 (18.8%)
	F-test	26.872	49.08	0.607	2.913	11.401	29.331	62.508	
	TSLS bias	0.0501	0.089	0.002	0.007	0.020	0.051	0.123	
	Hausman test	3.193	1.544	1.109	2.078	3.183	4.264	5.248	

Table 4.2: The performance of a Lewbel instrument relative to that of external instruments

*Continued on next page*

Table 4.2

**Notes**

The first stage  $R^2$  is based on the fit of the following Equation:

$$TAC_t = \alpha_0 + \alpha_1 CFO_t + \alpha_2 S_t + \xi_t, \tag{I}$$

where  $TAC_t$  is total accruals,  $CFO_t$  is cash flows from operations, and  $S_t$  is a placeholder for one of the following instruments:  $\Delta SALES_t$ ,  $SALES_t$ ,  $SALES_{t-1}$ ,  $PPE_t$ ,  $CFO_{t-1}$  or  $(CFO_{t+1} - \overline{CFO})^1 (TAC_t - \overline{TAC})^2$ .

Stock and Yogo [2002] provide the critical values for the null hypothesis of weak instruments based on the first-stage regression's F-statistic. The first stage F-statistic is for the test that the OLS estimated coefficients in the first-stage regression are jointly different from zero. In my single instrument setting, this translates into testing whether the OLS coefficient estimates in Equation (I) are different from zero. According to this test, an instrument is deemed weak if the bias in the TSLS estimator is greater than 10% of the bias in the OLS estimator, at the 5% level of significance. The critical value of the first-stage F-statistic for a single instrument is 9.08.

Let  $\widehat{TAC}_t$  and  $\widehat{\xi}_t$  be, respectively, the fitted values of  $TAC_t$  and the residuals from Equation (I). The regression-based Hausman [1978, 1982] test is obtained by estimating the following regression:

$$CFO_{t+1} = \alpha_0 + \alpha_1 CFO_t + \alpha_2 \widehat{TAC}_t \beta + \widehat{\xi}_t \rho + v_t.$$

If the coefficient estimate of  $\rho$ , based on the standard t test, is statistically significant, the TSLS estimate of  $\beta$  is consistent but its OLS estimate is not, thus rejecting Hausman's null hypothesis that OLS and TSLS estimators differ only by sampling error (see Wooldridge [2002, p. 118-119]).

*Continued on next page*

Table 4.2

Following Hahn and Hausman [2003], the small sample bias of  $\beta_{TSLLS}$ , the TSLLS estimate of  $\beta$  is estimable as:

$$E[\beta_{TSLLS}] - \beta \approx \frac{\text{corr}(\hat{u}, \hat{\varepsilon}) K (1 - R^2)}{TR^2}.$$

Effectively, the bias of  $\beta_{TSLLS}$  increases with endogeneity,  $\text{corr}(\hat{u}, \hat{\varepsilon})$ ; using numerous instrumental variables,  $K$ ; using a small sample size,  $T$ ; or using weak instruments as captured by the first stage  $R^2$ . I estimate  $\text{corr}(\hat{u}, \hat{\varepsilon})$  based on the correlation between residuals from the Equation (I), the first-stage regression, and those from the OLS regression of next-period cash flows on current-period cash flows and accruals.

Violations refer to the number of observations that lie outside the Gini bounds. The Gini [1921] upper and lower bounds are derived based on the OLS estimator, and the reciprocal of the reverse regression's OLS estimator. That is:

$$cfo_{t+1} = \alpha_0 + tac_t \beta + u_t \tag{4.6B}$$

$$tac_t = \phi_0 + cfo_{t+1} \delta + u_t. \tag{4.6C}$$

Define  $b$  and  $d$  as the OLS slope coefficient estimates of Equations (4.6B) and (4.6C) respectively. The Gini bound is:

$$|b| < |\beta_{TSLLS}| < \left| \frac{1}{d} \right|. \tag{4.6D}$$

In addition, the Hausman test rejects the null hypothesis that the TSLS and OLS estimators differ only by sampling error at the 5% level under the Lewbel instrument but not under the external instruments. Specifically, the regression-based T-statistic for this test has a mean (median) of 3.193 (3.183) based on the Lewbel instrument, but below 1.50 (1.30) based on external instruments.<sup>11</sup> Finally, the Lewbel instrument results in fewer violations (5,482 out of 29,180, i.e., 18.79%) of the Gini [1921] bounds than any external instrument. To summarize, all four criteria point to the internal Lewbel instrument outperforming the external instruments derived from accounting fundamentals.

The accrual measurement model can be refined by selecting the firm-specific setting in which the Lewbel instrument specified in Equation (4.10) works best. Specifically, I use the four econometric criteria specified in section 4.2 to select cash flow horizon at which the Lewbel instrument works best. Table 4.3 reports the performance of the Lewbel instrument based on this refined model.

As table 4.3 reports, refining the model reduces Gini bound violations by 90% and increases the mean (median) first-stage  $R^2$  to 53.4% (54.8%). More important, the mean (median) first-stage F-statistic improves to 51.367 (35.465) and even the 10<sup>th</sup> percentile firm has an F-statistic of 11.524, above the 9.08 critical value. The 10<sup>th</sup> percentile of the T-statistic for Hausman's [1978] test improves to 2.148. The mean bias in  $\beta_{TSLS}$  improves from 0.05 to 0.025; the median bias remains unchanged. Based on this improvement, I use the refined model to calculate the ANR used in my analysis.

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<sup>11</sup> Effectively, based on external instruments (the Lewbel instrument), we fail to reject the null hypothesis that accruals have no measurement error for about 75% (10%) of the sample firms.



	Mean	Std. Dev.	10%	25%	Median	75%	90%	Violations
Skewness	-0.979	1.818	-4.143	-2.195	-0.854	0.215	1.034	529
Lower bound	1.846	3.271	0.120	0.310	0.803	2.002	4.433	(1.8%)
$ (\beta_{TSLs}) $	3.853	6.632	0.532	1.060	2.198	4.543	8.741	
Upper Bound	23.927	124.514	2.478	4.621	9.364	19.582	40.014	
Attenuation	2.007	4.355	0.268	0.558	1.181	2.373	4.458	
Stage1 $R^2$	0.534	0.181	0.285	0.421	0.548	0.660	0.759	
Stage1 F-test	51.367	88.070	11.524	21.112	35.465	56.775	92.013	
TSLs Bias	0.025	0.027	0.008	0.012	0.019	0.030	0.047	
Hausman test	3.260	1.270	2.148	2.422	2.950	3.744	4.70	

Table 4.3: Performance of the Lewbel instrument based on the refined model

*Continued on next page*

### Table 4.3

#### Notes

Table 4.3 reports the performance of the Lewbel instrument:  $(CFO_{t+1} - \overline{CFO})^1 (TAC_t - \overline{TAC})^2$ , based on the refined model. To refine the model, I follow the following steps:

STEP1: I estimate the following firm-specific regression with quarterly data:

$$CFO_{t+s} = \alpha_0 + \alpha_1 CFO_t + \alpha_2 TAC_t + u_t, \quad (4.1B)$$

using the dependent variables  $CFO_{t+s}$  for  $s = 1, 2, 3, 4$  and  $\sum_{s=1}^S CFO_{t+s}$  for  $S = 2, 3, 4, 8, 12$ .

STEP2: For each of these dependent variables, I conduct the Hausman [1978] test using the Lewbel instrument on a firm-specific basis. I retain dependent variables in which: (1) the null hypothesis of the Hausman test is rejected and (2) the OLS coefficient estimate of  $\alpha_2$  is significant, both at the 10% level.

STEP3: I retain dependent variables for which the TSLS coefficient estimate does not violate the Gini bond, i.e., dependent variables for which the TLS coefficient estimate of  $\alpha_2$  using the Lewbel instrument is smaller than the reciprocal of the reverse regression's OLS coefficient estimate but bigger than the OLS estimate of  $\alpha_2$ , in absolute terms.

STEP4: Among the remaining dependent variables I drop the one with the biggest estimated TSLS small sample bias, unless it is the only dependent variable available for that firm.

STEP5: I select the model for which the first-stage  $R^2$  and F-statistic are highest.

Skewness is with respect to  $tac_t$  and Attenuation bias is the difference between the absolute value of the TSLS estimate and the absolute value of the OLS estimate of  $\alpha_1$ .

As table 4.3 reports, on the basis of this refined model, I find that the mean (median) firm in my sample has an ANR of 25% (17.4%), meaning that the contribution of accrual measurement error to the variation of total accruals is nontrivial.

To summarize, the Lewbel approach has the following advantages in my setting. First, ANR estimation does not impose restrictive assumptions on the distributions of the latent variable, observable variables or the measurement error. Rather, identification of accrual measurement error variance is derived from the skewness of the unobservable true variable. As table 4.3 documents, the conditional skewness of accruals given cash flows is nonzero. Second, this approach does not require any additional data outside the measurement error model's observable variables. Third, this approach yields a valid instrument that outperforms fundamentals-based accrual instruments based on four formal tests.

# Chapter 5

## Construct validity tests

A construct is a variable that is abstract and latent rather than concrete and observable. In my setting, the construct of interest is accrual reliability. Thus, my construct validation is an assessment of the extent to which ANR, the proposed measure, captures its underlying construct, accrual reliability.

While theory relates accrual reliability to other accounting constructs, only the relation between an observable measure of accrual reliability and the proxies of these external constructs can be directly tested. Such a test can provide only conditional inferences about ANR's construct validity. Specifically, ANR validation is a joint test: if theory that relates accrual reliability to a second construct is correct, and if a proxy that is strongly correlated with this second construct is available, and if ANR is correlated with this proxy as predicted, ANR is an inverse measure of accrual reliability. To minimize the risk of wrongful inference, I restrict the assessment of ANR's construct validity to settings in which: (1) theory relates accrual reliability to a second construct, and (2) based on previous research, a reasonable proxy that is strongly correlated with the second construct is available.

To illustrate, consider the validation of ANR with respect to earnings persistence based on the following 4 hypotheses:

- (H1) Earnings persistence and accrual reliability correlate positively.
- (H2) The AR1 coefficient of earnings is an observable measure of persistence.
- (H3) ANR is an observable inverse measure of accrual reliability.

(H4) ANR and the AR1 coefficient of earnings correlate negatively.

H3 is the test of interest; only H4 can be directly tested and endogeneity precludes unambiguous inference on H3 based only on a test of H4. However, if H1 and H2 are known to be correct, an empirical test of H4 allows a valid inference about H3, the hypothesis of interest. Thus, if theory relating persistence and reliability is correct, and if the AR1 coefficient of earnings is strongly correlated with earnings persistence, a significant negative correlation between ANR and this AR1 coefficient provides credible empirical evidence of ANR's construct validity.

## 5.1 Earnings persistence

Richardson et al. [2005] analytically show that earnings persistence<sup>1</sup> decreases with ANR. In a more general model, Staudenmeyer and Buonaccorsi [2005] show that the classical measurement error standard result of attenuation bias applies to ARIMA models. The intuition is that the random component of accrual measurement error is transitory; if this component as a proportion of earnings increases, earnings persistence will decline. Consistent with this view, Christensen, Feltham and Sabac [2005] observe that in general, accrual measurement errors reduce earnings persistence. Previous empirical research (e.g., Dechow and Dichev [2002]) is also consistent with this view. Thus, based on the both theory and empirical evidence from previous research, I expect that earnings persistence will decrease with ANR.

I interpret the AR1 coefficient from the quarterly EPS time-series as a measure of persistence. Specifically, I use four AR1 models: a seasonally unadjusted, a seasonal, a seasonally adjusted and a hierarchical model.<sup>2</sup> To the extent that: (1)

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<sup>1</sup> Persistence describes how a current shock affects future realizations of the series (Lipe and Kormendi [1994]).

<sup>2</sup> As Lipe and Kormendi [1994] explain, over short horizons, the AR1 or MA1 parameter is a reasonable representation of persistence. I use the preceding 8-year window of quarterly data used to estimate ANR to estimate firm-specific earnings persistence. In unreported robustness checks, I find that more elaborate ARIMA models lead to the same qualitative results but are noisier.

persistence and reliability are positively correlated as theory predicts; and (2) the AR1 coefficient is a valid measure of persistence, construct validation of ANR can be inferred from empirical evidence of the correlation between the AR1 coefficient and ANR.

## 5.2 Earnings timeliness

Ball, Kothari and Robin [2000] posit that, over short reporting periods, reported earnings capture economic income with a lag that is a function of accruals' inability to offset the serial correlation in operating cash flows. As Ball et al. [2000] point out, accruals' ability to offset the negative serial correlation in cash flow changes decreases with measurement error, which contributes to the deviation between accounting income and economic income. Accrual measurement error therefore exacerbates the lag with which current-period accounting income incorporates current-period economic income, hence reducing earnings timeliness. Effectively, Ball et al. [2000] hypothesize that timeliness and accrual unreliability correlate negatively. The authors infer earnings timeliness from the  $R^2$  of the following regression.

$$X_{i,t} = \beta_0 + \beta_1 RD_{i,t} + \beta_2 R_{i,t} + \beta_3 R_{i,t} * RD_{i,t} + \zeta_{i,t}, \quad (5.1)$$

where  $R_{i,t}$  is the annual stock return;  $X_{i,t}$  is annual basic *EPS* for fiscal year  $t$  excluding extra ordinary items, adjusted for stock dividends and stock splits and deflated by beginning-of-period price; and  $RD_{i,t}$  is an indicator variable equal to one if returns are negative and zero otherwise. The greater the  $R^2$  in Equation (5.1), the greater is earnings timeliness.

Insofar as the measurement error in a regression's dependent variable is uncorrelated with its regressors, econometric theory proves that such error reduces a regression's fit (see Wooldridge [2002, p. 72]). Accrual measurement error translates into error in the dependent variable in Equation (5.1). Thus, econometric theory also predicts that timeliness as measured in Ball et al. [2002], will correlate negatively with reliability. An 8-year window severely reduces the degrees of freedom

needed to accurately estimate the  $R^2$  of Equation (5.1). Accordingly, I estimate the model each year for each of the two-digit SIC code industry group that has at least 15 firm-years and obtain the residuals. I calculate the firm-specific variance of these residuals over the 8-year window, and measure timeliness as:  $Timeli = -var(\hat{\zeta}_t)$ .

A negative correlation between  $Timeli$  and ANR provides inference on the construct validity of ANR under two assumptions: (1) timeliness and reliability correlate positively as Ball et al. [2000] predict; and (2) the fit of Equation (5.1), as captured by  $Timeli$ , is positively correlated with timeliness.

### 5.3 The quality of management’s implementation decisions

The quality of management’s implementation decisions is a determinant of accrual reliability, so I predict that the two constructs should correlate positively. I use accounting discretion as an inverse measure of the quality of accounting implementation decisions. Specifically, I draw on Kasznik [1999] and Bowen, Rajgopal and Venkatachalam [2008] and infer the accounting discretion based on the fit of the following firm-specific modified Jones [1991] model:

$$TAC_t = \alpha_0 + \alpha_1(\Delta REV_t - \Delta REC_t) + \alpha_2\Delta CFO_t + \varepsilon_t. \quad (5.2)$$

Since Compustat reports gross property plant and equipment (PP&E) only in the fourth quarter for numerous sample firms, I omit PP&E from Equation (5.2) to avoid losing observations.<sup>3</sup> The bigger the  $R^2$  in equation (5.2), the smaller the level of accounting discretion. To the extent the fundamentals on the RHS are uncorrelated with accrual measurement error in the dependent variable, econometric theory predicts that the regression’s  $R^2$  will decrease with measurement error. I estimate Equation (5.2) using quarterly data over the same 8-year rolling window

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<sup>3</sup> In unreported tests, I find that for firm-years in which PP&E data are available, including PP&E does not substantially improve the explanatory power.

used to calculate ANR, and infer accounting discretion as:  $Disc = 1 - R^2$ .

A positive correlation between ANR and  $Disc$  provides inference on the construct validity of ANR under two assumptions: (1) the quality of management's implementation decisions and reliability correlate positively; and (2)  $Disc$  is negatively correlated with the quality of implementation decisions.

## 5.4 Ability to offset timing and matching problems in cash flows

The negative autocorrelation in cash flow changes arises from sales shocks and fluctuations in a firm's financing and investing decisions, and is indicative of the timing and matching problems in cash flows (Dechow [1994] and Dechow et al. [1998]). The function of accruals is to offset these timing and matching problems by delaying or anticipating the accounting recognition of cash flows, to generate earnings changes that are less autocorrelated than are cash flow changes. Following previous research, (e.g., Dechow [1994]), I measure this offsetting ability as earnings smoothness, defined as the negative of the correlation between cash flow changes and accrual changes:  $Smooth = -corr(\Delta CFO_t, \Delta TAC_t)$ . Based on Equation (4.2), it follows that:  $Smooth = -corr(\Delta CFO_t, \Delta TAC_t^* + \Delta \varepsilon_t)$ . To the extent cash flows are uncorrelated with accrual measurement error as my model assumes, an increase in  $\Delta \varepsilon_t$  as a proportion of  $\Delta TAC_t$  will reduce  $-corr(\Delta CFO_t, \Delta TAC_t)$ , implying accrual unreliability correlates negatively with earnings smoothness. This is consistent with Dechow and Dichev [2002]. Further, as Equation (4.8) indicates, by definition, ANR predicts that reliability and smoothness should correlate positively.

I interpret manipulative smoothing as the intentional manipulation of accruals to generate measurement errors that offset the negative correlation in cash flow changes. Manipulative smoothing reduces earnings' correlation with economic income. Because the classical measurement error model assumes that cash flows



and accrual measurement errors are uncorrelated, it does not accommodate manipulative smoothing. Effectively, insofar as accrual measurement error is actually uncorrelated with cash flow changes as my model assumes, I expect that accrual reliability increases with smoothness. On the contrary, systematic manipulative smoothing means that smoothness may be uncorrelated or even negatively correlated with accrual reliability. Which prediction dominates is an empirical question.

## 5.5 Accruals' ability to predict future cash flows

Previous research (e.g., Dechow et al. [1998] and Barth et al. [2001]) infers accruals' ability to predict future cash flows from the fit of a regression of future cash flows on current-period cash flows and accruals. Based on this research, accruals' ability to predict future cash flows decreases with accrual measurement error. In addition, econometric theory proves that measurement error in regressors reduces a regression's fit and attenuates its OLS coefficient estimates (see Carroll et al. [2006]). Further, based on Equation (4.8), ANR predicts that reliability increases with accruals' ability to predict future cash flows, holding constant current-period cash flows (i.e.,  $cov(cfo_{t+1}, tac_t)$ ). Empirically, I infer current-period accruals' ability to predict future cash flows, holding constant the effect of current-period cash flows, from the fit of the following regression:

$$cfo_{t+s} = \alpha_0 + \alpha_1 tac_t + \omega_t \quad (5.3)$$

I estimate Equation (5.3) with quarterly data, using the dependent variable  $cfo_{t+s}$  for  $s = 1, 2, 3, 4$  and  $\sum_{s=1}^S cfo_{t+s}$  for  $S = 2, 3, 4, 8, 12$ . I use the  $R^2$  criterion to select the best model specification. Specifically, let  $R_{max}^2$  be the maximum fit among models using the cash horizons specified above, I infer accrual's ability to predict future cash flows as:  $CPred = R_{max}^2$ .

If accruals' ability to predict future cash flows correlates positively with accrual reliability as previous research suggests, and if  $CPred$  correlates positively with

accruals' ability to predict future cash flows, a negative correlation between ANR and *CPred* provides evidence on the validity of ANR as an inverse measure of accrual reliability.

## 5.6 Competition in the products market

Competition in product markets increases volatility in sales and profit margins, leading to uncertainty about future firm performance. Indeed, the MD&A section in financial statements frequently cites competition to explain the uncertainty and potential error in forward-looking information regarding firm-performance or financial position.<sup>4</sup> To the extent uncertainty from competition impairs management's ability to anticipate future performance, accrual unreliability will increase with competition, *ceteris paribus*. In addition, competition can compromise the quality of management's implementation decisions.<sup>5</sup>

I estimate competition based on industry concentration (*Conc*) as captured by the Herfindhal Index, sales market share (*Mshr*) as captured by a firm's sales as a proportion of total sales in its 3-digit SIC industry code, and the number of firms in a firm's 3-digit SIC industry code (*IndM*). A positive correlation between *IndM* and ANR and negative correlation of ANR with both *Conc* and *Mshr* provides inference on the construct validity of ANR under two assumptions: (1) competition and

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<sup>4</sup> Here are two examples of disclaimers in forward-looking statements:

*“Forward-looking statements are based on our current assumptions and expectations and are subject to certain risks and uncertainties that could cause actual results to differ from those projected. We caution that forward-looking statements are qualified by the risk and challenges posed by increased competition (including the effects of competitor liquidation activities)...”*

*“Forward-looking statements are based on expectations, forecasts and assumptions by our management and involve a number of risks, uncertainties, and other factors that could cause actual results to differ materially from those stated, including, without limitation: continued decline in market share, continued or increased price competition resulting from industry overcapacity, currency fluctuations or other factors...”*

<sup>5</sup> For example, in an attempt to defend market share from a new entrant, an incumbent firm might incentivize the sales force, increase price discounts and relax customer credit terms. Slack credit terms imply that the estimation of allowance for doubtful debts requires greater judgment. Aggressive sales strategies and distribution arrangements which are intended to repel the entrant increase the potential for trade loading, resulting in revenue recognition issues.

reliability correlate negatively as as I hypothesize; and (2) the competition proxies are correlated with the level of product market competition.

## 5.7 Earnings informativeness

Following previous research (e.g., Teoh and Wong [1993]; Lundholm and Myers [2002]; Collins, Kothari, Shanken and Sloan [1994]; Subramanyam [1996]; Tucker and Zarowin [2006]) I consider earnings response coefficients (ERCs) and future earnings response coefficients (FERCs) as measures of earnings informativeness in both a short-window and a long-window test. In particular, Teoh and Wong [1993] and Subramanyam [1996] analytically link ERC to the earnings reliability ratio, defined as one minus the ratio of earnings measurement error variance to earnings variance, and show that ERC will decrease with accrual measurement error. The model formalizes the hypothesis that unreliability has a negative effect on informativeness. As such, to the extent that ERCs and FERCs strongly correlate with informativeness, a significantly negative effect of ANR on ERCs and FERCs would be a step towards external construct validation.

To assess the effect of ANR on ERC, I draw on Teoh and Wong's research design. I estimate the following pooled regression:

$$\begin{aligned}
 CAR_{i,t} = & a_0 + a_1 ANR_{i,t} + a_2 UE_{i,t} + a_3 ANR_{i,t} * UE_{i,t} \\
 & + \sum_{j=1}^4 a_{4j} Z_{ji,t} * UE_{i,t} + \sum_{j=1}^4 a_{5j} UE_{i,t} * Z_{ji,t} * ANR_{i,t} + \eta_{i,t},
 \end{aligned} \tag{5.4}$$

where  $CAR_{i,t}$  is firm returns less value weighted market returns cumulated over the (-1 to +1) announcement window,  $UE_{i,t}$  is unexpected quarterly earnings, calculated as calculated as the difference between current-quarter EPS and the EPS from the same quarter in the previous year, divided by price at the close of previous quarter, and  $Z_{ji,t}$  is controls including size, leverage, losses and market to book ratio. If theory is correct, and ANR is a measure of accrual reliability, the  $a_3$

coefficient in Equation (5.4) should be significantly negative.

To assess the effect of ANR on FERCs, my research design draws on Lundholm and Myers [2002] and Tucker and Zarowin [2006]. Specifically, I estimate the following regression:

$$\begin{aligned}
 R_{i,t} = & b_0 + b_1X_{i,t-1} + b_2X_{i,t} + b_3X_{i,t3} + b_4R_{i,t3} + b_5ANR_{i,t} & (5.5) \\
 & + b_6ANR_{i,t} * X_{i,t-1} + b_7ANR_{i,t} * X_{i,t} + b_8ANR_{i,t} * X_{i,t3} \\
 & + b_9ANR_{i,t} * R_{i,t3} + b_{10}Z_{i,t} + b_{11}Z_{i,t} * X_{i,t3} + \eta_{i,t},
 \end{aligned}$$

where  $R_{i,t}$  is annual stock returns;  $X_{i,t}$  is annual basic *EPS* for fiscal year  $t$  excluding extra ordinary items, adjusted for stock dividends and stock splits and deflated by beginning-of-period price;  $X_{i,t3}$  is the sum of *EPS* in fiscal years  $t + 1$  through  $t + 3$ , deflated by stock price at the beginning of fiscal year  $t$ ;  $R_{i,t3}$  is annually compounded annual stock returns for fiscal years  $t + 1$  through  $t + 3$ ; and  $Z_{i,t}$  is a control variable that includes size and book-to-market. If as theory hypothesizes, unreliability reduces earnings informativeness, returns should reflect less information about current and future earnings. Accordingly, *ceteris paribus*, the ERC and FERC of firms with low reliability accruals should be lower than those of firms with high accrual reliability. Thus, to the extent that ERC and FERC are measures of informativeness, the external validity of ANR can be inferred based on whether both  $b_7$  and  $b_8$  in Equation (5.5) above are significantly negative.

## 5.8 Results of ANR's correlation with proxies of accounting constructs

Table 5.1 reports the Pearson and Spearman correlations of ANR with proxies of other accounting constructs. The p-values of all reported correlations are smaller than 0.0001. The second column of table 4 reports the predicted correlation of ANR with the proxies of other accounting constructs.

As predicted, ANR correlates positively with proxies of persistence. As table 5.1

reports, the Pearson (Spearman) correlation between ANR and persistence, based on the four AR1 models of EPS ranges from -0.260 (-0.274) to -0.455 (-0.512). If persistence and reliability correlate positively as previous research predicts, and if my proxies for persistence correlate positively with persistence, this result validates ANR as an inverse measure of accrual reliability. In addition, as predicted, ANR correlates negatively with *Timeli*, the proxy for timeliness.

Variable	Mean	Std. Dev.	10%	25%	Median	75%	90%
ANR	0.250	0.228	0.025	0.066	0.174	0.377	0.600

  

Variable	Predict	ANR	Persist1	Persist2	Persist3	Persist4	Timeli	Smooth	Disc	CPred	Conc	MShr	IndM
ANR			-0.402	-0.512	-0.274	-0.471	-0.403	-0.509	0.687	-0.387	-0.199	-0.353	0.349
Persist1	-	-0.375		0.771	0.628	0.750	0.473	0.232	-0.310	0.401	0.063	0.180	-0.101
Persist2	-	-0.455	0.755		0.383	0.927	0.503	0.337	-0.424	0.436	0.099	0.258	-0.195
Persist3	-	-0.260	0.626	0.392		0.344	0.173	0.109	-0.215	0.322	0.021	0.060	-0.064
Persist4	-	-0.427	0.742	0.930	0.350		0.475	0.302	-0.386	0.363	0.103	0.234	-0.186
Timeli	-	-0.333	0.363	0.388	0.167	0.366		0.273	-0.296	0.209	0.045	0.319	-0.113
Smooth	?	-0.474	0.213	0.327	0.094	0.297	0.245		-0.426	0.085	0.126	0.202	-0.224
Disc	+	0.657	-0.300	-0.423	-0.219	-0.382	-0.266	-0.426		-0.234	-0.130	-0.252	0.273
CPred	-	-0.370	0.396	0.462	0.364	0.359	0.172	0.093	-0.262		0.035	0.102	-0.069
Conc	-	-0.162	0.062	0.094	0.004	0.102	0.025	0.102	-0.110	0.028		0.351	-0.696
MShr	-	-0.191	0.126	0.175	0.014	0.166	0.159	0.109	-0.147	0.060	0.475		-0.656
IndM	+	0.302	-0.096	-0.170	-0.061	-0.160	-0.051	-0.226	0.232	-0.068	-0.438	-0.290	

Table 5.1: ANR's distribution and correlations with proxies of other constructs

## Table 5.1

### Notes

ANR is the noise ratio of total accruals, calculated as specified in Equation (4.8):

$$ANR = \frac{\beta_{TSLs} var(tac_t) - cov(cfo_{t+1}, tac_t)}{\beta_{TSLs} [\hat{\theta}'_{tac} var(CFO_t) \hat{\theta}_{tac} + var(tac_t)]}. \quad (4.8)$$

where  $\beta_{TSLs}$  is the usual TSLs coefficient estimate of  $\beta$  in Equation 6:  $cfo_{t+1} = \alpha_0 + tac_t^* \beta + u_t$ ;  $\hat{\theta}_{tac}$  is the OLS coefficient estimate in a regression of current-period total accruals on current-period cash flows, and  $tac$  is the regression's residuals, as shown in Equation (4.5); and  $cfo_{t+1}$  is the cash flow autocorrelation residuals. The reported ANR distribution is based on a sample of 29,180 firm-years of estimated ANR from 5,026 distinct firms.

Pearson (Spearman) correlations are below (above) the diagonal. All p-values are smaller than 0.0001. The Second column, reports the predicted correlation of ANR with each variable. *Perst1-Perst4* capture persistence based on the following 4 models:

$$Model\ 1:\ Perst1: EPS_{t+1} = \rho_1 EPS_t + \varepsilon_t$$

$$Model\ 2:\ Perst2: EPS_{t+4} = \rho_2 EPS_t + \varepsilon_t$$

$$Model\ 3:\ Perst3: (EPS_{t+4} - EPS_t) = \rho_3 (EPS_{t+3} - EPS_{t-1}) + \varepsilon_t$$

The quarterly EPS series is nonstationary for a subset of the firms, meaning the  $\rho_1$  or  $\rho_2$  is greater than 1 or less than -1. To alleviate this concern, I consider a hierarchial model that as follows:

$$Model\ 4\ (Hierarchial\ Model):\ Perst4$$

$$\text{if } -1 < \rho_2 < 1 \text{ then } \rho_4 = \rho_2.$$

$$\text{if } (\rho_2 > 1 \text{ or } \rho_2 < -1) \text{ but } -1 < \rho_1 < 1 \text{ then } \rho_4 = \rho_1.$$

$$\text{if } (\rho_2 > 1 \text{ or } \rho_2 < -1) \text{ and } (\rho_1 > 1 \text{ or } \rho_1 < -1) \text{ but } -1 < \rho_3 < 1 \text{ then } \rho_4 = \rho_3.$$

*Continued on next page*

## Table 5.1

All four persistence models are estimated using quarterly EPS data over the same 8-year rolling window used to estimate ANR.

Timeliness,  $Timeli$ , is estimated based on the following regression:

$$X_{i,t} = \beta_0 + \beta_1 RD_{i,t} + \beta_2 R_{i,t} + \beta_3 R_{i,t} * RD_{i,t} + \zeta_{i,t}, \quad (5.1)$$

where  $X_{i,t}$  is  $EPS_{i,t}$  deflated by beginning of fiscal year stock price.  $R_{i,t}$  is stock returns compounded over the 12-month (-9 to +3) window.  $RD_{i,t}$  is an indicator variable equal to one if returns are negative and zero otherwise. I estimate Equation (5.1) each year for each 2-digit SIC code industry group that has at least 15 firm-years, and calculate  $Timeli = -var(\hat{\zeta}_{i,t})$  over the same rolling 8-year window.

$Smooth$  is smoothness is estimated based on annual data as:  $Smooth = -corr(\Delta CFO_t, \Delta TAC_t)$  and estimated over the same 8-year rolling window.

$Disc$  is accounting discretion, estimated based on the fit of the following firm-specific modified Jones [1991] model:

$$TAC_t = \alpha_0 + \alpha_1 (\Delta REV_t - \Delta REC_t) + \alpha_2 \Delta CFO_t + \varepsilon_t, \quad (5.2)$$

where  $TAC$  and  $CFO$  are total accruals and operating cash flows, respectively;  $REV$  and  $REC$  are, respectively, revenues (#2) and receivables (#37). I estimate regression (24) using quarterly data over the same 8-year rolling window used to calculate ANR, and infer  $Disc$  from the regression's fit as:  $Disc = (1 - R^2)$ .

$CPred$  is accruals' ability to predict future cash flows, holding the effect of current-period cash flows constant. I infer this ability from the fit of the following firm-specific regression:

*Continued on next page*



**Table 5.1**

$$cfo_{t+s} = \alpha_0 + \alpha_1 tac_t + \omega_t, \quad (5.3)$$

where  $cfo_{t+s}$  and  $tac_t$  are, respectively, the residuals from regressing  $CFO_{t+s}$  and  $TAC_t$  on  $CFO_t$ . I estimate the above Equation with quarterly data, using the dependent variable  $cfo_{t+s}$

for  $s = 1, 2, 3, 4$  and  $\sum_{s=1}^S cfo_{t+s}$  for  $S = 2, 3, 4, 8, 12$ . I use the  $R^2$  criterion to select the best

model specification, on the basis of which I infer accrual's ability to predict future cash flows as:

$$CPred = R_{max}^2.$$

*Conc* is industry concentration inferred from a Herfindahl Index that is calculated at the 3-digit SIC industry code.

*MShr* and *IndM* are, respectively, sales market share and the number firms in an industry, at the 3-digit SIC industry code.

As table 5.1 reports, the Pearson (Spearman) correlation between ANR and *Timeli* is -0.333 (-0.403). Thus, if timeliness and reliability correlate positively as previous research hypothesizes, and if *Timeli* positively correlates with timeliness, this result validates ANR. As predicted, if accrual measurement error is uncorrelated with cash flows, as my model assumes, ANR should correlate negatively with *Smooth*, my measure earnings smoothness. However, if systematic manipulative smoothing is prevalent among my sample firms, so that changes in cash flows systematically correlate negatively with changes in accrual measurement error, *Smooth* and ANR should correlate positively.

As table 5.1 reports, the Pearson (Spearman) correlation between ANR and *Smooth* is -0.474 (-5.09). Thus, among my sample firms, accruals' ability to offset negative cash flow autocorrelation, as captured by *Smooth* does not appear to be driven by manipulative smoothing. Moreover, if this offsetting ability positively correlates with accrual reliability, as previous research hypothesizes, and if *Smooth* positively correlates with this offsetting ability, this result suggests ANR is a valid inverse measure of accrual reliability.

As predicted, I find that ANR correlates positively with accounting discretion (*Disc*) but negatively accruals' ability to predict future cash flows (*CPred*). The respective Pearson (Spearman) correlations are 0.657 (0.687) and -0.370 (-0.387). If the quality of accounting implementation decisions and reliability correlate positively, and if *Disc* correlates negatively with this quality, this result validates ANR. Likewise, if accruals' ability to predict future cash flows increases with accrual reliability, and if *CPred* correlates positively with this predictive ability, this result validates ANR.

Finally, as predicted, ANR correlates positively with the number of firms in an industry (*IndM*) but negatively with industry sales concentration (*Conc*) and sales market share (*MShr*). The respective Pearson (Spearman) correlations are 0.302 (0.349), -0.162 (-0.199) and -0.191 (-0.353). Thus, if competition and accrual reliability correlate negatively, and if *IndM*, *Conc* and *Mshr* correlate with competition,

this result validates ANR.

Table 5.2 reports the results of estimating equation (5.4). The reported t-statistics are robust to heteroskedasticity. As predicted, the ERCs of firms with high ANR are lower than those of firms with low ANR. Specifically, the estimated value of  $a_3$ , the coefficient on the interaction term is -0.2185 ( $t = -3.59$ ). This coefficient remains significant after controlling for size, losses, market-to-book ratio, and leverage, suggesting that ANR is incremental to these factors in explaining cross-sectional variation in  $CAR$ . This result suggests that in cross-section, the information content of earnings significantly decreases with accrual unreliability.

Table 5.3 reports the results of estimating Equation (5.5), which accommodates both ERCs and future ERCs (FERCs). The reported t-stats are based on the Newey-West estimator. I find the coefficients on  $b_7$  and  $b_8$  are, respectively, -0.9841 ( $t = -1.99$ ) and -0.6547 ( $t = -2.79$ ). Thus, as predicted, both ERCs and FERCs decrease with ANR, even after controlling for size and book to market. Taken together, this result provides evidence of ANR's external validity with respect to earnings informativeness.

$$\begin{aligned}
CAR_{i,t} = & a_0 + a_1 ANR_{i,t} + a_2 UE_{i,t} + a_3 ANR_{i,t} * UE_{i,t} \\
& + \sum_{j=1}^4 a_{4j} Z_{ji,t} * UE_{i,t} + \sum_{j=1}^4 a_{5j} UE_{i,t} * Z_{ji,t} * ANR_{i,t} + \eta_{i,t}
\end{aligned} \tag{5.3}$$

VARIABLE	Coef.	Base model			Equation (5.3)		
		Pred	Est.	t-stat	Pred	Est.	t-stat
<i>intercept</i>	$a_0$	?	0.0059	13.78	?	0.0066	11.82
$ANR_{i,t}$	$a_1$		--	--	?	-0.0121	-4.96
$UE_{i,t}$	$a_2$	+	0.0517	17.96	+	0.2267	11.77
$ANR_{i,t} * UE_{i,t}$	$a_3$		--	--	-	-0.2185	-3.59
$SIZE_{i,t} * UE_{i,t}$	$a_{41}$		--	--	-	-0.0174	-6.36
$LOSS_{i,t} * UE_{i,t}$	$a_{42}$		--	--	-	-0.0808	-9.82
$MTB_{i,t} * UE_{i,t}$	$a_{43}$		--	--	-	-0.0016	-0.72
$LEV_{i,t} * UE_{i,t}$	$a_{44}$		--	--	-	-0.0105	-2.17
$R^2$			0.012			0.021	
# observations			31,995			31,995	

Table 5.2: The effect of ANR on earnings response coefficients (ERCs)

*Continued on next page*

## Table 5.2

### Notes

Table 5.2 reports the results of estimating Equation (5.4). *CAR*, cumulative abnormal return, is a stock's daily excess return relative to the value weighted return, compounded over the five day quarterly earnings announcement window (-1,+1). *UE* is unexpected quarterly earnings, calculated as the difference between current-quarter EPS and the EPS from the same quarter in the previous year, divided by price at the close of previous quarter. *ANR* is the noise ratio of total accruals, calculated over the preceding 8-year rolling window, as described in Equation (4.8). *SIZE* is the log of sales in quarter  $t$ , while *LOSS* is an indicator variable equal to 1 if earnings in quarter  $t$  is negative, and zero otherwise. *BM* is the lag of book-to-market value of equity, and *LEV* is leverage in quarter  $t$ .

$$\begin{aligned}
R_{i,t} = & b_0 + b_1X_{i,t-1} + b_2X_{i,t} + b_3X_{i,t3} + b_4R_{i,t3} + b_5ANR_{i,t} \\
& + b_6ANR_{i,t} * X_{i,t-1} + b_7ANR_{i,t} * X_{i,t} + b_8ANR_{i,t} * X_{i,t3} \\
& + b_9ANR_{i,t} * R_{i,t3} + b_{10}Z_{i,t} + b_{11}Z_{i,t} * X_{i,t3} + \eta_{i,t}
\end{aligned} \tag{5.5}$$

VARIABLE		Base Model			Equation (5.5)		
		Pred	Est.	t-stat	Pred	Est.	t-stat
<i>intercept</i>	$b_0$	?	0.1063	15.70	?	0.0139	0.54
$X_{i,t-1}$	$b_1$	-	-0.5605	-6.86	-	-0.6137	-4.18
$X_{i,t}$	$b_2$	+	0.5010	6.35	+	0.8578	6.06
$X_{i,t3}$	$b_3$	+	0.4340	11.83	+	0.4648	3.67
$R_{i,t3}$	$b_4$	-	-0.11504	-20.67	-	-0.1681	-16.01
$ANR(TAC)_{i,t}$	$b_5$	--	--	--	+	0.2418	5.16
$ANR_{i,t} * X_{i,t-1}$	$b_6$	--	--	--	?	0.5638	1.23
$ANR_{i,t} * X_{i,t}$	$b_7$	--	--	--	-	-0.9841	-1.99
$ANR_{i,t} * X_{i,t3}$	$b_8$	--	--	--	-	-0.6547	-2.79
$ANR_{i,t} * R_{i,t3}$	$b_9$	--	--	--	?	0.0019	0.04
$SIZE_{i,t}$	$b_{10}$	--	--	--	-	-0.0080	-2.44
$SIZE_{i,t} * X_{i,t3}$	$b_{11}$	--	-	--	+	0.0906	5.53
$BM_{i,t}$	$b_{12}$	--	--	--	+	0.0973	7.53
$BM_{i,t} * X_{i,t3}$	$b_{13}$	--	-	--	-	-0.3647	-6.68
$R^2$			0.09			0.12	
# Observations			7,618			7,587	

Table 5.3: The effect of ANR on current and future ERCs

## Table 5.3

### Notes

Table 5.3 reports the results of estimating Equation (5.5). All t-statistics are robust to heteroskedasticity and autocorrelation using the Newey-West estimator.  $R_{i,t}$  the dependent variable is annual stock returns, compounded over the (-8,+3) window.  $X_{i,t}$  is EPS for year  $t$  deflated by stock price at the beginning of fiscal year, both adjusted for stock dividends and stock splits (#27).  $X_{i,t3}$  is the sum of EPS in fiscal years  $t + 1$  to  $t + 3$ , deflated by stock price at the beginning of fiscal year  $t$ .  $R_{i,t3}$  is annually compounded annual stock returns for fiscal years  $t + 1$  through  $t + 3$ ;  $ANR$  is the noise ratio of total accruals, calculated as described in Equation (4.8).  $SIZE$  is the log of sales, while  $BM$  is the lag of book-to-market value of equity.

## 5.9 ANR's Divergent and Convergent Validity

I draw on psychometrics, a field of study concerned with the theory and technique of measuring latent constructs in psychology, to assess the divergent and convergent validity of ANR with respect to observable indicators of the determinants and characteristics of accrual reliability. In this literature, factor analysis is used to provide empirical evidence on the extent to which specified indicators measure the same or different underlying constructs.

*Convergent validity* is the extent to which different observable indicators measure the same underlying construct (Nunnally and Bernstein [1994, p. 92]; Kline [2005, p. 60]). *Divergent or discriminant validity* is the extent to which observable indicators measure different underlying constructs. A justifiable new measure of a construct must have divergent validity in the sense of measuring something different from existing measures [Nunnally and Bernstein [1994 p.93].

According to Nunnally and Bernstein [1994], no precise method can be stated to properly specify the set of observable indicators for a given construct. In particular, while the selection of indicators to include in the factor analysis is guided by theory, the selection process is itself necessarily exploratory. I conduct an exploratory factor analysis,<sup>6</sup> including variables that capture the determinants of reliability as well as firm characteristics in the factor analysis. Dechow and Dichev [2002] hypothesize and document that accrual estimation errors decrease with firm size, but increase with losses, length of operating cycle, magnitude of accruals and the volatilities of cash flows, accruals, sales and ROA. For completeness, I also explore these firm characteristics in my factor analysis.

Nunnally and Bernstein [1994] state that extant measures of a construct should also be included in this analysis in order to examine whether a proposed measure is novel. Previous accounting research (e.g. Dechow and Dichev [2002]; Francis et al.

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<sup>6</sup> Exploratory factor analysis allows the data to derive the factors and their correspondence to indicators, without imposing a priori hypotheses. In confirmatory factor analysis, the researcher explicitly specifies both the number of factors and their correspondence to the indicators.



[2004, 2005]) uses accruals quality (AQ) as a measure of accrual estimation errors.<sup>7</sup> To examine whether ANR is distinct from that measure of accrual reliability, I also include AQ in the exploratory factor analysis.

Table 5.4 reports the Pearson and Spearman correlations of ANR with these firm characteristics. The p-values of all reported correlations are smaller than 0.0001. As predicted, ANR does not appear to mimic the volatility in firms' operating environments. Specifically, the Pearson (Spearman) correlation of ANR with the volatilities of total accruals, working capital accruals, cash flows and sales are, respectively, 0.379 (0.333), 0.123 (0.079), 0.272 (0.227) and 0.036 (0.079). The correlation of ANR with losses and ROA volatility is 0.557 (0.597) and 0.450 (0.669), respectively.

The exploratory factor analysis uses: (1) ANR; (2) accrual variance; (3) cash flow variance; (4) firm size (5) smoothness; (6) accounting discretion; and (7) and accruals quality (AQ). Clearly, more variables can be used in this factor analysis. For example, one may think that accruals' ability to predict future cash flows, volatility in sales growth, length of operating cycle, and the level of competition in products markets should also be included. However, my exploration finds these additional variables provide no incremental information to the analysis. In particular, using additional variables reduces fit. Because extraneous variables increase the risk of drawing incorrect or ambiguous inference from factor analysis, parsimony is crucial. As such, I do not include additional variables in the factor analysis.

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<sup>7</sup> The variance of the residuals from a regression of working capital accruals on previous, current, and next fiscal year cash flows is interpreted as an inverse measure accruals quality (AQ). Schipper and Vincent [2003] posit that to the extent that this model captures accrual estimation errors that deviate reported earnings from Hicksian income, it captures accruals' representational faithfulness.

Variable	ANR	$v(TAC)$	$v(\Delta WC)$	$v(CFO)$	$v(sales)$	size	loss	$v(ROA)$	$v(Opc)$	$v(Sgrw)$	$ TAC $	AQ
ANR		0.333	0.079	0.227	0.079	-0.179	0.597	0.669	0.358	0.413	0.393	0.307
$v(TAC)$	0.379		0.771	0.757	0.416	-0.528	0.570	0.727	0.440	0.477	0.721	0.634
$v(\Delta WC)$	0.123	0.636		0.700	0.438	-0.499	0.361	0.477	0.334	0.331	0.490	0.771
$v(CFO)$	0.272	0.575	0.591		0.432	-0.557	0.504	0.666	0.463	0.482	0.575	0.555
$v(sales)$	0.036	0.218	0.310	0.251		-0.3140	0.246	0.368	0.392	0.396	0.274	0.398
size	-0.179	-0.415	-0.473	-0.483	-0.195		-0.407	-0.487	-0.329	-0.303	-0.361	-0.457
loss	0.557	0.527	0.356	0.544	0.126	-0.414		0.781	0.484	0.553	0.560	0.471
$v(ROA)$	0.450	0.718	0.378	0.643	0.158	-0.337	0.564		0.525	0.578	0.657	0.612
$v(Opc)$	0.296	0.358	0.255	0.448	0.243	-0.277	0.482	0.525		0.655	0.413	0.384
$v(Sgrw)$	0.316	0.381	0.244	0.491	0.205	-0.267	0.528	0.578	0.650		0.397	0.401
Disc	0.405	0.836	0.472	0.497	0.164	-0.319	0.531	0.657	0.349	0.349		0.460
AQ	0.290	0.563	0.793	0.506	0.267	-0.424	0.438	0.612	0.278	0.285	0.469	

Table 5.4: ANR's correlations with proxies of firm characteristics

*Continued on next page*

Table 5.4

**Notes**

The Correlations are estimated based on 15,979 observations. Pearson (Spearman) correlations are below (above) the diagonal. All the p-values are smaller than 0.0001. Variances and means of firm-characteristics described below are estimated with annual data, over the 8-year rolling window used to estimate ANR.

*ATA* is total assets(Average #6). *CFO* is cash flows from operations adjusted for discontinued operations and deflated by *ATA* ( $\# 308 - \#124$ )/*ATA*.

*TAC* is total accruals deflated by *ATA* ( $\# 123 - CFO$ )/*ATA*.  $\Delta WCA$  is working capital accruals, calculated as:  $-(\#302+\#303 + \#304 + \#305 + \#307)/ATA$ .

*sales* is the mean of sales (#12), *size* is mean of log(TA), *loss* is the frequency of losses over the 8-year rolling window. *ROA* is return on assets ( $\#123/\#6$ ). *Opc* is length of operating cycle, calculated as:  $360/(\text{sales}/\text{Average } AR) + 360/(CGS)/(\text{Average } INV)$ , where *CGS* is cost of goods sold (#41), *AR* is accounts receivable (# 2), and *INV* is inventory (#3). *Sgrw* is mean sales growth, calculated as  $\log(\text{sales})-\log(\text{lag}(\text{sales}))$ .

As in Dechow and Dichev [2002], accruals quality (AQ) is estimated based on the following firm-specific regression:  $\Delta WC_t = \beta_0 + \beta_1 CFO_t + \beta_2 CFO_{t-1} + \beta_3 CFO_{t+1} + v_t$ . I calculate  $AQ_t$  as the firm-specific standard deviation of the residuals.  $AQ_t$  is calculated for all firms with non-missing data over the 8-year rolling window used to calculate ANR.

Tables 5.5, 5.6 and 5.7 report the results of the exploratory factor analysis. The factor model fits well. As table 5.6 reports, all the off-diagonal residual correlations are smaller than 0.033, and the overall root mean square of these residuals is 0.015.<sup>8</sup> In addition, as table 5.7 reports, all the off-diagonal partial correlations are smaller than 0.065, and their overall RMSE is 0.031.<sup>9</sup> As table 5.5 reports, the factor analysis identifies two factors that explain between 31.1% and 71.1% (on average, 52.5%) of the cross-sectional variation in the variables. As the communalities show, the factors explain 71.1% of the variation in ANR. A communality above 30% is significant.

I find the first factor, factor A, primarily underlies ANR, accounting discretion and smoothness, while the second factor, factor B underlies AQ,  $v(CFO)$ ,  $v(TAC)$ , and *size*. In a regression of standardized ANR on both factors, the loading on factor A is 0.822 while that on factor B is 0.050. This means that an increase in one standard deviation of factor A increases ANR by 0.822 standard deviations, while an increase of one standard deviation of factor B increases ANR by 0.05 standard deviations. Likewise, the standardized regression coefficients of *Disc* and *Smooth* on factor A (factor B) are 0.799 (-0.030) and -0.573 (0.041), respectively. Further, the correlations of ANR, *Disc* and *Smooth* with factor A (factor B) are 0.842 (0.388), 0.787 (0.299) and -0.556 (-0.195), respectively.

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<sup>8</sup> These residuals represent the differences between the estimated and observed correlations between pairs of variables. If the estimated correlations estimate the actual correlations precisely, all the off diagonal elements of the matrix, and their overall RMSE will be zero. Moderate (0.05 to 0.10) or large residuals ( $> 0.1$ ) suggest there may be more factors remaining to be extracted (Tabachnick and Fidell [2001]).

<sup>9</sup> Partial correlations are the correlations among variables, after controlling for the latent factors. If the identified factors explain the observed variables well, the off-diagonal partial correlations should be near-zero. If partial correlations are large ( $> 0.1$ ) either factors are not doing a good job of explaining the data, or more factors need to be extracted.

	Factor loadings		Correlation with factors		
Variable	Factor A	Factor B	Factor A	Factor B	Communalities
ANR	0.822	0.050	0.842	0.388	0.711
<i>Disc</i>	0.799	-0.030	0.787	0.299	0.619
<i>Smooth</i>	-0.573	0.041	-0.556	-0.195	0.311
AQ	0.024	0.694	0.309	0.704	0.496
<i>v(CFO)</i>	-0.035	0.769	0.281	0.755	0.571
<i>v(TAC)</i>	0.137	0.707	0.428	0.764	0.599
<i>size</i>	0.095	-0.638	-0.168	-0.599	0.367
	$corr(\text{Factor A}, \text{Factor B}) = -0.411$				Avg = 0.525

Table 5.5: Results of exploratory factor analysis

*Continued on next page*

## Table 5.5

### Notes

Table 5.5 reports the results of the exploratory factor analysis using ANR, accounting discretion (*Disc*), earnings smoothness (*Smooth*), accruals quality (AQ), the variance of cash flows from operations ( $v(CFO)$ ), the variance of total accruals ( $v(TAC)$ ) and firm size (*size*), based on a sample of 15,979 observations. Factor loadings are coefficient estimates in a regression of each variable on the two factors:

$$StdVar_{i,t} = a_0 + a_1 FactorA_{i,t} + a_2 FactorB_{i,t} + w_{i,t},$$

where *StdVar* is the placeholder for ANR, *Disc*, *Smooth*, AQ,  $v(CFO)$ ,  $v(TAC)$  or *size*, each standardized to have a variance of 1 (i.e., by subtracting the mean and dividing by the standard deviation); and  $a_1$  and  $a_2$  are factor loadings that capture the change, in standard deviations, in the dependent variable arising from a change of one standard deviation of the factor. The factors themselves are always standardized.

Table 5.5 also reports the Pearson correlations between factors and each standardized variable. *Communalities* refer to the proportion of variation in a variable that is explained by both factors combined.

Variable	AQ	ANR	$v(TAC)$	<i>Smooth</i>	<i>Disc</i>	$v(CFO)$	<i>size</i>
AQ	0.504	0.001	0.023	-0.027	-0.016	-0.024	-0.004
ANR	0.001	0.289	-0.011	-0.006	0.000	0.003	-0.011
$v(TAC)$	0.023	-0.011	0.401	0.011	0.016	0.002	0.033
<i>Smooth</i>	-0.027	-0.006	0.011	0.689	0.008	0.011	0.001
<i>Disc</i>	-0.016	0.000	0.016	0.008	0.381	0.002	0.010
$v(CFO)$	-0.024	0.003	0.002	0.011	0.002	0.429	-0.028
<i>size</i>	-0.004	-0.011	0.033	0.001	0.010	-0.028	0.633

Root Mean Square Off-Diagonal Residuals: Overall = 0.015

Table 5.6: Residual correlations with uniqueness on diagonal

### Notes

Table 5.6 reports the residuals from the exploratory factor analysis. Residuals are the differences between the fitted correlations and actual correlations. If the factors perfectly predict variables, then the correlations among fitted variables are identical to actual correlations and residuals are zero. Thus, off-diagonal residual correlations that are close to zero are indicative of good fit. The root mean square of the off-diagonal residuals is a summary measure of the overall magnitude of residuals, and is analogous to the RMSE of a regression.

Variable	AQ	ANR	$v(TAC)$	<i>Smooth</i>	<i>Disc</i>	$v(CFO)$	<i>size</i>
AQ	1.000	0.002	0.050	-0.045	-0.037	-0.052	-0.007
ANR	0.002	1.000	-0.031	-0.014	0.000	0.010	-0.027
$v(TAC)$	0.050	-0.031	1.000	0.021	0.041	0.006	0.065
<i>Smooth</i>	-0.045	-0.014	0.021	1.000	0.015	0.020	0.001
<i>Disc</i>	-0.037	0.000	0.041	0.015	1.000	0.005	0.020
$v(CFO)$	-0.052	0.010	0.006	0.020	0.005	1.000	-0.053
<i>size</i>	-0.007	-0.027	0.065	0.001	0.020	-0.053	1.000

Root Mean Square Off-Diagonal partial correlations: Overall = 0.031

Table 5.7: Partial correlations controlling for factors

### Notes

Table 5.7 reports the partial correlations from the exploratory factor analysis. Partial correlations are the correlations of the standardized variables conditional on the factors. The off-diagonal elements are therefore the correlations of the residuals obtained by regressing each standardized variable on both factors. If the factors are effective in explaining the variation in variables, these off-diagonal correlations will be small. The root mean square of the partial correlations is a summary measure of the overall magnitude of these correlations.



Tables 5.6, 5.7 and 5.8 collectively provide evidence of ANR's *convergent validity* with respect to accounting discretion and earnings smoothness. In contrast, I find that the standardized regression coefficients of AQ,  $v(CFO)$ ,  $v(TAC)$  and *size* on factor A (factor B) are 0.024 (0.694), -0.035 (0.769), 0.137 (0.707) and 0.095 (-0.638), respectively; while the correlations are 0.309 (0.0.704), 0.281 (0.755), 0.428 (0.768) and -0.168 (-0.599), respectively. Collectively, this result suggests that factor A captures the quality of accounting implementation, while factor B captures uncertainty in a firm's operating environment. The negative inter-factor correlation of -0.411 suggests that the quality of implementation decreases with uncertainty in the operating environment.

I find that the variables that correlate strongly with one factor correlate weakly with the other factor. Specifically, I document *divergent validity* between ANR and AQ, suggesting that ANR is distinct from AQ. Further, factor B, the factor that underlies size and the volatilities of accruals and cash flows, explains about 15% of the cross-sectional variation in ANR. In comparison, factor A, which underlies accounting discretion and earnings smoothness, explains about 70% of the variation in ANR.<sup>10</sup> Thus, this result also documents ANR's *divergent validity* with respect to size and the volatilities of accruals and cash flows. Given its denominator, ANR behaves as expected in the sense that its relation with the volatility in a firm's operating environment is not one-to-one.<sup>11</sup>

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<sup>10</sup> The square of the correlation between a factor and a variable gives the proportion of that variable's variance that is explained by the factor; that is,  $0.15 = 0.388^2$  and  $0.70 = 0.842^2$ .

<sup>11</sup> To see the underlying rationale, consider two weather forecast systems, one in a desert where it rarely rains, the other in an area where it sometimes rains. Suppose in one year, both systems wrongly predict the following day will be rainy on 20 occasions. While both systems have equivalent measurement error, the desert weather system is much less reliable since desert weather is not volatile and is relatively easy to predict. In contrast, rain in an area where it sometimes rains is difficult to predict, so getting it wrong on only 20 occasions in one year is evidence of a reliable system.

## 5.10 Sensitivity of ANR to differences in reliability of accrual components

Richardson et al. [2005, p. 448, table 1] propose an ordinal reliability ranking of accrual components, based on the authors' subjective assessment of the level of judgment involved in estimating each component. In this test, I estimate the relative reliability of accrual components, and assess the extent to which these measures match with Richardson et al's [2005] ordinal reliability ranking of accrual components.

If ANR is actually measuring reliability, the sensitivity of ANR to percentage changes in accrual components should indicate the components' relative reliability. The rationale is as follows. Measurement error is not homogeneous across accrual components. In particular, unreliable accrual components contribute more to the measurement error of total accruals than do reliable components. If accounts receivable contribute more to the measurement error of total accruals than does accounts payable, a percentage increase in accounts receivable should generate a bigger increase in ANR than does an equal percentage increase in accounts payable, *ceteris paribus*. I make the notion of a percentage change in an accrual component operational in two ways: (1) I deflate each accrual component with its corresponding average balance sheet item; and (2) I use the absolute value of the deflated accrual component since my focus is on percentage change irrespective of its sign. To assess the sensitivity of ANR to percentage changes in accrual components, I regress ANR on the absolute value of the deflated accrual components. If ANR measures the reliability of total accruals, I expect the estimated coefficient on low reliability components to be bigger than that on high reliability components.

I use Richardson et al's [2005] three-level balance sheet decomposition of accruals into components. The level 1 accrual components, denoted as:  $\Delta WC$ ,  $\Delta NCO$  and  $\Delta FIN$ , are the changes in working capital accruals, noncurrent operating accruals and financing accruals, respectively. In the second level, these components

are further disaggregated into changes in current operating assets and liabilities,  $\Delta COA$  and  $\Delta COL$ , respectively; changes in non-current operating assets and liabilities,  $\Delta NCOA$  and  $\Delta NCOL$  respectively; and changes in financial assets and liabilities,  $\Delta FINL$  and  $\Delta FINL$ , respectively. In the third level, working capital accruals are disaggregated into changes in accounts receivable, inventory, accounts payable and other net current assets,  $\Delta AR$ ,  $\Delta INV$ ,  $\Delta AP$  and  $\Delta OTHER$  are, respectively. Let  $T$  be the number of nonmissing observations for accrual component  $\Delta COMP$  over the 8-year rolling window used to estimate ANR. I define  $dCOMP_{i,t}$ , the mean common-sized percentage change of this component as:<sup>12</sup>

$$dCOMP_{i,t} = \frac{1}{T} \sum_{t-7}^t \left| \frac{\Delta COMP_{i,t}}{0.5 (COMP_{i,t} + COMP_{i,t-1})} \right|.$$

I infer the relative reliability of accrual components based on the relative magnitudes of coefficient estimates from the following three cross-sectional regressions:

$$ANR_{i,t} = \beta_0 + \beta_1 dWC_{i,t} + \beta_2 dNCO_{i,t} + \beta_3 dFIN_{i,t} + \xi_{i,t} \quad (5.6)$$

$$ANR_{i,t} = \alpha_0 + \alpha_1 dCOA_{i,t} + \alpha_2 dCOL_{i,t} + \alpha_3 dNCOA_{i,t} + \alpha_4 dNCOL_{i,t} + \alpha_5 dFINL_{i,t} + \eta_{i,t} \quad (5.7)$$

$$ANR_{i,t} = \lambda_0 + \lambda_1 dAR_{i,t} + \lambda_2 dINV_{i,t} + \lambda_3 dAP_{i,t} + \lambda_4 dOTHER_{i,t} + \lambda_5 dNCOA_{i,t} + \lambda_6 dNCOL_{i,t} + \lambda_7 dFINL_{i,t} + \eta_{i,t}. \quad (5.8)$$

Because the data needed to compute some accrual components are infrequently reported on Compustat's *quarterly* data, I use *annual* data to compute all explanatory variables. Further, because data on short-term and long-term investments are frequently zero or missing, I exclude financial assets in this analysis. To limit outliers, I omit observations in which the accrual component is greater or less than 5 times its corresponding average balance sheet item, yielding a sample of 20,280 firm-years.

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<sup>12</sup> For example,  $dINV_{i,t}$  is calculated as the mean of the ratio of change in inventory to average inventory, calculated over the 8-year window used to estimate ANR.

Table 5.8 reports the results of matching relative reliability to the ordinal reliability ranking of accrual components. All reported t-statistics are robust to heteroskedasticity. Overall, I find that ANR's sensitivity to cross-sectional unit changes in accrual components decreases with the components' ordinal reliability ranking.

The ordinal reliability ranking of noncurrent operating accruals ( $\Delta NCO$ ), working capital accruals ( $\Delta WC$ ) and financing accruals ( $\Delta FIN$ ) is, respectively, low/medium, medium and high. The estimated relative reliability, based on ANR's sensitivity to unit changes in these accrual components is, respectively, 0.1922, 0.0975 and 0.0211. In addition, the ordinal reliability ranking of changes in current operating assets ( $\Delta COA$ ), noncurrent operating assets ( $\Delta NCOA$ ), noncurrent operating liabilities ( $\Delta NCOL$ ), current operating liabilities ( $\Delta COL$ ) and financial liabilities ( $\Delta FINL$ ) is, respectively, low, low, medium, high and high. The estimated relative reliability for these accrual components is, respectively, 0.2620, 0.1223, 0.0681, -0.0367, -0.0144.

Finally, the ordinal reliability ranking of changes in accounts receivable ( $\Delta AR$ ), inventory ( $\Delta INV$ ), accounts payable ( $\Delta AP$ ), and net all other current assets ( $\Delta OTHER$ ) is, respectively, low, low, high and unknown (i.e., the ordinal reliability ranking for  $\Delta OTHER$  is unknown). The estimated relative reliability of these accrual components is, respectively, 0.1194, 0.0818, 0.0426 and -0.0030. The estimated relative reliability of  $\Delta NCOA$ ,  $\Delta NCOL$  and  $\Delta FINL$  is, respectively, 0.1142, 0.0622 and -0.0233. The  $R^2$  of the regressions is about 14%, meaning the explanatory variables explain about 14% of the cross-sectional variation in ANR. With the exception of the coefficient estimate on  $\Delta OTHER$ , all other coefficient estimates are statistically significant at the 5% level.

$$ANR_{i,t} = \beta_0 + \beta_1 dWC_{i,t} + \beta_2 dNCO_{i,t} + \beta_3 dFIN_{i,t} + \xi_{i,t} \quad (5.6)$$

Component	Ordinal Ranking	Relative reliability Est.		
	Rank	Coef.	Est.	t-stat
dNCO	low/med	$\beta_2$	0.1922	24.60
dWC	medium	$\beta_1$	0.0975	28.07
dFIN	high	$\beta_3$	0.0211	6.00
$R^2$			0.138	

$$ANR_{i,t} = \alpha_0 + \alpha_1 dCOA_{i,t} + \alpha_2 dCOL_{i,t} + \alpha_3 dNCOA_{i,t} + \alpha_4 dNCOL_{i,t} + \alpha_5 dFINL_{i,t} + \eta_{i,t} \quad (5.7)$$

Component	Ordinal Ranking	Relative reliability Est.		
	Rank	Coef.	Est.	t-stat
dCOA	low	$\alpha_1$	0.2620	17.05
dNCOA	low	$\alpha_3$	0.1223	8.57
dNCOL	medium	$\alpha_4$	0.0681	19.84
dCOL	high	$\alpha_2$	-0.0367	-2.11
dFINL	high	$\alpha_5$	-0.0144	-3.03
$R^2$			0.144	

$$ANR_{i,t} = \lambda_0 + \lambda_1 dAR_{i,t} + \lambda_2 dINV_{i,t} + \lambda_3 dAP_{i,t} + \lambda_4 dOTHER_{i,t} + \lambda_5 dNCOA_{i,t} + \lambda_6 dNCOL_{i,t} + \lambda_7 dFINL_{i,t} + \eta_{i,t} \quad (5.8)$$

Component	Ordinal Ranking	Relative reliability Est.		
	Rank	Coef.	Est.	t-stat
dNCOA	low	$\lambda_5$	0.1142	8.42
dAR	low	$\lambda_1$	0.1194	11.94
dINV	low	$\lambda_2$	0.0818	9.82
dNCOL	medium	$\lambda_6$	0.0622	17.92
dAP	high	$\lambda_3$	0.0426	3.44
dFINL	high	$\lambda_7$	-0.0233	-4.94
dOTHER	?	$\lambda_4$	0.003	-0.83
$R^2$			0.152	

Table 5.8: ANR's relation with subjective reliability assessments

*Continued on next page*

Table 5.8

**Notes**

Table 5.8 reports the results from estimating Equations (5.6), (5.7) and (5.8). The reported t-stats are robust to heteroskedasticity.  $ANR_t$  is calculated as specified in Equation (4.8). The explanatory variables in these regressions are the absolute values of unit changes in accrual components calculated using annual data, and averaged over the rolling 8-year window used to calculate ANR. Specifically, each accrual component,  $\Delta COMP_t$ , enters the estimated equation as:

$$dCOMP_{i,t} = \frac{1}{T} \sum_{t=7}^t \left| \frac{\Delta COMP_{i,t}}{0.5 (COMP_{i,t} + COMP_{i,t-1})} \right|,$$

where  $T$  is the number of firm-years with nonmissing  $dCOMP_{i,t}$  for firm  $i$ , over the 8-year estimation window.

To mitigate outliers, I omit observations in which an accrual component is either greater than 10 times or less than 10 times its corresponding balance sheet item. In addition, on a regression-specific basis, I omit observations in the top and bottom 1% of the distributions of each explanatory variable. Specific accrual component definitions are provided in Appendix A.

# Chapter 6

## Summary and conclusion

In this study, I develop a classical accrual measurement error model that estimates a firm-specific accrual noise ratio (ANR) as a measure of accrual reliability. The model's estimation requires the use of accrual instruments in small samples. To alleviate the concern of weak and endogenous instruments, I follow Lewbel [1997] and construct instruments based on the moments of a joint distribution of cash flows and accruals. Based on formal econometric tests, I identify a Lewbel instrument that outperforms accrual instruments based on accounting fundamentals (i.e., levels, changes, and lags of sales, cash flows and property, plant and equipment). This result alleviates the concern that ANR is a carryover from weak or endogenous instruments and suggests that Lewbel accrual instruments have the potential for wide applications in accounting research.

ANR varies across firms, and its estimation does not rely on the perceptions of participants in the financial reporting process. This is important because like reliability, perception is a latent construct. ANR is particularly useful in empirical research settings where: (1) reliability perceptions are unavailable (e.g., infrequently traded stocks); (2) assumptions about the way investors process accrual reliability are too restrictive; or (3) inference based on cross-sectional variation in accrual reliability is required.

I conduct a series of validity tests to assess the extent to which the underpinnings of ANR translate into a measure of reliability in an accounting sense. The intent is to validate whether ANR captures the extent to which reported total accruals deviate from ideal accounting criteria. I empirically document ANR's divergent and convergent validity. In addition, I find that the relation between ANR and other accounting constructs is consistent with the predictions of previous research. Further, the relative sensitivity of ANR to cross-sectional variation in accrual components is consistent with Richardson et al's [2005] subjective ranking of the reliability of accrual components. While I focus on the ANR of total accruals, a possible extension is to examine the effect of the determinants of accounting reliability on the reliability of specific accrual components.



# Appendix A

## Accrual component definitions

Variable	Definition
<i>CFO</i>	Cash flows from operations (# 308 - item24)
<i>TAC</i>	Total accruals, obtained as: $TAC = \#18 - CFO$
<i>COA</i>	Current operating assets: $COA = \#4 - \#1$
<b><math>\Delta COA</math></b>	<b>Change in current operating assets</b>
<i>COL</i>	Current operating liabilities: $COL = \#5 - \#34$
<b><math>\Delta COL</math></b>	<b>Change in current operating liabilities</b>
<b><i>WCA</i></b>	<b>Working capital accruals: <math>WCA = \Delta COA - \Delta COL</math></b>
<i>NCOA</i>	Noncurrent operating assets: $NCOA = \#6 - \#4 - \#32$
<b><math>\Delta NCOA</math></b>	<b>Change in noncurrent operating assets</b>
<i>NCOL</i>	Noncurrent operating liabilities: $NCOL = \#181 - \#5 - \#9$
<b><math>\Delta NCOL</math></b>	<b>Change in noncurrent operating liabilities</b>
<b><math>\Delta NCO</math></b>	<b>Noncurrent operating accruals: <math>\Delta NCOA - \Delta NCOL</math></b>
<i>FINA</i>	Financial assets: $FINA = \#193 + \#32$
<i>FINL</i>	Financial liability: $FINL = \#9 + \#34 + \#130$
<b><math>\Delta FIN</math></b>	<b>Financing accruals: <math>\Delta FINA - \Delta FINL</math></b>
<b><math>\Delta AR</math></b>	<b>Change in accounts receivable (# 302)</b>
<b><math>\Delta INV</math></b>	<b>Change in inventory (# 303)</b>
<b><math>\Delta AP</math></b>	<b>Change in accounts payable (# 304)</b>
<b><math>\Delta TP</math></b>	<b>Change in taxes payable (# 305)</b>
<b><math>\Delta OTHER</math></b>	<b>Change in net other current assets (# 307)</b>

The bold faced notation indicates accrual component, and the # notation refers to Compustat annual data item.

# Appendix B

## ANR derivation

This appendix formally derives ANR based on the instrumental variable estimation of the univariate accrual measurement error model described by Equations (18) and (19) above. Suppose a vector of suitable instruments,  $\mathbf{S} = \{IV_1, IV_2, \dots, IV_K\}$ , that is correlated with  $tac_t^*$ , but uncorrelated with either  $\varepsilon$  or  $u$ , were available. The first-stage regression, estimated by OLS, is:

$$tac_t = \alpha_0 + \boldsymbol{\alpha}_1 \mathbf{S}_t + \xi_t. \quad (\text{B.1})$$

Let  $\widehat{tac}_t$  be the fitted value of  $tac_t$  from Regression (31); the second-stage regression is given by:

$$cfo_{t+1} = \alpha_0 + \widehat{tac}_t \beta + u_t. \quad (\text{B.2})$$

The usual TSLS estimator,  $\beta_{TSLS}$ , is obtained as the OLS slope coefficient estimator in Equation (32).

Next, I draw on Carroll et al. [2006] to show how the TSLS estimator can be used as a correction-for-attenuation estimator to estimate the variance of accrual measurement error. Consider the following classical accrual measurement error:

$$cfo_{t+1} = Z_t \alpha + tac_t^* \beta + u_t \quad (\text{B.3})$$

$$tac_t = tac_t^* + \varepsilon_t, \quad (\text{B.4})$$

where  $Z_t$  is an exogenous (i.e. uncorrelated with  $u_t$ ) explanatory variable (in a univariate regression,  $Z_t$  is a column of ones), and all other variables are as previously defined. The OLS estimator

consistently estimates *not* the true coefficients  $\alpha$  and  $\beta$ , but rather:

$$\begin{pmatrix} \tilde{\beta} \\ \tilde{\alpha} \end{pmatrix} = \begin{pmatrix} \sum_{tac,tac} + \sum_{\varepsilon,\varepsilon} & \sum_{tac,z} \\ \sum_{z,tac} & \sum_{z,z} \end{pmatrix}^{-1} \left\{ \begin{pmatrix} \sum_{tac,tac} & \sum_{tac,z} \\ \sum_{z,tac} & \sum_{z,z} \end{pmatrix} \begin{pmatrix} \beta \\ \alpha \end{pmatrix} + \begin{pmatrix} \sum_{u,\varepsilon} \\ 0 \end{pmatrix} \right\}, \quad (\text{B.5})$$

where  $\sum_{A,B}$  is the *population* covariance between random variables A and B. Thus, the OLS estimator is attenuated and inconsistent. Assume that  $\sum_{\varepsilon,\varepsilon}$  were known, and the classical assumption that  $\sum_{u,\varepsilon} = 0$  holds. Further, let  $S_{A,B}$  be the *sample* covariance between A and B. The method-of-moments estimator is a correction-for-attenuation estimator, and is given by:

$$\begin{pmatrix} S_{tac,tac} - S_{\varepsilon,\varepsilon} & S_{tac,z} \\ S_{z,tac} & S_{z,z} \end{pmatrix}^{-1} \begin{pmatrix} S_{tac,tac} \\ S_{z,cfo_{t+1}} \end{pmatrix}. \quad (\text{B.6})$$

The TSLS estimator is a special case of the method-moments-estimator. Carroll et al. [2004] and Lewbel [1997] use the TSLS estimator as a correction-for-attenuation estimator. Thus:

$$\begin{pmatrix} \beta_{TSLS} \\ \alpha_{TSLS} \end{pmatrix} = \begin{pmatrix} S_{tac,tac} - S_{\varepsilon,\varepsilon} & S_{tac,z} \\ S_{z,tac} & S_{z,z} \end{pmatrix}^{-1} \begin{pmatrix} S_{tac,cfo_{t+1}} \\ S_{z,cfo_{t+1}} \end{pmatrix}. \quad (\text{B.7})$$

Equation (37) can be rewritten as:

$$\begin{pmatrix} S_{tac,tac} - S_{\varepsilon,\varepsilon} & S_{tac,z} \\ S_{z,tac} & S_{z,z} \end{pmatrix} \begin{pmatrix} \beta_{TSLS} \\ \alpha_{TSLS} \end{pmatrix} = \begin{pmatrix} S_{tac,cfo_{t+1}} \\ S_{z,cfo_{t+1}} \end{pmatrix}. \quad (\text{B.8})$$

The approximate sample variance of accrual measurement error,  $S_{\varepsilon,\varepsilon}$ , is now estimable as:

$$\beta_{TSLS} S_{tac,tac} - \beta_{TSLS} S_{\varepsilon,\varepsilon} + \alpha_{TSLS} S_{tac,z} = S_{tac,cfo_{t+1}}.$$

In the special case of a univariate regression,  $Z_t$  is a column of ones, meaning that  $S_{tac,z} = 0$ .

Since  $S_{tac,tac} = \text{var}(tac)$ ,  $S_{\varepsilon,\varepsilon} = \text{var}(\varepsilon)$  and  $S_{tac,cfo_{t+1}} = \text{cov}(tac, cfo_{t+1})$ , it follows that:

$$\hat{\text{var}}(\varepsilon) = \text{var}(tac) - \frac{\text{cov}(cfo_{t+1}, tac_t)}{\beta_{TSLS}}. \quad (\text{B.9})$$

Thus, equation (39) provides the numerator of ANR, in Equation (15).

As Equation (15) shows, the denominator of ANR is  $var(TAC)$  and *NOT*  $var(tac)$ . Recall that  $tac_t = TAC_t - \theta_{tac}CFO_t$ . As such:

$$var(TAC) = var(tac) + \theta_{tac}var(CFO_t)\theta_{tac} + 2cov(tac_t, CFO_t).$$

However, since  $tac_t$  are residuals from an OLS regression of  $TAC_t$  on  $CFO_t$  as described in Equation (17), it follows that:  $cov(tac_t, CFO_t) = 0$ . Accordingly, ANR's denominator is:

$$var(TAC) = \theta_{tac}var(CFO_t)\theta_{tac} + var(tac),$$

as in the denominator of Equation (4.8).

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