The importance of broker size in determining the utility of IFRS8 segment data to financial analysts

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Abstract

This paper reveals the important role played by brokerage house size in determining the utility of segment data to financial analysts. Brokerage house size is a proxy both for analysts' access to company managers and for their access to in-house expertise. Using data for large UK firms, we reveal that the shift to International Financial Reporting Standard 8 (IFRS8) led to significant improvements in forecast accuracy for analysts in large brokerage houses but not for those in small brokerage houses. In addition, the forecasting ability of analysts in smaller brokerage houses was impaired when segments represented lines-of-business. No such effect was evident in the case of large brokers' analysts. We link these findings to the improved insight which analysts in large brokers obtained from their superior access to managers and in-house support.

Key Words: financial analysts; earnings forecasts; segment reporting; broker size; UK; IFRS8

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1. Introduction

UK segment reporting requirements are presently determined by International Financial Reporting Standard 8 *Operating Segments* (IFRS8, 2006), which emphasises the need for reported segments to mirror the internal operating units of the company.[1] This is often referred to as the 'management approach' to segment reporting and for most large European firms this manifests itself in the form of lines-of-business (LOB).[2] Although a major aim of segment disclosure is to provide investors with improved insight into future company performance, Aboud et al. (2018, p.2) note that prior evidence on the benefits of the management approach to segment reporting is mixed. We focus on the UK market, examining the impact of the analysts' environment on their ability to use segment data. We are not aware of any other research of this nature and to the best of our knowledge this paper is the first to follow this approach. Our paper also helps explain the mixed findings noted in prior studies.

The important role played by analysts as information intermediaries within the UK market is well-documented (Lee & Tweedie, 1981; Arnold & Moizer, 1984; Day, 1986; Pike et al., 1993; Barker, 1998, 1999; Clatworthy & Jones, 2008; Campbell & Slack, 2008). Analysts' forecasts of corporate earnings per share (EPS) are employed frequently in the accounting literature to assess the utility of accounting disclosures. This has been particularly evident in the literature on segment disclosures due to the role such data play in the formation of analysts' forecasts of earnings numbers (e.g. Baldwin, 1984; Emmanuel et al., 1989; Swaminathan, 1991; Boatsman et al., 1993; Hussain, 1997; Lobo et al., 1998; Berger & Hann, 2003; Kou & Hussain, 2007; Nichols et al., 2013; Andre et al., 2016; Aboud et al., 2018).

[1] The US Statement of Financial Accounting Standard 14 (SFAS14, 1976) and the International Accounting Standard 14 (IAS14, 1981) recommended that segments should be identified by both LOB and geographical areas to reflect economic risks and rewards, and that segments should disclose major items including sales and profits. The US standard SFAS131 (1997) formalised a shift towards the use of 'managerial' segments, which reflected how the firm was segmented for internal decision-making purposes. With the aim of achieving greater convergence with North American reporting, IAS 14 was revised in 1997 (IAS14R) to also incorporate the management approach, but with a risk and rewards qualification (Crawford et al., 2012, p.10). The move from a qualified management approach under IAS14R to the full management approach under IFRS8 was arguably less dramatic than the shift from SFAS14 to SFAS131 in the US.

[2] Crawford et al. (2012) and Nichols et al. (2013, p.273) indicate that around two-thirds of major UK and European firms, respectively, identify operating segments on the basis of some form of LOB format.

What is missing from the literature at present is an investigation of the degree to which analysts' ability to use accounting disclosures is influenced by institutional factors. UK analysts reside within a range of financial institutions, varying notably in size.[3] Interviews with UK analysts conducted by Marston (1996) reveal a perception that working for larger brokers gives analysts a significant advantage with regard to obtaining access to company managers. In addition, analysts working for larger brokers are more likely to have access to in-house expertise relating to the international economic environment, and IT support (Jacob et al., 1999).[4] Given that these characteristics are positively related to brokerage house size, and that they are both likely to aid analysts' understanding of accounting disclosures within a firm-specific context, the benefits of new accounting disclosures may vary across brokers. Two corollaries follow from this. Firstly, accounting standard-setting bodies should not assume that new reporting requirements will be equally useful to all analysts and investors. Secondly, it is questionable whether academic studies should rely solely on consensus analyst forecasts when examining the impact of new reporting requirements because such forecasts do not allow for discrimination between forecasts emanating from large brokers and small brokers.

Following Aboud et al. (2018) we examine forecasts made in the last two years of the previous standard, International Accounting Standard 14, revised (IAS14R, 1997), and the first two years of IFRS8. Our focus is on large UK firms, given Crawford et al.'s (2012) finding that the impact of IFRS8 on UK disclosure practices was greatest among the largest UK firms. Another rationale for our UK focus relates to the depth of prior research regarding analysts' working practices, particularly in the years preceding the implementation of IFRS8 (e.g. Arnold & Moizer, 1984; Day, 1986; Pike at al., 1993; Marston, 1996; 1999; Barker, 1998, 2000; Clatworthy & Jones, 2008). This prior research is important in guiding our examination of the broker-size effect and is generally lacking or limited for most other European countries. Our main findings can be summarised as follows:

i. UK analysts in both small and large brokerage houses benefit from segment reporting (the number of segments; the fineness of geographic segments; the reporting of segments which reflect the diversity of profitability across segments; the disclosure of geographic profits; the definition of segment profits to match profit in the consolidated accounts) across the four fiscal years studied here. Thus, UK segment disclosures possess utility for both sets of analysts.

[3] Hereinafter, the term 'broker' or 'brokerage house' will be used to denote any financial institution within which analysts work.

[4] Studies from both the US and UK markets demonstrate that differential accuracy in forecasts is associated with brokerage house size (Clement, 1999; Hussain, 2002), although there is no analysis of how analysts in different brokerage houses use accounting data.

ii. In the case of large brokers' analysts, the switch from IAS14R to IFRS8 resulted in a significant improvement in their forecasts, not evident in the forecasts of small brokers' analysts.

iii. For analysts in small brokers, accuracy is dependent on the form of reported segments. A LOB format is associated with reduced accuracy, reiterating a finding reported in Aboud et al. (2018). Analysts in large brokers are unencumbered by the segment reporting format.

The paper is structured as follows. Section 2 explains why brokerage house size is likely to be a significant factor in determining how analysts are able to process segment data and identifies our research hypotheses. Section 3 describes the sample and test methodology employed here. Section 4 presents the results and links these to the research hypotheses identified in Section 2. Section 5 is the discussion and Section 6 is the conclusion.

2. Broker size as a contextual factor for the utility of segment disclosures to UK analysts

2.1. Broker size and analysts' access to UK company managers

A major reason to hypothesise a broker-size effect among UK financial analysts is the claim of differential access to company personnel. It is well known that UK analysts value such contacts highly (Barker, 1998, p.16). The issue of analyst access to company decision-makers has been investigated in two UK studies by Marston (1996, 1999). Marston (1996) surveys finance directors for the 547 largest quoted UK companies, while Marston (1999) presents evidence from interviews with finance directors and investor-relations officers for FTSE100 companies, UK analysts and investment managers:

> '[The companies] … usually had a view about the relative importance of the different institutions and analysts. They tended to view large institutions … as more important.' Marston (1999, p.49).
>
> '[The analysts/investment managers] considered that because they were working for large organisations they were in a lucky position and their perception was that smaller institutions might not be able to arrange one-to-one meetings so easily.' (Marston, 1999, p.32).

Thus, the institutions within which analysts are employed are not all viewed in the same manner by company managers. Access to managers offers analysts the potential for a better understanding of the internal segmentation of the firm, including: how the segments are related to each other and the wider business entity; how the firm views each segment in terms of its long-term objectives and expansion plans; and how the firm views each segment in relation to the broader external markets in which each is located. Thus, analysts' ability to use segment disclosures may vary with broker size.

2.2. Broker size and in-house expertise

IFRS8 requires reported segments to reflect the managerial segments used within the company. These operating segments most commonly reflect either LOB or geographic regions. Analysts' ability to utilise these segment disclosures is dependent upon gaining insights into trends for these various business sectors and/or regions, which can then be used in conjunction with the disclosed segment results (e.g. Kinney, Jr., 1971; Roberts, 1989; Balakrishnan et al., 1990). Analysts' access to in-house economic expertise is an important dimension to this process. Large brokers often have their own in-house economists and IT specialists, as well as assistants and administrative staff to support their analysts (Jacob et al., 1999). Barker (1998, 1999) conducts interviews with analysts employed at a leading UK brokerage firm and identifies three important areas of in-house expertise: economists, market strategy experts, and technical analysts. Of these, in-house economists are the most highly rated in terms of perceived usefulness (Barker, 1998, p.11). The importance of support teams is reiterated by Clement (1999) who quotes the director of global equity research at Merrill Lynch:

> 'Today the senior analyst needs strong associates [assistants] and part of their job is to make the star look like a star.' (Clement, 1999, p.289)

Support for analysts in the form of databases and IT facilities are identified as important to the exploitation of segment data in one of the earliest UK studies (Arnold & Moizer, 1984, p.197). The importance of understanding the impact of both macroeconomic and industry-level variables on a company's prospects is reiterated in many later UK studies, such as Pike et al. (1993), Barker (1998, 1999), Weetman & Beattie (1999) and Clatworthy & Jones (2008). Analysts with the appropriate in-house support can best employ segment data for forecasting purposes.

2.3. Hypotheses

Aboud et al. (2018) demonstrate that the implementation of IFRS8 led to improvements in analysts' forecast errors in those European countries with strong enforcement systems for accounting standards. For the UK, therefore, it is expected that forecasts generated post-IFRS8 will exhibit improved accuracy. However, these predictive gains may be greater for analysts in large brokerage houses. One reason is that segment data need to be used in conjunction with knowledge of trends within specific industry-sectors or geographic regions (e.g. Kinney, Jr., 1971; Roberts, 1989; Hussain & Skerratt, 1992). Exploiting these disclosures will be easier when an analyst is supported by in-house experts and financial databases (Barker, 1998, p.11). Analysts in large brokerage houses also appear to benefit from superior access to company managers (Marston, 1996, 1999). Gaining a deeper understanding of how the firm operates internally should aid analysts in their understanding of reported segments identified under IFRS8. The first hypothesis to be tested examines differences in analysts' forecast errors based on broker size:

> **H1**: Reductions in UK analysts' earnings forecast errors associated with the implementation of IFRS8 are greater for analysts in large brokers.

Evidence of a broker-size effect (H1) could indicate that analysts in small brokers do not have sufficient support to make use of segment disclosures, or that analysts in small brokers are able to utilise only a subset of segment disclosures relative to analysts in large, well-resourced brokers. Our study will examine a wide range of different segment reporting characteristics, explained in Section 3. If analysts in small brokerage houses are unable to utilise segment data then no association is expected between their forecast errors and the various segment reporting characteristics. If analysts in small brokerage houses utilise only a subset of segment data, relative to analysts in large brokers, then this will be revealed via differences in the number of significant associations between the forecast errors and the various segment reporting characteristics.

> **H2**: Reductions in UK analysts' earnings forecast errors are associated with individual segment reporting characteristics for both large and small brokers' analysts.

This study hypothesises that the segment reporting format (e.g. LOB) should be a less significant factor for analysts with good insight into a firm's internal structure and knowledge of how these various segments relate to the overall firm. This information, obtained by discussions with managers and company personnel, appears to be more readily available to large brokers' analysts (Marston, 1996, 1999). For analysts with limited insight into the internal structure of the company, the format for the segment report may impact their forecast accuracy. Aboud et al. (2018, Tables 4 and 5) report a significant increase in European analysts' forecast errors when the reporting format reflects LOB, although they do not comment on their finding.

> **H3**: The impact of segment reporting format (e.g. LOB) on UK analysts' earnings forecast errors is greater for analysts in smaller brokers.

3. Sample, Variables, and Method

3.1. Sample

Crawford et al. (2012) compare pre- and post-IFRS8 segment disclosures for a sample of UK firms drawn from the FTSE100 and FTSE250 indices and find that changes in reporting are primarily driven by the largest UK firms. Given that our paper is concerned with the impact of IFRS8 disclosures on large and small brokers' analysts, we focus on the largest UK firms. Following Aboud et al. (2018) this study examines short-term earnings forecasts generated at horizons of less than 12 months in the two years pre- and post-implementation of IFRS8. Unlike Aboud et al. (2018) we do not use a single consensus forecast but the full set of individual analysts' forecasts: this allows us to examine differential forecasting ability across brokers. These data are extracted from the I/B/E/S Detail file for UK firms. This file allows identification of brokerage house and analyst, the number of analysts following a firm and the creation date for each individual forecast. The I/B/E/S Actuals file gives the actual EPS and the announcement date. All firm data (e.g. share price, market value) are collected from DataStream while segment data are taken directly from the annual reports. [5]

This study's focus on large UK firms means that any differential accuracy between large and small brokers is not driven by differences in the set of firms followed by these two groups of brokers. This is because FTSE100 firms are followed by analysts from both large and small brokers. Also, since large firms are heavily followed by UK analysts (Hussain, 2000) the forecasts for large firms are less likely to become stale and are therefore are more informative than for relatively neglected smaller firms. This is highlighted by Barker's (2000, p.100) observation that a single analyst was sometimes responsible for following the universe of small companies. While the FTSE100 index contains the UK's largest firms, it is not a constant list – its constituent firms are revised on a monthly basis.[6] This means that firms can shift between the FTSE100 and FTSE250 indices over a period of time. We identify 72 non-financial firms which are FTSE100 members during the IFRS8 test period, detailed in Appendix B. We also identify another 11 large non-financial firms that had similar average market values to the smallest of these 72 firms, and several of which became FTSE100 members at a later date, but which were primarily members of the FTSE250 index during the test period. These firms are among the largest FTSE250 members and are similarly distributed across sectors so there is little impact on the sector-mix of the overall sample (see Appendix C). Their inclusion/exclusion makes no material difference to this study.

[5] Most segment data were obtained from the notes to the accounts, which is the usual source for such data in the UK. We included any additional tables of segment data that appeared elsewhere in the annual report if these provided superior detail. However, references to segment data in other parts of the report were either primarily descriptive or repeating what was contained in the notes to the accounts. All the segment data were manually collected from annual reports by the first author and were reviewed by the second author.

[6] See *FTSE 100 Historic Additions and Deletions*, ftserussell.com, December 2019.

3.2. Dependent variable measurement

All forecasts are created at horizons of less than 12 months relative to the actual earnings announcement: this ensures that they were generated with the availability of the previous year's annual report and segment disclosures, so that the forecasts will reflect the insight provided by these disclosures. The lack of information on analysts' loss functions makes it difficult to arrive at any conclusive decision regarding error metric choice (Patz, 1989; Basu & Markov, 2004). However, the most commonly used metric within the international literature on analysts' forecasts of corporate EPS is the absolute error deflated by the share price (e.g. Capstaff et al. 1999). This metric remains popular, especially within the US literature (e.g. Altınkılıça et al., 2019; Jung et al., 2019). A log transformation is applied to this metric to reduce skewness. For a set of *J* individual analyst forecasts for a company's EPS for fiscal year *t* ($FEPS_{j,t}$), the error metric is a function of the forecast, the actual EPS for year *t* (EPS_t) and the start-of-period share price (P_{t-1}):

$$FE_{j,t} = ln\left[1 + \left|\left(\frac{FEPS_{j,t} - EPS_t}{P_{t-1}}\right)\right|\right]$$

3.3. Control variables

Year and industry sector dummies are employed to control for any fixed effects relating to these characteristics. The sectors are basic materials; consumer goods; consumer services; health care; industrials; oil and gas; technology; telecommunications; and utilities. Earnings forecasts are derived from individual analysts working for specific brokerage houses, as reported on the I/B/E/S Detail database. In our sample, there are 252 different brokers and we will define large brokers as the top-20, based on the number of analysts.[7] Despite representing less than 10 percent of all brokers, these top-20 brokers generate more than half of all short-term forecasts within our sample.

There has long been a consensus that forecast errors are negatively associated with firm size and analyst following, and positively associated with forecast horizon, gearing, and both the magnitude and direction of earnings changes (e.g. Baldwin, 1984; Foster, 1986; Patz, 1989; Capstaff et al., 1999; Hussain, 2002). Forecasting corporate earnings also appear to be more difficult for analysts where firms are loss-makers (e.g. Aboud et al., 2018). Evidence on how corporate governance impacts the forecast error is more limited but Byard et al. (2006) suggest that high-quality corporate governance is associated with better quality information being available to

[7] We also repeat our analysis using the top-10 brokers but results (untabulated) are materially similar.

financial analysts. They find that board size is negatively related to analyst forecast accuracy, but board independence is positively associated with accuracy.

This paper will include the following control variables: the forecast horizon relative to the announcement day (*HORZ*); firm size proxied by the natural log of market value of equity (*SIZE*); analyst following based on the number of analysts making short-term forecasts for a particular firm (*FOLLOW*); gearing defined here as debt to total assets, expressed as a percentage (*GEARING*); and loss-making, represented by a dummy variable which takes a value of one where current EPS are negative, and zero otherwise (*LOSS*). Earnings volatility is measured using two metrics and reflects the actual change which the analyst must predict rather than a measure of past volatility. This study examines both the sign and magnitude of the actual change in EPS. In the former case a dummy variable (*FALL*) takes a value of one where the actual change in earnings is negative, and zero otherwise. In the latter case, the magnitude of the earnings change (*EARNCHANGE*) is measured as follows, with a log transformation to reduce skewness:

$$EARNCHANGE_t = ln\left[1 + \left|\left(\frac{EPS_t - EPS_{t-1}}{|EPS_{t-1}|}\right)\right|\right]$$

The quality of corporate governance is measured here using two metrics. The UK Corporate Governance Code 2018 recommends that boards of directors should be large enough to provide diverse opinions but not so large as to become unwieldy. This suggests a non-linear relationship between board size and effective corporate governance. Board size is included in a quadratic form: the size of board (*BOARDSIZE*) and the size of board squared (*BOARDSIZESQD*). If the quality of corporate governance is associated with reduced errors and there is an optimum size for boards, a negative coefficient is expected for *BOARDSIZE* and a positive coefficient for *BOARDSIZESQD*. Board independence is also a potentially important factor. In the UK directors are appointed in a manner prescribed by a company's articles of association, which often set a minimum and maximum number of directors. However, the number of non-executive directors may not reflect the proportion within the board. We create a dummy variable for highly independent boards based both on the number of non-executive directors and their proportion on the board. If both of these are in the upper quartile then our dummy variable *HIBOARDINDEPEND* will take a value of one, and zero otherwise.

3.4. Segment reporting variables

The segment variables are constructed using manually collected data from firms' last two annual reports under IAS14R, and their first two annual reports under IFRS8. Cases where forecasts are generated in the presence of IFRS8 disclosures are indicated by the dummy variable (*STANDARD*) which takes a value of one in such cases, and a value of zero for pre-IFRS8 cases. Early adopters are identified by a dummy variable (*EARLY*) which takes a value of one for early adopting firms and zero otherwise.[8] Crawford et al. (2012) revealed that the characteristics which changed the most for large UK firms were the number of reported segments; the number of line items disclosed; the fineness of reported geographic segments; the definition of segments profits; and the disclosure of geographic profits. These results inform our choice of variables. The total number of line items (*LINEITEM*) is the number of different accounting items disclosed across all reported segments, while the total number of segments is *TOTSEG*.

The management approach to segment disclosure allows segment profits to be defined in a manner consistent with how data are reported internally. Thus, segment profit measures can vary notably across companies. Berger & Hann (2007, p.881) identify six different definitions used by US firms, under SFAS131. However, there are variations within these six definitions because items such as special charges are sometimes included or excluded within each definition. They also note that the definition of segment earnings is not always stated or is unclear.[9] Flexibility in the definition of reported segment profit also exists under IFRS8, a source of early criticism for the new standard among accountants (Murphy, 2007, p.7). Although segment profits should be reconciled to a measure of consolidated earnings, Crawford et al. (2012) have noted that the flexibility IFRS8 allows with regard to profit definition, there may be a sizeable reconciling item which conflates unallocated items with differences arising from non-IFRS measures. Segment data are likely to be more useful when they can be mapped directly to major line items within the annual report. We create a dummy variable (*PROFITDEFINE*) which takes a value of one if segment profits are defined on exactly the same basis as a profit measure in the consolidated accounts, and zero otherwise.

The potential predictive gains to geographic segment disclosures have been documented in a range of prior theoretical and empirical studies (e.g. Roberts, 1989; Balakrishnan et al., 1990; Hussain & Skerratt, 1992; Herrmann & Thomas, 1997, 2000; Hussain, 1997; Kou & Hussain, 2007). The disclosure of geographic profits by those firms which primarily use LOB segments is indicated here by a dummy variable (*GEOPROF*) which takes a value of one in such cases, and zero otherwise.

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[8] In their study of European companies, Aboud et al. (2018) report no significant association between early adoption of IFRS8 and analysts' forecast errors. *A priori*, the impact of early adoption of IFRS8 is potentially ambiguous. A change in reporting practices by a small number of firms may be difficult for analysts to properly assess in the initial stage, particularly when the majority of firms they are following are still using the earlier standard, IAS14R. This would suggest a positive association between early adoption and analysts' forecast errors. However, if IFRS8 generates a form of segment data that is better for analysts, then early adoption may be negatively associated with forecast errors.

[9] Differences in how consolidated and segment earnings are calculated have been examined in the US (e.g. Alfonso et al. 2012) and there is some evidence that the accounting reconciliations which result from this are linked to the mispricing of securities (Hollie & Yu, 2012).

Geographic disclosures will likely be drawn from enterprise-wide data, rather than from operating units. The fineness of segments is represented by a sales-weighted metric which follows prior research (e.g. Herrmann & Thomas, 1997; Hussain, 1997; Doupnik & Seese, 2001; Kou & Hussain, 2007):

$$QGEOSCR = \sum_{i=1}^{I} \left(GEOSCR_i \times \frac{S_i}{S} \right)$$

where *QGEOSCR* = the overall fineness score for geographic segments; S_i = sales for segment *i*; *S* = total sales for the company; $GEOSCR_i$ = the geographic fineness score for segment *i* taking discrete values from 1 to 5, described in Appendix A.[10]

Rather than employing *QGEOSCR* directly within our model we use a dummy variable *FINEGEO* which takes a value of one for *QGEOSCR* values of 4 or more and zero elsewhere. The rationale for this decision is the evidence of significantly improved country-level disclosure by UK firms under IFRS8 (Crawford et al., 2012). Achieving a *QGEOSCR* of 4 means that a firm is, on a sales-weighted average, reporting geographic segments at the equivalent level to several individual countries (e.g. UK & Ireland) or finer. Hence, the dummy variable distinguishes those UK firms which, on average, report geographic segments that equate to country-level segments rather than continents or other broad regions.

This study will also control for segment diversity. This follows from the claim that segment reporting is more useful if the segments fully reflect variations in rates of profitability across the company's various business activities (Andre et al., 2016, p.446). If these differences are masked by inappropriate aggregation of different business activities within reported segments, then the information content of the segment disclosures is reduced. The diversity of segment profit margins relative to the consolidated profit margin is measured using the variable *DIVERSEPROF*:

$$DIVERSEPROF = \frac{\sum_{i=1}^{I} |Seg\ PM_i - Cons\ PM|}{I}$$

where $Seg\ PM_i$ = segment profit margin for segment *i* (*i* = 1, …, *I*); *Cons PM* = consolidated profit margin.

Finally, we examine the impact of segment reporting format via a dummy variable (*LOB*) which takes a value of one where firms report LOB segments, and zero otherwise. Aboud et al. (2018) find that across a sample of international analysts' forecasts from 18 countries, forecast errors are larger where firms report segments on a LOB basis.

[10] Hussain (1997, p154) notes that the discrete *GEOSCR* values assigned to segments (1 to 5) are ordinal in nature, indicating a ranking of different categories of fineness, and do not necessarily represent a cardinal measure of fineness. Nevertheless, this metric allows researchers to distinguishing between those firms reporting the majority of their sales via broad highly aggregated regions, and those reporting sales at a finer level of detail.

3.5. Method

To examine H1 to H3, two regression models are employed to explain variations in the forecast error, *FE*. Model 1 is our primary model for examining analysts' forecast errors. The model is run on the two subsamples – forecasts from large brokers' analysts and forecasts from small brokers' analysts.

Model 1:

$$FE = b_0 + b_1 \cdot STANDARD + b_2 \cdot EARLY + b_3 \cdot TOTSEG + b_4 \cdot LINEITEM + b_5 \cdot DIVERSEPROF + b_6 \cdot PROFITDEFINE + b_7 \cdot FINEGEO + b_8 \cdot GEOPROF + b_9 \cdot LOB + \sum_{y=1}^{Y} b_{9+y} \cdot YEAR_y + \sum_{s=1}^{S} b_{9+Y+s} \cdot SECTOR_s + \sum_{c=1}^{C} b_{9+Y+s+c} \cdot CONTROLS_c + \varepsilon.$$

This regression tests hypotheses H1 to H3 for the large-broker and small-broker subsamples separately. If the implementation of IFRS8 is associated with a general reduction in the level of analysts' forecast errors, then the slope coefficient for *STANDARD* will be negative (H1). If the individual segment reporting characteristics are associated with reduced forecast errors, then the slopes for their respective variables (*TOTSEG, LINEITEM, DIVERSEPROF, PROFITDEFINE, FINEGEO* and *GEOPROF*) will be negative (H2). If a LOB format for segment reports is associated with increased forecast errors, then the slope for *LOB* will be positive (H3). To provide additional insight into the broker-size differential in forecast errors we employ a secondary model, Model 2, which examines differences in various slope coefficients between the two subsamples. This takes the same form as Model 1 but introduces interaction terms for the segment variables.

Model 2:

$$FE = g_0 + g_1 \cdot STANDARD + g_2 \cdot STANDARD \times LARGEBROKER + g_3 \cdot EARLY + g_4 \cdot EARLY \times LARGEBROKER + g_5 . TOTSEG + g_6 \cdot TOTSEG \times LARGEBROKER + g_7 \cdot LINEITEM + g_8 \cdot LINEITEM \times LARGEBROKER + g_9 \cdot DIVERSEPROF + g_{10} \cdot DIVERSEPROF \times LARGEBROKER + g_{11} \cdot PROFITDEFINE + g_{12} \cdot PROFITDEFINE \times LARGEBROKER + g_{13} \cdot FINEGEO + g_{14} \cdot FINEGEO \times LARGEBROKER + g_{15} \cdot GEOPROF + g_{16} \cdot GEOPROF \times LARGEBROKER + g_{17} \cdot LOB + g_{18} \cdot LOB \times LARGEBROKER + g_{19} \cdot LARGEBROKER + \sum_{y=1}^{Y} g_{20+y} \cdot YEAR_y + \sum_{s=1}^{S} g_{20+Y+s} \cdot SECTOR_s + \sum_{c=1}^{C} g_{20+Y+s+c} \cdot CONTROLS_c + \varepsilon.$$

Applying the model to the full sample allows us to assess the degree to which these slopes are larger or smaller for analysts in large brokers relative to those in small brokers (i.e. the slopes on each of the interactive variables, *segment variable*×*LARGEBROKER*). The next section reports the results from the empirical analysis.

4. Results

4.1. Descriptive statistics

Table 1 presents descriptive data for all observations used in the regression analysis (Panel A) and the Pearson correlations between the major explanatory variables to be used in the regression models (Panel B).[11] The latter demonstrates that no correlations are in the region of 0.80 to 1, which would provide evidence of serious multicollinearity. In addition, the correlations also demonstrate the need for the wide range of segment reporting variables employed here. There are several variables which relate to segment profits (*PROFITDEFINE*, *GEOPROF*, *DIVERSEPROF*) and several which relate to the manner in which segments are reported (*TOTSEG*, *LOB*, *FINEGEO*). While many of these have positive associations, Panel B reveals that these are much closer to zero than to one, indicating that these metrics are not merely replicating the same underlying characteristics.

Insert Table 1 about here

In Table 2 there is an examination of how the main segment reporting characteristics changed with the implementation of IFRS8. These results are based on mean and median values for the two pre-IFRS8 and two post-IFRS8 annual reports for the 83 firms in our sample. These changes are not the primary focus of our study but provide some useful background to the changes brought about by IFRS8 within the UK market. They also demonstrate the consistency of our data with that obtained in similar studies. Crawford et al. (2012) report that IFRS8 is associated with increases in the average number of segments disclosed. However, the average number of accounting line items disclosed by segment decreased under IFRS8. This reduction is much greater for geographic segments with a notable reduction in the disclosure of geographic profits. Similar trends in IFRS8 disclosures are documented elsewhere.[12]

Insert Table 2 about here

The results in Table 2 mirror those of prior studies. While the total number of segments reported (*TOTSEG*) has increased, the total number of line items disclosed (*LINEITEM*) has fallen.

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[11] It may be noted in Table 1, Panel A that the minimum value for the segment variables is zero. Two firms in our sample provided no segment data under IAS14R but provided segment data under IFRS8. The results are not materially impacted by the inclusion/exclusion of these cases.

[12] Nichols et al. (2012) examine reporting under IFRS8 for companies comprising the top tier index of 14 European stock exchanges, excluding the UK. They document an increase in the fineness of geographic segments but a reduction in the number of line items disclosed. Bugeja et al. (2015) examine disclosure practices by companies listed on the Australian Securities Exchange and they too report a decline in the disclosure of segment line items following the implementation of IFRS8, but an increase in the number of reported segments.

Although the fineness of geographic segments (*QGEOSCR*) has improved, the disclosure of geographic profits (*GEOPROF*) has fallen. In addition, this study can report that the use of segment profit definitions which match profit measures in the consolidated accounts (*PROFITDEFINE*) has fallen. These changes are statistically significant at the 5% level or less. The only segment reporting characteristics which have not changed significantly are the proportion of firms using a LOB reporting format (*LOB*), which remains at around two-thirds, and segment diversity (*DIVERSEPROF*) measured here using variations in segment profitability. Table 2 also provides initial evidence of improvements in forecast accuracy resulting from the implementation of IFRS8. The forecast error (*FE*) drops significantly post-implementation. However, caution is needed in interpreting this result since the *FE* metric is examined here without controls for firm characteristics or sector-year effects, hence the need for regression analysis.

4.2. Regression model results for H1 to H3

The main OLS model (Model 1) is estimated using the subsamples for large and small brokers. The secondary model (Model 2) is estimated using the full sample and provides insights into the differences in slope coefficients between the two subsamples of brokers. Table 3 (Panel A) shows the expected sign for each coefficient, and the hypotheses to which each coefficient relates. For all slope coefficients two-tail t-tests are employed throughout the analysis for consistency across models and with Aboud et al. (2018).

Insert Table 3 (Panels A & B) about here

H1 is tested via the Model 1 slope coefficient for *STANDARD* in Table 3 (Panel A). In the case of small brokers' analysts, the implementation of IFRS8 has no significant impact on the overall level of the forecast error. However, in the case of large brokers' analysts, the implementation of IFRS8 is associated with a significant reduction in the forecast error. Model 2 examines the differential impact between large and small brokers. Table 3 (Panel B) shows a significant and negative slope for the interactive variable *STANDARD*$\times$*LARGEBROKER* confirming the superior predictive gains to IFRS8 disclosures among large brokers' analysts relative to small brokers' analysts. Thus, H1 is supported.

H2 is tested via the Model 1 slope coefficients for the various individual segment reporting characteristics (*TOTSEG* to *GEOPROF*). The results in Table 3 (Panel A) are generally consistent across the two subsamples. They show that forecast errors are reduced with the number of segments disclosed (*TOTSEG*), the reporting of segments which reveal variations in profitability across segments (*DIVERSEPROF*), the definition of segment profits which matches profit in the consolidated accounts (*PROFITDEFINE*), the reporting of high-quality geographic segments (*FINEGEO*), and the disclosure of geographic profits alongside LOB profits (*GEOPROF*). The number of line items (*LINEITEM*) appears to be insignificant. This finding likely reflects the fact that UK analysts tend to focus on sales and profit data when forecasting earnings; other items are generally used little for forecasting earnings (see Emmanuel et al., 1989). Thus, with the exception of the number of line items, our results are supportive of H2 for both large and small brokers' analysts.

Table 3 (Panel B) shows that none of the interactive variables generate a significant slope indicating no significant difference in the utility of these specific segment disclosure characteristics to analysts in large and small brokers. Thus, the predictive gains to changes in these specific segment reporting characteristics are similar across both sets of analysts. Despite this, our results still indicate a general improvement in the forecasts of large brokers' analysts, as indicated by the significant and negative slope for *STANDARD*×*LARGEBROKER*. This demonstrates that the additional utility of IFRS8 disclosures to UK analysts in large brokers persists even when firm-year variations in segment reporting characteristics are captured by the model.

H3 is examined by running Model 1 on the small-broker and large-broker subsamples. Table 3 (Panel A) reveals that the slope for *LOB* is significant in the case of small brokers' analysts but not in the case of large brokers' analysts. The results are supportive of H3. Analysts in large brokers seem equally capable of using data relating to operating units identified on a LOB basis or on some other basis (e.g. geographic areas). To examine this further, Panel B presents the results of running Model 2 on the full sample. The slope for the *LOB*×*LARGEBROKER* interactive term is negative and significant, reinforcing the findings in Panel A. Coefficients for the control variables take their expected signs and are statistically significant in most cases. The insignificant slope for *LARGEBROKER* suggests no additional predictive gains to large brokers' analysts once we have controlled for the additional gains to segment data.

The main regression results presented in Table 3 provide evidence of a broker-size effect in relation to analysts' ability to process accounting data. Firstly, they suggest that IFRS8 benefitted analysts in well-resourced brokerage houses while those in smaller brokers did not gain significantly in regard to their ability to forecast future earnings. Secondly, they help explain why prior studies have generated mixed results on the benefits of managerial segments (Aboud et al. 2018, p.2); the common use of consensus forecasts does not allow for the differential processing ability across brokers. Hence, the results for a consensus-based study may be driven by the mix of large and small brokers within the consensus population. Even those prior studies which have used individual analysts' forecasts have not control for broker size.

UK segment information is used by both groups of analysts. Analysts in both large and small brokers benefit similarly from increases in the number of segments (*TOTSEG*), the fineness of geographic segments (*FINEGEO*), the diversity of profitability across reported segments (*DIVERSEPROF*), and the definition of segment profits which matches profit in the consolidated accounts (*PROFITDEFINE*). One of the casualties of IFRS8 has been the disclosure of geographic profits (*GEOPROF*), and yet our results support prior research suggesting this is an item of importance in regard to forecasting earnings (e.g. Roberts, 1989; Balakrishnan et al., 1990).

The number of segment line items (*LINEITEM*) does not impact accuracy significantly. However, Andre et al. (2016, Table 4) report that the disclosure of an excessive number of line items is often associated with impaired forecasting performance among European analysts. This difference may possibly reflect greater training and expertise among UK analysts, given that London has long been a major centre for equity research and trading. It is known that UK analysts primarily employ segment sales and profit data in their forecasting models, and that additional accounting items add little to forecast accuracy (see Emmanuel et al., 1989). This would explain why there may be little difference in cases where some firms disclose segment sales and profits only, and others that disclose 10 segment items. With regard to the format for segment disclosures, analysts in small brokers have difficulty when utilising LOB segments while their counterparts in large brokers are able to utilise LOB segments or other formats equally well. This likely reflects differences in analysts' insight into companies' internal structures, as explained further in the following section.

5. Discussion

5.1. The broker-size effect

This study reveals a persistent predictive gain to large brokers' analysts relative to small brokers' analysts, following the implementation of IFRS8. This broker-size effect can be seen in the significant and negative slope for *STANDARD* in Table 3, Panel A, and in the significant and negative slope for *STANDARD*×*LARGEBROKER* in Table 3, Panel B. The shift towards reporting segments which mirror a firm's managerial structure appears to have allowed analysts in large brokers to better utilise their knowledge of company structure when employing segment information into their forecasts. If analysts in large brokers have superior insight into the internal structure of UK firms then two outcomes would be expected: (i) that the format for reporting purposes (e.g. LOB) would be more easily understood by these analysts and therefore less likely to impact their forecast errors, and (ii) that predictive gains would exist beyond those explained by the main segment variables. Our results are supportive of both outcomes.

5.2. LOB format and analysts' forecasts

The majority of firms in our sample report operating segments that follow a LOB format. This study finds that this format is associated with a significantly higher forecast error in the case of small brokers' forecasts, but not in the case of large brokers' forecasts. While geographic segments are identified around well-understood units (e.g. countries, continents) LOB segments are not based on any formal external identification system – their names and boundaries are determined on the basis of firms' internal operating units. This means that reported segments frequently lack comparability across firms. This has long been recognised as a limitation to the managerial approach to segment identification. Indeed, the problem was flagged in the response of the External Relations Committee of the International Accounting Section, American Accounting Association to the original draft statement of principles which preceded SFAS131 (Salter et al., 1996). From the analyst's perspective, this problem means that their ability to use segment data in conjunction with external forecasts and industry knowledge may be limited (Hussain & Skerratt, 1992). Having access to company managers and personnel could allow analysts to obtain a significant benefit from these data, since they would now better understand the nature of these segments and how they relate to the overall business. The superior insight of analysts in large brokers allows them to overcome this hurdle but those in small brokers, with inferior access to managers, find this hurdle excessive and the impact is revealed within the forecast errors.

5.3. Policy implications

This paper provides a number of pointers for disclosure policy and accounting regulators.
(i) The overall findings of this paper suggest that the segment reports of the UK largest firms provide useful insights into future performance as reflected in EPS data. Analysts in both large and small brokers benefit from improvements in segment disclosure characteristics.
(ii) Although most firms report operating segments on a LOB basis, this format appears to be problematic for analysts in small brokers. We link this to their inferior insight into internal company structure, relative to fellow analysts in large brokers. Improvements to qualitative and descriptive disclosures in relation to segment structure may help reduce the large broker-small broker gap in terms of company insight.
(iii) The additional disclosure of geographic profits by LOB-reporting firms assists the forecasting process. This is not a current requirement under IFRS8 but should be encouraged or required.

It may be noted that early adoption of IFRS8 (*EARLY*) is associated with significant increases in the forecast errors, both for large and small brokers' analysts (Table 3, Panel A). Perhaps this is to be expected: even though most UK firms retained a LOB approach to reporting segments, the various characteristics of their segment disclosures changed notably (see Table 2). There is a learning-curve for analysts to negotiate, and it requires some adjustment on the part of analysts to ask the right questions of managers, even for those analysts with good access.

5.4. Additional empirical issues

The differential impact IFRS8 had on the accuracy of forecasts from large and small brokers is observable even in the absence of controls for firm-specific segment reporting characteristics. Model 1 is re-estimated on the two subsamples but with the segment reporting variables omitted. A significant negative slope for *STANDARD* is obtained in the case of large brokers but not in the case of small brokers (Table 4, Panel A). Thus, this broker-effect is not an artefact of this study's choice of segment reporting variables.

Insert Table 4 (Panels A & B) about here

This study's data are drawn from forecasts generated by individual financial analysts identified by their analyst code on the I/B/E/S Detail file. When forecasts are generated by the same individuals there is the possibility of clustered standard errors (Bilinski & Eames, 2019), so we also run regressions using an estimator which is robust to clustering at the level of the individual analyst. The findings are supportive of our original results with large and small broker subsamples generating identical conclusions regarding hypotheses H1 to H3 (Table 4, Panel B).[13] It may be noted that because our dependent variable FE has a lower bound of zero, we also estimated our main regression models using a Tobit estimator. The results are materially unchanged (untabulated). A final point relates to our geographic fineness score. For companies which provided no geographic data a score of zero is assigned to *QGEOSCR*. This score reflects the lack of any insight regarding geographic activity for these firms, but it could be argued that these should not be scored. The exclusion of these cases, which represent 5.06% of observations, does not materially impact our findings.

6. Conclusion

[13] As part of our robustness checks, we also conducted regression tests of H1 to H3 separately rather than within a single model. The findings are similar to our main results (untabulated).

This paper reveals the important role played by brokerage house size in determining the utility of segment data to financial analysts, as revealed through the accuracy of their corporate earnings forecasts. Broker size is a proxy both for analysts' access to company managers and for their access to in-house expertise. We reveal that while analysts in both large and small brokers gain utility from segment disclosures, the shift to IFRS8 led to significant improvements in forecast accuracy only for analysts in large brokers. In addition, analysts in small brokers appear to have difficulty utilising segment data were reported segments reflect operational units which follow a LOB format. This is not the case for analysts in large brokers. We link this to the improved insight which analysts in large brokers obtain from their superior access to managers and in-house expertise. The findings indicate that accounting standard-setting bodies should not assume that new reporting requirements will be of equal utility to all investors, and that academics should not rely solely on consensus forecasts when examining the impact of financial disclosures on market participants.

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Table 1
Variables and descriptive statistics.

Panel A. Descriptive statistics					
Variable	Mean	Median	Std. Dev.	Min	Max
Dependent variable					
FE	0.0078	0.0025	0.0182	0	0.9275
Segment variables					
EARLY	0.1777	0	0.3823	0	1
STANDARD	0.5243	1	0.4994	0	1
TOTSEG	8.2153	8	4.2967	0	23
LINEITEM	9.4517	9	3.4131	0	22
DIVERSEPROF	0.1666	0.0687	0.3749	0	5.6128
PROFITDEFINE	0.3952	0	0.4889	0	1
LOB	0.6433	1	0.4790	0	1
GEOPROF	0.1877	0	0.3905	0	1
QGEOSCR	3.6522	3.7225	0.8501	0	5
FINEGEO	0.4331	0	0.4955	0	1
Broker variable					
LARGEBROKER	0.6292	1	0.4830	0	1
Control variables					
SIZE	8.9613	8.1756	1.5744	4.2104	11.9567
HORZ	193.9189	194	106.30	1	365
GEARING	0.2432	0.2253	0.1317	0	0.8171
BOARDSIZE	10.7498	10	2.6715	5	20
BOARDSIZESQD	122.6942	100	61.0884	25	400
HIBOARDINDEPEND	0.2121	0	0.4088	0	1
FALL	0.3298	0	0.4701	0	1
EARNCHANGE	0.3507	0.2182	0.4524	0	3.7423
LOSS	0.0899	0	0.2861	0	1
FOLLOW	53.2483	53	16.5121	15	88

Continued

Table 1 (Continued)

Panel B: Correlation matrix

		1	2	3	4	5	6	7	8	9	10	11
1	*FE*	1										
2	*EARLY*	0.0431***	1									
3	*STANDARD*	–0.0189***	0.0348***	1								
4	*TOTSEG*	–0.1579***	0.0411***	0.1356***	1							
5	*LINEITEM*	–0.0716***	0.0356***	–0.2978***	0.1954***	1						
6	*DIVERSEPROF*	–0.0267***	0.1347***	–0.0059	–0.0669***	0.0084	1					
7	*PROFITDEFINE*	–0.0755***	0.0984***	–0.1614***	–0.0162***	0.0488***	0.0455***	1				
8	*LOB*	–0.0100*	–0.0592***	0.0210***	0.3240***	0.3892***	–0.0234***	–0.0171***	1			
9	*GEOPROF*	–0.0752***	–0.1253***	–0.1217***	0.0673***	0.5645***	0.0492***	–0.0469***	0.3603***	1		
10	*QGEOSCR*	–0.0191***	0.0633***	0.1292***	0.1994***	–0.1239***	0.1020***	0.0803***	0.1273***	–0.2040***	1	
11	*FINEGEO*	–0.0178***	0.1287***	0.1565***	0.0161***	–0.2246***	0.0645***	0.1540***	0.0823***	–0.2671***	0.8378***	1
12	*LARGEBROKER*	–0.0133**	0.0037	0.0283***	0.0538***	0.0071	–0.0220***	–0.0353***	0.0445***	–0.0024	–0.0429***	–0.0442***
13	*SIZE*	–0.1968***	0.0575***	0.0900***	0.4441***	0.1434***	0.0836***	0.0476***	–0.0071	0.1859***	–0.1464***	–0.2041***
14	*HORZ*	0.1064***	0.0077	0.0273***	–0.0073	0.0001	–0.0067	–0.0143***	0.0109**	0.002	–0.0035***	0.0062
15	*GEARING*	0.0927***	–0.1979***	–0.1685***	–0.0997***	–0.1525***	–0.0903***	0.1157***	0.0445***	–0.0249***	0.0597***	0.0899***
16	*BOARDSIZE*	–0.1282***	0.0474***	–0.0377***	0.1997***	0.2412***	0.1275***	0.0329***	0.0324***	0.2113***	–0.0526***	–0.1373***
17	*HIBOARDINDEPEND*	–0.1164***	–0.1728***	–0.0091*	0.3189***	–0.0010	–0.0291***	–0.0041	–0.0162***	0.0685***	–0.1210***	–0.2322***
18	*FALL*	0.1517***	–0.0107**	–0.0124***	–0.0472***	–0.0007	0.1729***	–0.0878***	0.0982***	–0.0123**	0.0306***	0.0143***
19	*EARNCHANGE*	0.0349***	0.0886***	0.1443***	–0.0569***	–0.0145***	0.2695***	–0.0765***	0.0500***	0.0737***	0.0226***	0.0204***
20	*LOSS*	0.0885***	0.0118**	0.1719***	0.0385***	–0.0827***	0.2523***	–0.0828***	0.0176***	–0.0198***	0.0471***	0.0400***
21	*FOLLOW*	–0.1197***	0.0043	–0.0212***	0.2654***	0.0324***	0.0863***	0.1448***	–0.0711***	0.0869***	–0.0420***	–0.0551***

Continued

Table 1 (Continued)

Panel B: Correlation matrix

		12	13	14	15	16	17	18	19	20	21
1	*FE*										
2	*EARLY*										
3	*STANDARD*										
4	*TOTSEG*										
5	*LINEITEM*										
6	*DIVERSEPROF*										
7	*PROFITDEFINE*										
8	*LOB*										
9	*GEOPROF*										
10	*QGEOSCR*										
11	*FINEGEO*										
12	*LARGEBROKER*	1									
13	*SIZE*	0.0387***	1								
14	*HORZ*	–0.0237***	–0.0224***	1							
15	*GEARING*	0.0201***	–0.0124**	–0.0058	1						
16	*BOARDSIZE*	0.0155***	0.6126***	–0.0208***	0.0724***	1					
17	*HIBOARDINDEPEND*	0.0197***	0.4832***	–0.0227***	0.0124**	0.4814***	1				
18	*FALL*	0.0260***	–0.0940***	–0.0065	0.0134**	0.0319***	–0.0597***	1			
19	*EARNCHANGE*	–0.0085	0.0192***	0.0024	–0.0989***	0.0905***	–0.1192***	–0.0143***	1		
20	*LOSS*	0.0107**	0.0492***	0.0101*	–0.0301***	0.0913***	–0.0359***	0.0064	0.2960***	1	
21	*FOLLOW*	–0.0166***	0.6586***	–0.0142***	–0.0579***	0.3796***	0.3159***	–0.0260***	0.0164***	0.0095*	1

Notes: ***, **, * indicate significant Pearson correlations at the 1%, 5%, and 10% levels, respectively.

Sample: 35,563 individual analysts' short-term (< 12 months ahead) forecasts of annual EPS for 83 large non-financial UK firms, generated in the last two years of IAS14R and the first two years of IFRS8. Due to variations in the year of adoption, these years are not the same across all firms. Years range from 2005 to 2011. Industry sectors covered listed in Appendix A. Results are not materially impacted by the inclusion/exclusion of utilities.

Table 2

The impact of IFRS8 on analysts' forecast errors and segment reporting characteristics for large UK firms.

	Mean Pre-IFRS8	Mean Post-IFRS8	*t*-test	Median Pre-IFRS8	Median Post-IFRS8	Wilcoxon *Z*
Forecast error						
FE	0.008	0.007	3.63***	0.003	0.002	6.35***
Segment variables						
TOTSEG	7.07	8.25	4.23***	7	8	3.99***
LINEITEM	10.29	8.53	−5.43***	10	8	−4.73***
DIVERSEPROF	0.13	0.15	0.40	0.06	0.06	0.42
PROFITDEFINE	0.45	0.33	−2.29**	0	0	−2.24**
LOB	0.67	0.67	0.00	1	1	0.00
GEOPROF	0.55	0.43	−2.78***	1	0	−2.67***
QGEOSCR	3.55	3.90	2.97***	3	4	2.80***

Notes: ***, **, * indicate significant changes at the 1%, 5%, and 10% levels, respectively.
Segment reporting characteristics derived from annual reports for 83 large non-financial UK firms across four years – the last two years of IAS14R and the first two years of IFRS8. Variables are defined in Appendix A.

Table 3

Analysts' forecasts, IFRS8 and segment reporting characteristics: the impact of broker-size.

Panel A: OLS estimation of Model 1 for large and small broker subsamples.

			Small Brokers			Large Brokers		
			Observations	13,236		Observations	22,327	
			F-stat	65.8***		F-stat	136.43***	
			R-squared	0.1412		R-squared	0.168	
			Adj R-squared	0.1391		Adj R-squared	0.1668	
	Hypothesis	Expected sign	Coef.	Sig.	t-stat	Coef.	Sig.	t-stat
STANDARD	H1	–	–0.000124		–0.19	–0.001442	***	–3.19
EARLY		–/+	0.006524	***	11.15	0.006372	***	15.31
TOTSEG	H2	–	–0.000387	***	–7.61	–0.000364	***	–9.82
LINEITEM	H2	–	–0.000011		–0.16	–0.000023		–0.45
DIVERSEPROF	H2	–	–0.004680	***	–10.99	–0.004431	***	–11.55
PROFITDEFINE	H2	–	–0.003487	***	–9.77	–0.003709	***	–14.48
FINEGEO	H2	–	–0.002124	***	–5.64	–0.001961	***	–7.26
GEOPROF	H2	–	–0.001760	***	–3.18	–0.002230	***	–5.85
LOB	H3	+	0.001736	***	4.18	0.000383		1.26
SIZE		–	–0.001942	***	–9.23	–0.001592	***	–10.39
HORZ		+	0.000019	***	13.06	0.000017	***	16.76
GEARING		+	0.000233	***	14.29	0.000174	***	14.90
FALL		+	0.004678	***	12.60	0.005580	***	21.60
EARNCHANGE		+	0.000491		1.27	0.000883	***	3.04
LOSS		+	0.006644	***	10.91	0.004230	***	9.84
FOLLOW		–	–0.000005		–0.33	–0.000069	***	–6.77
BOARDSIZE		–	–0.003030	***	–6.34	–0.004721	***	–13.93
BOARDSIZESQD		+	0.000118	***	5.94	0.000172	***	11.83
HIBOARDINDEPEND		–	0.000979		1.52	–0.000455		–0.97
Intercept		–/+	0.029877	***	9.95	0.046337	***	21.24
Sector Effects			Yes			Yes		
Year Effects			Yes			Yes		

Continued

Table 3 (Continued)

Panel B: OLS estimation of Model 2 for full sample.

	Expected sign	Coef.	Sig.	t-stat
		Observations	35,563	
		F-stat	150.08***	
		R-squared	0.1538	
		Adj R-squared	0.1527	
	Expected sign	Coef.	Sig.	t-stat
STANDARD	–	–0.000062		–0.14
STANDARD x LARGEBROKER	–/+	–0.001473	***	–3.60
EARLY	–/+	0.006741	***	14.65
EARLY x LARGEBROKER	–/+	–0.000416		–0.83
TOTSEG	–	–0.000384	***	–9.21
TOTSEG x LARGEBROKER	–/+	0.000009		0.19
LINEITEM	–	0.000007		0.11
LINEITEM x LARGEBROKER	–/+	–0.000020		–0.25
DIVERSEPROF	–	–0.004751	***	–12.90
DIVERSEPROF x LARGEBROKER	–/+	0.000511		1.06
PROFITDEFINE	–	–0.003629	***	–11.31
PROFITDEFINE x LARGEBROKER	–/+	0.000042		0.11
FINEGEO	–	–0.002237	***	–6.64
FINEGEO x LARGEBROKER	–/+	0.000248		0.60
GEOPROF	–	–0.001760	***	–3.50
GEOPROF x LARGEBROKER	–/+	–0.000475		–0.77
LOB	+	0.001554	***	4.17
LOB x LARGEBROKER	–/+	–0.000966	**	–2.10
LARGEBROKER	–/+	0.001025		1.25
SIZE	–	–0.001665	***	–13.50
HORZ	+	0.000018	***	21.18
GEARING	+	0.000200	***	21.02
FALL	+	0.005230	***	24.60
EARNCHANGE	+	0.000635	***	2.73
LOSS	+	0.005174	***	14.72
FOLLOW	–	–0.000044	***	–5.16
BOARDSIZE	–	–0.004108	***	–14.87
BOARDSIZESQD	+	0.000152	***	12.96
HIBOARDINDEPEND	–	–0.000040		–0.10
Intercept		0.039078	***	21.68
Sector Effects		Yes		
Year Effects		Yes		

Notes: ***, **, * indicate that slope is significantly different from zero at the 1%, 5% and 10% level, respectively.
Tests are conducted in the form of a two-tail test.

Table 4

Robustness tests

Panel A: Model 1 excluding segment reporting characteristics (OLS)

			Small Brokers		Large Brokers	
			Observations	13236	Observations	22327
			F-stat	70.16	F-stat	150.19
			R-squared	0.1205	R-squared	0.1484
			Adj R-squared	0.1188	Adj R-squared	0.1475
	Hypothesis	Expected sign	Coef.	t-stat	Coef.	t-stat
STANDARD	H1	–	0.000996	1.58	–0.001067	–2.46**
EARLY		–/+	0.003781	6.72***	0.004756	11.90***
SIZE		–	–0.001580	–7.81***	–0.001603	–11.01***
HORZ		+	0.000019	12.76***	0.000017	16.56***
GEARING		+	0.000222	14.68***	0.000167	15.06***
FALL		+	0.004421	12.04***	0.005484	21.40***
EARNCHANGE		+	0.000570	1.48	0.001058	3.64***
LOSS		+	0.005461	9.02***	0.003877	9.03***
FOLLOW		–	–0.000032	–2.11**	–0.000083	–8.13***
BOARDSIZE		–	–0.003770	–7.85***	–0.005206	–15.17***
BOARDSIZESQD		+	0.000138	6.90***	0.000186	12.65***
HIBOARDINDEPEND		–	0.001815	2.86***	0.000622	1.38
Intercept		–/+	0.026999	9.05***	0.043151	20.43***
Sector Effects			Yes	t-stat	Yes	
Year Effects			Yes		Yes	

Panel B: Model 1 estimated using OLS with standard errors clustered by individual analyst

			Small Brokers		Large Brokers	
			Observations	13236	Observations	22327
			F-stat	24.19***	F-stat	30.37***
			R-squared	0.1412	R-squared	0.168
			955 clusters		939 clusters	
	Hypothesis	Expected sign	Coef.	t-stat	Coef.	t-stat
STANDARD	H1	–	–0.000124	–0.12	–0.001442	–2.10**
EARLY		–/+	0.006524	5.28***	0.006372	6.92***
TOTSEG	H2	–	–0.000387	–5.46***	–0.000364	–5.72***
LINEITEM	H2	–	–0.000011	–0.12	–0.000023	–0.26
DIVERSEPROF	H2	–	–0.004680	–6.39***	–0.004431	–5.78***
PROFITDEFINE	H2	–	–0.003487	–5.65***	–0.003709	–7.57***
FINEGEO	H2	–	–0.002124	–3.01***	–0.001961	–3.48***
GEOPROF	H2	–	–0.001760	–2.44**	–0.002230	–3.81***
LOB	H3	+	0.001736	2.43**	0.000383	0.56
SIZE		–	–0.001942	–4.83***	–0.001592	–4.25***
HORZ		+	0.000019	10.22***	0.000017	11.85***
GEARING		+	0.000233	4.26***	0.000174	4.67***
FALL		+	0.004678	4.85***	0.005580	7.02***
EARNCHANGE		+	0.000491	1.10	0.000883	2.08**
LOSS		+	0.006644	3.82***	0.004230	2.94***
FOLLOW		–	–0.000005	–0.20	–0.000069	–2.50**
BOARDSIZE		–	–0.003030	–2.62***	–0.004721	–4.71***
BOARDSIZESQD		+	0.000118	2.63***	0.000172	4.28***
HIBOARDINDEPEND		–	0.000979	1.10	–0.000455	–0.50
Intercept		–/+	0.029877	4.04***	0.046337	7.31***
Sector Effects			Yes		Yes	
Year Effects			Yes		Yes	

Notes: ***, **, * indicate that slope is significantly different from zero at the 1%, 5% and 10% level, respectively.
Tests are conducted in the form of a two-tail test. These are robust to clustering of standard errors by analyst identifier code.

Appendix A: Variable definitions

Variable	Definition
Dependent variable	
FE	Forecast error defined as ln[1 + (actual EPS – forecast EPS/start-of-year share price)]
Independent variables	
A. Segment variables	
EARLY	Early adoption of IFRS8: Dummy variable equals 1 for firms which early adopted IFRS8, and 0 otherwise
STANDARD	Post-IFRS8 indicator: Dummy variable equals 1 where forecasts generated under IFRS8 disclosures, and 0 for forecasts generated under IAS14R disclosures
TOTSEG	Total number of reported segments in annual report
LINEITEM	Total number of line items reported by segment in annual report
DIVERSEPROF	Diversity of profits across a firm's reported segments: the average absolute deviation of segment profit margin from the consolidated profit margin
PROFITDEFINE	Segment profit definition: Dummy variable equals 1 where segment profits defined on same basis as consolidated profits, and 0 otherwise
LOB	Segment reporting format: Dummy variable equals 1 where segments are defined on a line-of-business basis, and 0 otherwise
GEOPROF	Dummy variable equals 1 where LOB reporting firms also disclose segment profits by geographic region, and 0 otherwise
QGEOSCR	A sales-weighted average fineness metric for geographic segments. A score of 5 if the segment is an individual country; 4 if a merger of several countries (e.g. UK and Ireland); 3 if a continent; 2 if a merger of two continents (e.g. Asia and Africa); 1 if described as 'Rest of the world' or similar; 0 if companies provide no geographic disclosures
FINEGEO	Indicator of a company disclosing a high proportion (by sales) of fine geographic segments: Dummy variable equals 1 where QGEOSCR is 4 or greater, and 0 otherwise
B. Broker variable	
LARGEBROKER	Large-broker indicator: Dummy variable equals 1 where forecasts generated by analysts working for the 20 largest brokerage houses, and 0 otherwise
C. Control variables	
SIZE	Firm size defined as ln(market value of equity)
HORZ	Forecast horizon is number of days from date of forecast creation to date of actual EPS announcement
GEARING	Total assets/total liabilities
BOARDSIZE	Number of directors on board
BOARDSIZESQD	$BOARDSIZE^2$
HIBOARDINDEPEND	Indicator of high degree of board independence: Dummy variable equals 1 where the number and percentage of independent directors are both in the upper quartile
FALL	Falling earnings: Dummy variable which equals 1 when EPS are falling for the forecast year, and 0 otherwise
EARNCHANGE	Earnings change in forecast year defined as ln[1 + (proportionate change in EPS for the forecast year)]
LOSS	Loss-making firms: Dummy variable equals 1 when EPS are negative for most recent year prior to forecast, and 0 otherwise
FOLLOW	Analyst following is the number of analysts contributing short-term earnings forecasts to I/B/E/S database (UK) for target year
D. Fixed effects	
YEARS	Dummy variables for each year: 2005 to 2011
SECTORS	Dummy variables for each sector: Basic materials, Consumer goods, Consumer services, Healthcare, Industrials, Oil & gas, Technology, Telecoms, and Utilities.

Appendix B: Sample construction

Sample selection process	Number
Firms in FTSE100 index at end of 2004	100
New firms added to FTSE100 during 2005-2011	+93
Firms added more than once 2005-2011	–17
Firms in FTSE100 at some point during 2005-2011	176
Financials and firms not in FTSE100 for IFRS8 period	–104
Non-financials in FTSE100 for IFRS8 period	72
Largest non-financials in FTSE250 for IFRS8 period	+11
Final sample of large UK non-financials	83

Appendix C: Industry sector characteristics of sample firms

	Full sample of large non-financial UK firms (n = 83)	Large non-financial UK firms that were members of the FTSE100 through the preponderance of years during the test period (n = 72)
Basic materials	15.45%	16.35%
Consumer goods	12.64%	11.75%
Consumer services	24.60%	24.64%
Healthcare	7.36%	7.51%
Industrials	17.86%	17.12%
Oil and gas	12.82%	12.83%
Technology	3.16%	3.34%
Telecommunications	4.11%	4.35%
Utilities	2.01%	2.13%