The Role of Disaggregation of Earnings in Stock Valuation and Earnings Forecasting

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Abstract

This paper compares and contrasts two accounting information systems, the aggregate earnings system and the disaggregated cash flow/accrual system, examining their relative performance in stock valuation and in forecasting of earnings. It finds, in general, that the forecasts of earnings and predicted market values from the cash flow and accrual system have smaller forecasting errors than those from the aggregate earnings system. The adjusted R-squareds from the disaggregated system are in the main higher than those from the aggregated system when considering the explanatory power of the model-predicted values. The results also show that the cash flow and accrual system forecasts in a large majority of industries.

Keywords: cash flow, accruals, components of earnings, forecasts of earnings, stock valuation **JEL**: C53 G12 M41

1. Introduction

Received wisdom suggests that models incorporating information about earnings components should generate better forecasts of future earnings and lead to a greater accuracy in stock valuation. Surprisingly, the valuation and forecasting implications of decomposing aggregate earnings into accrual and cash flow components are largely unexplored. One reason is that accruals are subject to accounting rules and can be manipulated by management. More importantly, existing theoretical literature provides only limited guidance on how to map earnings and its components into equity values. This paper investigates whether, and to what extent, decomposing aggregate earnings into operating cash flows and total accruals improves the forecasting of earnings and the valuation of equity.

The general belief is that in an accrual accounting system, current earnings are a better indicator of future earnings than cash flows. However, it is not clear whether, given the 'noisy' nature of accruals, the combined information content embedded in cash flows and accruals is inferior or superior to that in aggregate earnings. Accruals rely on accounting rules, which have discretionary elements, and many accruals involve estimates, which will unavoidably contain errors. Moreover, accruals may be manipulated by management. It is not surprising that financial analysts frequently focus on forecasting future earnings rather than its two components: cash flows and accruals. Nevertheless, the value-relevance of an earnings component relies on its ability to predict future (abnormal) earnings and cash flows (Dechow, 1994; Sloan, 1996; Ohlson, 1999; Barth, Cram and Nelson, 2001). Existing studies show that if the information dynamics of cash flows and accruals do not satisfy certain conditions, then they will attract different valuation weights (Feltham and Ohlson, 1995; Stark, 1997; Barth, Beaver, Hand and Landsman, 1999;

Walker and Wang, 2003; Pope, 2005). Since there is no one-to-one mapping between forecasting relevance and valuation relevance of an earnings component (Pope and Wang, 2005), it is worthwhile examining empirically the implications of the information content in the aggregated and disaggregated accounting systems for both earnings forecasting and stock valuation.

In examining the incremental role of accruals in valuation and forecasting, prior literature documents that accruals are mean-reverting and are less persistent than cash flows. Sloan (1996) argues that stock prices act as if investors do not understand the lower persistence of the accrual component of earnings, which leads to incorrect forecasts of future earnings and mispricing of stocks. Clubb (1996) shows that incremental information content for unexpected accrual/cash flow beyond aggregate earnings depends on the investment opportunity set. Dechow, Kothari and Watts (1998) explore the forecasting properties of cash flows and accruals. Consistent with Dechow (1994), they find that earnings are better predictors of future operating cash flows than are current operating cash flows. Pfeiffer and Elgers (1999) find accruals have less value relevance than cash flows as measured by the significance of the coefficients in regressions of stock returns. Barth et al. (1999) apply Ohlson (1999) to investigate the incremental role of cash flows and accruals in forecasting future abnormal earnings, given aggregate abnormal earnings, where abnormal earnings are defined as the difference between earnings and capital charges. Sloan (1999) suggests that cash flows and accruals may have different incremental roles in forecasting earnings due to different treatment of cash flows and accruals in the existing GAAP. More recently, Barth, Beaver, Hand and Landsman (2005) set out to determine whether industryspecific valuation parameters are an aid to predicting contemporaneous equity values. They document that accruals and cash flows have different abilities in forecasting abnormal earnings and find that the roles of abnormal earnings and accruals in stock valuation vary significantly across industries.

This paper differs from prior literature by directly modelling and contrasting two accounting information systems one describing an operating cash flow and total accrual system and another describing an aggregate earnings system. It examines the relative performance of each accounting system in stock valuation and in forecasting of earnings in terms of forecasting errors and the explanatory power of the model predicted values to the realisations of earnings and observed market values of equity.

It is well established that accounting rate of returns are mean reverting – a reflection of unsustainable economic conditions in profitability in a competitive market (see, for example, Beaver, 1970; Freeman, Ohlson and Penman, 1982; Sloan, 1996; Nissim and Penman, 2001).² The accounting information dynamics in this paper are accordingly based on the assumption that return on equity (ROE) follows a mean-reverting process. The definition of ROE depends on the accounting system being modelled. Specifically, one accounting information system specifies operating cash flows, total accruals and book value of equity; the other is based on the evolution of bottom line numbers, namely aggregate earnings and book value of equity. In the first accounting system I define two measures of ROE, one for each of the earnings components: cash flows divided by book value and accruals divided by book value. The assumption of mean reversion for all ROE measures is internally consistent in the sense that the persistence and ROE measures satisfy two specific restrictions, i.e., the persistence of earnings and its components are equal,

² Allen, Larson and Sloan (2010) argue that accounting accruals anticipate future economic benefits and must ultimately reverse. Others also examine the mean-reverting property of the accrual component, for example, Basu (1997), Fairfield, Whisenant and Yohn (2003), Richardson, Sloan, Soliman and Tuna (2005), Chan, Chan, Jegadeesh and Lakonishok (2006), and Ohlson (2010).

and the long-run mean aggregate ROE is equal to the sum of the long-run means of the cash-ROE and the accrual-ROE. This consistency in the theoretical models is important because it sets a common base for comparing the aggregated and the disaggregated accounting information systems.

The assumed accounting information dynamics enable me to obtain analytic form forecasts of earnings and market values of equity. I can therefore examine whether, and the extent to which, predicted earnings and equity values from each system explain reported earnings and observable equity values. In this exercise, the parameters for each of the accounting information dynamics are estimated using out-of-sample estimations on an industry basis. Because firms in the same industry compete for market share, analysis of the competitive structure of input and output markets is best conducted at the industry level (Lundholm and Sloan, 2007).

I find that the lower persistence of accruals in the disaggregated accounting system does not imply that the decomposed accounting system is inferior. On the contrary, the evidence shows that there is a clear advantage to decomposing aggregate earnings into cash flow and accrual components for stock valuation and earnings forecasting resulting in improved forecasts of observable market values and reported earnings. In general, the forecasts of earnings and predicted market values from the cash flow and accrual system have smaller relative errors than those from the aggregate earnings system. When examining the explanatory power of predictions of earnings and market values in each of the two systems, the adjusted R-squareds in the disaggregated accounting system are mostly higher than those from the aggregated system. The analysis also shows that the cash flow and accrual system forecasts dominate the aggregate earnings system forecasts in the sense that forecasts of earnings and predicted market values from the latter have no incremental information about the realisations of earnings and observed market values after controlling for forecasts of earnings and predicted market values from the former in a large majority of industries. While in general there is an advantage in decomposing earnings for the purpose of valuation and forecasting, whether, and the extent to which, the disaggregated system outperforms the aggregated system is industry-specific.

This paper contributes to the literature in several ways. First, it jointly models the generating processes for the operating cash flow element of ROE and the accrual element of ROE on the grounds of economic and accounting realism. Properties of the mean-reverting of individual accounting ratios are well established, but the impact of the correlations between these ratios are not explored in prior literature. Second, it establishes a formal theoretical link between the value of equity and components of earnings. This computationally-simple model can be useful for investment practice. Third, it provides evidence showing that splitting earnings into its operating cash flow and accrual components is likely to yield more precise forecasts of future payoffs and therefore better estimates of the value of equity. Finally, it shows that forecasts from the aggregated earnings system is largely redundant for forecasting and valuation if one controls for forecasts from the disaggregated cash flow and accrual system but not vice versa.

The rest of the paper is organised as follows. In Section 2, I describe the accounting information dynamics of aggregate earnings, cash flows and accruals, and then I derive the theoretical value for earnings forecasts and market value of equity. Section 3 explains the estimation procedures and research design; Section 4 describes the data and reports sample statistics; Section 5 presents the empirical results and robustness tests. Finally, Section 6 concludes the paper.

2. Model Development

In the spirit of Beaver (1970) and others, I assume that both the operating cash flow-ROE and the total accrual-ROE follow mean-reverting processes as below:

$$\frac{CFO_{t+1}}{b_t} - \mu_1 = \alpha_1 (\frac{CFO_t}{b_t} - \mu_1) + \alpha_{12} (\frac{ACC_t}{b_t} - \mu_2) + \mathcal{E}_{c,t+1},$$
(1)

$$\frac{ACC_{t+1}}{b_t} - \mu_2 = \alpha_2 \left(\frac{ACC_t}{b_t} - \mu_2\right) + \varepsilon_{a,t+1},\tag{2}$$

where CFO_t and ACC_t are respectively the two earnings components: cash from operations and total accruals, b_t is book value of the firm at time t.³ α_1 and $\alpha_2 > 0$ are persistence of the cash-ROE and the accrual-ROE.⁴ μ_1 and μ_2 are the expected long-run mean of the cash-ROE and long-run mean of the accrual-ROE respectively. The α_{12} term captures how the convergence of the accrual-ROE affects the convergence of the cash-ROE. $\varepsilon_{c,t+1}$ and $\varepsilon_{a,t+1}$ are two zero mean disturbance terms.⁵

The cash flow dynamic, (1), can be rewritten as

$$E_{t}[CFO_{t+1}] = \alpha_{1}CFO_{t} + \alpha_{12}ACC_{t} + ((1-\alpha_{1})\mu_{1} - \alpha_{12}\mu_{2})b_{t}.$$
(3)

Hence, the persistence in (1) are the persistence of the components of earnings in the cash flow dynamics after controlling for the book value of equity. The α_{12} term captures the importance of accruals as forecasts of future cash flows. It recognises the role of accruals in smoothing out cash flows and reduces the noise in performance measurement. This is consistent with Barth et al. (2001), who investigate the role of accrual components in cash flow forecasts and stock

³ Strictly speaking, ROE on the right-hand side of equations (1) and (2) should be ${}^{CFO}_{b_{t-1}}$ and ${}^{ACC}_{b_{t-1}}$. Using b_t as a deflator is for the parsimony of model development. This parsimony has its cost. ROE has a tendency but it can never approach its mean unless book value has no growth. The resulting information dynamics of cash flows and accruals are consistent with prior literature, see Barth et al. (2001) and Barth et al. (1999, 2005).

⁴ Note that low values of parameters, α_1 and α_2 , indicate high speeds of convergence of the cash-ROE and the accrual-ROE.

⁵ If cash flows and accruals are negatively correlated as documented (e.g. Barth et al., 1999), then the sum of the errors, $\varepsilon_{e,t+1} = \varepsilon_{e,t+1} + \varepsilon_{a,t+1}$ will be less volatile than the individual errors: $\varepsilon_{e,t+1}$ and $\varepsilon_{a,t+1}$. Perhaps this is the underlying reason for some analysts to believe that forecast of aggregate earnings should be the focus.

valuation. Feltham and Ohlson (1996) assume a similar cash flow dynamic, where accruals due to depreciation are their focus. Unlike Barth et al. (2001), the total accrual here is modelled jointly by the information dynamic (2), which can be rewritten as

$$E_{t}[ACC_{t+1}] = \alpha_{2}ACC_{t} + (1 - \alpha_{2})\mu_{2}b_{t}.$$
(4)

This is similar to the accrual system in Barth et al. (1999, 2005).⁶

I denote the expected earnings at time t+1 based on available information at time t, $E_t[e_{t+1}^{cfacc}]$, where the superscript *cfacc* refers to value derived from the cash flow and accrual dynamics. By construction, the earnings of the firm at time t, $e_t \equiv CFO_t + ACC_t$, and $E_t[e_{t+1}^{cfacc}] \equiv E_t[CFO_{t+1}] + E_t[ACC_{t+1}]$. Equations (3) and (4) imply:

$$E_{t}[e_{t+1}^{cfacc}] = \alpha_{1}CFO_{t} + (\alpha_{12} + \alpha_{2})ACC_{t} + ((1 - \alpha_{1})\mu_{1} + (1 - \alpha_{12} - \alpha_{2})\mu_{2})b_{t}$$

= $\alpha_{1}e_{t} - (\alpha_{1} - \alpha_{12} - \alpha_{2})ACC_{t} + ((1 - \alpha_{1})(\mu_{1} + \mu_{2}) + (\alpha_{1} - \alpha_{12} - \alpha_{2})\mu_{2})b_{t}.$ (5)

This is similar to Sloan (1996), which first documents accrual anomaly and hypothesises that investors naively fixate on aggregate earnings and do not appreciate the relative magnitudes of the coefficients α_1 and $(\alpha_{12} + \alpha_2)$ in the first line of equation (5), resulting in incorrect forecasts of earnings and the mispricing of stocks.

When cash flows and accruals are equally persistent in earnings dynamic (5), i.e. $\alpha_1 = \alpha_{12} + \alpha_2$, aggregate earnings is a sufficient earnings construct for forecasting. The following degenerate earnings dynamic follows:

$$\frac{E_t[e_{t+1}^{cfacc}]}{b_t} - (\mu_1 + \mu_2) = \alpha_1 (\frac{e_t}{b_t} - (\mu_1 + \mu_2)),$$

⁶ Note that Barth et al. (2001) and Barth et al. (1999, 2005) do not model the correlation between the persistence of earnings components and persistence of book value.

where $(\mu_1 + \mu_2)$ is the implied expected long-run mean of aggregate ROE in the disaggregated system.

This degenerate case often motivates the following second accounting system as a practice tool. Specifically it assumes that aggregate ROE follows a mean reverting process (Freeman et al., 1982):⁷

$$\frac{e_{t+1}}{b_t} - \mu = \alpha(\frac{e_t}{b_t} - \mu) + \varepsilon_{e,t+1},\tag{6}$$

where $\alpha > 0$ is the persistence of the aggregate ROE, and μ is the expected long-run mean of the aggregate ROE. $\varepsilon_{e,t+1}$ is a disturbance term with zero mean. Equation (6) implies that the expected aggregate earnings can be written as:

$$E_t[e_{t+1}^e] = \alpha e_t + (1-\alpha)\mu b_t, \tag{7}$$

where $E_t[e_{t+1}^e]$ denotes the expected earnings at time t+1 based on available information at time t, with the superscript *e* referring to forecasts derived from the aggregate earnings system. Similar to equation (5), equation (7) illustrates the importance of profitability and book equity in the generation of future earnings.

It is important to note that μ is the expected long-run mean of aggregate ROE corresponding to the aggregate earnings system (6), while $(\mu_1 + \mu_2)$ is the *implied* expected long-run mean of aggregate ROE corresponding to the disaggregated cash flow/accrual system (1) and (2). $E_t[e_{t+1}^e]$ in equation (7) and $E_t[e_{t+1}^{cfacc}]$ in equation (5) are generated by different dynamics, which describe different accounting items. For instance, if $\alpha_1 \neq (\alpha_2 + \alpha_{12})$, and an analyst believes that equations

⁷ Sloan (1996) assumes that earnings deflated by assets follow an autoregressive process, which effectively assumes that the accounting rate of return on assets follows a mean-reverting process. Note that equations (1) and (2) imply equation (6) if $\alpha = \alpha_1 = \alpha_2 + \alpha_{12}$, $\mu = \mu_1 + \mu_2$ and $\varepsilon_{e,t+1} = \varepsilon_{c,t+1} + \varepsilon_{a,t+1}$.

(1) and (2) are a correctly specified accounting system, then equation (6) will be mis-specified, and vice versa. As a consequence, empirical implementation may result in μ being a biased estimate of $(\mu_1 + \mu_2)$. For the convenience and clarity of exposition in the following analysis, I refer to the sum of the long-run means of cash-ROE and accrual-ROE from the disaggregated cash flow and accrual system as the implied expected long-run mean ROE μ' to differentiate it from μ .

Given the information dynamics of the earnings components in (1) and (2), we need to establish the evolution of the book value of equity for the purpose of stock valuation. This is important since a benchmark with which to assess the usefulness of decomposing aggregate earnings is prediction of the market value of equity.⁸ Maintaining parsimony, I follow prior literature by assuming that book values have an expected constant growth rate $\delta - 1$ (Feltham and Ohlson, 1995; Barth et al., 1999, 2005; Myers, 1999) as equation (8) below:

$$b_{t+1} = \delta b_t + \mathcal{E}_{b,t+1},\tag{8}$$

where $\delta < R$, which is 1 plus the cost of capital. $\varepsilon_{b,t+1}$ is a disturbance term with zero mean. Assuming that the clean surplus accounting relation holds, i.e., dividends are equal to earnings less change in book values of equity, the market value of equity in a no-arbitrage economy can be written in terms of the earnings components { *CFO_t*, *ACC_t* } and book values as follows:

$$MV_t^{cfacc} = (1 + \beta_0)b_t + \beta_1 CFO_t + \beta_2 ACC_t, \qquad (9)$$

where

⁸ Few prior studies establish a formal theoretical link between the value of equity and the incremental role of accruals. Two exceptions are Barth et al (1999, 2005).

$$\beta_{0} = \frac{1}{R - \delta} \left(R(\mu_{1} + \mu_{2}) \frac{1 - \alpha_{1}}{R - \alpha_{1}} + R\mu_{2} \frac{(\alpha_{1} - \alpha_{2} - \alpha_{12})(R - 1)}{(R - \alpha_{1})(R - \alpha_{2})} - R + 1 \right),$$

$$\beta_{1} = \frac{\alpha_{1}}{R - \alpha_{1}},$$

$$\beta_{2} = \frac{\alpha_{2}}{R - \alpha_{2}} + \frac{R\alpha_{12}}{(R - \alpha_{1})(R - \alpha_{2})} = \frac{\alpha_{1}}{R - \alpha_{1}} - R \frac{(\alpha_{1} - \alpha_{2} - \alpha_{12})}{(R - \alpha_{1})(R - \alpha_{2})}.$$
(10)

Proof of equation (9) can be found in Appendix A.

Equation (9) indicates that accrual accounting recognises accruals or noncash values as part of the value added. As argued by Sloan (1996), it is clear that the relative persistence of cash flows and accruals in the earnings dynamic (5), $\alpha_1 - (\alpha_2 + \alpha_{12})$, is one of the important factors in equity pricing. The long-run mean of accrual-ROE also plays a decisive role via the book value of equity. When cash flows and accruals are equally persistent, i.e. $\alpha_1 = \alpha_2 + \alpha_{12}$, aggregate earnings is a sufficient earnings construct not only for forecasting, but also for valuation, since the valuation weights on the two earnings components are the same ($\beta_1 = \beta_2 = \frac{\alpha_1}{R - \alpha_1}$).

When $\alpha_1 = \alpha_{12} + \alpha_2 = \alpha$, and $\mu_1 + \mu_2 = \mu$, equations (9) and (10) imply that the corresponding market value of equity in a no-arbitrage economy can be expressed in terms of the aggregate earnings and book value as follows:

$$MV_t^e = \left[1 + \frac{1}{(R-\delta)} \left(R\mu \frac{1-\alpha}{R-\alpha} - R + 1\right)\right] b_t + \frac{\alpha}{R-\alpha} e_t, \tag{11}$$

where MV_t^e is the market value of equity at time t based on aggregate earnings system.

In summary, the aggregate earnings information dynamic (6) can be viewed as a restricted version of the cash flow and the accrual information dynamics (1) and (2), when the persistence parameters in the information dynamics satisfy: $\alpha_1 = \alpha_{12} + \alpha_2 = \alpha$, and the long-run mean

aggregate ROE, μ , is equal to the implied expected long-run mean ROE, μ' , from the disaggregated system.⁹ Although such restrictions do not imply that one accounting information system is necessarily inferior/superior to the other, equations (5) and (7) (the forecasting equations) together with equations (9) and (11) (the valuation equations) provide us with a basis to compare and contrast the two accounting information systems.

One point needs to be emphasised here: my focus is on which accounting system better describes realised earnings and observed equity values, not on the absolute accuracy of the forecasts and valuations. The simple parsimonious information dynamics inevitably generate biased predictions because non-accounting information and growth components in forecasting and stock valuation are ignored in the analysis. Nevertheless, if capital market participants assume that 'other information' and investment decisions are independent of either accounting information system, then they can conveniently and fairly compare and contrast the performance of the two accounting information and forecasting.

3. Estimation Procedure and Empirical Design

To compare and contrast the two accounting information systems, we need to estimate persistence parameters, α s, and the long-run means, μ s, in equations (1), (2) and (6), as well as the growth parameter, δ , in equation (8).

In view of the possible correlations among the error terms in equations (1), (2) and (8) for the dynamics of the cash-ROE, the accrual-ROE and the book value of equity, I run the seemingly unrelated regressions:

⁹ This paper examines information dynamic (6) as an independent process, although it can be viewed as a reduced form of information dynamics (1) and (2).

$$\frac{CFO_{t+1}}{b_t} = c_1 + \alpha_1 \frac{CFO_t}{b_t} + \alpha_{12} \frac{ACC_t}{b_t} + \varepsilon_{c,t+1},$$

$$\frac{ACC_{t+1}}{b_t} = c_2 + \alpha_2 \frac{ACC_t}{b_t} + \varepsilon_{a,t+1},$$

$$\Delta b_{t+1} = c_3 + (\delta_1 - 1)b_t + \varepsilon_{b,t+1},$$
(12)

where $\Delta b_{t+1} = b_{t+1} - b_t$ and c_i (*i* = 1,2,3) are intercepts.¹⁰ While the persistence parameters, α_1 , α_{12} , and α_2 , can be directly estimated, the long-run mean cash-ROE and accrual-ROE can be derived from the corresponding intercepts and persistence as $\mu_1 = \frac{1}{1 - \alpha_1} (c_1 + \frac{\alpha_{12}c_2}{1 - \alpha_2})$ and $\mu_2 = \frac{c_2}{1 - \alpha_2}$. Similarly, I estimate the aggregate earnings dynamics by running the seemingly unrelated

regressions:

$$\frac{e_{t+1}}{b_t} = c_4 + \alpha \frac{e_t}{b_t} + \varepsilon_{e,t+1},$$

$$\Delta b_{t+1} = c_5 + (\delta_2 - 1)b_t + \varepsilon_{b,t+1},$$
(13)

where c_i (i = 4, 5) are intercepts. The long-run mean aggregate ROE can then be written as:

$$\mu = \frac{c_4}{1-\alpha}.$$

Since prior literature documents that valuation parameters are industry-specific, I estimate industry-specific information parameters from both the aggregated and disaggregated accounting systems. Following Barth et al. (2005), I use a jack-knifing procedure to estimate firm-industry specific parameters. Specifically, I run cross-sectional regressions using the previous five years of data for each firm-year in an industry without using that firm's data to generate parameters in either of the two accounting systems.¹¹ By doing so, the parameters are firm-industry-year specific estimates, which incorporate yearly updated information. For example, for firm i in

 ¹⁰ In order to deal with stationarity, I run regressions on change in book values.
 ¹¹ The results for these regressions are consistent with the results by using previous 10 years of data.

industry *j* in year 1991, the firm's specific information parameters, α s and μ s, are estimated based on 1987-1991 data for all other firms in the industry.¹²

The prediction of firm *i*'s earnings in year t+1 in industry *j* is the predicted value from the earnings models, $E[e_{i,t+1}^{efacc}]$ in (5) and $E[e_{i,t+1}^{e}]$ in (7), using parameters estimated from systems (12) and (13), and using all firms in industry *j* except firm *i*'s from year *t*-4 to year *t*. The resulting predictions are strictly out-of-sample since firm *i*'s data in year *t* are not used to estimate the coefficients. Similarly, the estimation of firm *i*'s equity market value in year *t* in industry *j* is the estimated value from the valuation models, $MV_{i,t}^{efacc}$ in (9) and $MV_{i,t}^{e}$ in (11), again using parameters estimated from systems (12) and (13), and using all firms in industry *j* except firm *i*'s from year *t*-4 to year *t*. The predictions in market values are consequently deemed out-of-sample.

To get a sense and assess the differences in prediction errors across accounting information systems, I calculate a commonly applied prediction error metric – the absolute percentage error in forecasting and in valuation. I calculate absolute errors because it is expected that the predicted stock values are underestimated by ignoring non-accounting information and any growth components in the systems. The errors in equity market capitalisation derived from both the cash flow and accrual dynamics, and the aggregate earnings dynamic are computed as below. For industry j, denote

 $MDMV_{j}^{cfacc}$ = Mean of absolute percentage Difference in Market Value, $(MV_{ijt}^{cfacc} - MV_{ijt}) / MV_{ijt}$ for all firm *i* and time *t* from cash flow and accrual dynamics,

¹² The firm-industry-year parameters are available from 1991 and onwards since operating cash flows are available from 1987 in Compustat by using 5-year data in the cross-sectional regressions. This approach contrasts with Barth et al. (2005), who estimate parameters for each firm that are constant over time. In other words, their parameters are firm-industry specific but not firm-industry-year specific. As noted in Barth et al. (2005), the jack-knifing approach effectively assumes that parameter estimates are generated from a randomly collected sample and that observations in the sample are independent. Therefore, the statistics obtained for hypothesis testing do not rely on unknown parametric distributions.

and

$$MDMV_{j}^{e}$$
 = Mean of absolute percentage Difference in Market Value, $(MV_{ijt}^{e} - MV_{ijt}) / MV_{ijt}$
for all firm *i* and time *t* from aggregate earnings dynamics,

(15)

(14)

where MV_{ijt} is market capitalisation for firm *i* at time *t* in industry *j*. The same prediction error metric is applied to the forecasted earnings on an industry basis. For industry j, denote

$$MDE_{j}^{cfacc} = \text{Mean of absolute percentage Difference in Earnings, } (e_{ijt}^{cfacc} - e_{ijt}) / e_{ijt}$$
for all firm *i* and time *t* from cash flow and accrual dynamics,
(16)

and

$$MDE_{j}^{e} = \text{Mean of absolute percentage Difference in Earnings, } (e_{ijt}^{e} - e_{ijt}) / e_{ijt}$$
for all firm *i* and time *t* from aggregate earnings dynamics,
$$(17)$$

where e_{ijt} is reported earnings for firm *i* at time *t* in industry *j*.

With the expected earnings derived from the cash flow and accrual information dynamics, $E[e_{i,t+1}^{efacc}]$ in (5), and the expected earnings derived from the aggregate earnings dynamics, $E[e_{i,t+1}^{e}]$ in (7), adjusted R-squareds, and Vuong Z-statistics (Mincer and Zarrowitz, 1969; Vuong, 1989; Dechow, 1994) can be used to examine whether $E[e_{i,t+1}^{efacc}]$ or $E[e_{i,t+1}^{e}]$ better explains the reported earnings, $e_{i,t+1}$. Similarly, with the estimated stock value derived from the cash flow and accrual information dynamics, $MV_{i,t}^{efacc}$ in (9), and the estimated stock value derived from the aggregate earnings dynamics, $MV_{i,t}^{efacc}$ in (11), adjusted R-squareds, and Vuong Z-statistics can be used to examine whether $MV_{i,t}^{efacc}$ or $MV_{i,t}^{e}$ better explains equity market capitalisation, $MV_{i,t}$. If the Z-statistic is positive and statistically significant, the test indicates that the cash flow and accrual

information dynamics are better than the aggregate earnings dynamics, in the sense that the residuals generated by the following regressions:

$$e_{i,t+1} = k_1 + \gamma_1 E_t [e_{i,t+1}^{cfacc}] + \varepsilon_{1i,t+1} \text{ and } MV_{i,t} = k_3 + \gamma_3 M V_{i,t}^{cfacc} + \varepsilon_{2i,t},$$
(18)

are smaller than those from the corresponding regressions in (19):

$$e_{i,t+1} = k_2 + \gamma_2 E_t[e_{i,t+1}^e] + \mathcal{E}_{3i,t+1} \text{ and } MV_{i,t} = k_4 + \gamma_4 M V_{i,t}^e + \mathcal{E}_{4i,t},$$
(19)

where k_i (*i*=1-4) are intercepts, and γ_i (*i*=1-4) are slopes. On the other hand, if the Z-statistic is negative and statistically significant, then the aggregate earnings dynamics are superior. Finally, I run an encompassing regression:

$$e_{i,t+1} = k_5 + \gamma_{51} E_t [e_{i,t+1}^{cfacc}] + \gamma_{52} E_t [e_{i,t+1}^e] + \mathcal{E}_{5i,t+1},$$
(20)

where k_5 is the intercept, and γ_{5i} (*i*=1-2) are slopes. If γ_{51} is close to 1 and statistically different from zero, and γ_{52} is not significantly different from zero, then the cash flow and accrual system forecasts can be said to dominate the aggregate earnings system forecasts. On the other hand, if γ_{51} is not statistically significantly different from zero, and γ_{52} is close to 1 and statistically different from zero, then the aggregate earnings system forecasts can be said to dominate the cash flow and accrual system forecasts. For other (statistically significant) values of the regression slope parameters, neither system forecasts dominate the other, so that both forecasts contain useful information about the realisation of earnings. Similarly, I run the following encompassing regression to see whether $MV_{i,t}^{cfacc}$ and/or $MV_{i,t}^{e}$ contain useful information about the observed equity values:

$$MV_{i,t} = k_6 + \gamma_{61} M V_{i,t}^{cfacc} + \gamma_{62} M V_{i,t}^e + \mathcal{E}_{6i,t},$$
(21)

where k_6 is the intercept, and γ_{6i} (*i*=1-2) are slopes.

4. Sample Description

I collect relevant accounting data from Compustat's entire dataset for years 1987-2009. Year 1987 is the first year when operating cash flows are available in Compustat. Aggregate earnings are measured as net income before extraordinary items (Compustat item: IB).¹³ Following Barth et al. (1999, 2005), total accruals are measured by the difference between aggregate earnings and operating cash flows (OANCF).¹⁴ Market capitalisation is equal to price per share multiplied by numbers of shares of outstanding (CSHO). Price per share is measured three months after the end of the fiscal year from the Center for Research in Security Prices (CRSP) to ensure that accounting information is known before value is computed. Firms with negative book values (CEQ) are deleted. To avoid the influence of small firms, I restrict the sample to firms with market capitalisation in excess of \$10 million.¹⁵ To mitigate the effects of outliers, firms in the extreme percentiles of earnings, book values, numbers of share outstanding, operating cash flows, accruals and ROEs are also excluded (Ball, Kothari and Robin, 2000; Barth et al., 1999, 2005). All variables are expressed in millions of dollars and measured as of fiscal year end, except equity market value.

<Insert Table 1 about here>

Panel A of Table 1 contains details of the sample. Summary descriptive statistics can be found in Panel B. It shows that less than 25% of firms have positive accruals and that the mean accrual is negative. The main reason for this is that depreciation expense is included in accruals but capital expenditures are included in investing cash flows (Sloan, 1996; Barth et al., 2001). The average

¹³ This may violate the clean surplus accounting assumption. However it eliminates potentially confounding effects of one-time items and is consistent with prior literature (Dechow et al., 1999; Barth et al., 2005).

¹⁴ Hribar and Collins (2002) suggest using the statement of cash flows to calculate accruals, due to problems with non-articulation events in using the balance sheet approach.

¹⁵ The results are similar when that cut-off is \$1.00 per share.

aggregate ROE is 5.6%, and the average cash-ROE and average accrual-ROE are 17.2% and -11.6% respectively over the sample period. Panel C of Table 1 shows the correlation matrix of the input variables. The Pearson correlation is the lower half and the Spearman correlation is the top half. They show that accruals are highly negatively correlated with market capitalisation, book value of equity, earnings and operating cash flows.

I base my industry classifications on those in Barth et al. (1998) and Barth et al. (1999, 2005). Panel D of Table 1 describes the industry composition of the sample. It reveals that industries with the largest concentrations of firm-year observations are Computers, 13.01%, Retail, 9.94%, Financial Institutions, 8.86%, and Services, 8.62%. Consistent with prior literature, I use a cost of capital of 11 percent in equity valuation models (9) and (11), and set negative predicted equity market values to zero.¹⁶

5. Empirical Results

5.1. Parameters in the two accounting information systems

Table 2 reports the persistence parameters, α , α_1 , α_{12} and α_2 , in the information dynamics (12) and (13), based on seemingly unrelated regressions on the pooled sample. The growth parameter of book value, δ , and the long-run means of returns, μ , μ_1 and μ_2 , are also reported.

<Insert Table 2 about here>

¹⁶ The number of negative predicted equity market values is approximately 10 percent. There is no doubt that 'other information' and growth options will contribute a positive equity value component. Unlike Barth et al (2005), the predicted equity market value in this paper is directly derived from earnings and its component information dynamics, rather than simultaneously estimated from both information dynamics and expected valuation model. Ashton and Wang (2012) suggest a plausible range for the cost of equity capital for US market over the period to be between 10% to 12%. Results are mainly unaltered when using 9% or 15% as a discount rate.

Table 2 shows that the persistence of cash flows is much larger than that of accruals, α_1 = $0.814 > \alpha_2 = 0.388$. In other words, the accrual-ROE reverts to its mean much more quickly than does cash-ROE. This of course reflects the nature of accrual accounting. A Wald test on the parameters of the fitted model shows that the null hypothesis of equality, $H_0: \alpha_1 = \alpha_2$, is strongly rejected. Table 2 also shows that $\alpha_1 = 0.814 > \alpha_{12} = 0.20$, i.e., high cash flow performance that is attributable to the cash flow component is more likely to persist than that which is attributable to the accruals. This implies that cash flows contain more information than accruals about the next period's cash flows (Barth et al., 2001). As shown in equation (5), the coefficient of accrual in earnings forecasting in the disaggregated accounting system is $(\alpha_{12} + \alpha_2)$. Table 2 shows that $\alpha_{12} + \alpha_2 = 0.589 < \alpha_1 = 0.814$. Here again the null hypothesis of equality, H₀: $\alpha_1 = \alpha_{12} + \alpha_2$, is strongly rejected. This is consistent with Sloan (1996), which finds that a good earnings performance that is attributable to the cash flow component is more likely to persist than that which is attributable to the accrual component of earnings. Note that the coefficient of accruals, $\alpha_{12} + \alpha_2$, in the earnings dynamic here is implied by jointly regressing cash flow dynamic and accrual dynamic, whereas in contrast Sloan's finding is based on directly regressing one period ahead earnings on current cash flows and accruals.

The long-run means of the cash-ROE and the accrual-ROE derived from the intercept terms and the coefficients of α_1 , α_{12} , α_2 are respectively $\mu_1 = 0.271$ and $\mu_2 = -0.063$. The negative long-run mean accrual-ROE reflects the smoothing effect of accruals on the long-run mean aggregate ROE. The growth rate of book value in both the accounting systems is roughly equal to 5.8% p.a. over the sample period.¹⁷ The persistence of earnings and the long-run mean ROE are shown in Panel B with $\alpha = 0.743$ and $\mu = 0.195$.

On an industry-by-industry basis, I use the jack-knifing approach to estimate firm-year parameters for the information dynamics (12) and (13) for each industry.¹⁸ In order to make the comparison meaningful on an industry-by-industry basis, I delete the Pharmaceuticals industry since its long-run mean aggregate ROE is negative ($\mu < 0$), which suggests other information could be significant in determining its future earnings and current equity value.¹⁹ The average values of the information parameters for each industry are reported in Table 3. These parameters are respectively the persistence of cash flows (α_1) and accruals (α_{12}) in the cash flow dynamics, the persistence of accruals (α_2), and the persistence of aggregate earnings (α), the long-run means of the cash-ROE (μ_1), the accrual-ROE (μ_2), and the aggregate ROE (μ), and the long-run growth rates of book value of equity (δ_1 and δ_2).

< Insert Table 3 about here>

Panel A of Table 3 shows characteristics similar to those in Table 2. Accruals revert to their mean more quickly than do cash flows for all sample industries (with persistence rates of $\alpha_2 = 0.385$ and $\alpha_1 = 0.74$ respectively). In the cash flow dynamic (3), cash flows are more persistent than accruals, with the mean persistence rates of $\alpha_1 = 0.74$ and $\alpha_{12} = 0.202$ respectively, indicating that cash flows contain more information than accruals about future cash flows. Hence a good earnings performance that is attributable to the cash flow component is more likely to persist than that which is attributable to the accruals component of earnings for all sample

¹⁷ A slight difference between the two intercepts for Δb is due to running seemingly unrelated regressions.

¹⁸ White (1980) corrections are used to the standard errors in the estimations.

¹⁹ Barth et al. (1999) also find that 'convergence failed to occur during system estimation for Pharmaceuticals firms.'

industries ($\alpha_{12} + \alpha_2 < \alpha_1$). A paired t-test of α_1 against $\alpha_{12} + \alpha_2$ based on the 18 industries has a t-value of 11.68, indicating that $\alpha_{12} + \alpha_2$ is statistically significantly different from α_1 .

Panel B of Table 3 shows that the mean value of $\alpha = 0.758$ for the sample industries, and $\alpha > \alpha_{12} + \alpha_2$, for all industries. A paired t-test of α_1 against α , based on the 18 industries has a t-value of -1.88, suggesting that α is not statistically significantly different from α_1 at the 5% level. The mean of long-run growth in book equity is 6.6% in each of the accounting systems over the sample period.

Table 3 also shows that the long-run accrual-ROE is negative for all sample industries ($\mu_2 < 0$). However, the implied expected long-run mean ROE $\mu'(=\mu_1 + \mu_2)$ from the disaggregated system is larger than the long-run aggregate ROE (μ), for all but one industry that of Financial Institutions.²⁰ The long-run mean cash-ROE for the sample industries is 25.5 percent, and the long-run mean accrual-ROE is about (negative) 12.9 percent. The implied expected long-run mean ROE μ' from the disaggregated system is 0.126 and the long-run mean aggregate ROE (μ) is 0.101. The test of $\mu = \mu'$ based on the 18 industries has a t-value of -3.68, suggesting that μ is significantly smaller than μ' . Therefore, the disaggregated accounting system differs from the aggregated system in both the persistence and long-run mean of ROEs: the persistence of accruals is lower than that of cash flows as documented in the existing literature, and the expected long-run mean aggregate ROE is less than the implied expected long-run mean ROE from the disaggregated system.

The industry-specific effect on the information parameters is clearly observed in both accounting systems. In Table 3, the three industries with the lowest mean persistence of accruals $(\alpha_{12} + \alpha_2)$

²⁰ This suggests that the accrual components for financial institutions may need to be interpreted differently. For example, inventory is not a predictor of future earnings for this industry.

in earnings forecasting are Computers, Machinery and Electrical Equipment. The three industries with the lowest long-run mean accrual-ROE (μ_2) are Extractive industries, Transportation, and Utilities, and two of these (Extractive industries, and Transportation) have amongst the three highest long-run mean cash-ROEs (μ_1). This suggests a negative relationship between the long-run cash-ROE and the long-run accrual-ROE.

5.2 The forecasting ability of the two accounting information systems

After estimating the firm-year information parameters for each industry in both the accounting systems, I calculate the expected earnings and market value of equity, $E[e_{t+1}^e]$, $E[e_{t+1}^{cfacc}]$, MV_t^e and MV_t^{cfacc} using equations (7), (5), (11) and (9) for each firm in each year. I then compute the forecast errors between the predicted earnings/stock values and the reported earnings/observed equity values. Finally I examine the explanatory power of these predicted earnings and stock values for the reported earnings and the observed equity values. To mitigate the effects of outliers, observations in the extreme percentiles of the information parameters, including α , α_1 , α_{12} , α_2 , μ , μ_1 , μ_2 , δ_1 and δ_2 are winsorised. Observations in the extreme percentiles of MV_t^{efacc} and MV_t^e are also winsorised in the analysis.

<Insert Table 4 about here>

Panel A and Panel B of Table 4 compare earnings and stock values respectively. Columns 2-4 show the ability of predictions of earnings, $E_t[e_{t+1}^{cfacc}]$, and market capitalisation, MV_t^{cfacc} , derived from the cash flows and accrual dynamics, to explain the reported earnings and observed market capitalisation (MV) on an industry by industry basis. Columns 5-7 show the equivalent results for predictions of earnings, $E[e_{t+1}^e]$, and market capitalisation, MV_t^e , derived from the aggregate

earnings dynamics. Column 8 reports Vuong Z-statistics from the earnings regression equations and from the valuation regression equations in Panel A and Panel B respectively.

Comparing Columns 2 and 5 in Panel A of Table 4, one observes that the means of absolute forecast errors for earnings from the cash flow and accrual system (MDE_j^{cfacc}) are smaller than those from the aggregate earnings system (MDE_j^e) except in 4 out of the 18 industries. The same columns in Panel B show that the means of absolute forecast errors for market values from the cash flow and accrual system ($MDMV_j^{cfacc}$) are all smaller than those from the aggregate earnings system ($MDMV_j^{cfacc}$) are all smaller than those from the aggregate earnings system ($MDMV_j^{cfacc}$) are all smaller than those from the aggregate earnings system ($MDMV_j^{cfacc}$).

Next, I use two-way cluster-robust standard errors to correct for both cross-sectional and timeseries dependence in a Mincer-Zarrowitz analysis (Petersen, 2009; Gow et al., 2010).²¹ Columns 3 and 6 illustrate that, both the means and the medians of the industry coefficients (γ_1 and γ_2 in equations (18) and (19)) in the earnings regressions in Panel A are close to 1 (with mean values of 1.015 and 1.037 and median values of 1.013 and 1.038 respectively) in the two accounting systems. The mean and median of industry coefficients (γ_3 and γ_4 in equations (18) and (19)) in market value regressions in Panel B are 1.377 and 1.429 respectively for the cash flow and accrual system, while the corresponding values in the aggregate earnings system are 1.2 and 1.135 respectively. As expected, the t-statistics in the industry-by-industry regressions indicate that the mean coefficient of γ_i (i=1-4) is not significantly different from one. In 14 out of the 18 industries the adjusted R-squareds ($R_{e,cface}^2$) in the earnings regressions from the cash flow and accrual system are higher than those ($R_{e,c}^2$) in the aggregate earnings system as can be seen in Columns 4 and 7 in Panel A. The equivalent number for the market value regressions is also 14

²¹ I thank Michell Petersen for the generous provision of some programming code.

as can be seen in Columns 4 and 7 in Panel B. The means of the adjusted R-squareds for earnings and market value regressions from the cash flow and accrual system are 66.0% and 40.4% respectively. These are larger than those from the aggregate earnings system which are 65.0% and 34.6% respectively.

I then test the null hypothesis that the two models are equally close in explaining the 'true data generating process' against the alternative that one model is closer using a Vuong test. Column 8 in Panel A of Table 4 shows that there are 8 industries with statistically significant positive Z-statistics and only 2 industries with negative Z-statistic at the 5% level in the earnings regressions. The same column in Panel B shows that there are 9 industries with statistically significant positive Z-statistics but no negative Z-statistic is significant at the 5% level in the market value regressions. The t-values suggest that the (positive) means of these Z-statistics are statistically significantly different from zero. Furthermore, as shown in Panel C of Table 4, a paired t-test of $R^2_{mv,eface} = R^2_{mv,e}$ has a t-value of 2.83, suggesting that $R^2_{mv,eface}$ is statistically significantly different from $R^2_{mv,e}$. The same test of $R^2_{e,cface} = R^2_{e,e}$ has a t-value of 2.94, indicating that $R^2_{e,cface}$ is also statistically significantly different from $R^2_{e,cface}$.

5.3. Incremental contribution from an alternative accounting system

I report results on the two encompassing regressions as in equations (20) and (21) on an industry basis in Table 5. Again, I use two-way cluster-robust standard errors to correct for both cross-sectional and time-series correlation in the analysis.

<Insert Table 5 about here>

Panel A and Panel B of Table 5 show the results for the earnings and stock value regressions respectively. Columns 2-3 present the intercept terms and their t-values. In contrast to the

intercepts in the earnings regressions where only three are statistically significant at the 5% level, most of the intercepts in the market value regressions are significant. This is likely because nonaccounting information, such as growth options, may play an important role in stock valuations. Columns 4-5 in Panel A show that 13 out of the 18 coefficients are significantly different from zero at the 5% level with an overall mean of 0.731, while Columns 6-7 show that only 6 out of the 18 coefficients are significantly different from zero with an overall mean of 0.295. The tstatistics in the industry-by-industry regressions indicate that the mean coefficient of γ_{51} is not significantly different from one. However, tests reveal that the mean coefficient of γ_{52} is significantly less than one and greater than zero. In other words, the cash flow and accrual system forecasts dominate the aggregate earnings system forecasts for most of the industries in earnings forecasts dominate the other, so that both forecasts contain useful information about the realisation of earnings. The pooled sample analysis shows that the regression coefficient of the forecasts in the disaggregated system is 0.83 (with t-value 7.51) against the regression coefficient of the forecasts 0.179 (with t-value 1.73) in the aggregated system.

Similarly, Columns 4-5 in Panel B show that 10 out of the 18 coefficients are significantly different from zero at the 5% level with an overall mean of 1.431, while Columns 6-7 show that only 3 out of the 18 coefficients are significantly different from zero with an overall mean of - 0.031. Again, the t-statistics in the industry-by-industry regressions indicate that the mean coefficient of γ_{61} is not significantly different from one, while the mean coefficient of γ_{62} is not significantly different from zero. Note also that for the Retail Industry, the incremental information contained in the predicted market values from the aggregate system is extremely inefficient (with significantly negative coefficient) though neither system forecasts dominate the

other. In the pooled sample analysis, the coefficient of the predicted value in the disaggregated system is 0.49 (with t-value 2.11) against the corresponding coefficient -0.02 (with t-value -0.11) in the aggregated system. This confirms my finding above that the cash flow and accrual system forecasts dominate the aggregate earnings system forecasts in most industries. Column 8 shows the adjusted R-squareds for the regressions. They are not much different from those in simple Mincer-Zarrowitz regressions as reported in Table 4.

In summary, the analysis shows that the disaggregated accounting system largely outperforms the aggregated system although there are exceptions for a few industries.

5.4. Robustness test

For robustness checks I repeat the above analysis for December fiscal year-end firms only. This allows for the estimation of the relationship between market value and accounting fundamentals at the same point in time for each firm-year observation. It results in 37,053 firm-years observations. I summarise the main results without tabulating the details.

I find that the means of absolute forecast errors for earnings from the cash flow and accrual system (MDE_j^{cface}) are smaller than those from the aggregate earnings system (MDE_j^e) except in 3 out of the 18 industries. The means of absolute forecast errors for market value from the cash flow and accrual system $(MDMV_j^{cface})$ are also smaller than those from aggregate earnings dynamic $(MDMV_j^e)$ except for 3 industries. For 14 out of the 18 industries the adjusted R-squareds $(R_{e,cface}^2)$ in the earnings regressions from the cash flow and accrual dynamics are higher than those $(R_{e,e}^2)$ from the aggregate earnings system. The equivalent number for the market value regressions is 13. The means of the adjusted R-squareds for the earnings and the market

value regressions from the cash flow and accrual dynamics are 64.5% and 44.5% respectively. These are larger than those from the aggregate earnings dynamics, 63.2% and 38.4% respectively.

Finally, I run the two encompassing regressions as in equations (20) and (21) on an industry basis. Again, I use two-way cluster-robust standard errors to correct for both cross-sectional and time-series dependence in the analysis. In contrast to the intercepts in the earnings regressions where only one is statistically significant, all but three intercepts in the market value regressions are significant at the 5% level. 11 out of the 18 coefficients of $E[e_{i,t+1}^{ofacc}]$ are significantly different from zero at the 5% level with an overall mean of 0.792, while only 2 out of the 18 coefficients of $E[e_{i,t+1}^{ofacc}]$ are significantly different from zero with an overall mean of 0.202. Similarly, 11 out of the 18 coefficients of predicted market values, $MV_{i,t}^{ofacc}$, are significantly different from zero at the 5% level with an overall mean of 0.1. This confirms my earlier findings based on the full sample that forecasts based on the cash flow and accrual system dominate those from the aggregate earnings system for most of the industries.

6. Conclusion

Investigating the consequences of decomposing aggregate earnings into cash flow and accrual components for stock valuation and the forecasting of earnings is important on both theoretical and practical grounds. This paper compares and contrasts two accounting information systems one specifying operating cash flows and total accruals the other aggregate earnings. The model focuses on the persistence of each of aggregate earnings, cash flows and accruals, and the

expected long-run mean accounting returns on book equity. Investigation of the properties of the information parameters enables an assessment of the consistency of these two information dynamics and an exploration of the implications of incremental information content for earnings forecasts and stock valuation.

I find that both the persistence of earnings and that of cash flows are larger than the persistence of accruals in forecasting of earnings. I also find that the expected long-run mean aggregate ROE (in the aggregate system) is less than the implied expected long-run mean ROE in the disaggregated system. The evidence shows that the disaggregated cash flow/accrual system generally outperforms the aggregate earnings system in both the forecasting of earnings and in stock valuation. Specifically, forecasts of earnings and the predicted market values from the cash flow and accrual system in general have smaller errors than those from the aggregate earnings system relative to the realizations of earnings and observed market values. The adjusted Rsquareds from the disaggregated accounting system are generally higher than those from the aggregated accounting system when examining the explanatory powers of the models. The results also show that the cash flow and accrual system forecasts dominate the aggregate earnings system forecasts in the sense that forecasts of earnings and predicted market values from the latter system provide no incremental information about the realisations of earnings and observed market values after controlling for forecasts of relevant values from the former system in a large majority of industries. While it is advantageous to decompose earnings for the purpose of valuation and forecasting, whether, and the extent to which, the disaggregated system outperforms the aggregated system remains industry-specific.

This study has implications for investment professionals and theoretical researchers. It is useful to bear in mind that splitting earnings into its components is likely to yield more precise forecasts

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of future payoffs and therefore better estimates of equity value. Researchers may model earnings components with the same notion proposed in this paper and derive a plausible theoretical value of equity to explore any mispricing. The results also appear to provide a basis for understanding some of the features of accounting practice. Although the analysis is presented in terms of only two earnings components, the intuition provides a rationale for the emergence of detailed line item disclosures in GAAP. Explicit modelling of accrual and cash flow dynamics leads to the establishment of a relationship between stock return and accounting accruals. This may shed light on understanding the accrual anomaly – stocks with high and low accruals are mispriced given their risk. I leave this investigation for future research.

Appendix A

In this Appendix, I first show how the market value of equity in a no-arbitrage economy can be written as a linear combination of the current book value and the earnings components representing cash flows from operations and accruals $\{b_t, CFO_t, ACC_t\}$. I then proceed to identify the mathematical structure of the coefficients in the linear valuation models as in equations (9), (10) and (11) in the main text.

The dividend discount model and the clean surplus relationship: $d_{t+1} = CFO_{t+1} + ACC_{t+1} - (b_{t+1} - b_t)$ enable us to write the market value of equity MV_t in terms of the *future* values of $\{b_{t+\tau}, CFO_{t+\tau}, ACC_{t+\tau}\}, \tau = 1, 2, ... \infty$. The three recurrence equations (1), (2) and (8), specifying the information dynamics for $\{b_t, CFO_t, ACC_t\}$, then enable us to express the market value of equity in terms of their *current* values. Hence the market value of equity, MV_t , can be written in a linear combination of $\{b_t, CFO_t, ACC_t\}$ as:

$$MV_t^{cfacc} = (1 + \beta_0)b_t + \beta_1 CFO_t + \beta_2 ACC_t.$$
(9)

Next, we need to show that the firm specific constants β_i (*i* = 0,1,2) can be expressed in the form as in equation system (10).

The no-arbitrage condition: $E_t[MV_{t+1} + d_{t+1}] = R \times MV_t$ implies that

$$E_{t}[(1+\beta_{0})b_{t+1}+\beta_{1}CFO_{t+1}+\beta_{2}ACC_{t+1}+d_{t+1}]=R((1+\beta_{0})b_{t}+\beta_{1}CFO_{t}+\beta_{2}ACC_{t}).$$

Using the clean surplus accounting relationship to substitute for d_{t+1} in the above, gives

$$(1+\beta_1)E_t[CFO_{t+1}] + (1+\beta_2)E_t[ACC_{t+1}] + \beta_0E_t[b_{t+1}] + b_t = R((1+\beta_0)b_t + \beta_1CFO_t + \beta_2ACC_t).$$

When we use the information dynamics (1), (2) and (8) to eliminate the t+1 terms, the above equation implies that

$$(1+\beta_{1})(((1-\alpha_{1})\mu_{1}-\alpha_{12}\mu_{2})b_{t}+\alpha_{1}CFO_{t}+\alpha_{12}ACC_{t})+(1+\beta_{2})((1-\alpha_{2})\mu_{2}b_{t}+\alpha_{2}ACC_{t})+(1+\delta\beta_{0})b_{t}$$

=R(1+\beta_{0})b_{t}+R\beta_{1}CFO_{t}+R\beta_{2}ACC_{t}.

Since this equation must hold for all t for each firm, by matching coefficients of CFO_t , ACC_t and b_t , we have:

$$CFO_t: \qquad \alpha_1(1+\beta_1)-R\beta_1=0,$$

 $ACC_{t}: \qquad \alpha_{12}(1+\beta_{1})+\alpha_{2}(1+\beta_{2})-R\beta_{2}=0,$

$$b_t: \qquad (1+\beta_1)(1-\alpha_1)\mu_1 + ((1+\beta_2)(1-\alpha_2) - (1+\beta_1)\alpha_{12})\mu_2 + 1 - R + (\delta - R)\beta_0 = 0.$$

Solving for β_0, β_1 and β_2 from the 3-equation system above, we get

$$\beta_{0} = \frac{1}{R - \delta} \left(R(\mu_{1} + \mu_{2}) \frac{1 - \alpha_{1}}{R - \alpha_{1}} + R\mu_{2} \frac{(\alpha_{1} - \alpha_{2} - \alpha_{12})(R - 1)}{(R - \alpha_{1})(R - \alpha_{2})} - R + 1 \right),$$

$$\beta_{1} = \frac{\alpha_{1}}{R - \alpha_{1}},$$

$$\beta_{2} = \frac{\alpha_{2}}{R - \alpha_{2}} + \frac{R\alpha_{12}}{(R - \alpha_{1})(R - \alpha_{2})} = \frac{\alpha_{1}}{R - \alpha_{1}} - R \frac{(\alpha_{1} - \alpha_{2} - \alpha_{12})}{(R - \alpha_{1})(R - \alpha_{2})}.$$
(10)

Finally, if we denote $\alpha = \alpha_1 = \alpha_{12} + \alpha_2$, and $\mu = \mu_1 + \mu_2$, we have

$$\beta_0 = \frac{1}{R-\delta} \left(R\mu \frac{1-\alpha}{R-\alpha} - R + 1 \right), \quad \beta_1 = \beta_2 = \frac{\alpha}{R-\alpha}.$$

The market value of equity from the aggregate earnings system can now be written as

$$MV_t^e = \left[1 + \frac{1}{(R-\delta)} \left(R\mu \frac{1-\alpha}{R-\alpha} - R + 1\right)\right] b_t + \frac{\alpha}{R-\alpha} e_t.$$
(11)

Appendix B: Definition of the Variables with the Relevant Mnemonics

MV: Market value of equity

- b: book value of equity
- e: net income before extraordinary items

CFO: operating cash flow

ROE: return on equity

ROCF: cash return on lagged book value of equity

ROACC: accrual return on lagged book value of equity

ROE1: earnings over book value

ROCF1: cash flows over book value

ROACC1: accruals over book value

 MDE_{j}^{cfacc} : mean of absolute % difference in earnings for all firms over the sample period in industry j from cash flow and accrual system

 MDE_{j}^{e} : mean of absolute % difference in earnings for all firms over the sample in

industry j from aggregate earnings system

- $MDMV_{j}^{cfacc}$: mean of absolute % difference in market values for all firms over the sample in industry j from cash flow and accrual system
- $MDMV_{j}^{e}$: mean of absolute % difference in market values for all firms over the sample in industry j from aggregate earnings system

 $E[e_{t+1}^{cfacc}]$: forecasted one period ahead earnings from the cash flow and accrual system

 $E[e_{t+1}^{e}]$: forecasted one period ahead earnings from the aggregate earnings system

 MV_t^{cfacc} : predicted market values from the cash flow and accrual system at time t

 MV_t^e : predicted market values from the aggregate system at time t

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Table 1: Sample Descriptive Statistics and Correlations

	ummary of d		A			<u> </u>						
	firm-years fins are obtained				nings, book	value and	operating	cash flows		123,508		
less : firms	with negativ	e book valu	le							<u>4,095</u>	110 410	
Less: Case	s for which th	nere is no n	natching o	perating ca	ash flow					<u>17,320</u>	<u>119,413</u> 102,093	
	less: 1% extreme observations of book value, earnings, dividend, operating cash flow, accrual and number of share outstanding											
less: firms	less: firms with market capitalisation less than 10 million dollars and top 1%											
1055. 111115	with market	capitalisatio	JII IESS tild		on donars a	id top 170				<u>7,802</u>	82,837	
less: Cases	for which th	ere is no m	atching la	gged book	value obser	vation				<u>14,867</u>	(7.070	
	extreme valu quity, accrua							quity, lagged	l cash	<u>7,764</u>	67,970	
	firm-years u		- •								60,206	
Panel B: Sa	ample Descri	ptive Statis	tics									
	MV	b	е	CFO	Accrual	ROE	ROCF	ROACC	ROE1	ROCF1	ROACC1	
Mean	740.50	350.90	31.95	73.36	-41.42	0.056	0.172	-0.116	0.052	0.152	-0.100	
Stdev	1257.00	580.60	81.74	144.60	90.19	0.204	0.217	0.169	0.176	0.188	0.154	
Q1	66.66	43.75	0.12	2.82	-40.64	0.003	0.065	-0.193	0.014	0.060	-0.169	
Median	225.50	127.20	7.44	17.27	-9.23	0.092	0.175	-0.097	0.090	0.159	-0.081	
Q3	796.10	388.10	36.62	74.77	-1.03	0.163	0.288	-0.022	0.145	0.258	-0.013	

raner C. Correlation Matrix (rearson Bottom, spearman 10p)											
MV	b	е	CFO	Accrual	ROE	ROCF	ROACC	ROE1	ROCF1	ROACC1	
1	0.880	0.674	0.751	-0.521	0.348	0.348	-0.057	0.305	0.318	-0.090	
0.788	1	0.673	0.812	-0.601	0.255	0.309	-0.071	0.250	0.308	-0.095	
0.750	0.750	1	0.757	-0.260	0.751	0.540	0.135	0.536	0.461	-0.022	
0.777	0.861	0.823	1	-0.713	0.456	0.706	-0.326	0.404	0.523	-0.196	
-0.566	-0.700	-0.413	-0.857	1	0.056	-0.504	0.731	-0.053	-0.320	0.319	
0.234	0.164	0.410	0.241	-0.014	1	0.627	0.224	0.668	0.493	0.037	
0.249	0.181	0.322	0.376	-0.311	0.682	1	-0.510	0.479	0.618	-0.253	
-0.037	-0.035	0.083	-0.192	0.382	0.338	-0.458	1	0.098	-0.225	0.379	
0.211	0.165	0.291	0.221	-0.091	0.647	0.513	0.126	1	0.570	0.216	
0.240	0.193	0.288	0.316	-0.246	0.540	0.644	-0.172	0.645	1	-0.575	
-0.052	-0.047	-0.020	-0.134	0.196	0.080	-0.200	0.354	0.357	-0.483	1	
	MV 1 0.788 0.750 0.777 -0.566 0.234 0.249 -0.037 0.211 0.240	MV b 1 0.880 0.788 1 0.750 0.750 0.777 0.861 -0.566 -0.700 0.234 0.164 0.249 0.181 -0.037 -0.035 0.211 0.165 0.240 0.193	MV b e 1 0.880 0.674 0.788 1 0.673 0.750 0.750 1 0.777 0.861 0.823 -0.566 -0.700 -0.413 0.234 0.164 0.410 0.249 0.181 0.322 -0.037 -0.035 0.083 0.211 0.165 0.291 0.240 0.193 0.288	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$							

Panel C: Correlation Matrix (Pearson Bottom; Spearman Top)

Panel D: Industry Composition

Industry Description	Primary SIC Codes	Obs.	%
Food	2000-2111	1299	2.16%
Textiles, printing & publishing	2200-2780	3251	5.40%
Chemicals	2800-2824, 2840-2899	1551	2.58%
Pharmaceuticals	2830-2836	2791	4.64%
Extractive industries	2900-2999, 1300-1399	2171	3.61%
Durable manufacturers			
Rubber, plastic, leather, stone, clay &			
galss	3000-3299	1320	2.19%
Metal	3300-3499	1881	3.12%
Machinery	3500-3569,3580-3599	2262	3.76%
Electrical equipment	3600-3669, 3680-3699	2767	4.60%
Transportation equipment	3700-3799	1225	2.03%
Instruments	3800-3899	4070	6.76%
Miscellaneous manufacturers	3900-3999	568	0.94%
Computers	7370-7379, 3570-3579,3670-3679	7831	13.01%
Transportation	4000-4899	2861	4.75%
Utilities	4900-4999	2707	4.50%
Retail	5000-5999	5982	9.94%

Financial institutions	6000-6411	5333	8.86%
Insurance & real estate	6500-6999	3289	5.46%
Services	7000-7369, 7380-8999	5189	8.62%
all other		<u>1858</u>	<u>3.09%</u>
total		60206	100%

Panel A Summarises data used in accounting system parameter estimation. Panel B shows descriptive statistics for 60,206 firm-years between 1987 and 2009. MV and *b* are market value and book value of equity respectively. *e* is net income before extraordinary items. CFO is operating cash flow. Accrual = e - CFO. ROE is return on equity, ROCF is cash return on (lagged book value of) equity and ROACC is accrual return on (lagged book value of) equity. ROE1 is earnings over book value, ROCF1 is cash flows over book value and ROACC1 is accruals over book value of equity. Firms in the extreme percentiles are deleted. Only firms with market capitalization > \$10 millions are included. The mean, standard deviation (Stdev), median and first (Q1) and third (Q3) quartiles are reported. Panel C shows the correlation matrix. The Pearson correlation is at the bottom and the Spearman correlation is at the top. All correlations are significantly different from zero at 1 percent level. Panel D describes industry composition. Industry classification is per Barth et al. (1999, 2005).

Panel A:	De	ependent variab	les	Panel B:	Dependent	Variables
	ROCF	ROACC	Δb		ROE	Δb
Intercept	0.063	-0.039	5.962	Intercept	0.05	6.086
	(.008)	(.007)	(6.08)		(.007)	(6.08)
α_1	0.814			α	0.743	
	(.003)				(.004)	
α_{12}	0.20					
	(.004)					
α_2		0.388				
		(.004)				
δ_1			1.058	δ_2		1.058
			(.001)			(.001)
μ_1	0.271			μ	0.195	
μ_2		-0.063				
\mathbb{R}^2	0.432	0.137	0.070	\mathbb{R}^2	0.427	0.070

 Table 2. Parameters in Accounting Information Dynamics Based on Pooled Sample

 Estimations

Test of coefficients of cash flow and accruals in the disaggregated system:

Wald tests: $\alpha_1 = \alpha_2$; $\chi^2(1) = 6217.01$, Prob > $\chi^2 = 0.0000$.

Wald tests: $\alpha_1 = \alpha_{12} + \alpha_2$; $\chi^2(1) = 2814.85$, Prob > $\chi^2 = 0.0000$.

Table 2 reports the persistence and the long-run means of cash-ROE, accrual-ROE and aggregate ROE in information dynamics below based on two seemingly unrelated regressions.

Cash flow and accrual system:

$$\frac{CFO_{t+1}}{b_t} = c_1 + \eta_{1,t} + \alpha_1 \frac{CFO_t}{b_t} + \alpha_{12} \frac{ACC_t}{b_t} + \varepsilon_{c,t+1},$$

$$\frac{ACC_{t+1}}{b_t} = c_2 + \eta_{2,t} + \alpha_2 \frac{ACC_t}{b_t} + \varepsilon_{a,t+1},$$

$$\Delta b_{t+1} = c_3 + \eta_{3,t} + (\delta_1 - 1)b_t + \varepsilon_{b,t+1},$$

Aggregate earnings system:

$$\frac{e_{t+1}}{b_t} = c_4 + \eta_{4,t} + \alpha \frac{e_t}{b_t} + \varepsilon_{4,t+1},$$

$$\Delta b_{t+1} = c_5 + \eta_{5,t} + (\delta_2 - 1)b_t + \varepsilon_{5,t+1},$$

where c_i (i=1-5) are intercepts, $\eta_{i,t}$ (i=1-5) are time dummies for each sample year,

$$\mu_1 = \frac{1}{1 - \alpha_1} (c_1 + \frac{\alpha_{12} c_2}{1 - \alpha_2}), \ \mu_2 = c_2 / (1 - \alpha_2) \text{ and } \mu = c_4 / (1 - \alpha).$$

Pooled sample consists of 60,206 observations from 1987-2009. ROE is aggregate return on equity. ROCF is cash flow scaled by lagged book value, ROACC is accrual scaled by lagged book value, and b is book value of equity. Values in parenthesis are standard errors.

		Panel A								Panel B		
Industry	α_1	α_{12}	α_2	μ_1	μ_2	$\alpha_{12}+\alpha_2$	$\mu_1 + \mu_2$	δ_1	Ν	α	μ	δ_2
Food	0.763	0.278	0.336	0.253	-0.107	0.615	0.146	1.056	1148	0.805	0.146	1.056
Textiles, printing & publishing	0.711	0.202	0.329	0.242	-0.120	0.531	0.122	1.036	2834	0.756	0.109	1.036
Chemicals	0.773	0.293	0.355	0.225	-0.111	0.648	0.114	1.030	1359	0.789	0.112	1.030
Extractive industries	0.706	-0.028	0.648	0.488	-0.321	0.621	0.167	1.079	1524	0.690	0.118	1.078
Rubber, plastic, leather, stone, etc	0.717	0.191	0.395	0.249	-0.118	0.586	0.131	1.029	1170	0.723	0.118	1.028
Metal	0.608	0.274	0.248	0.205	-0.100	0.522	0.105	1.035	1667	0.630	0.101	1.035
Machinery	0.722	0.232	0.233	0.203	-0.084	0.465	0.119	1.063	2017	0.734	0.101	1.061
Electrical equipment	0.713	0.231	0.266	0.164	-0.074	0.497	0.091	1.087	1586	0.694	0.063	1.086
Transportation equipment	0.694	0.266	0.307	0.236	-0.104	0.573	0.132	1.065	1003	0.769	0.120	1.064
Instruments	0.756	0.315	0.233	0.171	-0.061	0.547	0.111	1.107	3503	0.757	0.082	1.107
Miscellaneous manufacturers	0.704	0.274	0.227	0.157	-0.085	0.501	0.072	1.104	381	0.778	0.042	1.104
Computers	0.712	0.099	0.362	0.230	-0.139	0.461	0.091	1.103	4460	0.661	0.047	1.102
Transportation	0.863	0.040	0.682	0.448	-0.238	0.721	0.210	1.046	2566	0.857	0.102	1.046
Utilities	0.690	0.271	0.314	0.267	-0.148	0.585	0.119	1.038	2341	0.692	0.113	1.038
Retail	0.749	0.247	0.409	0.225	-0.121	0.657	0.105	1.070	5360	0.827	0.094	1.069
Financial Institutions	0.787	0.209	0.474	0.285	-0.120	0.683	0.165	1.096	4529	0.859	0.184	1.096
Insurance and real estate	0.838	0.067	0.649	0.277	-0.121	0.716	0.155	1.066	2995	0.787	0.103	1.066
Services	0.806	0.168	0.470	0.270	- 0.156	0.638	0.114	1.079	4626	0.826	0.069	1.079
Mean	0.740	0.202	0.385	0.255	-0.129	0.587	0.126	1.066	2504	0.758	0.101	1.066
Stdev	0.060	0.097	0.147	0.086	0.061	0.081	0.033	0.027	1463	0.066	0.034	0.027
Median	0.720	0.231	0.346	0.239	-0.119	0.585	0.119	1.066	2179	0.763	0.102	1.065
Max	0.863	0.315	0.682	0.488	-0.061	0.721	0.210	1.107	5360	0.859	0.184	1.107
Min	0.608	-0.028	0.227	0.157	-0.321	0.461	0.072	1.029	381	0.630	0.042	1.028

Table 3: Parameters in Cash Flows and Accrual Dynamics and Earnings Dynamics by Industry, Out-of-sample Estimations

Panel C: T-test

H₀: mean of α_1 = mean of α_{12} + mean of α_2 ; t =11.68 (with degree of freedom = 17)

H₀: mean of α_1 = mean of α ; t = -1.88 (with degree of freedom = 17)

H₀: mean of μ = mean of μ_1 + mean of μ_2 ; t = -3.68 (with degree of freedom = 17)

Table 3 reports the average parameters in the cash flow and accrual dynamics, and the earnings dynamics in systems (12):

$$\frac{CFO_{t+1}}{b_t} = c_1 + \alpha_1 \frac{CFO_t}{b_t} + \alpha_{12} \frac{ACC_t}{b_t} + \varepsilon_{c,t+1}, \quad \frac{ACC_{t+1}}{b_t} = c_2 + \alpha_2 \frac{ACC_t}{b_t} + \varepsilon_{a,t+1}, \quad \Delta b_{t+1} = c_3 + (\delta_1 - 1)b_t + \varepsilon_{b,t+1},$$

and (13):

$$\frac{e_{t+1}}{b_t} = c_4 + \alpha \frac{e_t}{b_t} + \varepsilon_{e,t+1}, \ \Delta b_{t+1} = c_5 + (\delta_2 - 1)b_t + \varepsilon_{b,t+1},$$

on an industry basis in each year by using previous 5-year data from 1991 to 2009, where $\mu_1 = \frac{1}{1-\alpha_1}(c_1 + \frac{\alpha_{12}c_2}{1-\alpha_2})$, $\mu_2 = \frac{c_2}{1-\alpha_2}$ and $\mu = \frac{c_4}{1-\alpha_1}$.

Estimations are based on cross-sectional seemingly unrelated regressions for each industry by applying the jack-knifing procedure. It is outof-sample in the sense that cross-sectional regressions for each firm-year in an industry without using that firm's data to generate parameters. Average numbers for each industry (N) are reported. 1% of dependent and independent variables are winsorised. The last five rows in Panels A and B show the statistics of the parameters, including mean, standard deviation, median, maximum and minimum values. Industry classification is per Barth et al. (1999, 2005).

Panel A: Earnings Forecasts	cash flow and	l accrual syste	em	aggregate ea	rnings system	1	Vuong- test
Industry	MDE ^{cfacc}	γ_1	$R_{e,cfacc}^2$	MDE ^e	γ_2	$R_{e,e}^2$	Z-stat
Food	0.0437	1.099	0.856	0.0436	1.115	0.864	-3.365
Textiles, printing & publishing	0.0606	1.001	0.620	0.0616	1.001	0.611	1.565
Chemicals	0.0506	0.930	0.652	0.0515	0.939	0.640	2.072
Extractive industries	0.0611	0.922	0.520	0.0613	0.940	0.534	-1.978
Rubber, plastic, leather, stone, clay & glass	0.0581	0.883	0.491	0.0590	0.859	0.452	2.850
Metal	0.0692	0.937	0.505	0.0689	0.953	0.518	-2.048
Machinery	0.0535	1.001	0.652	0.0544	1.024	0.631	2.507
Electrical equipment	0.0575	1.127	0.812	0.0584	1.267	0.800	1.578
Transportation equipment	0.0593	1.119	0.739	0.0583	1.091	0.733	0.986
Instruments	0.0509	1.056	0.694	0.0515	1.121	0.665	3.740
Miscellaneous manufacturers	0.0780	1.098	0.579	0.0781	1.114	0.537	1.067
Computers	0.0662	1.053	0.589	0.0675	1.202	0.577	1.280
Transportation	0.0574	0.923	0.586	0.0578	0.916	0.568	3.330
Utilities	0.0313	1.019	0.794	0.0312	1.036	0.791	2.801
Retail	0.0580	1.094	0.745	0.0587	1.045	0.735	5.770
Financial Institutions	0.0453	0.977	0.758	0.0458	0.959	0.744	6.893
Insurance and real estate	0.0485	1.006	0.659	0.0491	1.041	0.662	-0.857
Services	0.0601	1.021	0.638	0.0607	1.050	0.631	1.209
mean	0.0561	1.015	0.660	0.0565	1.037	0.650	1.633
t-value	22.82	57.14	26.15	22.94	42.46	24.91	2.67
t-value ($\gamma_1 = 1, \gamma_2 = 1$)		0.44			0.85		
median	0.0577	1.013	0.652	0.0584	1.038	0.636	1.572

Table 4. Forecast Errors from Regressing Reported Earnings and Observed Equity Market Capitalisation on Predicted Earnings and Market Value Vuo

min	0.0313	0.883	0.491	0.0312	0.859	0.452	-3.365
max	0.0780	1.127	0.856	0.0781	1.267	0.864	6.893
Panel B: Equity Valuations	cash flow and	l accrual syste	em	aggregate ear	rnings system	1	
Industry	MDMV ^{cfacc}	γ_3	$R^2_{mv,cfacc}$	MDMV ^e	γ_4	$R^2_{mv,e}$	Z-stat
Food	0.6335	2.259	0.734	0.6522	2.230	0.741	-1.577
Textiles, printing & publishing	0.6547	1.984	0.612	0.7030	2.231	0.630	-3.384
Chemicals	0.6859	2.127	0.582	0.6997	2.104	0.577	0.637
Extractive industries	0.9966	1.477	0.175	1.1054	0.354	0.076	2.021
Rubber, plastic, leather, stone, clay & glass	0.5678	2.118	0.623	0.5819	2.226	0.614	1.243
Metal	0.6617	1.390	0.467	0.6842	1.380	0.452	3.319
Machinery	0.7781	1.223	0.383	0.8446	1.082	0.320	5.122
Electrical equipment	1.2115	0.414	0.076	1.9666	0.209	0.050	0.621
Transportation equipment	0.6843	0.962	0.368	0.8131	0.428	0.191	2.311
Instruments	2.2111	0.255	0.162	2.5376	0.325	0.299	-3.738
Miscellaneous manufacturers	1.0887	0.837	0.287	1.4956	0.298	0.121	1.272
Computers	2.5053	0.316	0.111	3.6982	0.205	0.087	2.445
Transportation	0.7640	1.469	0.508	0.9098	1.973	0.414	5.169
Utilities	0.4980	1.697	0.786	0.5132	1.770	0.787	-0.829
Retail	0.8856	3.113	0.492	0.9739	2.821	0.392	11.156
Financial Institutions	2.4027	0.321	0.282	3.5906	0.188	0.156	7.990
Insurance and real estate	0.6808	1.867	0.472	0.7675	1.188	0.230	5.094
Services	1.0302	0.955	0.155	1.1466	0.596	0.091	1.687
mean	1.0523	1.377	0.404	1.3158	1.200	0.346	2.253
-value	6.99	7.35	7.90	5.63	5.64	6.07	2.56
-value ($\gamma_3 = 1, \gamma_4 = 1$)		1.05		- ·	0.19		
nedian	0.7710	1.429	0.425	0.8772	1.135	0.310	1.854
min	0.4980	0.255	0.076	0.5132	0.188	0.050	-3.738

Panel C: T-test H0: mean of $R_{e,cfacc}^2$ = mean of $R_{e,e}^2$; t = 2.94 (with degree of freedom = 17) H0: mean of $R_{mv,cfacc}^2$ = mean of $R_{mv,e}^2$; t = 2.83 (with degree of freedom = 17)

Table 4 shows mean forecast errors and the regression results for reported earnings and observed market capitalisation on the estimated earnings and market capitalisation on an industry basis. Two-way cluster-robust standard errors are considered (Petersen, 2009). Columns 2 and 5 report the forecast errors. MDE_{j}^{cfacc} and MDE_{j}^{cfacc} are means of absolute % difference in earnings for all firm i, time t and industry j from cash flow and accrual system and aggregate earnings system respectively as defined in equations (16) and (17). $MDMV_{j}^{cfacc}$ and $MDMV_{j}^{cfacc}$ are means of absolute % difference in market values for all firm i, time t and industry j from cash flow and accrual system and aggregate earnings system respectively as defined in equations (16) and (17).

Columns 3 and 4 report the coefficients and adjusted R-squareds of expected earnings in equation (5) and market capitalisation in equation (9) derived from cash flows and accrual dynamics in explaining the reported earnings and market capitalisation (MV) in a fixed effect robust model : $e_{i,t+1} = k_1 + \gamma_1 E[e_{i,t+1}^{cfacc}] + \varepsilon_{1i,t+1}$ and $MV_{i,t} = k_3 + \gamma_3 MV_{i,t}^{cfacc} + \varepsilon_{2i,t}$. (18)

Columns 6 and 7 report the coefficients and adjusted R-squared of expected earnings in equation (7) and market capitalisation in equation (11) derived from aggregate earnings dynamics in explaining the reported earnings and market capitalisation in a fixed effect robust model: $e_{i,t+1} = k_2 + \gamma_2 E[e_{i,t+1}^e] + \varepsilon_{3i,t+1}$ and $MV_{i,t} = k_4 + \gamma_4 MV_{i,t}^e + \varepsilon_{4i,t}$. (19)

Column 8 reports z-statistics from Vuong test in earnings and in valuation for two accounting systems. A positive Z-statistic indicates that the residuals generated by equation (18) are smaller than those from equation (19).

For slopes $\gamma_i(i=1-4)$, the t-statistic for whether the mean coefficient is different from one in the industry-by-industry regressions is also reported.

Table 5. Encompassing Regressions: Reported Earnings and Observed Market Value on Predicted Earnings and Market Value

Panel A: Earnings regressions: $e_{i,t+1} = k_5 + \gamma_{51} E[e_{i,t+1}^{cfacc}] + \gamma_{52} E[e_{i,t+1}^{e}] + \varepsilon_{5i,t+1}$.

Industry	Intercept	t-value	γ_{51}	t-value	γ_{52}	t-value	Adj- R^2
Food	-0.982	-0.859	0.223	0.813	0.892	3.027	0.864
Textiles, printing & publishing	-0.460	-0.203	0.709	2.308	0.299	1.081	0.621
Chemicals	4.904	1.909	0.888	1.751	0.043	0.086	0.652
Extractive industries	5.560	2.017	-0.383	-0.565	1.322	2.092	0.535
Rubber, plastic, leather, stone, clay & glass	3.167	1.498	1.786	3.336	-0.927	-1.689	0.505
Metal	2.008	1.159	-0.671	-0.974	1.623	2.276	0.521
Machinery	0.268	0.178	0.849	5.380	0.162	1.156	0.652
Electrical equipment	-0.732	-1.131	0.783	7.360	0.397	2.003	0.815
Transportation equipment	-4.430	-2.461	0.759	2.664	0.356	1.502	0.740
Instruments	-0.450	-0.616	1.191	5.760	-0.148	-0.585	0.694
Miscellaneous manufacturers	-2.034	-1.232	0.944	3.093	0.171	0.499	0.579
Computers	-0.858	-0.627	0.702	4.399	0.417	2.240	0.593
Transportation	4.620	2.274	1.190	4.247	-0.272	-0.923	0.587
Utilities	1.235	0.935	0.775	2.299	0.250	0.738	0.795
Retail	-1.140	-1.563	1.187	3.919	-0.090	-0.314	0.745
Financial Institutions	-0.760	-0.596	1.203	2.567	-0.225	-0.472	0.758
Insurance and real estate	-1.090	-1.129	0.374	1.734	0.658	3.283	0.663
Services	0.047	0.068	0.654	2.076	0.387	1.192	0.641
mean	0.493	-0.021	0.731	2.898	0.295	0.955	0.665
t-value	0.80	-0.07	5.38	5.85	2.13	2.89	27.01
t-value ($\gamma_{51} = 1, \gamma_{52} = 1$)			-0.78		-2.51		
median	-0.455	-0.400	0.779	2.616	0.274	1.119	0.652

min	-4.430	-2.461	-0.671	-0.974	-0.927	-1.689	0.505
max	5.560	2.274	1.786	7.360	1.623	3.283	0.864
Pooled sample:	0.466	0.750	0.830	7.510	0.179	1.730	0.683
Panel B: Market value regressions: $MV_{i,t} = k_6$	$+ \gamma_{61} M V_{i,t}^{cfacc} +$	$\gamma_{62}MV_{i,t}^e + \varepsilon_{62}$	6 <i>i</i> ,t •				
Industry	Intercept	t-value	$\gamma_{_{61}}$	t-value	$\gamma_{_{62}}$	t-value	Adj- R^2
Food	81.924	1.797	0.611	0.597	1.636	1.661	0.742
Textiles, printing & publishing	147.512	3.117	0.378	0.540	1.822	2.360	0.631
Chemicals	242.900	2.585	1.248	1.829	0.900	1.365	0.588
Extractive industries	770.867	4.736	1.320	4.692	0.114	1.426	0.180
Rubber, plastic, leather, stone, clay & glass	-20.424	-0.490	1.438	1.306	0.737	0.733	0.626
Metal	191.352	2.589	4.059	1.358	-2.704	-0.935	0.479
Machinery	339.834	3.981	2.528	3.350	-1.300	-1.910	0.407
Electrical equipment	512.147	6.616	0.632	2.357	-0.151	-1.118	0.080
Transportation equipment	389.575	3.022	1.005	3.615	-0.036	-0.373	0.368
Instruments	232.790	4.803	0.066	1.230	0.286	3.641	0.306
Miscellaneous manufacturers	221.060	2.107	0.869	2.052	-0.025	-0.233	0.286
Computers	528.732	5.297	0.647	2.322	-0.252	-1.527	0.121
Transportation	365.185	4.983	1.572	5.153	-0.168	-0.373	0.508
Utilities	54.934	2.947	0.773	1.934	0.971	2.336	0.789
Retail	267.291	4.236	4.490	6.900	-1.479	-2.310	0.504
Financial Institutions	360.825	3.903	0.495	4.127	-0.155	-1.321	0.305
Insurance and real estate	208.516	2.818	1.995	3.501	-0.158	-0.451	0.474
Services	504.342	7.572	1.628	1.737	-0.604	-1.058	0.172
mean	299.965	3.701	1.431	2.700	-0.031	0.106	0.420
t-value	6.52	8.45	5.05	6.71	-0.12	0.27	8.50
t-value ($\gamma_{61} = 1, \gamma_{62} = 1$)			0.65		-4.58		
median	255.095	3.510	1.127	2.187	-0.093	-0.373	0.441
min	-20.424	-0.490	0.066	0.540	-2.704	-2.310	0.080
min	-20.424	-0.490	0.066	0.540	-2.704	-2.310	0.

max	770.867	7.572	4.490	6.900	1.822	3.641	0.789
Pooled sample:	555.655	9.730	0.490	2.110	-0.020	-0.110	0.167

Table 5 reports the intercepts and coefficients of two encompassing regressions on an industry basis. Panel A shows the results of regressing realisations of earnings $(e_{i,t+1})$ on forecasted earnings from both disaggregated system $(E[e_{i,t+1}^{cfacc}])$ and aggregated system $(E[e_{i,t+1}^{e}])$. Panel B shows the results of regressing observed market value $(MV_{i,t})$ on predicted market values from both disaggregated system $(MV_{i,t}^{efacc})$ and aggregated system $(MV_{i,t}^{e})$. The last six rows in Panels A and B show the statistics of the intercepts and slopes, including mean, t-value, median, minimum, maximum and regression results on the pooled sample. For slopes $\gamma_{51}, \gamma_{52}, \gamma_{61}$ and γ_{62} , the t-statistic for whether the mean coefficient is different from one in the industry-by-industry regressions is also reported.