
What kind of earnings shape more market expectations?

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Abstract We study how earnings attributes affect investors expectations about future earnings reflected in market prices. We separate the contribution of current earnings to price setting through a valuation incorporating expectations informed only by the current value of earnings. Its pricing error measures the extent to which expectations are shaped by information other than current earnings.

We estimate the association between this pricing error and eleven earnings quality constructs commonly used in the empirical literature using a large sample of US non-financial firms over the period 1971-2014.

We find that, above all, quality earnings vary little (are sustainable) and are predictive of future earnings. Moreover, their low volatility is shared

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by their accrual component and is not due to aggressive smoothing. We document that time-series accrual quality proxies subsume measures based on popular residual accruals models in shaping expectations. How often firms report special items has a significant impact on current earnings relevance to expectation formation: the less often, the better.

Keywords Non-linear association · expectation formation pertinence · earnings quality · non-parametric regression

1 Introduction

We investigate the association between accounting earnings quality constructs and the usefulness of current earnings to the formation of investor's expectations of future abnormal earnings reflected in market prices. Specifically, we analyze the extent to which favorable values of eleven earnings quality constructs command smaller pricing errors in a specification of the Residual Income (RI) valuation model which emphasizes expectations informed only by the current value of earnings. The constructs we consider are suggested by prior research as capturing desirable features of earnings. Our research design formalizes the intuition that "better" (realized) earnings project future earnings more reliably and, hence, form the basis of a more accurate valuation. That is, their pertinence to the expectation formation process is higher.

Although earnings are relevant to stakeholders other than equity investors, recent survey evidence reveals that the valuation role dominates every other use of reported earnings¹ (Dichev et al (2013)). The precedence

¹ Nearly 95% of public company CFOs interviewed by Dichev et al (2013) consider earnings to be important to very important for investors in valuing their company.

of the valuation role is consistent with previous surveys of investors, analysts, and financial executives, with a long stream of research in capital markets (see, for example, Kothari (2001)), and with the expressed goals of standard setters.

The underlying assumption of our study is that, while earnings are a foremost source of firm specific information, the expectations about future earnings impounded in prices take into account other information in addition to observed earnings. Empirical research (Francis et al (2003), Liu et al (2002)) shows that investors rely on earnings more than on any other performance summary measure. Moreover, survey results point out that managers view earnings as the key measure assessed by investors and analysts (Graham et al (2005), Dichev et al (2013)). As such, their quality should play a prime role in the process of investors' expectation formation. However, the information shaping expectations about future earnings is not limited to observed earnings values. Alternative information might encompass from analysts' forecasts of next period earnings to firm's production and investment decisions and affect earnings expectations over horizons reaching from one or two periods to far in the future.

In the taxonomy of previous accounting research on earnings attributes, we consider "accounting-based" constructs². The quality constructs under investigation are: volatility and predictability of earnings, smoothness of cash flow and accruals, accrual quality measures based on residual accruals models, a measure of relative conservatism as well as the proportion of years with non-zero special items (SPI) in the most recent past.

Our study attempts to identify the distinct, un-biased impact on expectation formation process of *each* quality proxy under discussion. It is empirical

² Accounting-based attributes are measured using accounting information only.

and complements the scarce relevant theoretical literature. As a first step, we check if less favorable values of earnings constructs identified by prior research as desirable are associated to lower pertinence to the expectation formation process expressed in market prices. Then, in a *conditional analysis*, we test whether earnings attributes have a distinct impact on expectations or whether one or more attributes subsumes the others. The comprehensive analysis we conduct is made possible by two novel methodological aspects.

The first one regards the empirical implementation of the RI model for the purpose of hypothesis testing. We employ the novel perspective introduced in Kang and Starica (2016). For a given set of RI predictors, the approach consistently decomposes prices into a part that amounts to a valuation based on the observed values of the predictors and a correction due to other information. The magnitude of the pricing error measures the extent to which market prices are determined by other information than the current values of the predictors set.

From a methodological point of view this fact suggests the use of the absolute value of the pricing error as the dependent variable in the multiple regression which aims at disentangling the levels of association between prices and the various earnings quality constructs. From a semantic point of view, it motivates the interchangeable use of the expressions 'association between prices and accounting variables' and 'expectation formation pertinence of accounting variables'.

The novel approach is instrumental for a number of reasons. First, it is truthful to the economic relation specified by the RI model. By inferring how observable data are employed to form expectations about future abnormal earnings directly from data, it eliminates the likelihood of misspecifying the mechanism of expectation formation through unfitting assumptions. Second,

it is statistically coherent. It consistently estimate the subjacent economic relation of the RI model. Third, it is flexible. It can be used to analyze the association with prices of any accounting variable or set of variables that are relevant to projections of future abnormal earnings. Forth, it is intuitive. It's measure of the strength of the association between prices and earnings is a valuation error. Last but not least, it is suitable for conditional analyses: one can directly regress the association measure, the absolute value of a pricing error, on several quality proxies. Such regressions address the omitted variable bias in the individual analyses.

The second unconventional methodological aspect of our study concerns the implementation of the conditional analysis at the core of our investigation. As the assumption of a linear relation between the levels of quality constructs and their degree of pertinence to the price formation process is not plausible³, we make an atypical use of the linear regression as a tool for *testing differences in mean*. We convert the numerical values of the quality constructs in level indicators and test if firms with values of quality proxies under/above the median are priced more/less accurately by the non-linear valuation regression. Moreover, we employ a carefully designed set of alternative specifications to address the omitted variable bias in testing for the pertinence of earnings attributes *conditional on the others*.

We find that volatility and linear predictability of earnings seem to measure the same characteristic. Earnings volatility has the strongest relative relevance among all constructs. We contribute to the literature on the information content of earnings with respect to cash flows by documenting that earnings volatility subsumes cash flow volatility in shaping the expectations impounded in prices. We extend the literature on whether the smoothness

³ In section 6 we bring empirical evidence of significant non-linear relation between the expectation formation pertinence measure and the different quality proxies under study.

of a firm's earnings reflects variation in informativeness about fundamental performance by bringing empirical evidence that earnings that are extremely smooth relative to cash flows contribute less to shaping investors' expectations about future earnings impounded in prices. We add to the literature on the empirical validity of residual accrual models by establishing that simple time-series accrual quality proxies, such as accrual volatility and the correlation between accruals and cash flows, shape expectations beyond constructs based on widely used residual accrual models. Finally, we document that how often firms report special items has a significant impact on current earnings relevance to expectation formation: the less often, the better.

We are not aware of other references that *jointly* compare earnings quality measures with respect to their *impact on the expectation formation process impounded in prices*. On one hand, the pertinent theoretical literature is scarce and produces mixed results (e.g., Ewert and Wagenhofer (2012)). On the other hand, none of the few empirical studies investigating the impact of a broad set of earnings quality constructs on investors' resource allocation decisions focuses directly on the association with market value (Dechow et al (2010)). In a typical example, Francis et al (2004) look at seven quality measures and their association with the cost of equity capital measures. Finally, Perotti and Wagenhofer (2014), the study closest to ours, while investigating the association of a large (eight) number of earnings quality measures with a market value measure of relevance⁴, cannot perform a joint analysis due to methodological limitations. The study evaluates the association between the quality constructs and absolute excess returns using a hedge portfolio, an approach which fits neither the need to control for the many factors that might have an impact on the variability of the absolute excess returns nor

⁴ They use the absolute excess returns as a proxy for stock mispricing due to lower-quality information.

the requirements of an exhaustive conditional analysis needed to address the omitted variable bias. As a result, the authors are able to carry out only a very limited conditional analysis using at most two constructs at a time.

Our results are robust to a battery of sensitivity tests, including alternative econometric specifications, statistical estimations (alternative sample construction and alternative estimation techniques) and alternative measures of some earnings constructs.

2 An alternative perspective on the empirical implementation of the RIM

This section summarizes the approach to implementing the RI model in Kang and Starica (2016). They show that the RI valuation relation can be put in contact with observed data directly, without *a priori* assumptions on how current values project future abnormal earnings. For any given set of predictors of future residual earnings, they prove the existence of a specification of the RI valuation model that decomposes the price into a part that amounts to a valuation informed only by the observed values of the predictors and a left-over part that amounts to a pricing correction due to other information available to market participants. Consequently, the size of the correction is an indication of the extent to which future expectations incorporated in prices are shaped by information other than the observed levels of the given predictors.

The specifications are regressions, i.e., the left-over term is orthogonal (uncorrelated) to the predictor variables. Thus, these expressions of the RI valuation relation can be consistently estimated using proven techniques from the field of non-parametric regression. Their inference is theoretically guaranteed to be free of omitted variable bias.

2.1 Regression specifications of the RI valuation model

The RI valuation relation (Preinreich (1936) and (1938), Edwards and Bell (1961), Peasnell (1982)), expresses the value of firm i at time 0, as the book value (B) plus discounted future expected abnormal earnings ($NI - r \times B_{-1}$):

$$\begin{aligned} P_{i,0} &= B_{i,0} + \sum_{t=1}^{\infty} \frac{\mathbb{E}_0[NI_{i,t} - r_{i,0} \times B_{t-1}]}{(1 + r_{i,0})^t} = B_i + \sum_{t=1}^{\infty} \frac{\mathbb{E}_0[RI_{i,t}]}{(1 + r_{i,0})^t} \quad (1) \\ &= B_{i,0} \left(1 + \sum_{t=1}^{\infty} \frac{\mathbb{E}_0[RI_{i,t}/B_i]}{(1 + r_{i,0})^t} \right), \end{aligned}$$

(r_0 denotes the price of equity risk at time 0 while \mathbb{E}_0 stands for market's expectation conditional on all information available at time 0).

Denote by PREDICT.RI_0 a set of predictors of future residual earnings available at time 0. These include, but are not limited to, current values of drivers or components of drivers of residual income. By drivers of RI we mean the accounting profitability, ROE and growth in book. A representative example⁵ would be $\text{PREDICT.RI}_0 = (ROE_0, B_0/B_{-1})$, the pair of realized accounting profitability and realized book growth. With this notation, the main result in Kang and Starica (2016) can be stated as follows.

Proposition 1 (Theoretical frame of expectation formation pertinence).

1. For any set of predictors of future RI , there exists a specification of the RI valuation model that is a regression⁶ of prices on the observed values of the predictors

⁵ For more examples of sets of predictors, see Kang and Starica (2016).

⁶ The decomposition:

$$Y = f(X) + \epsilon$$

is called a *regression* if and only if

$$f(X) = \mathbb{E}[Y|X]$$

Suppose prices are given by equation (1) and let **PREDICT.RI** be a set of predictors of the future residual earnings (as specified above). Then there exist $\mathbf{m}_{i,0}$ and $\mathbf{m}_{i,0}$, two possibly non-linear, firm-specific functions and $\varepsilon_{i,0}$ and $\epsilon_{i,0}$, two error terms, such that:

$$P_{i,0} - B_{i,0} = \mathbf{m}_{i,0}(\text{PREDICT.RI}_{i,0} ; B_{i,0}, r_{i,0}) + \varepsilon_{i,0} \quad (2)$$

and

$$P_{i,0}/B_{i,0} - 1 = \mathbf{m}_{i,0}(\text{PREDICT.RI}_{i,0} ; r_{i,0}) + \epsilon_{i,0}, \quad (3)$$

where

$$\mathbb{E}[\varepsilon_{i,0} | \text{PREDICT.RI}_{i,0}] = 0 \quad \text{and} \quad \mathbb{E}[\epsilon_{i,0} | \text{PREDICT.RI}_{i,0}] = 0. \quad (4)$$

The functions $\mathbf{m}_{i,0}$ and $\mathbf{m}_{i,0}$ are specific to the set **PREDICT.RI**.

2. The regression functions are valuations incorporating expectations shaped only by the current values of the predictors

Moreover,

$$\mathbf{m}_{i,0}(\text{PREDICT.RI}_{i,0} ; B_{i,0}, r_{i,0}) := \sum_{t=1}^{\infty} \frac{\mathbb{E}[RI_{i,t} | \text{PREDICT.RI}_{i,0}]}{(1 + r_{i,0})^t}$$

and

$$\mathbf{m}_{i,0}(\text{PREDICT.RI}_{i,0} ; r_{i,0}) := \sum_{t=1}^{\infty} \frac{\mathbb{E}[RI_{i,t}/B_{i,0} | \text{PREDICT.RI}_{i,0}]}{(1 + r_{i,0})^t},$$

or equivalently, if the orthogonality condition

$$\mathbb{E}[\epsilon | X] = 0$$

holds.

i.e. the regression function in the decomposition (2) and (3) represent a valuation incorporating expectations of future abnormal earnings formed only on the basis of the current values of the predictors PREDICT.RI.

3. The error term is a measure of expectation formation pertinence of the predictors set

The error terms in the decomposition (2) and (3), $\varepsilon_{i,0}$ and $\epsilon_{i,0}$, amount to a correction due to other available information to a price set upon expectations shaped only by the observed values of the predictors PREDICT.RI. As such, their sizes reflect the extent to which these values inform the expectations of future earnings incorporated in prices.

The notation $\mathbf{m}_{i,0}(\cdot ; \cdot)$ and $\mathbf{m}_{i,0}(\cdot ; \cdot)$ in (2) and (3) emphasizes the fact that the regression functions depend both on a number of variables and on a number of parameters. The variables, that is PREDICT.RI_{*i,0*}, are listed before the semicolon while the parameters, ($B_{i,0}, r_{i,0}$) for $\mathbf{m}_{i,0}$ and $r_{i,0}$ for $\mathbf{m}_{i,0}$, are listed after. Moreover, the regression functions are predictor-set specific.

Kang and Starica (2016) further argue that one can assume that the (non-linear) functions $\mathbf{m}_{i,0}/\mathbf{m}_{i,0}$ for firms i in the *same industry I and of similar size S* are approximately equal:

$$\mathbf{m}_{i,0}(\cdot) \approx \mathbf{m}_{I,0}(\cdot ; S_i) \quad \text{and} \quad \mathbf{m}_{i,0}(\cdot) \approx \mathbf{m}_{I,0}(\cdot ; S_i), \quad i \in I.$$

This assumption has two consequences. First, it allows for consistent estimation of $\mathbf{m}_{I,0}/\mathbf{m}_{I,0}$ in cross-sections⁷. Second, it indicates the need to include

⁷ Without the relative constancy of the function $\mathbf{m}_{i,0}$ on industries, one needs to estimate it from the time-series of individual firm observations which would strongly bias the sample towards survivor firms. The industry-approach requires only a sufficient size cross-section of firms in a given industry at a given point in time. A second viable option estimates $\mathbf{m}_{I,0}/\mathbf{m}_{i,0}$ on a the panel-type sample combining time series with cross-sectional

size and the level of conservative accounting as extra parameters in the valuation regression functions when inferred cross-sectionally.

The literature on non-parametric regressions shows that conditions (4) guarantee that the specifications of the RI valuation model in (2) and (3) can be *consistently* estimated (Györfi et al (2002)). The issue of omitted variable bias is structurally ruled out.

Corollary 1 (Consistent estimation of economic relation in RI model).

The functions $\mathbf{m}_{i,0}$ and $\mathbf{m}_{i,0}$ in the regression specifications of the RI valuation model (2) and (3) can be consistently estimated using proven methods from the field of non-parametric regression.

The non-parametric estimation techniques are presented in section 4.1.

2.2 Regression error size as measure of price association

Proposition 1 indicates that the contribution of the set of predictors PREDICT.RI to expectation formation is reflected in the size of the error term:

$$\left| \frac{P_{0,i} - B_{0,i} - \hat{\mathbf{m}}_{i,0}}{P_{0,i}} \right| \quad \text{and} \quad \left| \frac{P_{0,i} - B_{0,i} \times (1 + \hat{\mathbf{m}}_{i,0})}{P_{0,i}} \right|,$$

respectively (where $\hat{\mathbf{m}}_{i,0}$ and $\hat{\mathbf{m}}_{i,0}$ denote estimates of $\mathbf{m}_{i,0}$ and $\mathbf{m}_{i,0}$, respectively). The relative error represents the proportion of the price corresponding to earnings expectations shaped by information *other* than the observed values of the predictors PREDICT.RI.

Measuring the association between prices and the observed predictor set by the size of the error term is instrumental in disentangling the effects of the observations. One achieves this way a sample that is large enough for statistical precision limiting nevertheless the issue of the survival bias.

many earnings attributes under discussion. It allows us to perform multiple regressions of the absolute values of the relative error on earnings quality constructs (see Section 7.2).

2.3 Predictor choice for earnings attributes study

Simple predictors of the *RI* drivers in proposition 1 include (but are not limited to) the realized value of accounting profitability, $ROE_{i,0}$, as a predictor of future profitability, the realized earnings, $NI_{i,0}$, as a predictor of future earnings or the realized book growth $B_{i,0}/B_{i,-1}$ as a forecast of future book growth.

The set of predictors needs to be chosen according to the research task. Since our aim is to separate the price impact of the current earnings from the contribution of other information, for the analyses in this paper, we specify the $P - B$ valuation regression in (2) as:

$$P_{i,0} - B_{i,0} = \mathbf{m}_{I,0}(NI_{i,0}; B_{i,0}, r_{i,0}, S_{i,0}) + \varepsilon_{i,0},$$

while the P/B valuation regression in (3) looks like:

$$P_{i,0}/B_{i,0} - 1 = \mathbf{m}_{I,0}(ROE_{i,0}; r_{i,0}, S_{i,0}) + \epsilon_{i,0},$$

where S stands for size (measured by market value, Sales or Total Assets).

3 Earnings quality: constructs and empirical questions

The concept of earnings quality is an expression of the general principle that financial reports should inform the resource allocation decisions of investors

and other capital providers. High-quality earnings should improve decision making and, hence, the efficiency of capital markets.

There is no generally accepted measure of earnings quality, but the accounting literature has developed a variety of proxies focusing on particular constructs. We investigate eleven earnings quality measures commonly used in the empirical literature.

Earnings properties are affected by the volatility of operations, the economic environment and the accounting systems employed. The quality measures we consider intend to capture all these factors. They include three type of constructs (e.g., Schipper and Vincent (2003)). The first group is derived from time-series properties of earnings and its components, i.e. cash flow and accruals, and lists the volatility of earnings, cash flow and accruals, predictability of earnings, three measures of the smoothing role of earnings and a measure of the frequency of reporting special items. The second type of constructs are derived from the relations among income, accruals, and cash. It includes a measure of accrual quality obtained from estimation of accruals-to-cash relations (Dechow and Dichev (2002)) and a direct estimation of unexpected (discretionary) accruals using accounting fundamentals (Jones (1991), Kothari et al (2005)). The third type corresponds to the implementation of the accounting rules and includes a measure of relative conservatism. Details on how these measures are empirically constructed are provided in section 5.2.

Sections 3.1, 3.2, 3.3 and 3.4 review previous research and theoretical considerations motivating the likely impact of individual quality proxies under study on the formation of expectations about future income streams. However, our study does not focus on individual constructs separately but looks at them *jointly*. We aim at identifying which constructs have a *significant*,

*unbiased*⁸ impact on the expectation formation process in a *joint analysis* of constructs that might shape investors expectations about future earnings. Since we are not aware of any theoretical grounding that disentangles the effects of different quality constructs on expectations formation, we do not formulate any beforehand hypotheses and address this issue empirically. The farthest-reaching *empirical question* we deal with can be formulated as:

Main EQ : *Identify the constructs with a significant, unbiased impact on expectation formation pertinence in a joint analysis of earnings quality proxies.*

The main empirical question formulated above will be articulated in a number of specific issues of particular relevance to the discourse on earnings quality to be stated as we introduce the quality constructs.

3.1 Earnings quality constructs derived from time-series properties of earnings

Time-series constructs associated with earnings commonly include persistence, predictive ability and volatility (or variability). Empirical evidence indicates that investors prefer smooth earnings in making capital allocation decisions. For instance, low earnings volatility is associated with greater analyst following (Lang et al (2003)) and a larger number of institutional investors (Badrinath et al (1989))

Volatility, defined as the (unconditional) standard deviation of earnings, $\sigma(NI)$, can be seen as measuring the accuracy of predicting next period

⁸ Since the quality proxies are correlated, apparently significant expectation formation pertinence of a construct from an individual analysis could be due to statistical bias caused by omitting the truly relevant proxy from the analysis and not to expectations being shaped by the construct under study.

earnings by a constant, the mean value of earnings. Less volatile earnings should be easier to forecast forming the basis for more accurate expectations of future income streams.

Most previous studies that discuss the valuation implications of earnings volatility focused on the relation between volatility and the cost of capital. In a survey of research relating accounting numbers to systematic risk, Ryan (1997) argued that earnings variability has been the accounting variable most strongly related to systematic equity risk. Our analysis offers another perspective on the issue as we focus on the expectation formation relevance of the construct.

While volatility admits a model-free definition, the constructs of persistence and predictability are usually model-based. Most studies investigating the impact of realized earnings on expectation formation (many of them part of the extensive literature on earnings response coefficients) commonly assume that earnings follow an auto-regressive process (Beaver et al (1980), Kormendi and Lipe (1987), Collins and Kothari (1989), Ali and Zarowin (1992a), Ali and Zarowin (1992b), Ball and Bartov (1996), Burgstahler et al (2002), among others) and define persistence as the parameter that captures the extent to which the current period innovation e_t becomes a permanent part of the earnings series.

The important simplifying assumption embodied in the auto-regressive structure of earnings is that the information available to the market in forecasting future earnings is reasonably approximated by a linear univariate time-series model of earnings. In other words, market uses *only* the information contained in realized earnings to construct expectations about future earnings. Moreover, the expectations are a linear function of realized earnings.

Even when other information is considered (as it is the case of Lipe (1990)), its restrictive definition⁹ (allowing only for a prediction of next period earnings) together with the linear assumptions on the evolution of earnings yield oversimplified models in which changes in future expectations are fully determined by revised expectations of at most two¹⁰ earnings shocks: e_t and e_{t+1} . In other words, the model assumes that all expectation formation-relevant knowledge revealed at time t provides no new information about the earnings shocks in period $t + 2$ or thereafter. This set-up excludes, for example, the probable event that information revealed at time t is likely to affect not only e_t and e_{t+1} but the earnings shocks of all future periods (e.g., announcements of an investment or acquisition decision).

Such simplifying assumptions stand in contrast with the more general frame of our study. First, we expressly assume that future earnings expectations are based on more information than just realized earnings. Our measure of pertinence gauges exactly the impact of other information than the values of earnings. The impact of information that goes beyond income numbers shapes the expectations of future earnings in complex ways.

Second, we see no good motivation (besides modeling convenience) to assume that contribution of current earnings to future earnings expectations is linear and we expressly allow for non-linearities in this relation. As such, the notion of persistence, *defined as a parameter of a linear mechanism of expectation formation including only past earnings values*, is of little relevance to our analysis.

⁹ The definition other information I_t , $I_t = NI_{t+1} + w_{t+1}$, is extremely reduced in scope as it only models the analysts prediction of next period earnings (w is a white noise).

¹⁰ In the case when only the earnings dynamics is responsible for the formation of future expectations, changes in future expectations are fully determined by revisions of the expectations on one single earning shock e_t .

Predictability is often introduced in the frame of an $AR(1)$ model of earnings:

$$NI_t = a + bNI_{t-1} + u_t,$$

where $-1 < b \leq 1$, u is a white noise satisfying $\mathbb{E}[u_t|NI_{t-1}] = 0$ or, even more restrictively, $\mathbb{E}_{t-1}(u_t) = 0$ (Lipe (1990), Dechow et al (2010), Francis et al (2004), Perotti and Wagenhofer (2014) among others). It is defined as the standard deviation of the innovation series u .

To avoid the over-simplifying assumption of a linear dynamics of earnings, we interpret the $AR(1)$ expression above as the decomposition of the next period earnings NI_t in the best linear prediction of by current period earnings $a + bNI_{t-1}$ plus error u_t . The best linear predictor exists for any pair (NI_{t-1}, NI_t) , independent of the type of dynamics followed by its elements.

In this interpretation, the linear relation between future and current earnings is not necessarily a regression, i.e. $\mathbb{E}[u_t|NI_{t-1}]$ need not be 0, and it does not define an $AR(1)$ process. Moreover, the coefficient b does not have a particular meaning and there is no claim about its consistent estimation. As such, no tests can be performed on it. The only quantity of interest is the variability of the error term u . The standard deviation of u measures the precision of the best linear predictor of next period earnings by current period earnings and is our measure of linear predictability. Section 11.1 in the Appendix gives more formal details on the substantial difference between the two interpretations.

Earnings that are better predicted by simple functions of realized earnings should be easier to forecast. Enhanced forecast accuracy facilitates the formation of expectations about future earnings. In particular, predictability is considered a desirable attribute of earnings by both standard setters and

analysts: it is an element of relevance in the FASBs Conceptual Framework and is an essential component of valuation (see Lee (1999) for a discussion).

Our results shed light on the relation between volatility and linear predictability as defined above. They indicate, first, that volatility and linear predictability are two highly correlated constructs (in our sample their correlation is 0.96). As such, they can be used interchangeably and are, practically, two equivalent measures of one earnings characteristic (that we refer to as *earnings predictability*). Second, they show that this characteristic has a strong impact on the expectation formation.

3.2 Earnings quality constructs derived from time-series properties of the components of earnings (cash flows and accruals)

Earnings variability naturally decomposes into the variability of cash flows (economic variability), the variability of accruals (accounting variability) and a term determined by their correlation¹¹ (the smoothing effect of accruals on cash flows). If earnings variability is relevant to the expectation formation, it is of interest to determine how do the three components articulate with each other to yield the better pricing accuracy associated with smoother income streams.

Two already well-researched themes are pertinent to this issue. First is the information content of earnings with respect to cash flows. While a basic tenet of accrual accounting is that the timing effect of accruals render earnings more informative about performance than cash flows, the results from the literature are mixed (Dechow et al (2010)). On one hand, research using market values as benchmark yields consistent results confirming that earnings

¹¹ As a natural result of the timing role of accruals, contemporaneous accruals and cash flows are negatively correlated (Dechow (1994)).

are more useful measure than cash flows at reflecting value (Penman and Sougiannis (1998), Ball and Brown (1968), Dechow et al (2010)). On the other hand, when researchers infer the relative ability of earnings and cash flows to shape expected future cash flow expectations using non-market based measures, the results are "contextual and dependent on research design and variable definitions". Our analysis contributes to this literature strand by investigating the following *specific empirical question*:

EQ1 : *Determine the relative expectation formation pertinence of volatility of cash flow and earnings.*

Our results indicate that earnings volatility subsumes cash flow volatility in shaping the expectations impounded in prices. They support the hypothesis of a greater information content of earnings with respect to cash flows and are in line with the findings of previous research that uses market value as the benchmark for the comparison.

The second theme is whether the smoothness of a firms earnings reflects variation in informativeness about fundamental performance. Earnings smoothness *per se* is an indication of neither greater decision usefulness nor higher earnings quality. The accruals might increase the information content of cash flows through smoothing timing fluctuations in cash payments and receipts or if managers use the discretion in the accounting to communicate their assessment of firms future profitability (Chaney and Lewis (1995)). However, through their smoothing effect they might hide the measurement of changes in fundamental performance, potentially decision-useful if revealed. In particular, income smoothing by accruals might make earnings noisier if the income numbers are intentionally distorted (Leuz et al (2003), Healy (1985), Fudenberg and Tirole (1995)).

The trade-off between the two contrasting effects is studied by the so-called *consequences studies* (Dechow et al (2010)), which "examine the relation between smoothness and decision outcomes such as equity market consequences". The use of discretionary accruals to smooth earnings seem associated with more informative earnings, although the number of studies dedicated to this issue is fairly limited (Tucker and Zarowin (2006), Subramanyam (1996)). Dechow et al (2010) concludes that "whether smoothness indicates greater decision usefulness is very much an open question". We contribute to this literature by investigating our *second specific empirical question*:

EQ2 : *Determine the impact of the smoothing effect of accruals on expectation formation.*

Our results indicate that, holding earnings and cash flow variability constant, the smoothing effect of accruals, measured by the correlation between cash flows and total accruals¹², is negatively related to the expectation formation pertinence of earnings. Earnings that are extremely smooth relative to cash flows contribute less to shaping investors expectations about future earnings impounded in prices.

3.3 Earnings Quality Constructs Derived from the Relations among Income, Accruals, and Cash

The two measures that fall under this category are derived from residual accruals models. The first stems from the decomposition of the accruals into "normal" and unexpected (or discretionary) accruals typically involving a

¹² A whole strand of literature associates strong negative correlation between cash flows and accruals with earnings management (see, for example, Myers et al (2007), Leuz et al (2003), and Burgstahler et al (2006) among others.

regression model such as the Jones (Jones (1991)) model or one of its many variants¹³.

According to such a decomposition, the earnings quality is measured by the extent to which accruals are well anticipated by a linear combination of revenues (adjusted for receivables) and PPE. More precisely, the *Unexpected ACC* quality construct is defined as the absolute value of the prediction error and measures the accuracy of the best linear predictor of total accruals by change in revenues and PPE. A larger absolute error indicate a weaker relation between total accruals and the two relevant accounting items.

A second accrual quality proxy measures the extent to which accruals map into operating cash flow realizations (Dechow and Dichev (2002)). Motivated by the assumption that accruals quality is affected by the measurement error in accruals, the model predicts accruals by a linear combination of cash from operations in the current period, prior period and future period. The unexplained portion of working capital accruals is an inverse measure of accruals quality: a greater unexplained portion means poorer quality. The *ACC estimation error* quality construct is the standard deviation of the error term and measures the prediction accuracy of the best linear predictor of current accruals by past, current, and future cash flows.

A number of *consequence studies* have documented the usefulness of the residual accruals constructs for capital market decisions. Francis et al (2004) find that firms with poorer mapping of accruals into cash flows have higher costs of capital as evidenced by lower debt ratings, larger realized costs of debt, larger industry-adjusted earnings-price ratios and larger equity betas while Francis et al (2005) find that larger accrual estimation error is associ-

¹³ Dechow et al (1995) compare five commonly-used models of discretionary accruals, and conclude that the Jones model works best. Nevertheless, all of the models give fairly similar results.

ated with larger costs of debt and equity. Moreover, Perotti and Wagenhofer (2014) find that residual accruals quality constructs have the largest impact¹⁴ on mis-pricing as they generate the largest spread in absolute excess returns.

While the residual accrual models mentioned above have been particularly popular instruments for measuring accounting information quality, they have been subject to a number of critiques. Dechow et al (1995), Kang and Sivaramakrishnan (1995) and Thomas and Zhang (2002) (among others) document that, despite the many items of information as input, Jones-type models are not very accurate in out-of-sample prediction. These findings are highly relevant to our investigation, since, in the expectation formation context¹⁵, the capacity of the model to anticipate future accruals is likely to play a primal role. With respect to the accrual estimation error model, Wysocki (2009) cites "a paucity of evidence on the analytic and empirical validity of the model".

Moreover, in an analysis of four versions of Jones model, Dechow et al (2003) document high positive correlations between the residuals of discretionary accruals models and total accruals (between 0.88 and 0.92) while Dechow and Dichev (2002) and Wysocki (2009) substantiate high correlations of standard deviation of the accrual estimation error with the standard deviation of accruals (75%), the standard deviation of earnings (82%) and that of cash flows (63%). Dechow and Dichev (2002) even state that "a simple practical way to gauge the quality of accruals is to assess the volatility of both earnings and accruals".

¹⁴ As mentioned in the introduction, due to methodological limitations, this study does not perform full joint analyses. Hence, the results might be tainted by omitted variable bias.

¹⁵ One of the particularities of the expectation formation framework consists in the importance of accurately predicting future values of earnings and their components.

In view of these empirical findings, it is of interest to investigate, in the particular context of expectation formation, if the relevance of the residual accrual models in the study goes beyond that of the other two simpler (model-free) accrual quality proxies: volatility of accruals (which measures the accuracy of a prediction based on the average realized values in a mean-reverting model) and correlation between cash flows and accruals. Hence our *third specific empirical question*:

EQ3 : *Establish if the model-based measures of accrual quality inform the expectation formation process beyond the model-free measures of accrual quality, i.e. volatility of accruals and correlation of accruals and cash flows.*

Our analysis shows that, while significant in an individual analysis, the contribution of model-based residual accrual quality constructs to expectation formation is subsumed by that of model-free accrual quality proxies in a joint analysis.

3.4 Earnings Quality Constructs Derived from Implementation Decisions

Accounting literature distinguishes between unconditional conservatism which refers to the application of conservative accounting policies and conditional conservatism, a event-driven construct (Beaver and Ryan (2005)). Examples of unconditional conservatism include expensing of R&D and advertising which leads to the omission of economic assets from the balance sheet.

The most frequently used measure of the effect of unconditional conservatism on earnings is a construct based on hidden reserves developed in Penman and Zhang (2002) (Mora and Walker (2015)). When a firm increases investment, conservative accounting leads to reported earnings that are lower

than they would have been otherwise. These lower earnings, however, create unrecorded reserves that provide managers with flexibility to report more income in the future. Management can increase the reserves (and reduce earnings) by increasing investment or it can release some of the reserves creating additional earnings, by reducing investment or the rate of growth in investment. If the change in investment is temporary, then the induced change in earnings is also temporary and not indicative of subsequent earnings. While reducing investment reduces future earnings, the conservative reporting increases current earnings, making them a poor indicator of future earnings and hence lowering their contribution to the formation of expectations of future earnings.

The $Q - score$ quality construct signals if a firm builds up its reserves at a rate faster/slower than that of the growth in its net operating assets or if its reserves build-up rate is different from the rate prevailing in the industry in which it operates. The further the build-up rate from the growth in the net operating assets or from the industry rate, the lower the earnings quality.

The intuition behind this measure is as follows. The growth in the unrecorded assets (reserves) is unusual if it differs from the growth in the recorded net operating assets. The measure benchmarks a change in a firm's reserve against the change in the firm's net operating assets. Deviations signal that reserves are being built (up or down) faster influencing negatively the information content of earnings. Similarly, if a firm's buildup of reserves relative to net operating assets differs from the industry median, then the firm's ratio will likely revert towards the industry median in the future. The part of the reserves that deviates from the industry median is likely to be temporary and when it reverts toward the median some of the firm's estimated reserves will flow into earnings.

Determining the expectations formation relevance of this measure falls under the broader reach of our main empirical question, i.e. we do not make any particular hypothesis about it. The joint analysis indicates that the effect of conservative accounting on earnings as measured by $Q - score$ is not relevant to the expectation formation process.

Finally, we consider a measure reflecting the frequency of reporting special items (SPI)¹⁶. Such a measure is motivated both by academic research as well as practitioners beliefs. Assumed to be largely transitory, the use of special items by managers to affect market perceptions of their performance is well established in the literature (e.g., Kinney and Trezevant (1997), McVay (2006) among others). Moreover, Elliott and Hanna (1996) bring evidence of the reduced importance of earnings as a firm reports sequential negative special items (write-offs). Their findings are consistent with a lessening of investors' confidence in their ability to understand and value the reported earnings. Furthermore, recent surveys indicate reporting of SPI to be a quality concern. 71.4% of the CFOs surveyed by Dichev et al (2013) believe that high quality earnings are earnings that do not include one-time items.

Given the strong motivation for the impact of such a measure on earnings quality we state the following hypothesis:

H₁ : *An increased frequency of reporting SPI negatively affects the capacity of current earnings value to inform expectations about future earnings.*

We find that, after controlling for the effect of the other earning quality constructs, the frequency of reporting special items significantly shapes investors expectations about future earnings. However, its relative significance is the lowest among the constructs that shape expectations.

¹⁶ Broadly, the Dechow et al (2010) review on earnings quality concludes that stock-based measures generally find that accruals help improve the ability of earnings to reflect value except when earnings include large write-downs or special items.

4 Other methodological particularities

The comprehensive analysis we present is made possible by two novel methodological features. The first one regards the overall research design. The details of the alternative framework and the contrast with the standard design were discussed in section 2. Section 4.1 discusses the issue of the estimation of the non-linear valuation regressions, the practical implementation of the valuation model at the center the expectation formation pertinence design.

The second unconventional aspect concerns the analysis of the relation between the pertinence measure of the alternative research design and the quality constructs defined in section 3. It consists of a non-standard use of the linear regression in a set-up where the assumption of linearity is not plausible and is discussed in section 4.2.

4.1 Estimation of the non-linear valuation regressions

The non-linear regression relations specified by equations (2) and (3) can be consistently estimated using techniques from the field of non-parametric statistics. We consider and compare other conceptually different estimation approaches: Additive Model (AM), Projection Pursuit Regression (PPR), Classification and Regression Trees (CART), Multivariate Adaptive Regression Splines (MARS).

Linear regression is a global model assuming a single predictive formula that holds over the entire data-space. It also falls into the category of so-called *parametric regressions*, which assumes the relationships (but not the specific parameters) between the dependent and independent variables to be known *a priori* (in our case this relation is linear). (By contrast, non-

parametric regression does not make any such assumption allowing instead the regression function to be "driven" directly by the data.)

When the independent variables interact in complex, non-linear ways, putting in place a parametric model can be difficult. Two conceptually distinct solutions to this issue can be considered. The first is to fit a global nonlinear regression form of the way the independent variables are associated to the independent one.

The AM and PPR methods belong to this approach. Both fit a linear combination of smooth, univariate, non-parametric functions. The 'non-parametric' term means that the shape of the regression functions are determined by the data as opposed to 'parametric' functions that are defined by a typically small set of parameters. This will allow for more flexible estimation of the underlying regression patterns without knowing upfront what these patterns might look like. The AM considers sums of functions taking arguments in the natural coordinates of the space of explanatory variables while PPR handles the case when the underlying function is additive with respect to variables formed by linear combinations of the original explanatory variables.

The second alternative is to partition the independent variable space into smaller regions where the relation between the regressors and the regressed is more manageable and to fit on each region a simple linear models. The main ingredient of such an approach is the *recursive partitioning* of the variables space to regions small enough to display a simple structure to which we can fit simple models. This alternative approach to linear regression yields the class of *recursive partitioning regression models*.

MARS and CART belong to this class of models. They are non-parametric approaches that build flexible models by fitting piece-wise linear models on

regions of the space of independent variables. CART fits local constants while MARS fits piece-wise linear regressions. In a comparison with the simpler one-dimensional set-up, MARS generalizes the piece-wise linear regression, where each break-point (estimated from the data) defines the "region of application" for a particular (very simple) linear regression equation.

More details about the three techniques can be found in section 11.2 of the Appendix. See also James et al (2014)) and Wasserman (2006).

4.2 An atypical use of linear regression

Section 2 identified the median absolute relative pricing error from the non-linear valuation regressions as the expectation formation pertinence measure of choice while Section 3 discussed in detail the earnings quality constructs. This section delineates our approach to investigating the relation between the pertinence measure and the quality attributes.

Since our goal is to disentangle the individual contributions of quality constructs to pricing accuracy of the valuation regression, a natural tool to use is the multiple regression which allows us to measure the impact of a construct while holding the level of the other constructs constant. However, there is no reason to assume a linear relation between the level of the quality constructs and accuracy. Contrary, it is very plausible that an incremental increase in the quality will affect accuracy conditional on the level of the construct (see section 6 for empirical evidence). As a consequence, the use of the plain vanilla linear regression might not be suitable.

Our atypical use of the linear regression exploits its versatility avoiding the assumption of linearity in the relation between the regressor and the independent variables. More precisely, our analysis uses the linear regression

as a tool for *testing differences in mean*. This section gives the details of this atypical usage.

It is well known that, when the independent variable in a linear regression is an indicator variable, testing the null hypothesis of zero regression coefficient is equivalent to testing that the means of the dependent variable conditional on the presence or absence of the character modeled by the binary variable are equal. In particular, if the indicator variable models contrasting values of a given character (e.g. high vs. low) a significant non-zero regression coefficient of the binary variable indicates statistically distinct means of the independent variable conditional on the level of the character that is modeled by the indicator variables.

More generally, if the range of values of the character is split in $l + 1$ intervals of equal probability¹⁷, $(a_{min}, a_1], (a_1, a_2], \dots, (a_{l-1}, a_l], (a_l, a_{max})$, l indicator functions modeling the different levels of the character will form the independent variable set while one level gets to be the reference. Details about the reference level will be given in section 7.1 which discusses the implementation details.

In this set-up, a significant non-zero regression coefficient of the j -th indicator variable means that the mean of the independent variable conditional on the character taking values in the j th bracket of the range of the character $(a_{j-1}, a_j]$ is statistically different from than when conditioning with the character's reference values. Significant non-zero coefficients are evidence of expectation formation pertinence of the construct.

This particular set-up of the linear regression allows us to take advantage of linear regression's versatility without imposing an assumption of linearity on the relationship between the variables. We can, first of all, control for

¹⁷ In this case a_i is the $i/(l + 1)$ -quantile.

factors that are known to affect the relation between pricing accuracy and different earnings quality constructs (like size, sign of the earnings, intangible intensity) and, second, estimate un-biased coefficients reflecting the true impact of a given constructs on the pricing accuracy of the valuation regression by including among the regressors other constructs which, when omitted, cause estimation bias.

5 Sample, variable measurement and data summary

This section presents the sample and discusses the details of the empirical construction of the expectation formation pertinence measure and of the quality constructs (section 5.2). It also presents the descriptive statistics of the variables and their dependency structure as measured by the correlation matrix (section 5.3).

5.1 Sample

Our initial sample, obtained from Compustat (accounting information) and CRSP (prices) data bases, covers the 53-year period between 1963 and 2015. It is used specifically to produce the expectation formation pertinence measure and the attribute proxies by constructing two samples of respective maximal size. The first sample (the *expectation formation pertinence sample*) includes all the firms-years for which the variables needed to run the P/B regression exist. This sample contains 218,418 firm-year observations with the number of firms meeting the requirements ranging from 214 to 6,543 per year, with an average of 3,739 firms per year. In total, the sample contains 18,709 distinct firms.

Using this sample, we estimate the non-linear valuation regressions (2) and (3) on a year-specific and industry-specific basis. We use the SIC 2 industry definition for constructing yearly cross-section sub-samples on which the non-linear regression is inferred¹⁸ by means of the non-parametric approaches described in sections 4.1 and 11.2 of the Appendix. We then construct the absolute pricing errors that are our measures of expectation formation pertinence.

We construct a second, shorter sample (the *earnings quality sample*) for putting together the quality constructs. We measure the attributes on firm-specific and year-specific basis. We calculate our earnings quality constructs over rolling 8-year windows. Consequently, a firm is included in the year t *earnings quality sample* if the data needed to calculate the quality proxies is available in years $t - 7$ to t . The *earnings quality sample* covers hence the shorter time period from 1971 to 2014. The data requirements constrain our sample to firms that are larger and longer-lived.

The use of the firm as its own benchmark is motivated by a number of reasons. First, it mitigates concerns that differences among firms in a given industry give rise to noisy measures of the attributes, as would be the case if we measured the attributes relative to industry norms. Second, a number of important quality measures are intrinsically time-series constructs: earnings and accruals volatility as well as the accruals smoothing effect measures $\sigma(NI_{i,t})/\sigma(CFO_{i,t})$, $\rho(CFO_{i,t}, TACC_{i,t})$ and $\rho(\Delta TACC_{i,t}, \Delta CFO_{i,t})$. Overall¹⁹, we believe that the benefits afforded by the use of the firm as its own benchmark offset the sample bias towards more stable and longer-lived firms.

¹⁸ For the sake of consistency, we require a sample size of the cross-sectional SIC 2 industry sub-sample not smaller than 30.

¹⁹ As part of our robustness analysis, we ran analyses with the constructs were obtained, where possible, cross-sectionally. The analyses using the cross-sectional constructs yield qualitative similar results (see Section 9).



Fig. 1: Sample size

The final sample is obtained as the intersection of the *expectation formation pertinence sample* with the *earnings quality sample* and it contains all the firms in the original sample for which we were able to construct the expectation formation pertinence measure and all the earnings quality proxies²⁰. It covers the period from 1970 to 2015 and contains 101,809 firm-year observations. Figure 1 shows that the number of firms meeting the requirements ranges from 151 to 3,148 per year, with an average of 2,213 firms per year. In total, the sample contains 9,196 distinct firms. All accounting data are winsorized at the 1% level to control for outliers.

²⁰ The final sample coincides practically with the smaller earnings quality sample.

5.2 Variable measurement

5.2.1 The valuation regressions

Besides the predictors, empirically specifying the non-linear valuation regressions (2) and (3) requires also a measures of size, firm-specific cost of equity and level of conservative accounting. As a proxy for size we use the logarithm of the previous year market value, $\log(Mkt\ Value_{-1})$. We use the previous period earnings-to-price ratio, $NI_{i,-1}/P_{i,-1}$ as proxy of equity risk compensation. Our choice is motivated by several reasons. First, under certain assumptions (i.e. zero growth rate and 100% dividend payout ratio) E/P ratio is identical to the firms cost of equity capital. Second, prior empirical research also suggests that the earnings to price ratio (E/P) is a reasonable proxy for equity cost of capital. Basu (1983) documents a positive relation between average returns and E/P ratios. Fama and French (1992) and Botosan et al (2014) use E/P ratio as a risk proxy. Botosan (1997) brings evidence that the E/P ratio adjusted for growth and dividend payout ratio can be used to estimate cost of equity capital. Francis et al (2005) use the E/P ratio as the dependent variable in their analysis of the association between accrual quality measure and the cost of equity. Third, other risk proxies commonly used in the empirical literature, as the implied cost of equity capital derived from the dividend discount formula or the implied cost of equity capital derived from the price-earnings growth model, need significant more information (which is not available) to construct.

To summarize, the specifications of the non-linear valuation regressions in proposition 1 that we estimate in this paper are:

$$P_{i,0} - B_{i,0} = \mathbf{m}_{i,0}(NI_{i,0}; B_{i,0}, NI_{i,-1}/P_{i,-1}, \log(\text{Mkt Value}_{i,-1})) + \varepsilon_{i,0},$$

and

$$P_{i,0}/B_{i,0} - 1 = \mathbf{m}_{i,0}(ROE_{i,0}; NI_{i,-1}/P_{i,-1}, \log(\text{Mkt Value}_{i,-1})) + \epsilon_{i,0},$$

respectively.

5.2.2 Quality measures

We define our earnings quality measures following the literature (Francis et al (2005), Dechow et al (2010), Perotti and Wagenhofer (2014)) and the discussion in section 3. The descriptive statistics of all variables are given in section 5.3. The base earnings measure is net income before extraordinary items (NI). We calculate total accruals ($TACC$) with the indirect approach²¹ (Kothari et al (2005), Francis et al (2004), Perotti and Wagenhofer (2014)) which uses information from the balance sheet and income statement. They are calculated as $TACC = \Delta CA - \Delta CL - \Delta CASH + \Delta STDEBT - DEPR$, where the variables are change in current assets, change in current liabilities, change in cash, change in short-term debt, and depreciation in the fiscal year ending at time t . Cash flow from operations (CFO) is calculated as $CFO = NI - ACC$. Current accruals ($CACC$) is computed as $CACC =$

²¹ We use the indirect approach rather than the statement of cash flows advocated by Hribar and Collins (2002) because of the issue of the data availability. Using the direct method would drastically reduce the sample size as the information needed for our accrual quality constructs would not be available for the first three decades of the actual sample. Moreover, Compustat statement of cash flow data are less complete than balance sheet and income statement data. Hence we prefer the indirect method because it provides for a larger cross-section of observations.

TACC + DEPR. Accrual quality measures are estimated for each firm and year for rolling 8-year periods from $t - 7$ to t .

As explain in section 3.1, we define predictability as the ability of earnings to *linearly* predict itself. In contrast to extant literature which defines predictability in the frame of an auto-regressive ($AR(1)$) dynamics of returns, we decompose future earnings $NI_{i,t}$ into the best linear prediction of next period earnings by current period earnings plus an error term²²:

$$NI_{i,t} = \phi_{i,0} + \phi_{i,1}NI_{i,t-1} + u_{i,t}$$

and then estimate the standard deviation of u to construct our measure of *linear predictability*. As shown in section 11.1 of the Appendix, the coefficients $\phi_{i,0}$ and $\phi_{i,1}$ can be estimated as:

$$\begin{aligned}\hat{\phi}_{i,1} &= \hat{\rho}(NI_{t-1}, NI_t) \frac{\hat{\sigma}(NI_{t-1})}{\hat{\sigma}(NI_t)}, \\ \hat{\phi}_{i,0} &= \hat{\mathbb{E}}(NI_t) - \hat{\phi}_{i,1}\hat{\mathbb{E}}(NI_{t-1}),\end{aligned}$$

where $\hat{\mathbb{E}}$, $\hat{\sigma}$ and $\hat{\rho}$ are the sample mean, sample standard deviation and sample correlation, respectively.

The two estimates formally coincide with the Mean Square Error (MSE) estimates of a regression of current earnings on past earnings. Nevertheless, and in spite of this similarity, our definition of predictability does not impose a linear dynamics on earnings. It does not regard the equation relating current and future earnings above as a regression whose coefficients need to be consistently estimated. As such, the estimated $\hat{\phi}_{i,0}$ and $\hat{\phi}_{i,1}$ are not the coef-

²² We make no assumptions on $\mathbb{E}[u_{i,t}|NI_{i,t-1}]$ or on the correlation between $NI_{i,t-1}$ and $u_{i,t}$. While in the case of an $AR(1)$ the two quantities are *necessary* 0, in the best linear predictor frame they can take arbitrary values.

ficient estimates in a regression that linearly ties the future and the current earnings. They are the coefficients in the expression of the best linear predictor in a pair $(NI_t, NI_{t,1})$ that is animated by a dynamic that is complex and possibly non-linear.

Variance of earnings decomposes into economic (exogenous) variability and variability due to accrual accounting. The later is determined by the variance of accruals and by the smoothing effect of accruals on the cash flow:

$$\begin{aligned} Var(NI) = & Var(CFO) + Var(TACC) \\ & + 2\rho(TACC, CFO) \times \sigma(CFO) \times \sigma(TACC). \end{aligned} \quad (5)$$

The total variability of earnings will be measured by earnings volatility $(\sigma(NI))$. Economic variability of earnings will be measured by cash flow volatility $(\sigma(CFO))$ while the variability of accruals will be quantified by TACC volatility $(\sigma(TACC))$. Volatility is estimated by taking the standard deviation of the deflated item²³ for the most recent eight years. It is worth noting that volatility constructs measure the prediction accuracy of the next period by the average past values.

The smoothing role of accruals is measured by three alternative measures. The first measure, $\sigma(NI)/\sigma(CFO)$, is the ratio of the standard deviation of earnings over the standard deviation of cash flow from operations,

$$\hat{\sigma}(NI_{i,t})/\hat{\sigma}(CFO_{i,t}),$$

the second, $\rho(TACC, CFO)$, is the correlation of accruals and cash flow from operations,

$$\hat{\rho}(TACC_{i,t}, CFO_{i,t}).$$

²³ Following the literature we deflate by total assets at the beginning of period

while the third measure, $\rho(\Delta TACC, \Delta CFO)$, is the contemporaneous correlation between changes in accounting accruals and changes in operating cash flows

$$\hat{\rho}(\Delta TACC_{i,t}, \Delta CFO_{i,t}).$$

(All variables are scaled by total assets at the beginning of period t .) Larger values of the three measures of accruals smoothing role indicate lower²⁴ smoothness of earnings relative to the cash flow.

In line with Francis et al (2005) we define the *ACC estimation error* based on the firm-level specification²⁵ of the model:

$$ACC_{i,t} = b_{i,0} + b_{i,1}CFO_{i,t-1} + b_{i,2}CFO_{i,t} + b_{i,3}CFO_{i,t+1} + v_{i,t}.$$

We use current accruals (as in Dechow and Dichev (2002)) as well as total accruals (following McInnis and Collins (2011), Barth et al (2012), and Bushman et al (2016), among others) on the premise that total accruals best capture the difference between accrual accounting and cash accounting. The empirical results are identical. The two accrual quality constructs, one based on *CACC* and the other based on *TACC*, are practically indistinguishable with a correlation of 0.98 in our sample.

To obtain the *Unexpected ACC* construct, the second measure of accruals quality, we follow prior studies (Dechow et al (1995), Subramanyam (1996), Kothari et al (2005)) that estimate the modified-Jones model subtracting the change in accounts receivable ($\Delta AR_{i,t}$) from change in revenues ($\Delta REV_{i,t}$)

²⁴ Note that $\rho(\Delta ACC, \Delta CFO)$ is usually negative

²⁵ Dechow and Dichev (2002) state that the firm-level specification of the model has a better theoretical grounding and better empirical fit.

prior to estimating Jones model (Jones (1991)):

$$TACC_{i,t} = \gamma_0 + \gamma_1(1/A_{i,t-1}) + \gamma_2(\Delta REV_{i,t} - \Delta AR_{i,t}) + \gamma_3 PPE_{i,t} + w_{i,t}$$

where PPE is gross property, plant and equipment. The unexpected accruals measure is the median absolute residual $|w_{i,s}|$, $s = t - 7, t - 6, \dots, t$. Note that this quality construct is close²⁶ to the standard deviation of the error term $w_{i,t}$. It is also less volatile than just the current absolute residual $|w_{i,t}|$ giving a more comprehensive idea of the size of the unexpected accruals by looking at all the residual terms over the time window of eight years. (All variables in the regressions defining the accrual quality measures are scaled by A_{t-1} , the total assets at the beginning of period t .)

We want to emphasize that the expressions of the two models can be read as decomposition of accruals into a best linear predictor plus the error term. Accordingly, the accrual estimation error construct determines the accuracy of linearly predicting current accruals by cash from operations (in current, prior and future period) while the unexpected accruals measure the accuracy of linearly predicting $TACC$ by the difference between change in revenues and change in accounts receivable and by the level of gross property, plant and equipment. In other words, the two constructs are different measures of the *predictability of accruals*.

The Q – score, a measure of the effect of conservative accounting on earnings, is a combination of two parts. The first is calculated as:

$$Q_{i,t}^A := ER_{i,t}/NOA_{i,t} - ER_{i,t-1}/NOA_{i,t-1}$$

²⁶ The two measures have a correlation of 0.9.

where $ER_{i,t}$ denotes the estimated reserves created by the effect of the conservative accounting on the balance sheet:

$$ER_{i,t} = INV_{i,t}^{res} + RD_{i,t}^{res} + ADV_{i,t}^{res}$$

with $INV_{i,t}^{res}$. The expression puts forth three sources of reserves: first, inventory reserve, $INV_{i,t}^{res}$, equals the LIFO reserve reported in the financial statement footnotes, second, R&D reserve, $RD_{i,t}^{res}$, is calculated as the estimated amortized R&D assets that would have been on the balance sheet if R&D had not been expensed (R&D expenditures are capitalized and then amortized using the sum-of-the-years-digits method over five years), and, third, advertising reserve, $ADV_{i,t}^{res}$, is the estimated brand assets created by advertising expenditures (the advertising expenses are capitalized and then amortized using a sum-of-the-year's digits method over two years).

The second component of the Q – score compares a firm's reserves to the median for its SIC two-digit industry code:

$$Q_{i,t}^B := ER_{i,t}/NOA_{i,t} - \text{Industry median}(ER_{i,t}/NOA_{i,t}).$$

The Q – score combines these two measures:

$$Q_{i,t} = 0.5 \times Q_{i,t}^A + 0.5 \times Q_{i,t}^B.$$

Both high (positive) and low (negative) Q – scores can indicate that current earnings are of poor quality, and a Q – score of zero indicates good quality.

Finally, the *SPI* measures represent the percentage²⁷ of years with non-zero special items ($SPI \neq 0$) and the percentage of years with negative special items ($SPI < 0$), respectively, among the most recent eight years.

It is worth noting that, besides the proxies for relative smoothness, relative conservatism and the *SPI* proportion, all other constructs are measures of (linear) prediction accuracy of earnings and their components. Earnings, cash flow and accruals volatility measure the accuracy of forecasting future values with the mean of past values. Earnings predictability and the two accruals quality proxies are measures of accuracy of the best linear prediction of the construct by relevant quantities: past earnings, past, current and future cash flows and revenues and PPE, respectively.

5.3 Data summary

Table 1 gives the summary statistics of the variables used to construct the pricing errors, our expectation formation pertinence measure (Panel A), those needed for constructing the quality attributes (Panel B) and of the attributes themselves (Panel C)

Table 2 gives the values of Spearman (lower triangle) and Pearson (upper triangle) correlation between the attributes. It shows that the quality constructs are correlated, most of them positively. As they supposedly have an impact on the size of the pricing errors, the table shows that the conditions for the occurrence of the omitted variable bias in individual regressions are fulfilled. It indicates that special attention needs to be paid to consistent estimation of the expectation formation pertinence of each construct motivating the regression analysis set-up presented in section 7.2.

²⁷ We have also considered the median value of *SPI* (deflated by total assets at the beginning of period) over the most recent eight years. The retained measures has a stronger expectation formation pertinence.

Variable	Mean	SD	10%	25%	50%	75%	90%
Panel A: Variables for the non-linear pricing regression							
P_0/B_0	1.95	1.41	0.60	0.96	1.54	2.53	3.94
ROE_0	0.07	0.19	-0.17	0.02	0.11	0.18	0.25
$\log(\text{Mkt Value}_{-1})$	5.17	1.97	2.54	3.59	5.10	6.71	7.92
B_0/B_{-1}	1.06	0.21	0.81	0.97	1.07	1.16	1.28
$(E/P)_{-1}$	0.02	0.12	-0.12	0.01	0.05	0.09	0.13
Panel B: Variables for generating the quality constructs							
NI	0.02	0.09	-0.09	0.00	0.04	0.08	0.12
CFO	0.06	0.10	-0.07	0.02	0.08	0.13	0.17
$CACC$	0.01	0.05	-0.06	-0.02	0.01	0.04	0.08
$TACC$	-0.04	0.06	-0.12	-0.08	-0.04	-0.00	0.04
$PPEGT$	0.63	0.34	0.20	0.35	0.58	0.88	1.15
$Sales$	1.23	0.65	0.43	0.72	1.16	1.64	2.14
$Receivables$	0.17	0.10	0.04	0.09	0.16	0.25	0.32
INV^{res}	0.03	0.02	0.00	0.01	0.02	0.04	0.06
RD^{res}	0.05	0.05	0.01	0.01	0.03	0.08	0.13
ADV^{res}	0.02	0.02	0.00	0.01	0.02	0.03	0.05
Panel C: Quality constructs							
$\sigma(NI)$	0.07	0.07	0.01	0.02	0.04	0.09	0.16
$Linear\ Predictability$	0.06	0.06	0.01	0.02	0.04	0.08	0.14
$\sigma(NI)/\sigma(CFO)$	0.72	0.32	0.29	0.44	0.71	0.98	1.16
$\rho(TACC, CFO)$	-0.65	0.33	-0.97	-0.92	-0.78	-0.47	-0.11
$\rho(\Delta TACC, \Delta CFO)$	-0.74	0.31	-0.98	-0.96	-0.87	-0.62	-0.23
$\sigma(CFO)$	0.09	0.06	0.03	0.04	0.07	0.11	0.18
$\sigma(TACC)$	0.07	0.04	0.02	0.04	0.06	0.09	0.13
$Unexpected\ ACC$	0.04	0.03	0.01	0.02	0.03	0.05	0.08
$ACC\ est.\ error$	0.02	0.02	0.00	0.01	0.01	0.03	0.05
$Conservatism$	0.02	0.02	0.00	0.01	0.02	0.03	0.06
$\%(SPI \neq 0)$	0.44	0.24	0.12	0.25	0.38	0.62	0.75
$\%SPI < 0$	0.35	0.20	0.12	0.12	0.38	0.50	0.62

Table 1: **Descriptive statistics.** *Panel A:* variables needed to construct the expectation formation pertinence measure, *Panel B:* variables used for quality constructs, *Panel C:* earnings quality measures.

Table 2 underscores also the need for a sensible choice of the variables to be included in the specifications of the regression analysis addressing the

	1	2	3	4	5	6	7	8	9	10	11
1. $\sigma(NI)$	-	0.97	0.7	0.71	0.67	0.77	0.55	0.48	0.73	0.27	0.33
2. <i>LinearPredict.</i>	0.97	-	0.67	0.68	0.7	0.76	0.55	0.48	0.73	0.27	0.34
3. $\sigma(NI)/\sigma(CFO)$	0.7	0.67	-	0.95	0.85	0.15	0.01	0	0.45	0.14	0.35
4. $\rho(TACC, CFO)$	0.71	0.68	0.95	-	0.88	0.2	-0.04	-0.03	0.43	0.13	0.36
5. $\rho(\Delta TACC, \Delta CFO)$	0.67	0.7	0.85	0.88	-	0.22	-0.02	-0.04	0.44	0.13	0.38
6. $\sigma(CFO)$	0.77	0.76	0.15	0.2	0.22	-	0.8	0.69	0.6	0.29	0.15
7. $\sigma(TACC)$	0.55	0.55	0.01	-0.04	-0.02	0.8	-	0.84	0.62	0.3	0.01
8. <i>Unexpected ACC</i>	0.48	0.48	0	-0.03	-0.04	0.69	0.84	-	0.57	0.27	-0.01
9. <i>ACC est. error</i>	0.73	0.74	0.46	0.43	0.44	0.6	0.62	0.58	-	0.27	0.21
10. <i>Conservatism</i>	0.27	0.27	0.13	0.13	0.12	0.28	0.3	0.28	0.27	-	0.05
11. $\%SPI \neq 0$	0.32	0.33	0.34	0.36	0.38	0.15	0.01	-0.01	0.21	0.05	-

Table 2: **Correlation between the quality constructs.** *Lower triangle:* Spearman correlation, *Upper triangle:* Pearson correlation.

issue of omitted variable bias discussed in in section 7.2. We note that the variability and linear predictability of earnings are the most correlated pair with a correlation close to 1 (0.97). In the multivariate analysis in section 7 we will emphasize the unconditional proxy for two main reasons. First, it is a more direct construct as it does not need a statistical estimation. Second, the earnings variance can be naturally decomposed in terms that capture separately the economic variability, the accounting variability and their interaction:

Note that, as a result of the smoothing role of accruals, the economic and the accounting variability terms in the decomposition are strongly correlated ($\rho(\sigma(CFO), \sigma(TACC)) = 0.80$).

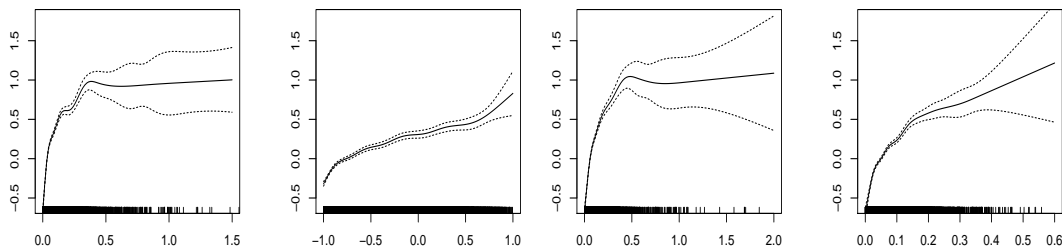
The three measures of the smoothing role of accruals, $\sigma(NI)/\sigma(CFO)$, $\rho(TACC, CFO)$, and $\rho(\Delta TACC, \Delta CFO)$, are also highly correlated (correlation of 0.96 between the first two and of 0.89 between the last two, respectively). In the empirical analysis section 7 we will emphasize $\rho(TACC, CFO)$ as being one of the terms of the decomposition of earnings variance (5).

6 Non-linear relations between individual constructs and expectation formation pertinence

This section presents empirical evidence of a non-linear relation between quality constructs and pricing accuracy. This evidence motivates the particular use of the linear regression described in section 4.2.

Concretely, we estimated non-parametrically the relation between the eleven quality constructs described in section 3 and the absolute pricing errors defined in section 2.2. The results of the estimation are displayed in the graphs in Figure 2. Each graph contains three curves: the estimated mean absolute error conditional on the level of the construct together with the 95% confidence interval.

A. $\sigma(NI)$, $\rho(TACC, CFO)$, $\sigma(CFO)$, $\sigma(TACC)$



B. Unexpected ACC, ACC estimation error, conservatism, $\%(SPI \neq 0)$

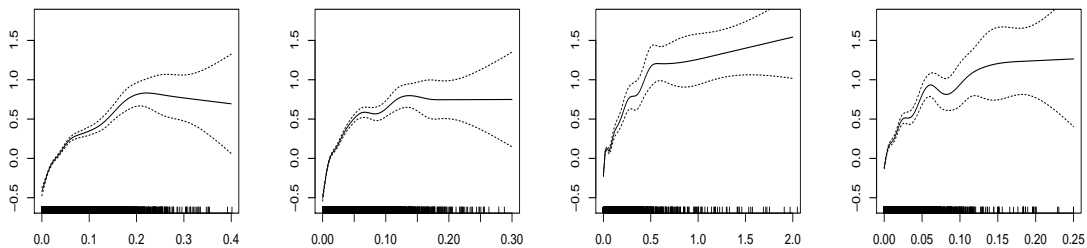


Fig. 2: The relation between the expectation formation pertinence measure and the quality constructs. The graphs display non-parametric estimates (using smooth splines) of the regression of log absolute pricing error on the individual quality constructs (the curve in the middle) together with the 95% confidence intervals. It highlights the non-linearity of the relation under investigation.

Figure 2 displays non-parametric estimates of the regression of log absolute pricing error on the individual quality constructs. The method used is smooth splines (for details see Wasserman (2006)). It shows, in particular, that the impact of an incremental increase in the quality on the importance of the construct in the formation of expectations is *conditional* on the level of the construct. As a consequence, the use of the plain vanilla linear regression is not suitable and particular care is needed for the regression analysis of the relation between the expectation formation pertinence measure and the quality measures.

7 Implementation, presentation and interpretation of results

This section addresses the concrete implementation issues of the methodological choices discussed in sections 2 and 4.2 and the presentation of results. Section 7.1 details the atypical use of the linear regression. Section 7.2 discusses the model selection procedure for addressing the omitted variable bias while section 7.3 considers the manner in which the results are presented and interpreted. The section ends with a presentation of the results of the empirical analysis.

7.1 Linear regression for testing differences in means

The estimating set-up is constructed as follows. The dependent variable is the *absolute value of the relative pricing error*. The range of all independent variables is divided in 20 intervals of equal probability (half-deciles) and 19 indicator variables are constructed associated to the 19 intervals starting from the first up to the 20th omitting the reference interval. For ease of presentation, this consists of either the values around the median, (0.5 –

quantile, 0.55–*quantile*] when the relevance measure vary a lot with the level of the construct or the highest values of construct if the relevance does not depend much on the level of the construct. The test that the coefficient of the j -th indicator ($1 \leq j \leq 20$, reference level excluded) is equal to zero provides statistical evidence on the difference between the mean pricing error of firms with construct values in the j -th half-decile and the mean pricing error of firms with constructs in the reference interval. Significant negative/positive coefficients would indicate expectation formation pertinence.

Given the large number of parameters involved and test performed, the results of the analysis are presented through graphs instead of tables. For a given regression and a given construct, we display three curves. The first one traces the 19 coefficients of the indicator variables modeling the half-deciles of the construct and is shown using a full line. The other two trace the lower and the upper limits of the nineteen 95% confidence intervals²⁸ and are shown as dotted lines. Such a graph tests 19 hypothesis of equal mean valuation error (that is, equal expectation formation pertinence), one for each of the levels 1 to 20 of the construct, the reference level excepted. The tests are done by checking if 0, the null difference between the two mean absolute errors, belongs to each of the 19 confidence intervals.

7.2 Model specifications addressing the omitted variable bias

The goal of our analysis is the *consistent estimation* of the effect of each quality construct on pricing accuracy measured by the errors in section 2.2. The

²⁸ The confidence intervals are based on heteroskedasticity-consistent (HC) estimation of the covariance matrix of the coefficient estimates in the regression model. Long and Ervin (2000) conduct a simulation study of HC estimators in the linear regression model (HC0 to HC3; HC0 is Whites estimator (White (1980)) while the other estimators are refinements of this), recommending to use of the so-called HC3 estimator which we used consistently through the analysis. Qualitatively identical results were obtain using alternative HC estimators.

challenge we face is the omitted variable bias. Since other constructs that are correlated with the proxy of interest potentially determine the expectation formation pertinence omitting them from the regression will result in biased inference of the expectation formation pertinence of the former. The solution to this problem is to include these constructs (or, more precisely, the indicator variables identifying their levels) as additional regressors in the multiple regression. When we do this, the coefficients of the level indicator variables corresponding to the construct of interest will measure the additional expectation formation pertinence of its levels *holding constant the levels of other constructs*.

The classical approach to the challenge of potential omitted variable bias is twofold (e.g., Stock and Watson (2012)). First, a base set of regressors is selected based on integrating expert judgment to economic theory. The regression so obtained is referred to as *base specification*. It contains the indicator levels of the construct of interest and the control variables suggested by accounting judgment, theory, and relevant references. In our case, the list of control variables include controls for the industry (SIC 3-digit code), year (year dummy), size (total assets, market value, sales), intangible intensity (price-to-book ratio, SG&A intensity, R&D intensity), level and sign of earnings, and the level of total accruals²⁹.

The second step consists in elaborating a list of *alternative specifications*, i.e. alternative sets of regressors which include other constructs that determine the expectation formation pertinence and are correlated to the construct of interest. If the estimates of the coefficients of the indicator variables corresponding to its levels are statistically similar over the alternative

²⁹ The level of accruals variable is motivated by Sloan (1996) while the level of earnings variable is motivated by much existing research, which documents that extreme earnings tend to mean-revert faster, i.e. level of earnings is a determinant of earnings volatility.

specifications, then this provides evidence that the estimates from the base specification are consistent. Estimates that change significantly across specifications provide evidence that the base specification was affected by omitted variable bias.

7.3 Presentation and interpretation of different model specifications

Normally, the results of an analysis consisting in a number of alternative specifications would be presented in a table where each line corresponds to a construct and each column to a specification of the model, i.e. the (i, j) entry in the table would be the estimated coefficient and its standard error for the construct i in the specification j . Statistical constancy of the coefficients on the row i , i.e. coefficients of the construct i corresponding to different model specifications, is evidence that the estimate from the base specification is consistent. Estimates that change significantly across columns provide evidence that the base specification coefficient of the construct i was affected by omitted variable bias.

Due to our atypical use of the linear regression, the table of values described above is replaced by a table of graphs where the (i, j) entry displays the 19 estimated coefficients of the indicator variables modeling the levels of the construct i (drawn by a full line) together with the 95% confidence intervals (drawn with dotted lines). The coefficients are inferred in the j th model specification. The interpretation of the table of graphs is identical to that of the table of values.

8 Empirical results

This section presents the results of the two-stage analysis as described in section 7.2 for the P/B regression inferred using the Additive Model (AM) approach. They are qualitatively unchanged if instead we estimate the $P - B$ regression or if the inference is based on the PPR, CART or MARS approaches.

A joint analysis of all constructs is not feasible as $\sigma(NI)$, $\sigma(CFO)$, $\rho(TACC, CFO)$ and $\sigma(TACC)$ are joined by the variance decomposition of earnings expression (5). Including them all into a regression would invalidate the results. Consequently, we proceed by analyzing the relative relevance of constructs within groups of related proxies avoiding the trap of co-linearity. While the group analyses answer the specific empirical questions in section 3, putting together their results yields the answer to the main empirical issue. The groups we analyze are, in order, the quality constructs appearing in the variance decomposition of earnings, the accrual quality constructs (time-series vs. model-based) and, finally, the two constructs related to conservatism and *SPI* reporting.

8.1 Answers to *EQ 1* and *EQ 2*

Since we cannot analyze the four constructs in the variance decomposition of earnings through a joint regression, we specify two (of the four) alternatives involving three of the measures: $(\sigma(NI), \sigma(CFO), \rho(TACC, CFO))$ and $(\sigma(NI), \sigma(CFO), \sigma(TACC))$. The two alternative specifications are chosen as such to control for both $\sigma(NI)$ and $\sigma(CFO)$. They shed light on the impact of accruals (measured by the other two variables $\rho(TACC, CFO)$)

and $\sigma(TACC)$) on the accounting passage from cash flows to earnings and will allow us to answer the first two specific empirical questions.

Figure 3 reports the results of the base specifications as well as those of the relative analysis of the constructs appearing in the variance decomposition. The presentation follows the frame described in section 7.3. Each graph displays the 19 coefficients of the indicator variables modeling the half-deciles of a quality construct (full line) together with the 95% confidence intervals (dotted lines).

The figure contains three columns: the first refers to the base specifications while the second and the third refer to alternative specifications that include earnings and cash flow volatility (both) and the correlation of cash flows with accruals (second column) and accruals volatility (third column). Each line corresponds to the quality construct identified by the labels above the lines.

While the base specifications seem to indicate that all of the constructs are expectation formation relevant, the analyses in columns two and three paint a more subtle relation between the components of earnings variance.

Overall, the graphs in figure indicate that earnings volatility has the strongest relative relevance among all the constructs.

The answer to the first empirical specific item is given by the graphs in panel B of figure 3. Holding earnings volatility and either accrual volatility or the measure of the smoothing effect of accruals constant shows no significant contribution to expectation formation of the information contained in cash flow volatility.

The second graph in panel C of figure 3 yields the answer to the second empirical specific question. Holding earnings and cash flow volatility constant reveals the negative impact of strong negative correlation between cash flow and accruals on the contribution of current earnings value to shap-

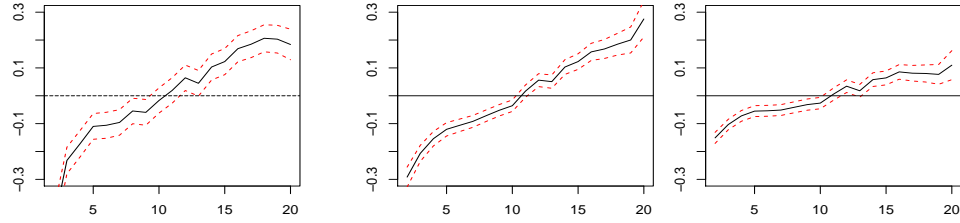
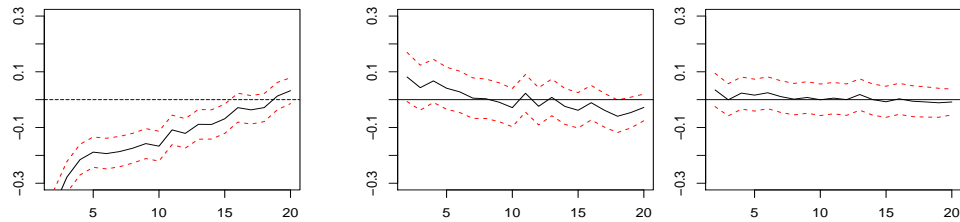
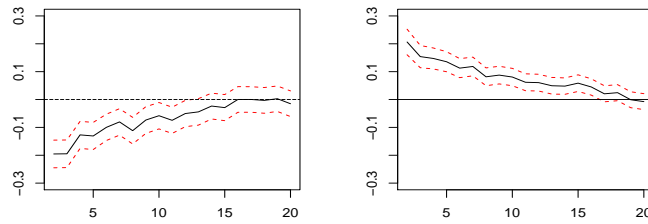
A. Earnings volatility - $\sigma(NI)$ B. CFO volatility - $\sigma(CFO)$ C. Smoothing role of accruals - $corr(TACC, CFO)$ D. ACC volatility - $\sigma(TACC)$ 

Fig. 3: **Construct level coefficients in multiple regressions - earnings variance decomposition constructs.** The graphs display the regression coefficients of the 19 indicator variables modeling half-deciles of construct values (full line) together with the 95% confidence intervals (dotted lines) in the regression of absolute pricing errors on the indicator variables corresponding to the named constructs. *Columns (specifications)*: first - the base specification (for the list of control variables see section 7.2), second - ($\sigma(NI)$, $\sigma(CFO)$, $corr(TACC, CFO)$), third - ($\sigma(NI)$, $\sigma(CFO)$, $\sigma(TACC)$). A significant non-zero value on the j -th abscissa position indicates a significant difference between the mean absolute pricing error of firms with attribute values in the j -th half-decile and that of firms with values in the reference level (median values for $\sigma(NI)$, the largest values for the rest).

ing expectations about future earnings. While less negative values do not have a significant impact on the pricing accuracy of the valuation regression, extreme negative correlation command pricing errors significantly larger indicating that over-smoothed earnings are perceived by the investors as less relevant to the expectation formation process.

Panel D of figure 3 sheds light on the relevance of accruals volatility. Among the firms with same earnings and cash flow volatility levels, those with less volatile accruals command smaller valuation errors. Their earnings are contributing more to shaping the price impounded expectations.

To summarize, in passing from cash flows to net income, earnings with an accrual component that does not smooth excessively and that is not volatile are more relevant to future earnings expectations.

8.2 Answer to *EQ 3*

This section takes a closer look at the proxies that subsume the unexpected accrual and accrual estimation error constructs.

Figure 4 displays the results of the individual analysis of the expectation formation pertinence of the two model-based accrual quality constructs. They seem to confirm that the two residual accrual measures shape investors expectations impounded in prices (higher levels of accrual quality are associated with lower pricing accuracy). Next we investigate if these measures contain relevant information beyond that already present in the accrual time-series constructs.

Figure 5 displays the results of the multivariate regression of absolute pricing errors on the indicator variables corresponding to unexpected accruals (column 1 and 2) and accrual estimation error when we control for the level of $\sigma(CFO)$ (column 1) and $\sigma(TACC)$ (column 2) for unexpected

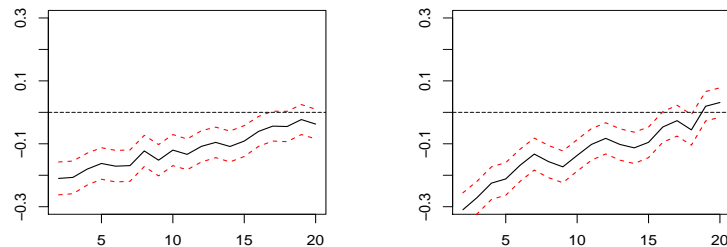


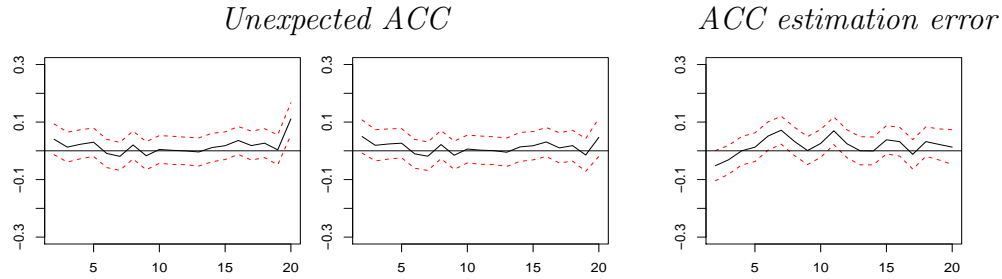
Fig. 4: **Construct level coefficients in multiple regressions - base specification for Unexpected ACC and ACC estimation error.** The graphs display the regression coefficients of the 19 indicator variables modeling half-deciles of the construct values (full line) together with the 95% confidence intervals (dotted line) in the base specifications corresponding to *Unexpected ACC* (left) and *ACC estimation error* (right). The other control variables include the two-digit SIC code industry, year, size (as measured by market value, sales and total assets), intangible intensity (as measured by the price-to-book ratio, S&GA intensity and R&D intensity), the sign of earnings, the level of earnings and the level of total accruals. A significant non-zero value on the j -th abscissa position indicates a significant difference between the mean absolute pricing error of firms with the attribute values in the j -th half-decile and that of firms with attribute values around the median of the construct.

accruals and for the levels of $\sigma(TACC)$ and $\rho(TACC, CFO)$ for the accrual estimation error³⁰, respectively. Each column presents the results of a multivariate regression. The graphs in the second and third column gauge the magnitude of the omitted variable bias in the estimations of the base specifications.

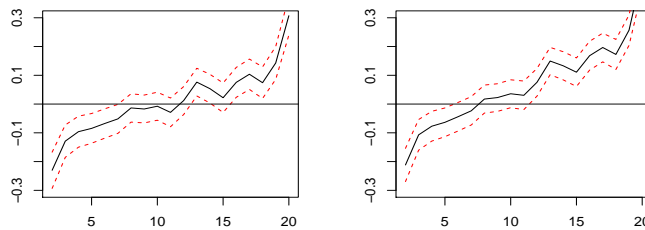
The graphs in the first two columns of figure 5 show that controlling for the variability of cash flow, $\sigma(CFO)$ or for that of accruals, $\sigma(TACC)$, does away with the significance of the unexpected accrual construct to expectation formation. In other words, either cash flow volatility or total accrual volatility subsumes the unexpected accrual proxy in the expectation formation. This finding seem to support a number of conclusions. First, since volatility measures the accuracy of predicting a variable by its past mean value, it indicate that Jones model is less useful to investors than a mean reverting model of

³⁰ The other controls are those of the *base specification*.

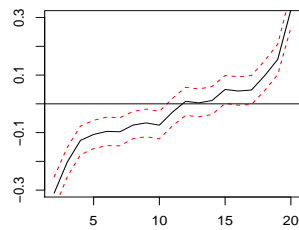
A. Model-based accrual quality constructs



B. ACC volatility - $\sigma(TACC)$



C. CFO volatility $\sigma(CFO)$



Smoothing role of accruals $corr(TACC, CFO)$

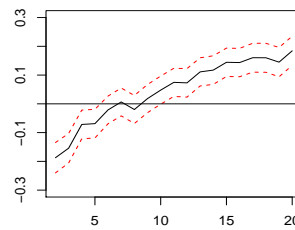


Fig. 5: Construct level coefficients in multiple regressions - alternative specifications for *Unexpected ACC* and *ACC estimation error* The graphs display the regression coefficients of the 19 indicator variables modeling half-deciles of the construct values (full line) together with the 95% confidence intervals (dotted line) in alternative specifications for *Unexpected ACC* (column 1 and 2) and for *ACC estimation error* (column 3). Column correspond to specifications controlling for the level of $\sigma(CFO)$ (column 1) and $\sigma(TACC)$ (column 2) in the case of *Unexpected ACC* and for the levels of $\sigma(TACC)$ and $\rho(TACC, CFO)$ in the case of *ACC estimation error* (column 3), respectively. The other control variables include the two-digit SIC code industry, year, size(as measured by market value, sales and total assets), intangible intensity (as measured by the price-to-book ratio, S&GA intensity and R&D intensity), the sign of earnings, the level of earnings and the level of total accruals. A significant non-zero value on the j -th abscissa position indicates that the mean absolute pricing error for firms with attribute values in the j -th half-decile is significantly different from that of firms with attribute values around the reference level (the median for $\sigma(CFO)$, $\sigma(TACC)$ and $\rho(TACC, CFO)$ and the higher values for *Unexpected ACC* and *ACC estimation error*.

cash flows or total accruals. Second, it strengthens the evidence against the usefulness of accrual forecasting models in line with previous findings³¹ (Dechow et al (1995), Bernard and Skinner (1996), Thomas and Zhang (2000)).

The third column of figure 5 shows that the accrual estimation error construct becomes insignificant when controlling for the levels of accrual variability and that of accruals smoothing effect on cash flow streams. In other words, accruals predictability (measured by $\sigma(TACC)$) and the smoothing effect of accruals $\rho(TACC, CFO)$ subsume³² the accrual estimation error construct in shaping the expectations about future earnings.

This result can be explained by existing theoretical considerations and empirical findings. McNichols (2002) notes that variability in the residual of the accrual estimation error model is increasing in variability in accruals while Dechow and Dichev (2002) documents a strong positive correlation (0.75) between the variability in the residuals of the model and accruals volatility. Moreover, the correlation between accruals and cash flows determines the estimated coefficient of the current cash flow term in the equation defining the accrual estimation error. Since the coefficients of the past and future cash flows are small compared with the coefficient of the current cash flow, if one holds the later constant (by controlling for the smoothing effect of accruals), the residual is basically the accruals. Holding the correlation between cash flows and accruals constant, the variance of residual accruals becomes practically equivalent to the variance of accruals.

³¹ Thomas and Zhang (2000) concludes that "even though the different models considered use substantial amounts of relevant information to predict accruals, they exhibit little ability to predict accruals out of sample. A simple forecast model that predicts that all firms will have accruals equal to -5% of last year's TA outperforms most models."

³² The results remain the same if the variability of total accruals is replaced by that of the current accruals.

To summarize, our findings indicate that, when it comes to future earnings expectations formation, the time-series accrual quality proxies $\sigma(TACC)$ and $\rho(TACC, CFO)$ subsume the accrual quality measures based on widely used residual accruals models.

Our finding that popular accrual models lack relevance to the expectation formation process call into question the meaning of the estimation of residual accruals. It seems that simple time-series measures, i.e. the volatility of accruals and their correlation with cash flows, are sufficient constructs for shaping future earnings expectations.

8.3 Test of H_1

Figure 6 displays the results of the analysis of the expectation formation pertinence of the measure of conservatism (first row) and SPI reporting frequency (non-zero SPI - second row, negative SPI - third row).

We use the same scale as figure 3 to facilitate comparison. The first column is the base specification while the second column corresponds to alternative specifications that control for earnings volatility and any combination of two of the other three constructs in the decomposition of earnings variance (the results are identical for all the combinations). For clarity of visualization the reference indicator corresponds to the highest values of constructs. An expectation formation pertinence relevant proxy is characterized by an increasing graph of negative mean values of valuation accuracy (higher values correspond to less relevance). The base specifications seem to confirm that the three measures shape investors expectations with the conservatism construct barely significant. The second column investigates if these measures contain relevant information beyond the constructs in the decomposition of earnings variance (5). Its graphs indicate that, while the apparent pertinence of the

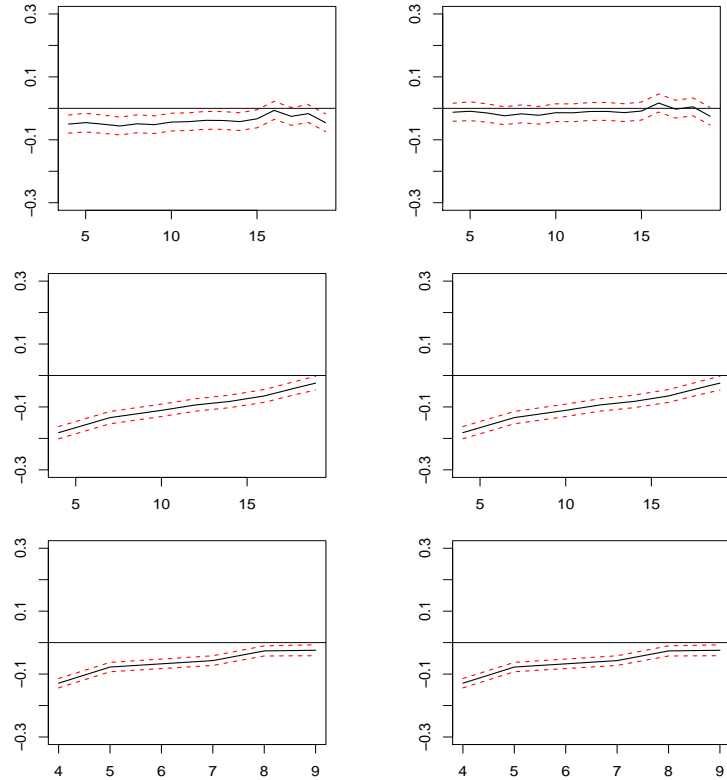


Fig. 6: **Construct level coefficients in multiple regressions - *Conservatism*, $\%SPI \neq 0$ and $\%SPI < 0$.** The graphs display the regression coefficients of the 19 indicator variables modeling the half-deciles of the construct values (full line) together with the 95% confidence intervals (dotted line) in the base (first column) and alternative specifications (second column) corresponding to *Conservatism* (first line), $\%SPI \neq 0$ (second line) and $\%SPI < 0$ (third line). The alternative specification controls for earnings volatility and (any) combination of two of the other three constructs in the decomposition of earnings variance. A significant negative value on the j -th abscissa position indicates that the mean absolute pricing errors for firms with the attribute values in the j -th half-decile is significantly lower than the mean absolute pricing errors for firms with the highest attribute values.

conservatism construct is due to the omitted variable bias, the *SPI* reporting frequency remains significantly relevant to expectation formation. Moreover, not only the frequency of reporting negative *SPI* matters: the frequency of reporting non-zero *SPI* seems to have a slightly stronger significance.

8.4 The answer to the *Main Empirical Question*

To summarize, volatility and linear predictability of earnings seem to measure the same characteristic. Earnings volatility has the strongest relative relevance among all constructs. It subsumes the cash flow volatility in expectation formation. Strong negative correlation between cash flow and accruals has a significant negative impact on how much current earnings value shapes expectations about future earnings. Investors seem to perceive over-smoothed earnings as less relevant to the expectation formation process. For same earnings and cash flow variability, more volatile accruals reduce the relevance of earnings. In other words, on the passage from cash flows to earnings, aggressive smoothing or volatile accruals have a negative impact on earnings relevance. The time-series accrual quality proxies subsume the accrual quality measures based on widely used residual accruals model. The measure of conservatism is not expectation formation pertinent while the frequency of *SPI* reporting is. We find that not only the frequency of reporting negative *SPI* matters: the measure of how often a firm reports *SPI* (independent of the sign) seems to be (slightly) more significant.

Our findings mostly align with recent survey results on CFOs rating of the importance of commonly-used earnings quality characteristics. According to Dichev et al (2013) and Dichev et al (2016), the surveyed CFOs believe that "high quality earnings are (i) sustainable (80.5%); (ii) earnings that predict future earnings (78.6%) [...]; (iii) accruals that are eventually realized as cash flows (75.7%); (iv) earnings that do not include one-time items (71.4%)." Interpreting 'sustainable'³³ as earnings that do not change much, the CFO

³³ "Sustainable" is defined as "able to be maintained at a certain rate or level" (Oxford Dictionaries) or as "able to continue over a period of time" (Cambridge Dictionary) while "to sustain" appears equivalent to "to keep up" (Merriam-Webster Dictionary).

ranking is consistent with the prime contribution to expectation formation of earnings smoothness and earnings predictability put forth by our analysis.

We disagree with the interpretation of "sustainable" as "persistent" proposed by Dichev et al (2013) for a number of reasons. First, as mentioned already in section 3.1, the definition of persistence as a parameter of a linear time series dynamics of earnings is rather reductive, in particular when the alternative is a characteristic that is model-free, i.e. unconditional variability. Second, as already noticed by Lipe (1990) and Schipper and Vincent (2003), there is a contradiction between persistence and sustainability interpreted as 'the capacity of maintaining at a certain level over time': highly persistent earnings (a random walk, for example) will have a variance that tends to infinity, i.e. income flows that depart ever more from the original level. Contrary to that, interpreting 'sustainable' as a low variance stream of earnings makes sense: low variability means earnings that maintain a level close to a constant mean.

The pertinence of the frequency of reporting special items is also recognized by the ranking. It is worth noting the apparent lack of expectation formation pertinence of the accrual estimation error construct of Dechow and Dichev (2002) which intends to measure the third most quoted earnings characteristics in the survey. As we have seen, this construct is subsumed by time-series accrual quality measures. Base on our results, "accruals that are eventually realized as cash flows" could be expressed more formally as accruals that do not excessively smooth cash flows and that, in their acting on timing of expense and revenue recognition, are not too volatile.

9 Robustness

We validated our results by considering alternatives to a number of key steps in our analysis. They regard the inference of the expectation formation pertinence measure as well as the construction of the quality measures. We re-run our analyses on combinations of variations of the expectation formation pertinence measure and of earnings quality proxies and obtained qualitatively similar results.

We constructed alternative pricing errors by, first, changing the type of valuation regression ($P - B$ vs. P/B), second, varying the definition of the sample on which we estimated the valuation regression, third, by changing the statistical approach to inference, and fourth, by extending the set of controlling variables with a measure of the level of conservatism. As an alternative to the cross-sectional estimation of the valuation regression described in section 5.2.1, we estimated the non-linear relation between the multiple and the RI drivers on industry-specific panel-type sub-samples. Concretely, for a given year t , we constructed the sub-samples containing the firm-year observations of the firms with a given SIC 3 code over the years $t - 7, t - 6, \dots, t$. We constructed the set of alternative valuation errors by estimating³⁴ the P/B regression on the so-defined panel-type sub-samples.

We want to emphasize that the panel-type estimation sub-samples are very different from the cross-sectional sub-samples. First of all, the later ones are derived from the *pricing error sample* which, at 135,122 firm-years, is a much large sample than the *earnings quality sample* (size 51,355 firm-year observations) which forms the basis of the panel-type sub-samples. Moreover, as mentioned in section 5.2, due to the data requirements, the *earnings quality*

³⁴ For the sake of consistency we require that the sample size for each panel-type sub-sample should be not smaller than 32, i.e. the SIC 3 industry should contain at least 4 firms.

sample sample is composed of firms that are larger and longer-lived. As such, besides differences in the size, the structure of the two types of sub-samples is quite different.

Second, the cross-sectional sub-samples contain more heterogeneous firms as the industry selection is made on the SIC 2 identifier but are time-homogeneous as all the firm-years observations belong to the same year. In contrast to that, while the panel-type sub-samples are made up of more similar firms (identified by the SIC 3 industry code), they contain the firm-years observations of the companies in the narrower industry description over the previous seven year period³⁵. As a result, the estimation frame for the expectation formation pertinence measure is quite different for the two set-ups.

Besides changing the data on which the P/B regressions were estimated, we analyzed also the robustness of our results to variation of the expectation formation pertinence measure due to the type of non-parametric approach to inference. We investigated three conceptually different and widely-used non-parametric methods (AM, PPR, CART and MARS) described in sections 4.1 and 11.2 of the Appendix.

In the accounting-based valuation literature, researchers often follow Feltham and Ohlson (1995) in defining conservative and unbiased accounting in terms of how book value differs from market value. Under conservative accounting reported net assets will be less than market value in the long run. Following relevant literature (Zhang (2000), Pae et al (2005), Beaver and Ryan (2005), Roychowdhury and Watts (2007)) we employ the lagged ration between market value and book value as a proxy of the level of conservative accounting. As an alternative proxy, we measured the difference in book value of equity

³⁵ While the cross-sectional construction assumes that the regression function in (3) is similar for firms with the same SIC 2 industry code, the second construction makes the same assumption for a narrower industry definition but extends the constancy hypothesis over the recent past period of seven years.

between unbiased and conservative accounting by the size of estimated reserve (ER), as in Penman and Zhang (2002) (see also section 5.2.2). Results in Feltham and Ohlson (1996) and Gjesdal (2004)³⁶ imply that the estimated reserve is positive under conservative accounting and the higher the estimated reserve, the more conservative the accounting system. The empirical results for the two alternative proxies for the level of conservative accounting are qualitatively identical.

We also investigated the sensitivity of the reported relations between the expectation formation pertinence and earnings quality to how earnings quality was measured. We performed two types of robustness checks. First, we estimated the predictability measure and the two measures of accruals conditional variability on yearly cross-sections. While qualitatively our results do not change, we found that, for the cross-sectional earnings quality proxies, the differences in mean are, overall, smaller in size than those estimated on time series.

Second, we estimated alternative specifications of the models yielding accruals quality measures. We constructed the accrual quality measure using the McNichols (2002) extension of the model in Dechow and Dichev (2002) (see also Francis et al (2005)):

$$ACC_{i,t} = b_{i,0} + b_{i,1}CFO_{i,t-1} + b_{i,2}CFO_{i,t} + b_{i,3}CFO_{i,t+1} \\ + b_{i,4}\Delta REV_{i,t} + b_{i,5}PPE_{i,t} + v_{i,t}.$$

We also constructed the Jones model unexpected accrual (estimated cross-sectionally each year using all firm-year observations in the same two-digit

³⁶ These references define conservative accounting such that the carrying value assigned to investments yields an expected accounting rate of return greater than the internal rate of return.

SIC code or in the panel-type set-up using all firm-year observations in the same three-digit SIC code in the current year and the previous seven years):

$$TACC_{i,t} = \gamma_0 + \gamma_1(1/A_{i,t-1}) + \gamma_2\Delta REV_{i,t} + \gamma_3PPE_{i,t} + w_{i,t}$$

where ΔREV is the change in revenues and PPE is gross property, plant and equipment.

10 Conclusions

To summarize, we shed some light on the issue of the quality constructs the investors emphasize in the process of forming their expectations about future earnings (as summarized by the market value). Our study is empirical and complements the scarce pertinent theoretical literature. We extend previous research on the relevance of earnings quality constructs to financial stakeholders which has considered desirable attributes of earnings one or a few at a time by considering eleven widely used attributes both individually and, more importantly, conditional on the others. Moreover, we look at the relation between market prices and earnings quality proxies from an angle that has not been investigated so far, that of the expectation formation pertinence.

Two methodological particularities form the econometric basis of our study. First, we employ an alternative, statistically sound, research design introduced by Kang and Starica (2016). Formally, the alternative design replaces specifications of the Ohlson linear specification of the RI valuation model, not guaranteed to yield consistent estimates in cross-sections, with a non-linear regression that can be consistently inferred. It also substitutes the linear regressions R^2 , the common measure of the strength of the association

between prices and accounting variables, with a dispersion measure of the regressions error term.

The alternative research design is intuitively appealing: it assesses the association between prices and accounting information through the level of accuracy of a valuation in which the expectation formation takes into account only the information contained in the current earnings. The valuation gap is an indication of the extent to which future earnings expectations incorporated in prices are formed using information *other* than the size of current earnings. To summarize, the alternative framework investigates expectation formation pertinence of current earnings.

Second, we investigate the relation between the expectation formation pertinence measure and quality constructs through a non-standard use of the linear regression that takes advantage of linear regression's versatility without imposing the assumption of linearity on the relationship under study.

Our analysis delineates an overall picture of the relevance of the earnings quality constructs under discussion. Earnings are more informative than cash flows: former's volatility subsumes the variability of the later in the process of expectation formation. Moreover, in converting cash flows into earnings through accruals, aggressive smoothing or volatile accruals have a negative impact on earnings relevance. Time-series accrual quality proxies shape expectations beyond constructs based on widely used residual accrual models. How often firms report special items has a significant impact on current earnings relevance to expectation formation: the more often, the worse.

Our results are in line with CFOs beliefs as accounted by Dichev et al (2013) and Dichev et al (2016): above all, quality earnings vary little (are sustainable) and are predictive of future earnings. We believe that our find-

ings underscore research opportunities in identifying the accounting factors that affect variability and the long-term prediction of earnings.

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11 Appendix

11.1 Best linear predictor of Y given X

Except for the case that (X, Y) is a bi-variate normal distribution, the conditional expectation $E(Y|X)$ could be a complicated nonlinear function of X . So we can instead consider the best linear predictor of Y given X

$$g(X) = \alpha + \beta X$$

where the coefficients α and β are obtained by minimizing $E[(Y - (\alpha + \beta X))^2]$. Since

$$E[(Y - (\alpha + \beta X))^2] = E[Y^2] - 2\alpha\mu_y - 2\beta E[XY] + \alpha^2 + 2\alpha\beta\mu_x + \beta^2 E[X^2]$$

where $\mu_x = E[X]$ and $\mu_y = E[Y]$, we can obtain the corresponding values of α and β by solving the system:

$$\begin{aligned} \frac{\partial}{\partial \alpha} E[(Y - (\alpha + \beta X))^2] &= -2\mu_y + 2\alpha + 2\beta\mu_x = 0 \\ \frac{\partial}{\partial \beta} E[(Y - (\alpha + \beta X))^2] &= -2E[XY] + 2\alpha\mu_x + 2\beta E[X^2] = 0. \end{aligned}$$

Using the notations $\sigma_x^2 = \text{Var}(X)$, $\sigma_y^2 = \text{Var}(Y)$, and $\rho = \text{Cov}(X, Y)/(\sigma_x\sigma_y)$, the solution can be expressed as:

$$\begin{aligned} \beta &= \frac{E[XY] - E[X]E[Y]}{E[X^2] - (E[X])^2} = \rho \frac{\sigma_y}{\sigma_x}, \\ \alpha &= \mu_y - \beta\mu_x = \mu_y - \rho \frac{\sigma_y}{\sigma_x} \mu_x. \end{aligned}$$

To summarize, the best linear predictor of Y given X , $g(X)$, is given by

$$g(X) = \mu_y + \rho \frac{\sigma_y}{\sigma_x} (X - \mu_x). \quad (6)$$

Note that, replacing the parameters in (6) by their sample versions yields an expression formally similar to the Mean Square Error (MSE) estimates of a linear regression. The MSE formulae can hence be interpreted either as the legitimate, consistent estimates of a linear regression, i.e. a relation between the components of the pair (X, Y) for which the condition $E[Y|X] - \alpha X - \beta = 0$ holds for some α and β or, more generally, as the sample version of the coefficients of the best linear predictor of Y given X in a general pair (X, Y) .

In the particular case of the pair (NI_t, NI_{t-1}) , the two interpretations above correspond, the first, to a stationary, $AR(1)$ linear dynamics for the earnings stream and, second, to the best linear predictor of future period earnings by the current period earnings in a pair that is not necessarily animated by a linear dynamics. While the extant literature adopts the first interpretation, in this study we focus on the second.

11.2 Non-parametric regression estimation

The AM and PPR model belongs to the first alternative paradigm to linear regression. AM is a powerful and yet simple technique. They were introduced by Hastie and Tibshirani (1986). The AM framework is based on an two appealing and simple assumptions. First, the relationships between the individual predictors and the dependent variable follow smooth patterns (that can be linear or non-linear). Second, we can estimate these smooth relationships *simultaneously* and then predict the dependent variable by simply adding

them up.

$$E(Y|X) = \alpha + s_1(X_1) + \dots + s_p(X_p), \quad (7)$$

where Y is the dependent variable, $E(Y|X)$ denotes the expected value of Y conditional on X . The terms $s_1(X_1), \dots, s_p(X_p)$ denote smooth, non-parametric functions. Note that the shape of predictor functions are fully determined by the data as opposed to parametric functions that are defined by a typically small set of parameters. This allows for more flexible estimation of the underlying regression patterns without knowing upfront what these patterns look like. Moreover, this helps us find patterns we may have missed with a parametric model. Predictor functions are automatically derived during model estimation.

The PPR model fits a global non-linear regression model to the data by first projecting the matrix of explanatory variables in a directions that optimizes the model fit before applying smoothing functions to the projected explanatory variables. As a new projection is found, the data are reduced by removing the component along that projection, and the process of finding a new projection is repeated. This is the "pursuit" aspect that gives the name to the technique. The final model looks like

$$Y = \beta_0 + \sum_{j=1}^r f_j(\beta_j' X) + \varepsilon, \quad (8)$$

where X are the independent variables (in number of p), β_j is a collection of (unknown) directions, f_j are univariate non-linear regression functions to be estimated while r is the number of modeled smoothed non-parametric functions to be used as constructed explanatory variables. The value of r is found through cross-validation.

In words, PPR fits non-linear functions f_j of linear combinations in the explanatory variables X . For large values of r and an appropriate set of functions f_j , the PPR approach can estimate any continuous function in R^p .

The other two techniques we use belong to the second alternative to linear regression: that where one partitions the independent variable space into smaller regions where the relation between the regressors and the regressed is more manageable and one fits on each region a simple linear models. The main ingredient of such an approach is the *recursive partitioning* of the variables space to regions small enough to display a simple structure to which we can fit simple models. This alternative approach to linear regression yields the class of *recursive partitioning regression models*.

Regression trees use the concept of a *tree* to represent the recursive partition. Each of the terminal nodes of the tree represents a cell of the partition and has attached to it a simple model which applies in that cell only. Both models under discussion admit a tree representation: CART fits local constants while MARS fits piece-wise linear regressions.

For classic regression trees (CART), the model in each cell is just a constant estimate of Y . That is, suppose the points $(x_1, y_1), (x_2, y_2), \dots, (x_c, y_c)$ are all the data points in a given cell. Then our estimated model for the cell is just

$$\hat{Y} = \frac{1}{c} \sum_{i=1}^c y_i, \quad (9)$$

i.e., the sample mean of the dependent variable for the data points in that cell. This is a piece-wise-constant model. There are several advantages to this approach. Making predictions is fast: just look up constants in the tree. It is easy to understand which explanatory variables are important by look at the tree structure. Since the model yields a jagged response, it can work when the true regression surface is not smooth. If the regression surface is smooth, the

piece-wise-constant response surface can approximate it arbitrarily closely. Moreover, there are fast and reliable algorithms to construct the trees.

MARS extends the linear models to automatically consider non-linearities and interactions between variables. The models has the following form

$$Y = \sum_{i=1}^k c_i B_i(X) + \varepsilon \quad (10)$$

where $B_i(x)$ are basis functions and c_i unknown coefficients (to be estimated). The basis functions are constants, univariate functions of the form $\max(0, x - \text{const})$ called *hinge functions* or (multivariate) products of two or more hinge functions. In words, the model is a weighted sum of non-linear basis functions $B_i(X)$. The parameters of the non-linear basis functions as well as their weights need to be estimated.

MARS automatically selects variables, the values of the constants in the basis functions and estimates the coefficients c_i . The hinge functions automatically partition the input data, so the effect of outliers is reduced. MARS is flexible enough to model non-linearity and variable interactions, yet the constrained form of basis functions prevents too much flexibility.

For more details see James et al (2014) and Wasserman (2006).