


# Fair value intensity and analyst forecasts

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Analysts' earnings and book value forecasts play an important role in price discovery in equity markets. As the role of fair value measurements in accounting increases, the impact on analysts' ability to accurately forecast earnings and book values is unclear. This article develops a method to calculate the degree of fair value measurement in financial statements and investigates the impact thereof on the accuracy of analysts' book value and earnings forecasts, using a sample of firms listed in the United States and the United Kingdom from 2010 to 2014. Relying on multivariate regression findings, the article shows that greater fair value intensity decreases the 12-month analyst forecast accuracy for earnings in both countries. Moreover, there is some evidence that higher fair value intensity decreases the accuracy of analysts' book value forecasts. It therefore appears that increased fair value intensity under a mixed measurement approach limits the ability of analysts to forecast earnings, without a compensating impact on forecasts of book values.

## Introduction

Equity valuation models often incorporate actual or forecasted accounting numbers (Nissim & Penman 2001). Fair value accounting complicates earnings forecasts as earnings tend to be more volatile than under the historical cost basis (Liang & Riedl 2014:1156). As earnings and book values are interrelated, fair value accounting could also complicate book value forecasts. Furthermore, the rules under accounting standards limit the degree to which fair values can be recognised (Badenhorst 2014; Palea & Maino 2013) and fair value forecasts are about more than predicting future accounting data, as they must incorporate potential future changes in valuation multiples. The forecasts and equity valuations of all market participants cannot be investigated as they are not generally observable, but analysts provide book value and earnings forecasts for many firms. Therefore, this article considers the impact of fair value accounting on the accuracy of analysts' 12-month (i.e. the forecast for the next financial year) book value and earnings forecasts as a proxy for the forecasts of all market participants.

This study uses a sample of non-financial firms listed in the United States (applying United States Generally Accepted Accounting Principles, i.e. US GAAP) and United Kingdom (applying International Financial Reporting Standards, i.e. IFRS) from 2010 to 2014 and focusses on the impact of fair value accounting within each country and does not necessarily compare the two. Both countries are investigated as they each have well-developed financial markets under differing financial reporting frameworks. Analysts in these countries should have greater capacity to assimilate the complexities of modern financial reporting. To investigate the impact of fair value accounting on analyst forecast accuracy, a measure of fair value intensity (i.e. the degree to which fair value accounting is used in the financial statements) is developed which ranks firms based on their degree of fair value accounting.

Multivariate regression findings show that greater fair value intensity significantly decreases analyst forecast accuracy (increases analyst forecast errors) for earnings in the United Kingdom. Although results for the United States are initially insignificant, limiting the sample to those firms for which fair value accounting is detected, the results are similar to those of the United Kingdom. With respect to book value forecasts, the study reveals a significant decrease in analyst forecast accuracy in the United Kingdom as fair value intensity increases. However, results for the United States remain consistently insignificant. Consequently, findings show that increased fair value intensity decreases analysts' earnings forecast accuracy (increases forecast errors). With respect to book value forecasts, fair value intensity at best does not affect forecasts. However, there is some evidence that it is detrimental to analysts' book value forecast accuracy.

This study contributes to the existing literature in several ways. Firstly, prior research on the effect of fair value accounting considered only a specific assets class (Liang & Riedl 2014) or limited

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investigations to earnings forecasts in the United States (Ayres, Huang & Myring 2017). This article investigates a range of different operating and non-operating assets and liabilities as well as earnings and book value forecast for two major equity markets. This article, therefore, sheds light on the impact of fair value accounting on analyst forecast accuracy, irrespective of the financial reporting framework. The results of this study will be of interest to analysts, as well as to those who use such forecasts, as they highlight an important risk to forecast accuracy. Those involved in the fair value accounting debate should also be interested in these findings, as they highlight practical consequences thereof.

## Theoretical valuation, literature review and hypotheses development

### Theoretical valuation

The information in financial statements is an important source of inputs for equity valuation models, such as the residual income model (Ohlson 1995). This model uses book value and abnormal earnings to determine market value of equity:

$$M_t = BVE_t + \sum_{\tau=1}^{\infty} R^{-\tau} E_t [\chi_{t+\tau}^a] \quad [\text{Eqn 1}]$$

where  $M_t$  is the market value of equity;  $BVE_t$  is the book value of equity;  $\chi^a$  is abnormal earnings, calculated as net income in excess of the opening book value times the discount rate (required return);  $R$  is the discount rate; and  $E_t[\cdot]$  is the expected value operator at time  $t$ .

Importantly, both actual and forecasted book values could be relevant for valuations. This becomes apparent when model 1 is rewritten to include a 12 month forecasted book value:

$$M_t = BVE_t + \Delta BVE_{t+1} + \sum_{\tau=1}^{\infty} R^{-\tau} E_t [\chi_{t+1+\tau}^a] \quad [\text{Eqn 2}]$$

where  $\Delta$  denotes change and all other variables are as previously defined. Model 2 shows that a market participant could potentially rely on analysts' book value forecasts ( $\Delta BVE_{t+1}$ ) to develop a valuation. Indeed, the fact that forecasted book values are supplied by analysts implies that a demand for this information exists. It could be shown, using a similar process, that valuation models can incorporate analysts' earnings forecasts.

The theoretical analysis, therefore, shows that forecasted earnings and book values are important for equity valuation under at least one valuation model. If fair value accounting disrupts the forecasting ability of analysts, it could also disrupt the results of the valuation process. The 'Literature review and hypotheses development' section considers the extent to which prior research sheds light on this question.

### Literature review and hypotheses development

The use of fair value measurements in financial statements has long been controversial. On the one hand, fair value measurements have been criticised as impeding effective contracting (Holthausen & Watts 2001; Watts 2003), preventing the assessment of stewardship (Kothari, Ramanna & Skinner 2010) and limiting reliability (Biondi et al. 2012) amongst others. Conversely, other researchers have found that fair value measurements are decision-useful for a range of diverse items, including derivative financial instruments (Ahmed, Kilic & Lobo 2006) and intangible assets (Kallapur & Kwan 2004). However, despite the ongoing debate, fair value measurements have been increasingly incorporated into financial statements, to the extent that some consider the trend to be self-reinforcing (Power 2010).

Fair value measurements alter the predictability of financial statement information. It is well established that the properties of accounting information change over time (Collins, Maydew & Weiss 1997; Dichev & Tang 2008; Givoly & Hayn 2000) and at least some of these changes are attributable to fair value accounting (Dichev & Tang 2008:1432; Mozes 2002:8). However, the properties of accounting information can also differ cross-sectionally between firms, based on the extent of fair value accounting used in the financial statements (i.e. fair value intensity). Fair value intensity is the result of several factors, including accounting policy choices and the accounting standards applicable to a firm's assets and liabilities.

Fair value intensity complicates earnings forecasts, as fair value earnings tend to be more volatile than historical cost earnings (Liang & Riedl 2008:1156). Forecasts of book values are also complicated by fair value intensity, as the accounting standards limit the degree to which fair values can be recognised. Determining which information is to be incorporated into a fair value measurement is an extremely complex decision, especially in the case of liabilities (Bradbury 2000). The core issue here is the possibility that market participants do not adequately deal with complex fair value accounting to develop inputs to valuation models. As forecasts of all market participants are not directly observable, this study uses the accuracy of analyst forecasts as a proxy.

A previous study which considers the impact of fair value accounting on analysts' forecasts is that of Liang and Riedl (2014). In a cross-country comparison, they find that fair value accounting decreases the analyst forecast accuracy of earnings for a sample of investment property firms (whose sole asset of significance is investment property). By contrast, for the same sample, they find that fair value accounting increases the analyst forecast accuracy of net asset value. However, the net asset value forecasts utilised by Liang and Riedl are fair value forecasts (irrespective of the underlying accounting policy). This differs from book value forecasts in other industries, which take underlying accounting policies into account (Liang & Riedl 2014:1152). Book values in most industries contain a mix of fair values and historical cost. In other words, while the findings of

Liang and Riedl suggest that fair value accounting assists in the prediction of future fair values, it may prove to be less helpful when future book values are forecasted. Furthermore, the results of Liang and Reidl could simply be highlighting cross-country differences, including differences in financial reporting systems and environments. This study, therefore, considers the impact of fair value intensity on analyst forecast accuracy across different industries *within* each of the sample countries individually.

The first hypothesis for this study (in null form) is:

**H1:** The fair value intensity of a firm's financial statements does not impact on the accuracy of analysts' book value forecasts.

With respect to earnings forecasts, the finding of Liang and Riedl (2014) that fair value accounting decreases analyst forecast accuracy of earnings does not necessarily translate to other industries. Their findings apply to the operating assets of the investment property industry, whereas the operating assets of different industries have different fair value measurement requirements and economic implications. For example, revaluing property, plant and equipment affects earnings in a more predictable way (through depreciation) than annual fair value adjustments on investment property. This could potentially explain the contrasting finding of Ayres et al. (2017) that increased fair value accounting is associated with higher analyst forecast accuracy for earnings across industries within a United States sample. Therefore, the second hypothesis for this article (in null form) is:

**H2:** The fair value intensity of a firm's financial statements does not impact on the accuracy of analysts' earnings forecasts.

## Research design

The regression model is the following for firm  $i$  in year  $t$ :

$$\text{DEPENDENT}_{i,t} = \alpha_0 + \beta_1 \text{SIZE}_{i,t} + \beta_2 \text{FOLLOW}_{i,t} + \beta_3 \text{CROSS}_{i,t} + \beta_4 \text{LOSS}_{i,t} + \beta_5 \text{PER}_{i,t} + \beta_6 \text{CHANGE}_{i,t} + \beta_7 \text{MTB}_{i,t} + \beta_8 \text{LEV}_{i,t} + \beta_9 \text{VOL}_{i,t} + \beta_{10} \text{INSIDER}_{i,t} + \beta_{11} \text{INTENSE}_{i,t} + \varepsilon \quad [\text{Eqn 3}]$$

The dependent variable is alternatively specified as BPS\_FE and EPS\_FE, where BPS\_FE (EPS\_FE) is the absolute percentage forecast error, calculated using the actual book value (earnings) per share reported for year  $t$  compared with the mean 12-month analyst forecast of 30 working days, that is, approximately 6 weeks, after the reporting date. Measuring the dependent variable in this manner ensures consistency in analyst forecast horizons. In addition, this measurement also allows analyst forecasts to incorporate information after reporting date. This is important as such information could potentially relate to fair values at reporting date.

The first group of control variables reflect that a larger analyst following should lead to lower forecast errors. As larger firms

tend to attract more analysts, the model controls for SIZE, measured as the natural log of the market value of the firm in US dollars (Lang & Lundholm 1996). To control for larger analyst following independent of size, FOLLOW represents the number of forecasts included in the mean (Lys & Soo 1995). A richer information environment leads to lower analyst forecast errors (Siegel, Lessard & Karim 2011). As cross-listed firms have a richer information environment, the model also contains an indicator variable (CROSS) set to one if a firm is cross-listed and zero otherwise. PER controls for the mechanical increase in BPS\_FE (EPS\_FE) when book value (earnings) per share is small in absolute terms and is calculated as actual book value (earnings) per share scaled by share price.

In addition, the model incorporates control variables related to operating volatility which proxy for inherent risk or growth complications in forecasts. LOSS is an indicator variable set to one if a firm reports negative basic earnings per share and zero otherwise (Heflin, Subramanyam & Zhang 2003). CHANGE is the change in actual book value (earnings) per share from the previous year, scaled by share price at the end of the year for dependent variable BPS\_FE (EPS\_FE) (Lang & Lundholm 1996). Changes in book values automatically incorporate changes in earnings. The market-to-book ratio (MTB) controls for the growth options of the firm (Siegel et al. 2011), while LEV is the total long-term debt to total assets ratio, reflecting financial risk. VOL is the standard deviation of the firm's daily returns for the year, representing the market assessment of forecasting risk (i.e. the degree of dispersion in potential outcomes) for the specific firm (Liang & Riedl 2014). Following Liang and Riedl (2014), firms must have at least 200 daily returns to be included in the sample. The last control variable, INSIDER, represents the percentage shares held by insiders per Worldscope and controls for the impact of information asymmetry. In the interest of brevity, the supporting literature for each of the variables included in the model has not been discussed in detail. For more comprehensive reviews, refer to Lang and Lundholm (1996), Liang and Reidl (2014) and Siegel et al. (2011).

The variable of interest is INTENSE, which ranks the fair value intensity of the financial statements of the sample firms (higher values reflect higher fair value intensity). INTENSE is calculated for each firm year, using the following relationship:

$$\text{INTENSE}_{i,t} = (1 + \text{TA}_{i,t}) \times (1 + \text{TL}_{i,t}) \quad [\text{Eqn 4}]$$

TA (TL) reflects the assets (liabilities) per share for which fair value accounting is permitted by the accounting standards, scaled by share price at reporting date. Share price is selected in preference to other possible scalars, as prior research shows that market value tends to reliably compensate for incorrect inferences because of scale effects when financial data is scaled (Barth & Clinch 2009; Easton & Sommers 2003) and to ensure consistency with other scalars used in the model. The multiplicative calculation of INTENSE also reflects that a simple average would understate fair value intensity, as few liabilities are measured at fair value for

sample firms. The reasoning behind this approach is best illustrated by way of an example.

Two otherwise identical firms differ in the composition of their fair value measurements. Firm A measures 80% of its assets at fair value, but all liabilities at amortised cost; Firm B measures 40% of both assets and liabilities at fair value. A simple average results in a 0.40 score for both firms. By contrast, using calculation 4 results in a 1.80 score for Firm A and 1.96 for Firm B. The simple average, therefore, rates both firms equally, while calculation 4 rates Firm B as more difficult to forecast. Arguably, this is indeed the case for Firm B, as fair value measurements for liabilities are more complex than those of assets (cf. Bradbury 2000) and analysts will need to consider the degree to which fair value measurements are likely to offset when both assets and liabilities are measured at fair value.

The specification of calculation 4 implies that *INTENSE* has a minimum value of 1 when no assets or liabilities are measured at fair value (these firms are retained within the sample) and a maximum value of 4 when all assets and liabilities are measured at fair value. A higher value for *INTENSE* indicates the greater presence of fair value accounting and is a relative (rather than a precise) measure of fair value intensity.

In this respect, it should be clear that an accurate measurement of *INTENSE* would require detailed information from the notes to the financial statements. In the interest of generalisability, which is a key objective and contribution of this article, only assets and liabilities which are available as data items on Datastream are used in the calculation of fair value intensity to ensure a broad sample. However, this article also mitigates against potential inaccuracies introduced by utilising these simplifying assumptions in several ways. Firstly, calculations of *INTENSE* have been separately defined and performed for firms reporting under IFRS and those reporting under US GAAP to reflect differences in the underlying reporting frameworks. Secondly, as *INTENSE* incorporates both items for which fair value measurement is required and those for which it is permitted, results are reported using both a minimum score (which arguably reflects mandatory fair value measurement) and a maximum score (a wider measure). Thirdly, a robustness test is performed where *INTENSE* is replaced by an indicator variable which measures the presence or absence of fair value measurement as opposed to a scale (ranking) variable, thereby mitigating against inaccuracies of measurement within *INTENSE*. Finally, many firms without any identified assets or liabilities measured at fair value is included in the sample, which reduces the likelihood of finding significance for *INTENSE* (in either direction) if the measurement is an inaccurate estimate.

The details of the assets and liabilities included in the calculation of *INTENSE* (as well as Datastream item codes) are set out in Appendix A.

## Sample, data and descriptive statistics

The sample for this study consists of listed firms in the United Kingdom (London Stock Exchange) and the United States (Nasdaq and New York Stock Exchange) with reporting dates ending from 01 January 2010 to 31 December 2014. This sample period firstly avoids the confounding effects of the financial crisis of 2007–2008 (Sidhu & Tan 2011) and secondly ensures that analysts are familiar with the impact of IFRS, which the United Kingdom sample firms adopted during 2005 and 2006. The sample selection, therefore, allows two independent investigations of the impact of fair value intensity under two different financial reporting frameworks in well-developed financial markets.

Firms for which data items are not available for all variables are removed from the initial sample. This study is, particularly, concerned with the impact of fair value accounting on analyst forecasts for non-financial services firms. Therefore, financial services firms, including real estate firms, are identified from Datastream classifications and removed from the sample. A final restriction ensures that all the United States (the United Kingdom) sample firm-years represent US GAAP (IFRS) reports.

Importantly, the main sample for this study is not limited to firms for which fair value accounting has been identified from the available data items. This increases the importance of the findings, as no fair value accounting is detected for a large portion of the final sample firms. However, a subsequent analysis considers the impact of limiting the sample to firm-years for which the presence of fair value accounting has been detected. As reflected in Table 1, the final sample, therefore, consists of 1940 (425) unique firms from the United States (the United Kingdom).

Table 1 also contains the descriptive statistics for sample firms. Interestingly, the median values for most variables are very similar across the two sample countries (mean values exhibit somewhat greater differences). It is also immediately evident that analysts' earnings forecast errors are higher than their book value forecast errors. In Panel A, reflecting the United States, the mean (median) earnings forecast error is 144.2% (31.3%) compared with a mean (median) book value forecast error of 134.8% (13.6%). A similar distribution is evident for the United Kingdom in Panel B. Note, however, that these statistics reflect the structural advantage inherent in (cumulative) book values, rather than inconsistency in forecasting ability.

The variable of interest, *INTENSE*, detects the presence of fair value accounting in both samples with mean and median values greater than 1. Unsurprisingly, given the broader scope for fair value accounting under IFRS compared with US GAAP, fair value intensity under both definitions is higher for the United Kingdom sample. The mean (median) fair value intensity score under the wider definition is 1.062

**TABLE 1:** Sample numbers and descriptive statistics.

Variable	Mean	Median	Standard deviation
<b>Panel A: The United States</b>			
BPS_FE	1.348	0.136	35.145
EPS_FE	1.442	0.313	10.944
SIZE	14.782	14.734	1.620
BPS_FOLLOW	3.621	3.000	2.708
EPS_FOLLOW	14.269	13.000	8.692
CROSS	0.442	0.000	0.497
LOSS	0.190	0.000	0.392
BPS_PER	0.484	0.406	0.519
EPS_PER	0.006	0.045	0.446
BPS_CHANGE	-0.015	0.023	0.512
EPS_CHANGE	-0.003	0.005	0.377
MTB	3.726	2.328	36.134
LEV	0.233	0.209	0.219
VOL	0.028	0.021	0.301
INSIDER	0.112	0.032	0.165
INTENSE_max	1.062	1.002	0.343
INTENSE_min	1.055	1.002	0.322
Number of firm-years	6605	-	-
Number of unique firms	1940	-	-

<b>Panel B: The United Kingdom</b>			
BPS_FE	0.418	0.143	2.216
EPS_FE	0.857	0.284	2.768
SIZE	14.190	14.103	1.734
BPS_FOLLOW	5.501	4.000	4.211
EPS_FOLLOW	12.582	11.000	8.097
CROSS	0.121	0.000	0.326
LOSS	0.111	0.000	0.314
BPS_PER	0.521	0.409	0.619
EPS_PER	0.042	0.056	0.183
BPS_CHANGE	-0.010	0.021	0.378
EPS_CHANGE	0.003	0.006	0.213
MTB	4.217	2.329	27.555
LEV	0.165	0.138	0.166
VOL	0.025	0.020	0.060
INSIDER	0.192	0.100	0.215
INTENSE_max	1.091	1.022	0.280
INTENSE_min	1.091	1.022	0.280
Number of firm-years	1398	-	-
Number of unique firms	425	-	-

**BPS\_FE** The absolute percentage forecast error for book value per share, calculated by comparing the mean analyst forecast 30 working days after reporting date to the actual book value per share.

**EPS\_FE** The absolute percentage forecast error for earnings per share, calculated by comparing the mean analyst forecast 30 working days after reporting date to the actual earnings per share.

**SIZE** The natural log of the market value of the firm in US dollars.

**BPS\_FOLLOW** The number of forecasts included in the mean analyst forecast for book value per share.

**EPS\_FOLLOW** The number of forecasts included in the mean analyst forecast for earnings per share.

**CROSS** An indicator variable set to one if a firm is cross-listed and zero otherwise.

**LOSS** An indicator variable set to one if basic earnings per share is negative and zero otherwise.

**BPS\_PER** Actual book value per share scaled by share price at the end of the year.

**EPS\_PER** Actual earnings per share scaled by share price at the end of the year.

**BPS\_CHANGE** The change in book value per share from the previous year, scaled by share price at the end of the year.

**EPS\_CHANGE** The change in earnings per share from the previous year, scaled by share price at the end of the year.

**MTB** The market-to-book ratio at the end of the year.

**LEV** The long-term debt to total assets ratio.

**VOL** The standard deviation of the firm's daily returns for the year. Firms must have at least 200 daily returns to be included in the sample.

**INSIDER** The percentage shares held by insiders at the end of the year.

**INTENSE\_max** The maximum fair value intensity of the firm. Details of the calculation are set out in Appendix A.

**INTENSE\_min** The minimum fair value intensity of the firm. Details of the calculation are set out in Appendix A.

(1.002) in the United States compared with a mean (median) score of 1.091 (1.022) in the United Kingdom. This fact offers an initial suggestion that fair value intensity is less likely to affect analyst forecasts in the United States, which is further investigated in the sections which follow.

## Univariate investigations

The results of Pearson's correlations for both dependent variables are contained in Table 2. With respect to book value forecast errors, increased analyst following (FOLLOW) in both countries significantly reduces such errors. Interestingly, cross-listing (CROSS) significantly reduces forecast errors for the United States at the 5% level ( $p = 0.030$ ) but has the opposite effect in the United Kingdom ( $p = 0.032$ ). This suggests that cross-listing by itself does not necessarily resolve forecasting complexity introduced by

**TABLE 2:** Univariate investigations.

Variable	BPS_FE		EPS_FE	
	The United States	The United Kingdom	The United States	The United Kingdom
SIZE	-0.024** (0.047)	-0.027 (0.307)	-0.087*** ( $< 0.001$ )	-0.089*** (0.001)
FOLLOW	-0.028** (0.024)	-0.044* (0.098)	-0.026** (0.036)	-0.014 (0.605)
CROSS	-0.027** (0.030)	0.057** (0.032)	-0.027** (0.026)	0.051* (0.057)
LOSS	-0.011 (0.386)	0.024 (0.371)	0.180*** ( $< 0.001$ )	0.390*** ( $< 0.001$ )
PER	0.001 (0.987)	-0.053** (0.048)	-0.127*** ( $< 0.001$ )	-0.590*** ( $< 0.001$ )
CHANGE	0.001 (0.949)	-0.023 (0.393)	-0.152*** ( $< 0.001$ )	-0.278*** ( $< 0.001$ )
MTB	-0.002 (0.884)	-0.001 (0.982)	-0.003 (0.789)	-0.025 (0.353)
LEV	-0.008 (0.516)	0.013 (0.620)	0.038*** (0.002)	0.062** (0.020)
VOL	-0.001 (0.975)	-0.006 (0.811)	0.006 (0.654)	0.033 (0.212)
INSIDER	-0.011 (0.377)	0.010 (0.701)	0.033*** (0.007)	0.093*** (0.001)
INTENSE_max	-0.001 (0.922)	0.012 (0.665)	0.072*** ( $< 0.001$ )	0.370*** ( $< 0.001$ )
INTENSE_min	-0.001 (0.966)	0.012 (0.665)	0.072*** ( $< 0.001$ )	0.370*** ( $< 0.001$ )
<i>N</i>	6605	1398	6605	1398

**BPS\_FE** The absolute percentage forecast error for book value per share, calculated by comparing the mean analyst forecast 30 working days after reporting date to the actual book value per share.

**EPS\_FE** The absolute percentage forecast error for earnings per share, calculated by comparing the mean analyst forecast 30 working days after reporting date to the actual earnings per share.

**SIZE** The natural log of the market value of the firm in US dollars.

**FOLLOW** The number of forecasts included in the mean analyst forecast.

**CROSS** An indicator variable set to one if a firm is cross-listed and zero otherwise.

**LOSS** An indicator variable set to one if basic earnings per share is negative and zero otherwise.

**PER** Actual book value (earnings) per share scaled by share price at the end of the year.

**CHANGE** The change in book value (earnings) per share from the previous year, scaled by share price at the end of the year.

**MTB** The market-to-book ratio at the end of the year.

**LEV** The long-term debt to total assets ratio.

**VOL** The standard deviation of the firm's daily returns for the year. Firms must have at least 200 daily returns to be included in the sample.

**INSIDER** The percentage shares held by insiders at the end of the year.

**INTENSE\_max** The maximum fair value intensity of the firm. Details of the calculation are set out in Appendix A.

**INTENSE\_min** The minimum fair value intensity of the firm. Details of the calculation are set out in Appendix A.

Note:  $p$ -values for two-tailed significance from Pearson's correlations are indicated in brackets.

\*, \*\* and \*\*\* indicate significance at the 10%, 5% and 1% levels, respectively.

other characteristics of a firm. All other correlations with book value forecast errors are insignificant for one or both sample countries, including correlations with fair value intensity

In contrast to the findings for book value forecast errors, univariate correlations with earnings forecast errors are significant for several variables. Notably, larger firms (SIZE), higher actual earnings per share (PER) and greater changes (CHANGE) therein all consistently correlate with lower earnings forecast errors at the 1% level of significance in both countries. Similarly, increased shareholding by insiders (INSIDER) as well as negative net income (LOSS) lead to larger earnings forecast errors at the 1% level of significance. Cross-listed firms (CROSS) reflect similar findings to those for book value forecasts. More importantly (and in contrast to book value forecasts), increased fair value intensity is associated with higher earnings forecast errors. INTENSE is significantly correlated with the dependent variable at the 1% level ( $p < 0.001$ ) in both sample countries and under both definitions.

The results from the univariate investigations, therefore, offer an initial suggestion that fair value intensity does not affect analysts' ability to forecast book values. By contrast, increased fair value intensity detracts from analysts' ability to forecast earnings. However, this study relies on the multivariate regression results for inferences, which are discussed in the sections that follow.

## Multivariate regression results

In preference to using fixed firm and year effects, all reported multivariate regression results in this article are based on robust standard errors clustered by firm and year which compensates for both fixed and variable serial and cross-sectional correlation (Gow, Ormazabal & Taylor 2010; Petersen 2009; Thompson 2011). Influential observations are identified in an initial regression using Cook's distance (Cook 1977) and deleted when they exceed the conventional ratio of  $4/n$ .

The first two columns of Table 3 reflect the main multivariate regression results for analysts' book value forecast errors. They show that the mechanical relationship between actual book value per share and book value forecast errors (PER) is an important control variable as it is consistently negative and significant at the 1% level. However, none of the other control variables is consistently significant across sample countries and fair value intensity definitions. With respect to fair value intensity, the results show that greater fair value intensity (INTENSE) is associated with higher book value forecast errors in the United Kingdom at the 1% level ( $p = 0.001$ ) under both definitions. However, results for the United States are consistently insignificant.

The findings for analysts' earnings forecast errors are contained in the last two columns of Table 3. These results show that negative net income (LOSS) consistently leads to

higher earnings forecast errors at the 1% level of significance. Similarly, greater shareholding by insiders (INSIDER) increases earnings forecast errors, albeit at lower levels of significance. With respect to the variable of interest, results show that greater fair value intensity (INTENSE) consistently leads to significantly higher earnings forecast errors for the United Kingdom sample at the 5% level ( $p = 0.012$ ). However, results for the United States are again insignificant under both fair value intensity definitions.

In summary, greater fair value intensity reduces analyst forecast accuracy (increases analyst forecast errors) for both book value and earnings in the United Kingdom. However, these results do not translate to the United States and implies that analyst forecast accuracy is not affected by fair value accounting in the United States. In the next section, the results of additional analyses and robustness tests are detailed.

## Additional analyses and robustness tests

### Ensuring the presence of fair value accounting

The main sample does not require the presence of fair value accounting for a specific firm to be included in results. This implies that the main regression results apply even when fair value accounting requirements do not affect the financial results for a substantial subset of the sample. While this increases the importance and generalisability of results, it also reduces the power to detect the impact of fair value intensity. Therefore, the regressions are also run where firm-years with INTENSE scores of 1 (i.e. no fair value accounting detected) have been excluded from the sample. The results of these regressions are detailed in Table 4.

Findings with respect to fair value intensity are qualitatively similar to those of the main regression when the dependent variable represents book value forecast errors. However, in contrast to earlier findings, fair value intensity (INTENSE) is now associated with higher earnings forecast errors at the 10% level of significance ( $p = 0.076$ ) in the United States using the broader definition. Under the narrower definition, the level of significance increases to the 5% level ( $p = 0.025$ ). In addition, fair value intensity remains significant at the 5% level ( $p = 0.023$ ) in the United Kingdom under both definitions. Importantly, the only difference between the narrow and the broad definition of fair value intensity is the carrying amount of financial assets. As this variable on Datastream (WC02255) includes financial assets measured at amortised cost, the stronger results for the narrower definition, therefore, support a conclusion that the findings of this study are because of fair value accounting.

In summary, the results of this robustness test strengthen conclusions that fair value accounting decreases analyst forecast accuracy with respect to earnings. This finding is also true for forecasts of book values in the United Kingdom, although no significant impact is detected in the United States.

TABLE 3: Main regression results.

Variable	BPS_FE		EPS_FE	
	The United States	The United Kingdom	The United States	The United Kingdom
<b>Panel A: Regression results for INTENSE_max</b>				
SIZE	-0.036 (0.293)	-0.025 (0.278)	-0.120*** ( $< 0.001$ )	-0.023 (0.450)
FOLLOW	-0.003 (0.861)	-0.005 (0.353)	0.016*** ( $< 0.001$ )	0.001 (0.842)
CROSS	-0.155 (0.117)	0.092* (0.085)	-0.025 (0.411)	0.037 (0.553)
LOSS	0.038 (0.603)	0.010 (0.813)	2.080*** ( $< 0.001$ )	0.828*** ( $< 0.001$ )
PER	-0.239*** (0.007)	-0.183*** ( $< 0.001$ )	-1.306* (0.069)	-5.817*** ( $< 0.001$ )
CHANGE	-0.016 (0.850)	-0.038 (0.408)	-1.695*** ( $< 0.001$ )	0.698*** (0.027)
MTB	-0.001 (0.218)	0.001 (0.300)	-0.001* (0.051)	-0.001** (0.043)
LEV	0.850** (0.041)	0.009 (0.946)	0.478*** (0.001)	-0.095 (0.538)
VOL	0.688 (0.243)	-0.098 (0.321)	-0.284 (0.920)	0.005 (0.969)
INSIDER	0.145 (0.260)	0.102 (0.328)	0.264* (0.057)	0.233** (0.044)
INTENSE_max	0.079 (0.471)	0.257*** (0.001)	-0.058 (0.783)	0.685** (0.012)
N	6597	1379	6526	1354
R <sup>2</sup> (%)	0.7	3.2	27.6	46.5
<b>Panel B: Regression results for INTENSE_min</b>				
SIZE	-0.036 (0.294)	-0.025 (0.278)	-0.119*** ( $< 0.001$ )	-0.023 (0.450)
FOLLOW	-0.003 (0.863)	-0.005 (0.353)	0.016*** ( $< 0.001$ )	0.001 (0.842)
CROSS	-0.157 (0.107)	*0.092 (0.085)	-0.023 (0.428)	0.037 (0.553)
LOSS	0.037 (0.608)	0.010 (0.813)	2.077*** ( $< 0.001$ )	0.828*** ( $< 0.001$ )
PER	-0.238*** (0.007)	-0.183*** ( $< 0.001$ )	-1.335** (0.046)	-5.817*** ( $< 0.001$ )
CHANGE	-0.014 (0.871)	-0.038 (0.408)	-1.683*** ( $< 0.001$ )	0.698*** (0.027)
MTB	-0.001 (0.216)	0.001 (0.300)	-0.001* (0.051)	-0.001** (0.043)
LEV	0.846** (0.043)	0.009 (0.946)	0.482*** (0.002)	-0.095 (0.538)
VOL	0.649 (0.294)	-0.098 (0.321)	-0.273 (0.924)	0.005 (0.969)
INSIDER	0.146 (0.257)	0.102 (0.328)	0.262* (0.063)	0.233** (0.044)
INTENSE_min	0.119 (0.513)	0.257*** (0.001)	-0.117 (0.709)	0.685** (0.012)
N	6597	1379	6526	1354
R <sup>2</sup> (%)	0.7	3.2	27.6	46.5

$$\text{DEPENDENT}_{i,t} = \alpha_0 + \beta_1 \text{SIZE}_{i,t} + \beta_2 \text{FOLLOW}_{i,t} + \beta_3 \text{CROSS}_{i,t} + \beta_4 \text{LOSS}_{i,t} + \beta_5 \text{PER}_{i,t} + \beta_6 \text{CHANGE}_{i,t} + \beta_7 \text{MTB}_{i,t} + \beta_8 \text{LEV}_{i,t} + \beta_9 \text{VOL}_{i,t} + \beta_{10} \text{INSIDER}_{i,t} + \beta_{11} \text{INTENSE}_{i,t} + \varepsilon$$

BPS\_FE The absolute percentage forecast error for book value per share, calculated by comparing the mean analyst forecast 30 working days after reporting date to the actual book value per share.

EPS\_FE The absolute percentage forecast error for earnings per share, calculated by comparing the mean analyst forecast 30 working days after reporting date to the actual earnings per share.

SIZE The natural log of the market value of the firm in US dollars.

FOLLOW The number of forecasts included in the mean analyst forecast.

CROSS An indicator variable set to one if a firm is cross-listed and zero otherwise.

LOSS An indicator variable set to one if basic earnings per share is negative and zero otherwise.

PER Actual book value (earnings) per share scaled by share price at the end of the year.

CHANGE The change in book value (earnings) per share from the previous year, scaled by share price at the end of the year.

MTB The market-to-book ratio at the end of the year.

LEV The long-term debt to total assets ratio.

VOL The standard deviation of the firm's daily returns for the year. Firms must have at least 200 daily returns to be included in the sample.

INSIDER The percentage shares held by insiders at the end of the year.

INTENSE\_max The maximum fair value intensity of the firm. Details of the calculation are set out in Appendix A.

INTENSE\_min The minimum fair value intensity of the firm. Details of the calculation are set out in Appendix A.

Note: *p*-values for two-tailed significance are indicated in brackets. Standard errors are robust standard errors clustered by firm and year (Gow et al. 2010; Petersen 2009; Thompson 2011). N differs from that of previous tables because influential observations identified in an initial regression were deleted.

\*, \*\* and \*\*\* indicate significance at the 10%, 5% and 1% levels, respectively.

TABLE 4: Regression results with definite fair value accounting.

Variable	BPS_FE		EPS_FE	
	The United States	The United Kingdom	The United States	The United Kingdom
<b>Panel A: Regression results for INTENSE_max</b>				
SIZE	-0.023 (0.484)	-0.055* (0.089)	-0.068** (0.028)	-0.023 (0.475)
FOLLOW	0.009 (0.653)	0.007 (0.355)	0.011** (0.018)	0.002 (0.644)
CROSS	-0.248 (0.132)	0.010 (0.150)	-0.053 (0.305)	0.026 (0.713)
LOSS	-0.074* (0.082)	-0.015 (0.775)	2.055*** ( $< 0.001$ )	0.911*** ( $< 0.001$ )
PER	-0.308*** (0.006)	-0.230*** (0.001)	-3.322*** ( $< 0.001$ )	-5.542*** ( $< 0.001$ )
CHANGE	-0.026 (0.835)	-0.071 (0.186)	-1.375*** (0.001)	0.315 (0.492)
MTB	-0.001 (0.144)	-0.002 (0.559)	-0.001** (0.023)	-0.001 (0.445)
LEV	1.042* (0.094)	0.030 (0.903)	0.347* (0.055)	-0.112 (0.584)
VOL	0.696 (0.178)	-0.121 (0.290)	3.028 (0.436)	0.015 (0.921)
INSIDER	0.174 (0.248)	0.078 (0.551)	0.511** (0.014)	0.108 (0.418)
INTENSE_max	0.090 (0.465)	0.238*** (0.002)	0.298* (0.076)	0.655*** (0.023)
N	3965	1114	3924	1091
R <sup>2</sup> (%)	0.8	3.4	35.0	50.4
<b>Panel B: Regression results for INTENSE_min</b>				
SIZE	-0.022 (0.483)	-0.055* (0.089)	-0.070** (0.024)	-0.023 (0.475)
FOLLOW	0.010 (0.653)	0.007 (0.355)	0.011** (0.012)	0.002 (0.644)
CROSS	-0.250 (0.124)	0.010 (0.150)	-0.061 (0.224)	0.026 (0.713)
LOSS	-0.077* (0.075)	-0.015 (0.775)	2.044*** ( $< 0.001$ )	0.911*** ( $< 0.001$ )
PER	-0.307*** (0.006)	-0.230*** (0.001)	-3.298*** ( $< 0.001$ )	-5.542*** ( $< 0.001$ )
CHANGE	-0.024 (0.854)	-0.071 (0.186)	-1.396*** (0.001)	0.315 (0.492)
MTB	-0.001 (0.143)	-0.002 (0.559)	-0.001** (0.018)	-0.001 (0.445)
LEV	1.040* (0.096)	0.030 (0.903)	0.331* (0.066)	-0.112 (0.584)
VOL	0.660 (0.224)	-0.121 (0.290)	2.969 (0.442)	0.015 (0.921)
INSIDER	0.175 (0.245)	0.078 (0.551)	0.518** (0.012)	0.108 (0.418)
INTENSE_min	0.120 (0.516)	0.238*** (0.002)	0.494** (0.025)	0.655*** (0.023)
N	3965	1114	3924	1091
R <sup>2</sup> (%)	0.8	3.4	35.0	50.4

$$\text{DEPENDENT}_{it} = \alpha_0 + \beta_1 \text{SIZE}_{it} + \beta_2 \text{FOLLOW}_{it} + \beta_3 \text{CROSS}_{it} + \beta_4 \text{LOSS}_{it} + \beta_5 \text{PER}_{it} + \beta_6 \text{CHANGE}_{it} + \beta_7 \text{MTB}_{it} + \beta_8 \text{LEV}_{it} + \beta_9 \text{VOL}_{it} + \beta_{10} \text{INSIDER}_{it} + \beta_{11} \text{INTENSE}_{it} + \varepsilon$$

BPS\_FE The absolute percentage forecast error for book value per share, calculated by comparing the mean analyst forecast 30 working days after reporting date to the actual book value per share.

EPS\_FE The absolute percentage forecast error for earnings per share, calculated by comparing the mean analyst forecast 30 working days after reporting date to the actual earnings per share.

SIZE The natural log of the market value of the firm in US dollars.

FOLLOW The number of forecasts included in the mean analyst forecast.

CROSS An indicator variable set to one if a firm is cross-listed and zero otherwise.

LOSS An indicator variable set to one if basic earnings per share is negative and zero otherwise.

PER Actual book value (earnings) per share scaled by share price at the end of the year.

CHANGE The change in book value (earnings) per share from the previous year, scaled by share price at the end of the year.

MTB The market-to-book ratio at the end of the year.

LEV The long-term debt to total assets ratio.

VOL The standard deviation of the firm's daily returns for the year. Firms must have at least 200 daily returns to be included in the sample.

INSIDER The percentage shares held by insiders at the end of the year.

INTENSE\_max The maximum fair value intensity of the firm. Details of the calculation are set out in Appendix A.

INTENSE\_min The minimum fair value intensity of the firm. Details of the calculation are set out in Appendix A.

Note: *p*-values for two-tailed significance are indicated in brackets. Standard errors are robust standard errors clustered by firm and year (Gow et al. 2010; Petersen 2009; Thompson 2011). N differs from that of previous tables because influential observations identified in an initial regression were deleted.

\*, \*\* and \*\*\* indicate significance at the 10%, 5% and 1% levels, respectively.



## Using an indicator variable

To investigate the possibility that results are swamped by a subset of firms with high fair value intensity, a robustness test where INTENSE is replaced with an indicator variable is conducted. This variable (INDIC) is set to one if INTENSE is higher than the median score under the narrow definition and zero otherwise. This implies that the firm-years with marginal fair value accounting are viewed as identical to firms where none has been detected. This robustness test, therefore, considers two possibilities. Firstly, the chance that limited use of fair value accounting is effectively the same as the lack thereof, and secondly, the risk that inaccurate measurement of INTENSE results in an incorrect ranking of sample firms. The results of this robustness test are presented in Table 5.

**TABLE 5:** Regression results using an indicator variable.

Variable	BPS_FE		EPS_FE	
	The United States	The United Kingdom	The United States	The United Kingdom
SIZE	-0.029 (0.211)	-0.024 (0.270)	-0.118*** ( $< 0.001$ )	-0.025 (0.399)
FOLLOW	-0.010 (0.326)	-0.004 (0.451)	0.017*** (0.001)	0.001 (0.938)
CROSS	-0.047 (0.325)	0.100* (0.066)	-0.060* (0.064)	0.078 (0.231)
LOSS	0.132*** (0.001)	0.032 (0.353)	2.041*** ( $< 0.001$ )	0.833*** ( $< 0.001$ )
PER	-0.195*** (0.009)	-0.159*** (0.001)	-1.552* (0.074)	-5.935*** ( $< 0.001$ )
CHANGE	-0.002 (0.977)	-0.132* (0.055)	-1.681*** ( $< 0.001$ )	0.647** (0.046)
MTB	-0.001 (0.578)	0.001 (0.406)	-0.004* (0.076)	-0.001** (0.030)
LEV	0.533** (0.017)	0.113 (0.358)	0.443*** (0.004)	-0.075 (0.605)
VOL	1.077* (0.088)	-0.043 (0.659)	1.820 (0.574)	0.246 (0.441)
INSIDER	0.165 (0.265)	0.092 (0.394)	0.280** (0.042)	0.287** (0.015)
INDIC	0.016 (0.679)	0.057 (0.173)	0.143*** ( $< 0.001$ )	0.120*** (0.008)
N	6595	1378	6532	1353
R <sup>2</sup> (%)	1.4	3.6	28.2	52.8

$$\text{DEPENDENT}_{it} = \alpha_0 + \beta_1 \text{SIZE}_{it} + \beta_2 \text{FOLLOW}_{it} + \beta_3 \text{CROSS}_{it} + \beta_4 \text{LOSS}_{it} + \beta_5 \text{PER}_{it} + \beta_6 \text{CHANGE}_{it} + \beta_7 \text{MTB}_{it} + \beta_8 \text{LEV}_{it} + \beta_9 \text{VOL}_{it} + \beta_{10} \text{INSIDER}_{it} + \beta_{11} \text{INTENSE}_{it} + \varepsilon$$

**BPS\_FE** The absolute percentage forecast error for book value per share, calculated by comparing the mean analyst forecast 30 working days after reporting date to the actual book value per share.

**EPS\_FE** The absolute percentage forecast error for earnings per share, calculated by comparing the mean analyst forecast 30 working days after reporting date to the actual earnings per share.

**SIZE** The natural log of the market value of the firm in US dollars.

**FOLLOW** The number of forecasts included in the mean analyst forecast.

**CROSS** An indicator variable set to one if a firm is cross-listed and zero otherwise.

**LOSS** An indicator variable set to one if basic earnings per share is negative and zero otherwise.

**PER** Actual book value (earnings) per share scaled by share price at the end of the year.

**CHANGE** The change in book value (earnings) per share from the previous year, scaled by share price at the end of the year.

**MTB** The market-to-book ratio at the end of the year.

**LEV** The long-term debt to total assets ratio.

**VOL** The standard deviation of the firm's daily returns for the year. Firms must have at least 200 daily returns to be included in the sample.

**INSIDER** The percentage shares held by insiders at the end of the year.

**INTENSE\_max** The maximum fair value intensity of the firm. Details of the calculation are set out in Appendix A.

**INTENSE\_min** The minimum fair value intensity of the firm. Details of the calculation are set out in Appendix A.

Note: *p*-values for two-tailed significance are indicated in brackets. Standard errors are robust standard errors clustered by firm and year (Gow et al. 2010; Petersen 2009; Thompson 2011). N differs from that of previous tables because influential observations identified in an initial regression were deleted.

\*, \*\* and \*\*\* indicate significance at the 10%, 5% and 1% levels, respectively.

In this robustness test, fair value intensity (represented by INDIC in this instance) is insignificant for book value forecast errors in both countries. By contrast, INDIC is now positive and significant at 1% level in both sample countries when earnings forecast errors are the dependent variable. These findings, therefore, support a conclusion that fair value intensity is detrimental to analyst earnings forecast accuracy. However, they also imply that marginal fair value intensity does not affect book value forecast accuracy.

## Using earlier analyst forecasts

The main regression results use mean analyst forecasts 30 working days (approximately 6 weeks) after reporting date. However, prior research suggests that later forecasts could be more accurate, as managers have an incentive to guide analysts to issue forecasts which will be met (Richardson, Teoh & Wysocki 2004). In this respect, it is to the benefit of analysts to cooperate with management, as their own forecast accuracy is improved (Yu 2008:264). Guidance to analysts is likely to occur before results are released, but after reporting date, as managers have better information available. Therefore, the regression is also run where the dependent variables (forecast errors) are determined at reporting date.

Although some minor differences are noted, findings (untabulated) for the control variables are qualitatively similar to those of the main regression. Most of the findings for the variable of interest (INTENSE) are qualitatively unchanged. However, regardless of definition, earnings forecast errors in the United Kingdom are now only significant at the 10% level. The findings of this robustness test, therefore, imply that guidance by management subsequent to reporting date does not mitigate the impact of fair value intensity on analyst forecast accuracy.

## Identifying influential observations using studentised residuals

In the regression results of this article, influential observations are identified and deleted using Cook's distance (Cook 1977). However, it is also possible to identify outlying observations on the basis of distance (as distinct from leverage) on its own. Therefore, the main regression is also run where observations with studentised residuals more than 2.58 standard deviations from the mean are identified in an initial regression and deleted. Although some minor differences are noted, untabulated results show that inferences remain qualitatively unchanged.

## Relaxing restrictions on daily returns

To be included in the main sample, the standard deviation of daily stock returns (*VOL*) for each firm year must be represented by at least 200 daily returns. Untabulated results reveal that relaxing this restriction to include firm-years with fewer daily returns improves the significance of fair value intensity (INTENSE) for analyst's earnings forecast errors in the United Kingdom to the 1% level under both definitions.

All other inferences for the variable of interest remain qualitatively unchanged.

### Other robustness tests

To address the risk that the variables introduced in this study materially affect reported results, the regressions for book value and earnings forecasts are run excluding the variables CROSS, PER and INTENSE. The signs on control variables with significance in both regressions remain unchanged, apart from CHANGE, which becomes negative and insignificant for earnings forecast errors in the United Kingdom.

There is a risk that PER and MTB are collinear in the book value forecast model. However, VIF-scores do not detect multicollinearity in any of the regressions and omitting MTB from the model leaves inferences qualitatively unchanged. As multicollinearity only affects inferences for the variables concerned (and therefore leaves the variable of interest, INTENSE, unaffected), both variables have been retained in the book value forecast analyses to ensure consistency with the earnings forecast model.

### Summary and conclusion

This article investigates a null hypothesis that fair value intensity (the degree to which fair value accounting is used in the financial statements) does not affect analyst forecast accuracy, using a sample of firms listed in the United States and United Kingdom from 2010 to 2014. Based on multivariate regression findings, the null hypothesis is rejected with respect to analysts' earnings forecasts. Although results for the United States are initially insignificant, limiting the sample to those firms for which fair value accounting is detected, produces results similar to those of the United Kingdom. While the null hypothesis is also rejected for analysts' book value forecasts in the United Kingdom, results for the United States sample fails to do so. Consequently, findings show that increased fair value intensity decreases analysts' earnings forecast accuracy (increases forecast errors). With respect to book value forecasts, fair value intensity at best does not affect forecasts. However, there is some evidence that it is detrimental to analysts' book value forecast accuracy.

This study contributes to the existing literature by considering a range of different operating and non-operating assets and liabilities as well as earnings and book value forecast for two major equity markets operating under different financial reporting frameworks. However, to achieve this degree of generalisability, some accuracy in the degree with which fair value intensity has been measured in this article has been sacrificed. While findings are robust to the use of an indicator variable and other mitigating research design choices, future researchers may want to investigate whether increased accuracy of measurement impacts inferences. In addition, findings are specific to the sample countries used and might not generalisable to other countries.

Lastly, this study provides a broad understanding of the impact of fair value intensity on analyst forecasts. Future research could investigate and compare the impact on specific industries.

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#### Competing interests

The author declares that he has no financial or personal relationships which may have inappropriately influenced him in writing this article.

### References

- Ahmed, A.S., Kilic, E. & Lobo, G.J., 2006, 'Does recognition versus disclosure matter? Evidence from banks' recognized and disclosed derivative financial instruments', *Accounting Review* 81(3), 567–588. <https://doi.org/10.2308/accr.2006.81.3.567>
- Ayres, D., Huang, X. & Myring, M., 2017, 'Fair value accounting and analyst forecast accuracy', *Advances in Accounting, Incorporating Advances in International Accounting*, 37, 58–70.
- Badenhorst, W.M., 2014, 'Fair value measurements of control premiums', *Accounting Perspectives* 13(3), 173–188. <https://doi.org/10.1111/1911-3838.12030>
- Barth, M.E. & Clinch, G., 2009, 'Scale effects in capital markets-based accounting research', *Journal of Business Finance and Accounting* 36(3 & 4), 253–288. <https://doi.org/10.1111/j.1468-5957.2009.02133.x>
- Biondi, Y., Glover, J., Jamal, K., Ohlson, J.A., Penman, S.H., Sunder, S. et al., 2012, 'Some conceptual tensions in financial reporting', *Accounting Horizons* 26(1), 125–133. <https://doi.org/10.2308/acch-50087>
- Bradbury, M.E., 2000, 'Issues in the drive to measure liabilities at fair value', *Australian Accounting Review* 10, 19–25. <https://doi.org/10.1111/j.1835-2561.2000.tb00059.x>
- Collins, D.W., Maydew, E.L. & Weiss, I.S., 1997, 'Changes in the value-relevance of earnings and book values over the past forty years', *Journal of Accounting and Economics* 24, 39–67. [https://doi.org/10.1016/S0165-4101\(97\)00015-3](https://doi.org/10.1016/S0165-4101(97)00015-3)
- Cook, R.D., 1977, 'Detection of influential observation in linear regression', *Technometrics* 19(1), 15–18.
- Dichev, I.D. & Tang, V.W., 2008, 'Matching and the changing properties of accounting earnings over the last 40 years', *Accounting Review* 83(6), 1425–1460. <https://doi.org/10.2308/accr.2008.83.6.1425>
- Easton, P.D. & Sommers, G.A., 2003, 'Scale and the scale effect in market-based accounting research', *Journal of Business Finance and Accounting* 30(1 & 2), 25–55. <https://doi.org/10.1111/1468-5957.00482>
- Givoly, D. & Hayn, C., 2000, 'The changing time-series properties of earnings, cash flows and accruals: Has financial reporting become more conservative?', *Journal of Accounting and Economics* 29, 287–320. [https://doi.org/10.1016/S0165-4101\(00\)00024-0](https://doi.org/10.1016/S0165-4101(00)00024-0)
- Gow, I.D., Ormazabal, G. & Taylor, D.J., 2010, 'Correcting for cross-sectional and time-series dependence in accounting research', *Accounting Review* 85(2), 483–512. <https://doi.org/10.2308/accr.2010.85.2.483>
- Heflin, F., Subramanyam, K. & Zhang, Y., 2003, 'Regulation FD and the financial information environment: Early evidence', *Accounting Review* 78(1), 1–37. <https://doi.org/10.2308/accr.2003.78.1.1>
- Holthausen, R.W. & Watts, R.L., 2001, 'The relevance of the value-relevance literature for financial accounting standard setting', *Journal of Accounting and Economics* 31, 3–75. [https://doi.org/10.1016/S0165-4101\(01\)00029-5](https://doi.org/10.1016/S0165-4101(01)00029-5)
- Kallapur, S. & Kwan, S.Y.S., 2004, 'The value relevance and reliability of brand assets recognised by UK firms', *Accounting Review* 79(1), 151–172. <https://doi.org/10.2308/accr.2004.79.1.151>
- Kothari, S.P., Ramanna, K. & Skinner, D.J., 2010, 'Implications for GAAP from an analysis of positive research in accounting', *Journal of Accounting and Economics* 50, 246–286. <https://doi.org/10.1016/j.jacceco.2010.09.003>
- Lang, M. & Lundholm, R., 1996, 'Corporate disclosure policy and analyst behavior', *Accounting Review* 71(4), 467–492.
- Liang, L. & Riedl, E.J., 2014, 'The effect of fair value versus historical cost reporting model on analyst forecast accuracy', *Accounting Review* 89(3), 1151–1177. <https://doi.org/10.2308/accr-50687>
- Lys, T. & Soo, L.G., 1995, 'Analysts' forecast precision as a response to competition', *Journal of Accounting, Auditing and Finance* 10, 751–765. <https://doi.org/10.1177/0148558X9501000404>
- Mozes, H.A., 2002, 'The value-relevance of financial institutions' fair value disclosures: A study in the difficulty of linking unrealised gains and losses to equity values', *Abacus* 38(1), 1–15. <https://doi.org/10.1111/1467-6281.00095>
- Nissim, D. & Penman, S.H., 2001, 'Ratio analysis and equity valuation: From research to practice', *Review of Accounting Studies* 6, 109–154. <https://doi.org/10.1023/A:1011338221623>
- Ohlson, J.A., 1995, 'Earnings, book values and dividends in equity valuation', *Contemporary Accounting Research* 11, 661–887. <https://doi.org/10.1111/j.1911-3846.1995.tb00461.x>

- Palea, V. & Maino, R., 2013, 'Private equity fair value measurement: A critical perspective on IFRS 13', *Australian Accounting Review* 23(3), 264–278. <https://doi.org/10.1111/auar.12018>
- Petersen, M.A., 2009, 'Estimating standard errors in finance panel data sets: Comparing approaches', *Review of Financial Studies* 22(1), 435–480. <https://doi.org/10.1093/rfs/hhn053>
- Power, M., 2010, 'Fair value accounting, financial economics and the transformation of reliability', *Accounting and Business Research* 40(3), 197–210. <https://doi.org/10.1080/00014788.2010.9663394>
- Richardson, S., Teoh, S. & Wysocki, P., 2004, 'The walk-down to beatable analyst forecasts: The role of equity issuance and inside trading incentives', *Contemporary Accounting Research* 21, 885–924. <https://doi.org/10.1506/KHNW-PJYL-ADUB-ORP6>
- Sidhu, B. & Tan, H.C., 2011, 'The performance of equity analysts during the global financial crisis', *Australian Accounting Review* 21, 32–43. <https://doi.org/10.1111/j.1835-2561.2010.00116.x>
- Siegel, P.H., Lessard, J.P. & Karim, K.E., 2011, 'Analyst forecast accuracy and firm growth', *Advances in Quantitative Analysis of Finance and Accounting* 9, 1–31.
- Thompson, S.B., 2011, 'Simple formulas for standard errors that cluster by both firm and time', *Journal of Financial Economics* 99, 1–10. <https://doi.org/10.1016/j.jfineco.2010.08.016>
- Watts, R.L., 2003, 'Conservatism in accounting, part I: Explanations and implications', *Accounting Horizons* 17(3), 207–221. <https://doi.org/10.2308/acch.2003.17.3.207>
- Yu, F., 2008, 'Analyst coverage and earnings management', *Journal of Financial Economics* 88, 245–271. <https://doi.org/10.1016/j.jfineco.2007.05.008>

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## Appendix A

This appendix provides the details of the assets and liabilities included in the calculation of INTENSE for firms reporting under IFRS and those reporting under US GAAP.

### IFRS calculation

For the purposes of calculating the maximum INTENSE score, the TA and TL for entities reporting under IFRS have been calculated using the carrying amounts of the following items from Datastream:

- Non-current assets (WC18353; WC18354) and liabilities (WC18159; WC18314) held for sale, as such disposal groups are measured at the lower of carrying amount and fair value less cost to sell.
- Biological assets (WC18277) as these assets must be measured at fair value under nearly all circumstances.
- Net defined benefit plan assets (WC02653) and liabilities (WC03261), as plan assets form a major component of the net asset or liability and plan assets are measured at fair value.
- Financial assets (WC02255), which include equity investments, debt investments and derivative financial assets, as a significant portion of financial assets is required to be measured at fair value.
- Only derivative financial liabilities (WC18286; WC18287) are identified as fair value measurements, as most financial liabilities are measured at amortised cost.

Importantly, these assets and liabilities have little in common beyond fair value measurement. For example, derivative financial liabilities tend to be operational liabilities, whereas non-current liabilities held for sale are not; biological assets are tangible assets

whereas defined benefit plan assets are not. Consequently, the findings of this article relate to the only common characteristic, namely measurement at fair value.

Other assets that could potentially be measured at fair value under IFRS include investment property, property, plant and equipment and intangible assets. These items are, however, not considered for the purposes for the study. Investment property is excluded as Datastream does not collect information for these assets outside of the property industry (which firms are excluded from the sample of this article). Property, plant and equipment as well as intangible assets are excluded as they tend to be measured mostly at historical cost, despite a fair value measurement alternative being available.

For the minimum INTENSE score, TA and TL are calculated using the same data items, with the exception of financial assets. Financial assets are excluded from the minimum score, as the database does not distinguish financial assets measured at amortised cost from financial assets measured at fair value.

### US GAAP calculation

A similar process is followed to calculate the minimum and maximum INTENSE scores for firms reporting under US GAAP. However, biological assets are excluded from the calculation, as US GAAP does not permit these assets to be measured at fair value. Although US GAAP allows the measurement of inventory at fair value, this is only permissible under limited circumstances. Therefore, as the inventory balance is likely to be dominated by entity-specific measurements (cost and, to a lesser extent, net realisable value), inventory has been excluded from the calculation of INTENSE.