Accounting information vs. analysts forecasts in market's expectations formation

Catalin Starica · Jian Kang

Abstract We find that the expectations about future earnings incorporated in prices are mainly informed by the analysts earnings forecasts. Neither the stock nor the flow accounting items considered do not contribute significantly to shaping investors price setting expectations.

Keywords Analysts earnings forecast · accounting information · non-linear association · non-parametric regression

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1 Introduction

Liu and Thomas (2000) and Dechow et al. (1999) suggest that analysts earnings predictions are important in explaining contemporaneous prices/returns. The first paper shows that they strengthen the estimated return-earnings relation. The second finds that the explanatory power of a price levels regression (a model regressing prices on book values and earnings) is enhanced by adding analysts forecasts to the explanatory variables. Moreover, current earnings lose the statistical significance to stock prices in the enhanced model indicating that analysts forecasts of next year earnings subsume the value relevant information in current earnings.

This study takes a closer look at the interplay between current accounting information and analysts earnings forecasts in the frame of their pertinence to the expectation formation process. We find that, while expectations of future earnings reflect both type of information when considered separately, the accounting information does not add significantly to expectations informed by the analysts' forecasts. Analysts forecasts subsume the expectation formation pertinent information in current accounting items.

2 The direct implementation of the RI valuation model

This section summarizes the approach to implementing the RI model in KS, the basis of the research design that we detail in the next section. KS show how the RI valuation relation can be inferred 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 which expresses the price as a valuation informed only by the observed values of the predictors plus a left-over part that amounts to a pricing correction due to other information available to market participants.

The specifications of the RI model are regressions, i.e., the correction 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.

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 ($NI - r \times B_{-1}$):

$$P_{i,0} = B_{i,0} + \sum_{t=1}^{\infty} \frac{\mathbb{E}_0[NI_{i,t} - r_{i,0} \times B_{t-1}]}{(1+r_{i,0})^t} = B_i + \sum_{t=1}^{\infty} \frac{\mathbb{E}_0[RI_{i,t}]}{(1+r_{i,0})^t} \qquad (1)$$

(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). In order to simplify the notation we will suppress the 0 under-script whenever possible. By default, the valuation happens at time 0.

Denote by $\texttt{PREDICT.RI}_0$ a set of predictors of future residual earnings available at time 0.

Proposition 1 (`Price = valuation informed by PREDICT.RI + investors correction`).

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

[1] The decomposition:

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

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* $\mathbf{m}_i$ *a possibly non-linear, firm-specific function and* ε_i*, an error term, such that:*

$$P_i - B_i = \mathbf{m}_i(\texttt{PREDICT.RI}_\texttt{i};\ r_i) + \varepsilon_i \tag{2}$$

where

$$\mathbb{E}[\varepsilon_i \mid \texttt{PREDICT.RI}_i] = 0 \tag{3}$$

The function $\mathbf{m}_i$ *is specific to the set* PREDICT.RI*.*

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

   Moreover,

$$\mathbf{m}_i(\texttt{PREDICT.RI}_i\ ;\ B_i,\ r_i) := \sum_{t=1}^{\infty} \frac{\mathbb{E}[RI_{i,t} \mid \texttt{PREDICT.RI}_i]}{(1+r_i)^t}$$

   i.e. the regression function in the decomposition (2) represents 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 terms are investors corrections to these valuations

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is called a *regression* if and only if

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

or equivalently, if the orthogonality condition

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

holds.

The error terms in the decomposition (2), ε_i, amounts 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`.

The notation $\mathbf{m}_i(\,\cdot\,;\,\cdot\,)$ in expression (2) emphasizes the fact that the regression functions depend both on a number of variables and on a number of parameters. The variables, that is $\texttt{PREDICT.RI}_i$, are listed before the semicolon while the parameters, at this point of the discussion, r_i, are listed after. Moreover, the regression function is *predictor-set specific.*

KS further argue that one can assume that the (non-linear) functions $\mathbf{m}_i$ for firms i in the *same industry I, of similar size S and level of conservative accounting C* are approximately equal:

$$\mathbf{m}_i(\cdot\,;\,r_i) \approx \mathbf{m}_I(\cdot\,;\,r_i,\,S_i, C_i), \quad i \in I.$$

This assumption has two consequences. First, it allows for consistent estimation of $\mathbf{m}_I$ in cross-sections[2]. Second, it indicates the need to include 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 (3) guarantee that the specifications of the RI valuation model in (2) can be *consistently* estimated (Györfi et al (2002)). The issue of omitted variable bias is structurally ruled out.

[2] Without the relative constancy of the function $\mathfrak{m}_i$ 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 $\mathbf{m}_I$ on a the panel-type sample combining time series with cross-sectional observations. One achieves this way a sample that is large enough for statistical precision limiting nevertheless the issue of the survival bias.

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

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

3 The research design

For the analyses in this paper, we specify the $P - B$ valuation regression in (2) as:

$$P_i - B_i = \mathbf{m}_I(\texttt{PREDICT.RI}_i \,;\, r_i,\ S_i,\ C_i) + \varepsilon_i, \tag{4}$$

where the firm i belongs to the industry I, r, S and C stand for equity risk, size and level of conservative accounting, respectively, while the function $\mathbf{m}_I$ is specific to the predictor set.

For a given set of predictors `PREDICT.RI`, we consistently estimate the regression function in (4) each year and for each industry I. We denote by $\widehat{\mathbf{m}}_I$ this consistent estimate. The inference yields a valuation of each of the firms in the sample:

$$\widehat{P}_i := B_i + \widehat{\mathbf{m}}_I(\texttt{PREDICT.RI}_i \,;\, r_i,\ S_i,\ C_i), \quad i \in I.$$

The size of the *valuation error*:

$$|P_i - \widehat{P}_i|, \tag{5}$$

reflects the magnitude of investors correction of a valuation (of firm i) informed only by the set of predictors `PREDICT.RI`. It measures the pertinence of the information contained in the levels of the set of predictors to the process of expectation formation. The larger the error, the less pertinent `PREDICT.RI`.

3.1 Choice of the predictor sets

Since our study focuses on the interplay between accounting information and analysts earnings projections in the expectation formation process, the predictor sets `PREDICT.RI` will be of three types: accounting items, analysts consensus earnings forecasts one- and two-year ahead and unions of the two previous types.

Our choice of accounting variables comprises twelve items that prior research established as pertinent to valuation and that are available over the sample period. We consider earnings (NI) and the book value of equity (B) because they are the focus of prior research on the value relevance of accounting information. We include three cash-related firm characteristics, that is, cash flow from operations (CFO), dividends (DIV), and cash holdings, motivated by the extensive literature that relates cash to valuation (e.g., Barth, Beaver, Hand, and Landsman, 1999). We incorporate three items that play a prominent part in the accounting of the New Economy: research and development expenses (RD), recognized intangible assets ($INTAN$), and advertising expense (ADV) (e.g., Aboody and Lev, 1998; Core, Guay, and Van Buskirk, 2003). We include special items (SPI) and other comprehensive income (OCI), by reason of the attention they received lately from both regulators and academics (e.g., Jones and Smith, 2011). We also add revenues (REV) and total assets ($ASSETS$) as two important items from the income and financial statements.

The twelve items separate into flow and stock variables. The flow items are

$$\mathcal{F} := \{NI,\ CF,\ DIV,\ REV,\ SPI,\ OCI,\ RD,\ ADV\}$$

while the stock variables are

$$\mathcal{S} := \{B,\ ASSETS,\ CASH,\ INTAN\}.$$

Analysts consensus estimate set, denoted by $\mathcal{A}$, includes the one-year ahead (EPS_1) and two-year ahead (EPS_2) per share earnings predictions:

$$\mathcal{A} = \{EPS_1,\ EPS_2\}.$$

3.2 Comparison of expectation formation pertinence

To evaluate the specific contribution of the accounting information to the formation of expectations about future residual earnings, we compare the expectation formation pertinence of a given set of individual accounting items predictors (e.g., all stock variables, all flow variables or their union) to that of the set augmented with analysts consensus earnings estimates. If the pertinence of the larger predictor set is significantly bigger we conclude that analysts predictions contain information beyond that in the accounting items in the predictors set.

Similarly, to asses the distinct contribution of analysts predictions to the formation of expectations about future residual earnings, we measure the expectation formation pertinence of analysts forecasts against that of a predictors set that includes, besides the one- and two-year ahead forecasts, the given set of individual accounting items (eg., all stock variables, all flow variables or their union). If the pertinence of the larger set is not significantly bigger, we conclude that analysts predictions are at least as informative as the accounting variables or, in other words, that the accounting items do not contain information that goes beyond that in analysts previsions.

Concretely, lets suppose we want to test the hypothesis that analysts information $\mathcal{A}$ shapes the expectations about future earnings beyond the information in the set of flow accounting items $\mathcal{F}$. In other words, we want to evaluate the specific expectation formation contribution of analysts information $\mathcal{A}$ with respect to that of the set of flow accounting items $\mathcal{F}$. We will proceed as follows.

For each firm $i \in I$, we perform the following two valuations

$$\widehat{P}_i^{\mathcal{F}} = B_i + \widehat{\mathbf{m}}_I^{\mathcal{F}}(\mathcal{F}_i\,\mathbf{;}\, r_i,\ S_i,\ C_i),$$

and

$$\widehat{P}_i^{\mathcal{F}\cup\mathcal{A}} = B_i + \widehat{\mathbf{m}}_I^{\mathcal{F}\cup\mathcal{A}}(\mathcal{F}_i \cup \mathcal{A}_i\,\mathbf{;}\, r_i,\ S_i,\ C_i), \quad i \in I,$$

respectively, and construct the two valuation errors:

$$VE_i^{\mathcal{F}} := P_i - \widehat{P}_i^{\mathcal{F}} \quad \text{and} \quad VE_i^{\mathcal{F}\cup\mathcal{A}} := P_i - \widehat{P}_i^{\mathcal{F}\cup\mathcal{A}}.$$

Then we statistically compare the distributions of the two errors $VE^{\mathcal{F}}$ and $VE^{\mathcal{F}\cup\mathcal{A}}$. A distribution of the valuation error $VE^{\mathcal{F}\cup\mathcal{A}}$ that is more concentrated than that of $VE^{\mathcal{F}}$ is evidence of smaller size errors for the valuation informed by the union of accounting and analyst information. Since the investors need to correct this valuation less than that informed only by the accounting items, we would conclude that analysts predictions inform the expectation formation process beyond the extent that flow accounting items do. In other words, analysts predictions contain specific expectation formation pertinent information that is not part of that of flow accounting items.

The last element in the research design is the statistical approach to comparing the distributions of two valuation errors. The next section addresses this issue.

3.3 An overall accuracy comparison measure

We believe that the concept of stochastic dominance gives the natural set-up for comparing the pertinence of competing predictor sets to the expectation formation process. While stochastic dominance has been extensively used in finance research, especially for the comparison of portfolios' performance, it has not yet been applied for the analysis of valuation accuracy.

The stochastic dominance criterion is both intuitively appealing and comprehensive. We say that valuation $\mathcal{X}$ (informed by the predictors set $\mathcal{X}$) dominates pricing method $\mathcal{Y}$ (informed by the competing predictors set $\mathcal{Y}$) if the proportion of firms valued within a specified error is higher for valuation $\mathcal{X}$ than for valuation $\mathcal{Y}$, for all error levels.

This definition can be stated formally making use of the cumulative distribution functions (CDF) $F_{\mathcal{X}}$ and $F_{\mathcal{Y}}$ of the absolute errors $|VE^{\mathcal{X}}|$ and $|VE^{\mathcal{Y}}|$ of the two valuations informed only by the level of the predictors $\mathcal{X}$ and $\mathcal{Y}$, respectively. The valuation $\mathcal{X}$ dominates[3] valuation $\mathcal{Y}$ (we write $\mathcal{X} \geq \mathcal{Y}$), if

$$F_{\mathcal{X}}(e) \geq F_{\mathcal{Y}}(e), \quad \text{i.e.} \quad P(|VE^{\mathcal{X}}| \leq e) \geq P(|VE^{\mathcal{Y}}| \leq e), \tag{6}$$

[3] For our purpose, we had to adjust the common definition of *stochastic dominance* which states that *distribution Y dominates distribution X stochastically* at first order if, for any argument e, $F_{\mathcal{X}}(e) \geq F_{\mathcal{Y}}(e)$ where $F_{\mathcal{X}}$ stands for the cumulative distribution function (CDF) of the distribution $\mathcal{X}$. This definition fits the case where smaller probabilities of low values are desirable, like in the study of poverty. In our case small values mean higher precision and are hence desirable.

for all errors e. In this case, the predictors set $\mathcal{X}$ is more expectation formation pertinent than the predictors set $\mathcal{Y}$.

If e denotes a specific absolute error, say 20%, then the inequality $F_{\mathcal{X}}(e) \geq F_{\mathcal{Y}}(e)$ in the definition (6) means that the percentage of firms whose values based on expectations informed by the predictors set $\mathcal{X}$ are within 20% of the actual price is greater than, or equal to, the percentage of firms for which the value informed by the predictors set $\mathcal{Y}$ lies within 20% of the actual price. If method $\mathcal{X}$ dominates method $\mathcal{Y}$, then whatever error level we may choose, there is always more precision delivered by the predictors set $\mathcal{X}$ than by the set $\mathcal{Y}$.

Inequality (6) implies a clear relationship between the corresponding percentiles of the two error distributions. Since for a $p \in [0, 1]$, the $(p * 100)\%$ percentile of the distribution $\mathcal{X}$ is defined as $F_X^{-1}(p)$, if method $\mathcal{X}$ dominates method $\mathcal{Y}$, then

$$(p * 100)\% \text{ percentile of } |VE^{\mathcal{X}}| \leq \ (p * 100)\% \text{ percentile of } |VE^{\mathcal{Y}}|, \tag{7}$$

for all $p \in [0, 1]$. In words, all percentiles of $|VE^{\mathcal{X}}|$ are smaller than the corresponding $|VE^{\mathcal{Y}}|$-percentiles. In particular, the median absolute error of a valuation informed by the predictors set $\mathcal{X}$ is smaller than that of a valuation informed by the competing predictors set $\mathcal{Y}$.

The notion of dominance, summarized in Table 1, yields the most exhaustive criterion for comparing the valuation accuracy of competing predictor sets.

In practice, before performing a comparison of the accuracy of two valuation methods $\mathcal{X}$ and $\mathcal{Y}$, $F_{\mathcal{X}}$ and $F_{\mathcal{Y}}$, the CDF of the corresponding absolute errors, need to be estimated, and the statistical error needs to be taken into account when establishing a performance relationship between the valuation

Relation	When	Expectation formation
$\mathcal{X} > \mathcal{Y}$ or $F_{\mathcal{X}}(e) > F_{\mathcal{Y}}(e), \forall e$	$\sup_e(F_{\mathcal{X}}(e) - F_{\mathcal{Y}}(e)) > 0$	Predictors set $\mathcal{X}$ is more pertinent than predictors set $\mathcal{Y}$
$\mathcal{X} < \mathcal{Y}$ or $F_{\mathcal{X}}(e) < F_{\mathcal{Y}}(e), \forall e$	$\inf_e(F_{\mathcal{X}}(e) - F_{\mathcal{Y}}(e)) < 0$	Predictors set $\mathcal{Y}$ is more pertinent than predictors set $\mathcal{X}$
$\mathcal{X} = \mathcal{Y}$ or $F_{\mathcal{X}}(e) = F_{\mathcal{Y}}(e), \forall e$	0	Predictors set $\mathcal{X}$ is as pertinent as predictors set $\mathcal{Y}$
Neither set dominates the other	not defined	The 2 predictors sets cannot be compared

Table 1: **Dominance measure.** The table defines the dominance measure $dm(\mathcal{X}, \mathcal{Y})$ between two valuations informed by the predictors sets $\mathcal{X}$ and $\mathcal{Y}$, respectively. $F_{\mathcal{X}}$ and $F_{\mathcal{Y}}$ denote here the CDF of the absolute valuation errors $|VE^{\mathcal{X}}|$ and $|VE^{\mathcal{Y}}|$ of valuations informed only by the predictors set $\mathcal{X}$ and $\mathcal{Y}$, respectively.

approaches. For details about how this is done rigorously, see section A in the Appendix.

4 The sample

The sample is the intersection of Compustat and I/B/E/S data bases.

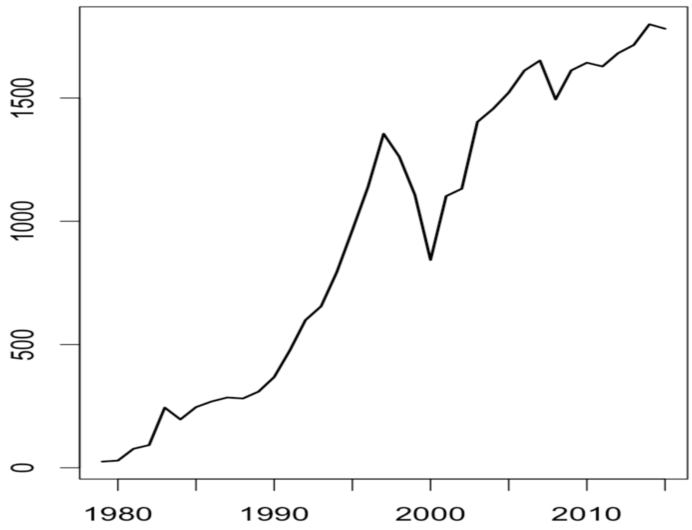

Fig. 1: Sample size

5 Empirical results

According to the discussion in section A in the Appendix, to comparing the distributions of errors corresponding to valuations informed by competing predictor sets $\mathcal{X}$ and $\mathcal{Y}$, we calculate two statistics

$$M(\mathcal{X}, \mathcal{Y}) := \max_e (\widehat{F}_{\mathcal{X}}(e) - \widehat{F}_{\mathcal{Y}}(e)) \tag{8}$$

and

$$m(\mathcal{X}, \mathcal{Y}) := \min_e (\widehat{F}_{\mathcal{X}}(e) - \widehat{F}_{\mathcal{Y}}(e)) \tag{9}$$

and compare them to the significance threshold values $c(n_{\mathcal{X}}, n_{\mathcal{Y}}) := 1.36 \times \sqrt{1/n_{\mathcal{X}} + 1/n_{\mathcal{Y}}}$ and $-c(n_{\mathcal{X}}, n_{\mathcal{Y}})$, respectively ($n_{\mathcal{X}}$ is the size of the sample of errors of valuation informed by the $\mathcal{X}$ predictor set).

When $M(\mathcal{X}, \mathcal{Y}) > c$ and $m(\mathcal{X}, \mathcal{Y}) \geq -c$, we conclude that the set of predictors $\mathcal{X}$ is more expectation formation pertinence than the set $\mathcal{Y}$.

$M(\mathcal{X}, \mathcal{Y}) \leq c$ and $m(\mathcal{X}, \mathcal{Y}) < -c$ is evidence that the set of predictors $\mathcal{Y}$ is more expectation formation pertinence than the set $\mathcal{X}$.

If $M(\mathcal{X}, \mathcal{Y}) \leq c$ and $m(\mathcal{X}, \mathcal{Y}) \geq -c$, we conclude that the two sets of predictors are equally expectation formation pertinent.

The results of the comparison are presented in graphs displaying four curves. Two of the curves (full line) represent the time evolution of the statistics $M(\mathcal{X}, \mathcal{Y})$ (the upper blue curve) and $m(\mathcal{X}, \mathcal{Y})$ (the lower black curve). The dotted lines represent the lower and upper thresholds corresponding to non-significance of the two statistics, that is $-c(n_{\mathcal{X}}, n_{\mathcal{Y}})$ and $c(n_{\mathcal{X}}, n_{\mathcal{Y}})$. The graphs test the null hypothesis of equal expectation formation pertinence of the two predictor sets for each year in the sample. In other words, they synthesize 36 hypothesis tests. For a given year, a M statistic outside the significance bands rejects the null hypothesis in the favor of higher pertinence of the predictor set $\mathcal{X}$ in the year under scrutiny. Both M and m statistics within significance band indicate that there is no evidence against the null of equal expectation formation pertinence.

The first graph in figure 2 shows that the expectation formation pertinence of the set $\{EPS_1, EPS_2\}$ is strictly larger than that of the set $\{EPS_1\}$ (after 1990) indicating that the two year ahead forecast informs expectations beyond the one year ahead predictions. The second graph in figure 2 brings evidence that the expectation formation pertinence of the set $\{EPS_1, EPS_2\}$ is equal to that of the larger set $\{EPS_1, EPS_2, LTG\}$ indicating that the long term growth does not add anything to expectations informed by the one and two year ahead predictions.

The graphs in figure 3 show that the expectation formation pertinence of the set $\{EPS_1, EPS_2\}$ is strictly larger than that of the accounting item sets $\{\mathcal{S}\}$, $\{\mathcal{F}\}$, $\{\mathcal{S}, \mathcal{F}\}$ (after 1990) indicating that analysts forecasts informs expectations beyond accounting items.

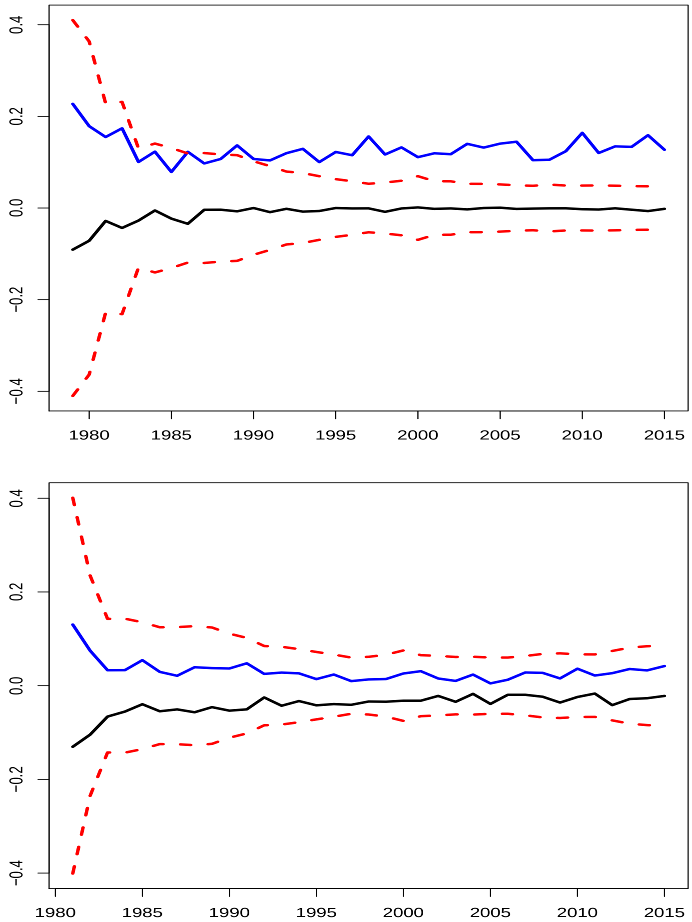

Fig. 2: **Analysts prediction information content**. The competing predictors sets are $\mathcal{X} = \{EPS_1, EPS_2\}$ and $\mathcal{Y} = \{EPS_1\}$ (first) and $\mathcal{X} = \{EPS_1, EPS_2, LTG\}$ and $\mathcal{Y} = \{EPS_1, EPS_2\}$ (second), respectively. The graphs display the time evolution of the statistics $M(\mathcal{X}, \mathcal{Y})$ (the upper blue curve) and $m(\mathcal{X}, \mathcal{Y})$ (the lower black curve). The dotted lines represent the lower and upper thresholds corresponding to non-significance of the two statistics, that is $-c(n_{\mathcal{X}}, n_{\mathcal{Y}})$ (lower dotted) and $c(n_{\mathcal{X}}, n_{\mathcal{Y}})$ (upper dotted). The null hypothesis corresponding to the significance band is that of equal expectation formation pertinence of the two predictor sets. A M statistic outside the significance bands rejects the null hypothesis in the favor of higher pertinence of the predictor set $\mathcal{X}$. Both M and m statistics within significance band indicate no evidence against the null hypothesis.

The graphs in figure 4 bring evidence that the expectation formation pertinence of the set $\{EPS_1, EPS_2\}$ is equal to that of the larger sets $\{EPS_1, EPS_2, \mathcal{S}\}$, $\{EPS_1, EPS_2, \mathcal{F}\}$, $\{EPS_1, EPS_2, \mathcal{S}, \mathcal{F}\}$ indicating that accounting items do

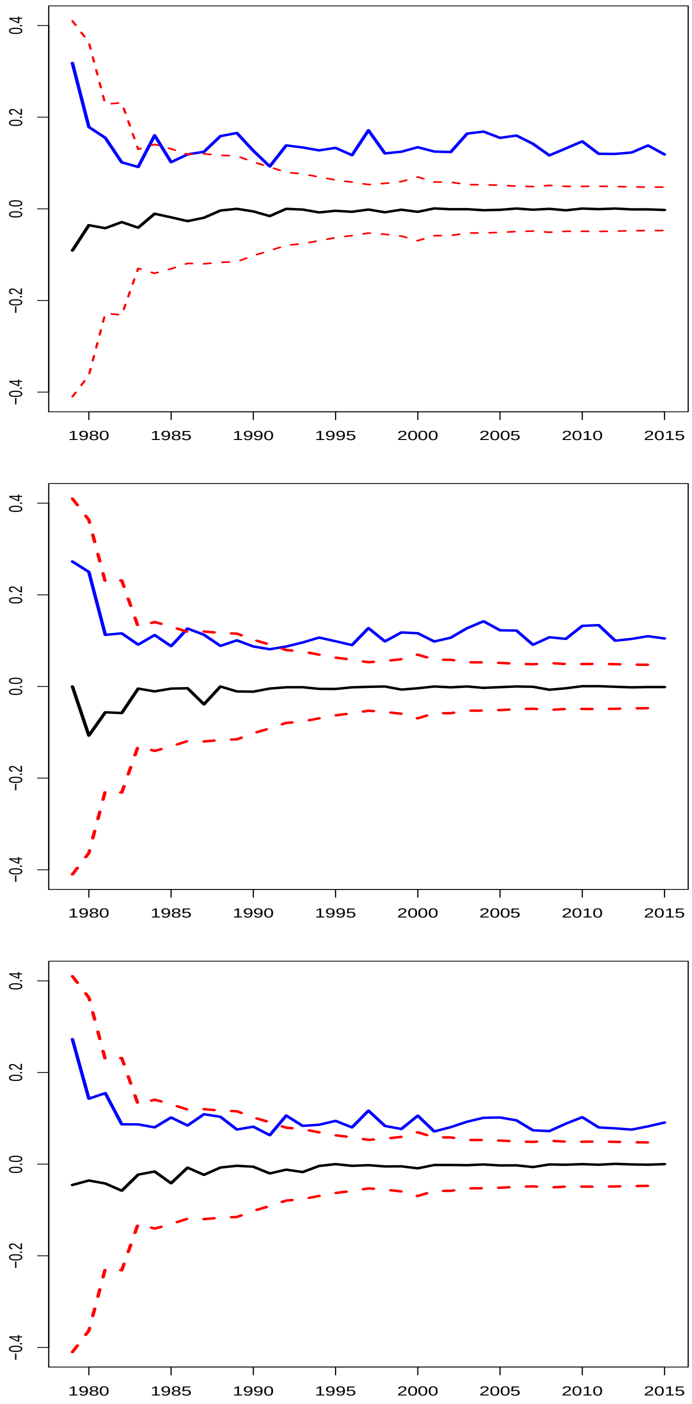

Fig. 3: **Analysts prediction over accounting items information content**. The competing predictors sets are $\mathcal{X} = \{EPS_1, EPS_2, \mathcal{S}\}$ and $\mathcal{Y} = \{\mathcal{S}\}$ (first), $\mathcal{X} = \{EPS_1, EPS_2, \mathcal{F}\}$ and $\mathcal{Y} = \{\mathcal{F}\}$ (second), and $\mathcal{X} = \{EPS_1, EPS_2, \mathcal{S}, \mathcal{F}\}$ and $\mathcal{Y} = \{\mathcal{S}, \mathcal{F}\}$ (third). The graphs display the time evolution of the statistics $M(\mathcal{X}, \mathcal{Y})$ (the upper blue curve) and $m(\mathcal{X}, \mathcal{Y})$ (the lower black curve). The dotted lines represent the lower and upper thresholds corresponding to non-significance of the two statistics, that is $-c(n_{\mathcal{X}}, n_{\mathcal{Y}})$ (lower dotted) and $c(n_{\mathcal{X}}, n_{\mathcal{Y}})$ (upper dotted). The null hypothesis corresponding to the significance band is that of equal expectation formation pertinence of the two predictor sets. A M statistic outside the significance bands rejects the null hypothesis in the favor of higher pertinence of the predictor set $\mathcal{X}$.

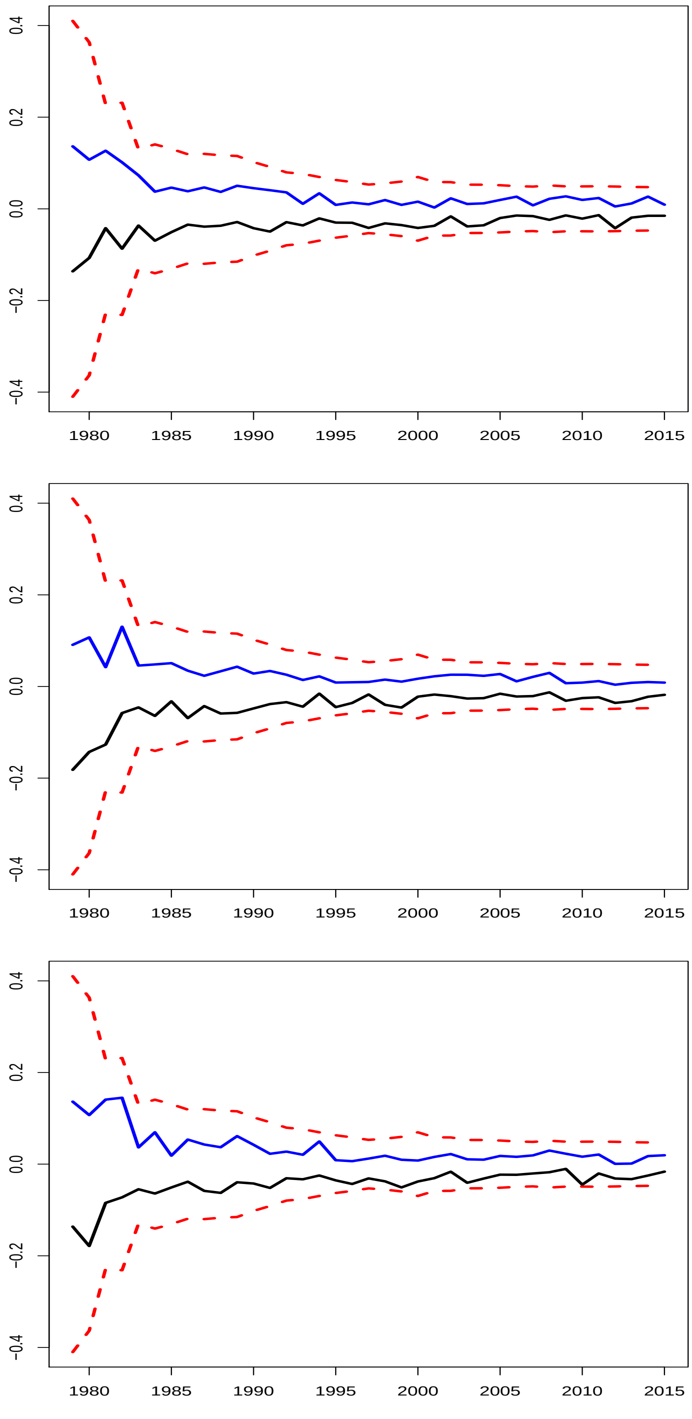

Fig. 4: **Accounting items over analysts prediction information content**. The competing predictors sets are $\mathcal{X} = \{EPS_1, EPS_2, \mathcal{S}\}$ and $\mathcal{Y} = \{EPS_1, EPS_2\}$ (first), $\mathcal{X} = \{EPS_1, EPS_2, \mathcal{F}\}$ and $\mathcal{Y} = \{EPS_1, EPS_2\}$ (second), and $\mathcal{X} = \{EPS_1, EPS_2, \mathcal{S}, \mathcal{F}\}$ and $\mathcal{Y} = \{EPS_1, EPS_2\}$ (third). The graphs display the time evolution of the statistics $M(\mathcal{X}, \mathcal{Y})$ (the upper blue curve) and $m(\mathcal{X}, \mathcal{Y})$ (the lower black curve). The dotted lines represent the lower and upper thresholds corresponding to non-significance of the two statistics, that is $-c(n_{\mathcal{X}}, n_{\mathcal{Y}})$ (lower dotted) and $c(n_{\mathcal{X}}, n_{\mathcal{Y}})$ (upper dotted). The null hypothesis corresponding to the significance band is that of equal expectation formation pertinence of the two predictor sets. Both M and m statistics within significance band indicate no evidence against the null hypothesis.

not add anything to expectations informed by the one and two year ahead predictions.

6 Conclusions

Our analysis indicates that the expectations of future earnings incorporated in prices are mainly informed by the analysts earnings forecasts. Neither the stock nor the flow accounting items considered do not contribute significantly to shaping investors price setting expectations.

Appendix

A Statistical details

For a given sample of errors $(e_1, e_2, \ldots, e_{n_\mathcal{X}})$, the estimator of $F_\mathcal{X}$, the CDF of the absolute error $|E_\mathcal{X}|$ of method X, is the *empirical cumulative distribution function*:

$$\widehat{F}_{X,n_\mathcal{X}}(x) := \frac{1}{n_\mathcal{X}} \sum_{i=1}^{n_\mathcal{X}} I_{(-\infty,x]}(|e_i|) = \frac{\#\text{ of } |\text{ errors }| \leq x}{n_\mathcal{X}}, \tag{10}$$

where $I_A(x)$ is the indicator function:

$$I_A(x) = \begin{cases} 1, & \text{if } x \in A \\ 0, & \text{if } x \notin A. \end{cases}$$

The statistical estimation error is described by the asymptotic distribution of the two sample Kolmogorov-Smirnov statistic:

$$D_{n_\mathcal{X},n_\mathcal{Y}} := \sup_x |\widehat{F}_{X,n_\mathcal{X}}(x) - \widehat{F}_{Y,n_\mathcal{Y}}(x)|. \tag{11}$$

Under the null hypothesis that $F_\mathcal{X} = F_\mathcal{Y}$,

$$D_{n_\mathcal{X},n_\mathcal{Y}} \leq c(\alpha)\sqrt{\frac{1}{n_\mathcal{X}} + \frac{1}{n_\mathcal{Y}}}$$

with probability $1 - \alpha$. We use $\alpha = 0.05$ and $c(0.05) = 1.36$.

To summarize, if $\widehat{F}_\mathcal{X}$ and $\widehat{F}_\mathcal{Y}$ denote the two estimated CDF of the absolute errors $|E_\mathcal{X}|$ and $|E_\mathcal{Y}|$ corresponding to the valuation methods X and Y, respectively, we define conclude:

$$\begin{cases} F_{\mathcal{X}}(e) > F_{\mathcal{Y}}(e), & \text{if } \max_e(\widehat{F}_{\mathcal{X}}(e) - \widehat{F}_{\mathcal{Y}}(e)) > c_{KS} \text{ and} \\ & \min_e(\widehat{F}_{\mathcal{X}}(e) - \widehat{F}_{\mathcal{Y}}(e)) \geq -c_{KS}, \\ F_{\mathcal{X}}(e) < F_{\mathcal{Y}}(e)), & \text{if } \min_e(\widehat{F}_{\mathcal{X}}(e) - \widehat{F}_{\mathcal{Y}}(e)) < -c_{KS} \text{ and} \\ & \max_e(\widehat{F}_{\mathcal{X}}(e) - \widehat{F}_{\mathcal{Y}}(e)) \leq c_{KS}, \\ F_{\mathcal{X}}(e) = F_{\mathcal{Y}}(e)), & \text{if } -c_{KS} \leq \min_e(\widehat{F}_{\mathcal{X}}(e) - \widehat{F}_{\mathcal{Y}}(e)) \text{ and} \\ & \max_e(\widehat{F}_{\mathcal{X}}(e) - \widehat{F}_{\mathcal{Y}}(e)) \leq c_{KS}, \end{cases} \tag{12}$$

where $c_{KS} = c(\alpha)\sqrt{\frac{1}{n_{\mathcal{X}}} + \frac{1}{n_{\mathcal{Y}}}}$, with $c(\alpha)$ as above, $n_{\mathcal{X}}$ and $n_{\mathcal{Y}}$, the sample sizes used to estimate the two cdfs $\widehat{F}_{\mathcal{X}}$ and $\widehat{F}_{\mathcal{Y}}$, respectively.

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