# The Impact of Segment Definition on the Accuracy of Analysts' Earnings Forecasts

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**Abstract**—This study investigates forecast error determinants for a set of forecasts of annual corporate earnings, generated by UK analysts 22 months prior to the announcement dates. This study is particularly concerned with the impact of segmental data on forecast errors; the hypothesis under test is whether finer segment definitions provide market participants with improved insight. If segments are too broad or vague (e.g. *rest of the world*) it is unlikely that data for such segments will provide analysts with any additional information regarding the current corporate position or future prospects. The results of this study provide evidence of predictive gains to both line-of-business data and geographic data, although these gains appear to be concentrated within a sub-sample of firms for which analysts appear to have specific difficulty in forecasting earnings, i.e. those experiencing negative changes in earnings. The results also indicate that forecast errors are: negatively related to firm size; positively related to the magnitude of the change in earnings which the analyst must predict; and not significantly affected by the number of reported segments.

## 1. Introduction

One of the main rationales for segmental disclosure is that it provides investors with improved predictive ability regarding corporate prospects (e.g. earnings). The UK accounting standard SSAP 25, *Segmental Reporting* (ASC, 1990) identifies the two main bases for segmental analysis as (i) the class of business, and (ii) the geographical areas in which a company is engaged. SSAP 25 provides extensive guidelines for segment identification; it lists a wide range of factors that may be taken into account when determining reportable segments. However, the list is so diverse that many differing approaches are consistent with the SSAP 25 guidelines. In addition, there is little to prevent the inappropriate amalgamation of lines-of-business or geographic regions. The same criticism also applies to the US accounting standard SFAS 14 (FASB, 1976), whose guidelines for segment identification are very similar to those given in SSAP 25. Both standards allow companies to define segments in almost any manner they find suitable.

The result is a wide range of differing reporting practices across UK companies, some of which are likely to be of limited use for investors' purposes. Too broad or vague segments (e.g. *rest of the world* or *other activities*) provide users with little additional insight. The problem of poorly identified segments has long been recognised as a major issue in segmental reporting (see Emmanuel and Gray, 1977: 37). Surveys of UK analysts' forecasting procedures (Arnold and Moizer, 1984; Day, 1986) show that many use a break-down and build-up approach to forecasting earnings. Segmental data is used in conjunction with specialist industrial and economic forecasts, to predict future consolidated earnings. However, data for industrial segments, for example, can only be utilised effectively if the segments correspond to recognised industry sectors for which analysts can obtain past data and forecasts. The aim of this study is to investigate the impact of segment definition on the accuracy of analysts' earnings forecasts.

## 2. Previous research

One approach to analysing predictive gains to segmental data is to generate forecasts of consolidated earnings using a set of forecasting models; some of the models utilise segment data, while others utilise consolidated data only. This form of analysis concentrates on either line-of-business data (Kinney, 1971; Collins, 1976; Emmanuel and Pick, 1980) or geographic data (Roberts, 1989; Balakrishnan, Harris and Sen, 1990), but not both. These studies indicate that segmental sales and profit data allow the construction of superior fore-

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casts. However, there is no evidence of significant additional predictive gains where both segment sales and segment profit data are used in the same model.

Other studies have investigated the impact of segmental reporting on analysts' earnings forecasts. One reason for preferring analysts' forecasts to model-based forecasts is the evidence of greater accuracy for analysts. Evidence indicating analysts' superiority is provided by Brown and Rozeff (1978), Collins and Hopwood (1980), Fried and Givoly (1982), Cooper and Taylor (1983), Cooper (1984), Bhaskar and Morris (1984), O'Brien (1988) and Patz (1989). Rational investors will use the most accurate source of forecasts to form their expectations, and evidence that analysts' forecasts are a superior proxy for market expectations of earnings is provided by Fried and Givoly (1982) and Brown, Griffin, Hagerman and Zmijewski (1987). A major rationale for segmental disclosure is that it may improve analysts' and investors' predictive ability, so leading to more informed investment decisions and, therefore, more efficient allocation of capital resources (see Baldwin 1984: 376). Only those forecasts that are used by investors have implications for the allocation of capital resources. An important point to note is that if analysts use a wider information set than statistical models, as appears to be the case, it cannot be concluded that the impact of segment information identified using model forecasts will necessarily be the same as for analysts' forecasts. This is another reason for using analysts' forecasts instead of model forecasts.

Studies by Baldwin (1984) and Swaminathan (1991) investigate the impact of the Securities and Exchange Commission's 1970 line-of-business reporting requirements on analysts' earnings forecasts. Baldwin finds that the introduction of the SEC's reporting requirements leads to a reduction in forecast errors, and that these predictive gains increase with the forecast horizon. This finding is consistent with the general view that segmental data is used by analysts for the construction of longer-term earnings forecasts, i.e. 12–24 months ahead (see Emmanuel and Garrod, 1987). The study by Swaminathan finds that the spread of earnings forecasts, across different analysts, is reduced in the presence of segmental data, indicating an increased degree of consensus. Studies by Barefield and Comiskey (1975a) and Emmanuel, Garrod and Frost (1989) attempt to measure the impact of different amounts of segment data on analysts' forecast errors. Barefield and Comiskey measure the amount of line-of-business segmental data using a scoring system devised by Kochanek (1974); they find a negative association between forecast errors and the amount of segmental data measured by the segmental reporting score. Emmanuel, Garrod and Frost present 15 analysts with financial data for a real (but unnamed) company and ask them to predict earnings using this data. By increasing the amount of segmental data in a step-by-step manner, they find that the greatest improvements to forecast accuracy arise from the provision of segment sales and profit data; other data (e.g. assets) has little impact.

There has been no empirical study of the impact of segment definition on analysts' forecasts. This is an unusual omission, given the importance of the topic in early segmental studies (Mautz, 1968; Backer and McFarland, 1968) and the extensive guidelines for segment identification provided in accounting standards like SSAP 25. The issue of segment definition has arisen only in studies that make suggestions for segment definitions, based on some rationale (Solomons, 1968; Emmanuel and Gray, 1978; Hussain and Skerratt, 1992); and studies which survey preparers' views (Emmanuel and Garrod, 1987; Edwards, 1995) and current reporting practices (Rennie and Emmanuel, 1992; Hussain, 1996).

## 3. The data set and the measurement of variables

The earnings forecasts used in this study are provided by a large, well-known brokerage house. From casual inspection, these are representative of companies listed on the London Stock Exchange. One advantage of this data set is that the precise creation date is available for all forecasts.[1] The importance of dating forecasts precisely is discussed by O'Brien (1988) with reference to forecasts on the International Brokers Estimate System (IBES), a commonly used source for earnings forecasts. O'Brien finds that the time between the creation of a forecast and its first appearance on IBES averages 34 trading days.

The selection criteria for the inclusion of an observation in this study are as follows:

- Earnings forecasts are available for the 22 months prior to an announcement.
- Both forecast and reported earnings numbers are positive. This is a common procedure used, for example, by O'Hanlon and Whiddett (1991) and Baldwin (1984), to eliminate (what might be) unusual observations and the need to interpret the percentages of negative numbers.
- There are no changes in the companies' lines-of-business, as identified by Dun & Bradstreet's *Key British Enterprises*, over the forecast period. Changes in a company's activities may provide an additional source of forecast error.

[1] It is possible that an analyst may have constructed a forecast prior to this date and delayed its release, but since this is an inhouse database, it is unlikely that there would be significant incentives for such delays.

• There are no major changes in fiscal year-ends over the forecast period.

The above selection criteria lead to a final sample of forecasts for 197 company announcements, reporting over the fiscal periods 1987–90.

### *3.1. The Forecast Error Metric (FE)*

This study uses forecasts made 22 months prior to the announcement of earnings for fiscal year t. The rationale for this is that evidence from surveys (Emmanuel and Garrod, 1987) and empirical studies (Baldwin, 1984) indicate that the impact of segment data is greatest for longer-term forecasts.

The error metric chosen is the absolute proportionate forecast error, used in a wide range of studies of analysts' forecasts, such as Basi, Carey and Twark (1976), Brown and Rozeff (1978) and Patz (1989). It is defined as:

$$FE_j = \frac{\left|F_{j,22} - A_{j,t}\right|}{A_{j,t}}$$

$FE_j$ = forecast error for firm j

$A_{j,t}$ = reported earnings for company j for fiscal year t.

$F_{j,22}$ = forecast of $A_{j,t}$ made 22 months prior to the announcement of $A_{j,t}$.

The two most commonly-used deflators for error metrics are actual earnings (used here), and forecasted earnings. Patz (1989) addresses the problem of selecting a suitable deflator.

> 'There is a practical problem with using actual earnings as the measurement base, since such measures are materially distorted when actual earnings are near zero...Yet it is difficult to circumvent the Lorek (1979) argument that the use of forecasted earnings as a base implies measurement of a firm's ability to achieve a predicted result, rather than a predictor's ability to forecast an outcome' (Patz 1989: 269, footnote 4).

Of the two points mentioned by Patz, it is the latter, the Lorek (1979) argument, that appears the stronger. The Lorek criticism of the use of forecasted earnings as a deflator is simple yet convincing. The first point Patz makes, regarding actual earnings values near zero, appears relatively weak because Patz gives no indication why actual earnings should be more likely to take values near zero than forecasted earnings. Another possible choice for a deflator is a market variable, e.g. the stock price or market value. However, Basi, Carey and Twark (1976) reject this approach for studies purely concerned with forecast accuracy.

> 'We avoided the temptation to use a price-normalised ..[error metric].. since we are looking at forecast errors themselves rather than at possible uses of the forecasts, such as in forming expectations about future price performance' (Basi, Carey and Twark 1976: 247).

The use of market value as a deflator would also mean that where two companies had identical reported earnings ($A_{j,t}$) and identical forecasted earnings ($F_{j,22}$), forecast errors would be lower for the company with the larger market value, implying greater accuracy. For a study concerned solely with forecast accuracy, this would not be a desirable outcome.

### *3.2. Firm Size (Market Value, MV)*

Evidence that the share prices of larger companies convey more information about future earnings than the share prices of smaller companies is provided by a number of studies (Atiase, 1985; Bamber, 1986; Freeman, 1987; Collins, Kothari and Rayburn, 1987). In addition, several other studies also suggest a similar firm size effect in analysts' earnings forecasts. Brown, Richardson and Schwager (1987) find evidence that the superiority of analysts' forecasts over those generated by time-series models is positively related to market value. Patz (1989) also finds analyst forecast accuracy positively related to market value. Thus, market value is included as an explanatory variable in this study.

### *3.3. The Absolute Change in Earnings over the Forecast Period [EC]*

The variability in past earnings is sometimes mentioned as an important factor determining forecast accuracy (e.g. Baldwin, 1984: 380). However, Barefield and Comiskey (1975b: 315–16) note that past earnings variability may not be a good proxy for the riskiness or uncertainty of future earnings. For this reason, the study here does not use a measure of past earnings variability but an ex post measure of the new information arriving over the forecast period.

$$EC_j = \frac{\left|A_{j,t-2} - A_{j,t}\right|}{A_{j,t}}$$

$EC_j$ = absolute change in earnings, from year t-2 to year t.

$A_{j,t}$ = reported earnings for company j for fiscal year t.

$A_{j,t-2}$ = reported earnings for company j for fiscal year t-2, announced around two months prior to the creation of the forecast.

### *3.4. The Quality of Reported Segments [QLOB and QGEO]*

Since the forecast horizon employed here is 22 months prior to the announcement of $A_{j,t}$, the rel-

**Table 1**
**The quality of reported lines-of-business**

| *QLOB* | *Segment description* | |
|---|---|---|
| 0 | Broader than Division, or not consistent with a Division | |
| 1 | Division | (1-digit SIC) |
| 2 | Class | (2-digit SIC) |
| 3 | Group | (3-digit SIC) |
| 4 | Activity | (4-digit SIC) |
| 5 | Line-of-business | (5-digit SIC) |
| 6 | Finer than line-of-business. | |

*Note:* Where no segmental information is disclosed, the consolidated accounts are treated as one segment. A quality measure is then given to this 'segment', based on the lines-of-business reported in the company's entry for that year in Dun & Bradstreet's *Key British Enterprises*.

**Table 2**
**The quality of reported geographic areas**

| *QGEO* | *Segment description* |
|---|---|
| 0 | Broader than a single continent. |
| 1 | Single continent or group of individual countries. |
| 2 | Individual country. |

*Note:* Where no segmental information is disclosed, the consolidated accounts are treated as one segment. A quality measure is then given to this 'segment' based on the geographic areas reported in the company's entry for that year in Dun & Bradstreet's *Key British Enterprises*.

evant published accounts for identifying segment definitions are those for fiscal year t-2 (published around 24 months prior).

For company j, each reported line-of-business segment (m = 1,2,...M) is assigned a quality score based on the UK's Standard Industrial Classification (SIC) system.[2] The SIC identifies activities at different levels of detail, from the broadest (*Divisions*) to the finest (*Lines-of-business*). These scores take values between zero and six, and are shown in Table 1.

To obtain a quality measure for the whole firm, these scores are weighted by sales.

$$QLOB_j = \sum_{m=1}^{M} \left[ QLOB_{m,j} \cdot \frac{S_{m,j}}{S_j} \right]$$

$QLOB_j$ = quality of LOB segments (firm j).

[2] This study uses the 1980 version of the SIC system.

$QLOB_{m,j}$ = quality of LOB segments (segment m of firm j).

$S_{m,j}$ = sales of LOB segment m of firm j.

$S_j$ = total sales for firm j.

Sales are a convenient weighting variable. First, segmental analyses are more common for sales than for other items, such as profits, assets, etc. Second, the use of segment profits as a weighting variable would pose problems because it is not uncommon for individual segments to report losses. In addition, segment profits can be greatly distorted by the accounting treatment of common costs. In relation to the use of assets as a weighting variable, it must be noted that segment asset disclosures are much less frequent than segment sales disclosures, and also that the definition of assets disclosed in segment analyses differs across companies, i.e. net assets, total assets, etc.

A similar procedure is used to measure the quality of geographic segments. Individual geographic

**Table 3**
**Descriptive statistics for the variables in this study**

*Whole sample: 197 observations used*

| *Variable* | *Mean* | *Std. Dev.* | *Minimum* | *Maximum* |
|---|---|---|---|---|
| FE | 0.26561 | 0.47960 | 0.0000 | 4.634 |
| EC | 0.38357 | 0.25819 | 0.0064 | 2.507 |
| MV | 1563.4 | 2955.4 | 20.90 | 17380 |
| QLOB | 2.0219 | 1.4933 | 0.0000 | 6.000 |
| QGEO | 1.4974 | 0.57060 | 0.0000 | 2.000 |
| NLOB | 3.0812 | 2.0287 | 1.000 | 11.00 |
| NGEO | 3.9695 | 2.1874 | 1.000 | 10.00 |
| $A_t$ | 163.17 | 338.23 | 1.970 | 2437.0 |
| $F_{22}$ | 157.22 | 334.32 | 2.6 | 2500.0 |

*Definitions*
$A_t$ = The reported earnings for year t (£m)
This variable is used as the deflator for FE and EC.
$F_{22}$ = The 22-month ahead forecast of $A_t$ (£m)
FE = Forecast error $= |A_t - F_{22}|/A_t$.
EC = Absolute change in earnings $= |A_t - F_{t-2}|/A_t$.
MV = Market value (£m).
QLOB = Quality of line-of-business segments ($0 \leqslant \text{QLOB} \leqslant 6$)
QGEO = Quality of geographical segments ($0 \leqslant \text{QGEO} \leqslant 2$)
NLOB = Number of reported lines-of-business.
NGEO = Number of reported geographic areas.

segments (n = 1,...N) are scored between zero and two, using the scoring system shown in Table 2.

Geographic segmentation can be either by geographic origin (i.e. where products are produced) or geographic market (i.e. where products are supplied to). A large proportion of companies that disclose geographic segment information do not identify the method of segmentation but simply refer to it as *analysis of geographic area*. Therefore, for practical purposes, this study makes no attempt to distinguish between geographic analyses by market and by origin. A minority of companies provide an analysis by both origin and market. If one analysis of sales is much more detailed than the other, then QGEO is calculated using the data for the more detailed analysis.

$$QGEO_j = \sum_{n=1}^{N} \left[ QGEO_{n,j} \cdot \frac{S_{n,j}}{S_j} \right]$$

$QGEO_j$ = quality of GEO segments (firm j).
$QLOB_{n,j}$ = quality of GEO segments (segment n of firm j).
$S_{n,j}$ = sales for GEO segment n of firm j.
$S_j$ = total sales for firm j.

### *3.5 The Number of Reported Segments [NLOB and NGEO]*

This variable is included because some research indicates that analysts' incentives to revise forecasts, and therefore the accuracy of their forecasts, could be influenced by the number of lines-of-business. Bhushan (1989a) provides a theoretical analysis showing that the marginal information content of earnings announcements is a positive function of the number of lines-of-business. Evidence consistent with this hypothesis is given in Bhushan (1989b), where a significant negative association is found between the number of analysts following a company and the number of lines-of-business. This evidence would indicate that forecast errors may be positively related to the number of lines-of-business. There appears to be little evidence on the impact of the number of geographic segments on analysts' forecasts.

The number of lines-of-business (NLOB) and geographic areas (NGEO) for company j are the maximum number of segments reported for any accounting item. Invariably, this is the number of segments reported for sales data, in the annual report for fiscal year t-2.

Descriptive statistics for all variables are presented in Table 3.

Table 3 shows that the mean forecast error (FE) for these 22-month ahead forecasts is 0.265 or 26.5%. This result is very similar to the 25.4% mean forecast error reported by Patz (1989: 272) for UK analysts' long-term earnings forecasts. It can also be seen that the mean absolute change in earnings (EC) from fiscal year t-2 to year t, averages around 38%; however, there is great variation across companies. Absolute changes in earnings range from less than 1% to 250.7%. The same

**Table 4**
**Correlation Matrix for the variables in this study**

| | *1-FE* | *2-EC* | *3-MV* | *4-QLOB* | *5-QGEO* | *6-NLOB* | *7-NGEO* |
|---|---|---|---|---|---|---|---|
| 1-FE | 1.0000000 | | | | | | |
| 2-EC | 0.7380385 | 1.0000000 | | | | | |
| 3-MV | −0.1555053 | −0.1377198 | 1.0000000 | | | | |
| 4-QLOB | −0.1284897 | −0.1218936 | 0.2412721 | 1.0000000 | | | |
| 5-QGEO | −0.0634325 | −0.0113306 | −0.0116196 | 0.0052655 | 1.0000000 | | |
| 6-NLOB | −0.0323810 | −0.0784115 | 0.2736324 | 0.0850828 | 0.0412010 | 1.0000000 | |
| 7-NGEO | −0.0509888 | −0.0103624 | 0.0776574 | −0.0285036 | 0.0367170 | 0.2523447 | 1.0000000 |

*Definitions:* As for Table 3.

point can be made for the forecast error, which has an even greater range, from zero to 463%.

The metric for line-of-business quality (QLOB) averages around 2. This score is equivalent to segments with a 2-digit (*Class*) level of detail under the UK SIC system. The mean metric value for the quality of geographic segments (QGEO) is around 1.5, indicating a level of detail finer than continents, but broader than individual countries. This is consistent with the reporting practices of many UK companies; geographic segments are usually a mixture of continental segments and individual countries. It can also be seen that the sample of companies used for this study are diverse in terms of market values (MV) and the numbers of business and geographic segments (NLOB and NGEO). For additional information, the level of reported earnings ($A_t$)—used as a deflator for FE and EC—and the level of forecasted earnings ($F_{j,22}$), are also described in Table 3.

## 4. Model specification

One possible method of estimating the effect of segment definition on forecast error would be to analyse the variables in a linear additive regression model. However, this would be to assume that all variables have an independent impact on the forecast error. This is clearly not the case; the impact of the variables on the forecast error will obviously depend on the change in earnings over the forecast period. For example, if earnings change little over the two-year period, then there may not be much forecast error to explain. The correlation matrix in Table 4 shows that the forecast error (FE) and earnings change variable (EC) are highly correlated. It also shows that simple linear association between the forecast error and the segment quality measures (QLOB and QGEO) is of the expected sign, but is not strong.

Thus, the regression model is specified in a multiplicative format.

### 4.1. *Regression Model 1*

$FE_j = B_1 + B_2.EC_j + B_3.[MV_j . EC_j] + B_4.[QLOB_j . EC_j] + B_5.[QGEO_j . EC_j] + B_6.[NLOB_j . EC_j] + B_7.[NGEO_j . EC_j] + \varepsilon_j$

$B_{1,...}B_7$ = regression coefficients.

$\varepsilon_j$ = disturbance term following usual assumptions of zero mean and constant variance.

This form of model implies that the impact of each independent variable on the forecast error is determined by the regression coefficient and the magnitude of EC (see Pindyck and Rubinfeld, 1991: 103–04).

It should be noted that heteroscedasticity affects the regressions in this study; it is detected using the Breusch-Pagan (1979) test statistic, for which chi-squared tables may be used to assess significance levels. The statistic tests the null-hypothesis of homoscedastic errors; this null-hypothesis is rejected for the regressions carried out in this study. Traditional model transformations failed to solve the problem, so the White (1980) correction for heteroscedasticity is employed here. This procedure generates standard errors robust to heteroscedasticity, which may be used in conjunction with ordinary least squares (OLS) parameter estimates to construct t-values. The procedure has been utilised in a number of studies (e.g. Bhushan 1989b; Ali, Klein and Rosenfeld, 1992). The results for regression Model 1 are presented in Table 5.

The results reported in Table 5 support the use of the multiplicative regression format. Using either the OLS or the White (1980) t-values, significant slope coefficients are found for the following variables:

- *The absolute change in earnings over the forecast period (EC).* This coefficient generates a positive coefficient, as expected. The greater the change in earnings the analyst must predict, the larger the forecast error.
- *The company's size measured by market value (MV).* The negative slope for market value is consistent with the large amount of previous research on prices and analysts' forecasts, indicating that

**Table 5**
**Explaining analysts' forecast errors: regression model 1**

$$FE_j = B_1+B_2.EC_j+B_3[MV_j.EC_j]+B_4.[QLOB_j.EC_j]+ B_5.[QGEO_j.EC_j]+B_6.[NLOB_j.EC_j]+B_7.[NGEO_j.EC_j]+\varepsilon_j$$

| | |
|---|---|
| Sample: | All firms |
| Sample size: | 197 |
| Adjusted R-squared: | 0.60 |
| Breusch-Pagan (1979)$\chi^2$: | 145.2 (critical value = 12.6) indicating significant heteroscedasticity. |

| *Variable* | *OLS coefficient* | *OLS t-value* | *White t-value* |
|---|---|---|---|
| Intercept | −0.172 | −4.00** | −2.33** |
| EC | 1.83 | 11.33** | 4.20** |
| $MV^M$ | −0.00006 | −2.53** | −3.27** |
| $QLOB^M$ | −0.091 | −2.56** | −2.47** |
| $QGEO^M$ | −0.329 | −3.58** | −2.29** |
| $NLOB^M$ | 0.054 | 2.25** | 1.24 |
| $NGEO^M$ | −0.025 | −1.07 | −0.83 |

$^M$indicates multiplicative variable: $X^M = X . EC$
**significant at 0.05 level (two-tail test)
*significant at 0.10 level (two-tail test)

*Definitions:* As for Table 3

market participants' insight into future earnings changes is positively related to firm size.

• *The quality of line-of-business and geographic segments (QLOB and QGEO).* The negative coefficients for both QLOB and QGEO provide support for the main hypothesis of this study: that segment definitions do influence analysts' forecast errors. The finer the segment definition, the greater the predictive gains.

The number of lines-of-business (NLOB) generates a positive slope coefficient, consistent with the hypothesis that multi-segment forecasts are costly to generate, but the heteroscedastic corrected t-value is not significant at the 0.05 level. The number of geographic segments (NGEO) appears to have little impact on the forecast error.

Further analysis indicates that the results presented in Table 5 are primarily driven by a sub-sample of observations for which the change in earnings over the forecast period is negative. There are 21 observations in this sub-sample, and the descriptive statistics are presented in Table 6.

The special nature of these observations has been noted in previous studies of analysts' earnings forecasts. Studies of UK analysts' forecasts, by Cooper and Taylor (1983) and Cooper (1984), make note of analysts' failure to identify changes in the direction of earnings changes. The difficulty analysts have in predicting falling earnings numbers may be seen by comparing the mean values of the forecast error (FE) and the earnings change (EC) for the whole sample (Table 3) and the sub-sample of firms with falling earnings (Table 6). The mean absolute earnings change for firms with falling earnings is only 1.32 times larger than for the whole sample; however, the mean forecast error is larger by a factor of 4.05. Of course, error metric volatility may also be due to observations where the level of actual earnings—which is used as the deflator for EC and FE—are small.[3]

To provide a test of the importance of the negative earnings change sub-set on the regression results presented earlier, the regression model is repeated, with dummy variables introduced on the intercept and all slopes; this dummy represents negative earnings changes.

### *4.2. Regression Model 2*

$$FE_j = B_1 + B_{D1}.D_{1j} + B_2.EC_j + B_{D2}.[D_{2j}.EC_j] + B_3.[MV_j. EC_j] + B_{D3}. [D_{3j}. MV_j. EC_j] + B_4.[QLOB_j. EC_j] + B_{D4}. [D_{4j}. QLOB_j. EC_j] + B_5.[QGEO_j. EC_j] + B_{D5}. [D_{5j}. QGEO_j. EC_j] + B_6.[NLOB_j. EC_j] + B_{D6}. [D_{6j}. NLOB_j. EC_j] + B_7.[NGEO_j. EC_j] + B_{D7}. [D_{7j}. NGEO_j. EC_j] + \varepsilon_j$$

$B_1,\dots B_7$ = regression coefficients.
$B_{D1},\dots B_{D7}$ = coefficients for intercept and slope dummies.
$D_{1j},\dots D_{7j}$ = negative earnings change dummy for firm j
$D_1,\dots D_7$ take same value for firm j (i.e. 1 if earnings change is negative, and 0 otherwise). The sub-

[3] See Test 2 in Section 5.

**Table 6**
**Descriptive statistics for firms with negative earnings changes**

*21 observations used*

| *Variable* | *Mean* | *Std. Dev.* | *Minimum* | *Maximum* |
|---|---|---|---|---|
| FE | 1.0774 | 1.1276 | 0.1669 | 4.634 |
| EC | 0.50585 | 0.62739 | 0.0064 | 2.507 |
| MV | 260.49 | 496.75 | 22.30 | 2284.0 |
| QLOB | 1.6776 | 1.2986 | 0.0000 | 5.300 |
| QGEO | 1.4223 | 0.65037 | 0.0000 | 2.000 |
| NLOB | 2.8571 | 2.2646 | 1.000 | 8.000 |
| NGEO | 3.7143 | 1.9011 | 1.000 | 7.000 |
| $A_t$ | 29.096 | 49.945 | 1.97 | 223.4 |
| $F_{22}$ | 54.852 | 104.44 | 3.0 | 490.0 |

*Definitions:* As for Table 3.

scripts 1,...7 are merely used to identify which coefficient the dummy relates to.
$\varepsilon_j$ = disturbance term following usual assumptions of zero mean and constant variance.

The results for regression Model 2 are presented in Table 7.

The results in Table 7 provide support for the hypothesis that a sub-set of observations is driving the results presented in Table 5. The regression results indicate the following:

- The coefficient for the intercept dummy $D_1$ is positive and significant. This provides evidence of the greater level of forecast error where earnings changes are negative.
- Both the slope coefficient ($B_2$) and the slope dummy ($B_{D2}$) are positive and significant. This supports the positive association between the magnitude of the earnings change and the forecast error. The coefficient determining this relationship is larger where earnings changes are negative.
- The impact of market value remains unaffected by poor earnings performance. The slope coefficient ($B_3$) is negative and significant, while the slope dummy ($B_{D3}$) is not significant at any reasonable probability level.
- The slope coefficients for the quality of lines-of-business ($B_4$) and geographic areas ($B_6$) are no longer significant, but the respective slope dummies ($B_{D4}$ and $B_{D5}$) are both negative and significant. This suggests that the impact of segment quality is most important for earnings forecasts for companies with negative earnings changes.

The coefficients for non-dummy variables ($B_1$,...,$B_7$) represent the coefficients for the sub-set of companies with positive earnings changes, assuming both positive and negative earnings change sub-sets have a common error structure. This can be checked by running regression Model (1) for the 176 firms with positive earnings changes. The estimated coefficients—not reported here—are materially similar to those for the non-dummy variables in Table 7.

## 5. Discussion and additional analyses

The results of regression Models 1 and 2 (see Tables 5 and 7) provide further support for the firm size effect in analysts' earnings forecasts. The results show a significant negative association between the market value (MV) of a firm and the magnitude of the forecast error. This finding is consistent with the wider sets of information available for large firms, and also with the greater financial incentives for analysts to follow large firms. Large firms offer greater opportunities for profitable trading where mispriced securities are identified.[4]

The absolute change in earnings (EC) over the forecast period is the main explanatory variable in these multiplicative regression models. As expected, there is a strong positive association between EC and the forecast error (see Tables 5 and 7). However, it is interesting to note that the coefficient for the slope dummy—variable $D_2$ in Table 7—is also positive and significant. This indicates that large earnings changes have an even greater impact on the forecast error where earnings changes are negative. This finding is consistent with the suggestion that analysts have special difficulty in predicting earnings for this sub-set of firms.

The quality of both line-of-business segments (QLOB) and geographic segments (QGEO) have a significant negative association with the forecast error (see Table 5). This is consistent with the improved insight that segment data gives analysts, especially at longer horizons [e.g. Baldwin, 1984]. However, once dummy variables for negative

[4] For a discussion of this issue, see Freeman (1987: 196–98).

**Table 7**
**Explaining analysts' forecast errors: regression model 2**

| | |
|---|---|
| Sample: | all firms |
| Sample size: | 197 |
| Adjusted R-squared: | 0.89 |
| Breusch-Pagan (1979)$\chi^2$: | 69.9 (critical value = 22.4) indicating significant heteroscedasticity. |

$$FE_j = B_1 + B_{D1}.D_{1j} + B_2.EC_j + B_{D2}.[D_{2j}.EC_j] + B_3.[MV_j.EC_j] + B_{D3}.[D_{3j}.MV_j.\ EC_j] + B_4[QLOB_j.\ EC_j] + B_{D4}.[D_{4j}.\ QLOB_j.EC_j] + B_5.[QGEO_j.\ EC_j] + B_{D5}.[D_{5j}.\ QGEO_j.\ EC_j] + B_6.[NLOB_j.\ EC_j] + B_{D6}.\ [D_{6j}.\ NLOB_j.\ EC_j] + B_7.[NGEO_j.\ EC_j] + B_{D7}.\ [D_{7j}.\ NGEO_j.\ EC_j] + \varepsilon_j$$

| *Variable* | *OLS coefficient* | *OLS t-value* | *White t-value* |
|---|---|---|---|
| Intercept | 0.027 | 0.87 | 0.63 |
| $D_1$ | 0.307 | 4.61** | 3.25** |
| EC | 0.472 | 3.33** | 3.29** |
| $D_2$.EC | 2.198 | 9.26** | 10.77** |
| $MV^M$ | −0.00003 | −2.17** | −3.08** |
| $D_3.MV^M$ | 0.00004 | 0.46 | 0.57 |
| $QLOB^M$ | −0.009 | −0.42 | −0.57 |
| $D_4.QLOB^M$ | −0.321 | −4.34** | −2.56** |
| $QGEO^M$ | 0.012 | 0.22 | 0.25 |
| $D_5.QGEO^M$ | −0.570 | −3.85** | −4.69** |
| $NLOB^M$ | −0.057 | −1.21 | −1.32 |
| $D_6.NLOB^M$ | 0.007 | 1.31 | 1.54 |
| $NGEO^M$ | 0.0004 | 0.01 | 0.01 |
| $D_7.NGEO^M$ | 0.0014 | 0.284 | 0.36 |

$^M$indicates multiplicative variable: $X^M = X\ .\ EC$
**significant at 0.05 level (two-tail test)
*significant at 0.10 level (two-tail test)

*Definitions:*
$D_{1j},..D_{7j}$ = Negative earnings change dummy for firm j.
$A_t$ = The reported earnings for year t (£m).
This variable is used as the deflator for FE and EC.
$F_{22}$ = The 22-month ahead forecast of $A_t$ (£m)
FE = Forecast error = $|A_t - F_{22}|/A_t$.
EC = Absolute change in earnings = $|A_t - A_{t-2}|/A_t$
MV = market value (£m).
QLOB = Quality of line-of-business segments ($0 \leq QLOB \leq 6$).
QGEO = Quality of geographic segments ($0 \leq QGEO \leq 2$).
NLOB = Number of reported lines-of-business.
NGEO = Number of reported geographic areas.

earnings changes are introduced (see Table 7) it can be seen that these associations are driven by the sub-set of firms with negative earnings changes. It may be that the forecasting processes used by analysts are poor predictors of earnings where earnings are falling; only with good segmental data are analysts able to gain sufficient insight to overcome this problem. However, it may also be that there are incentives for analysts to avoid generating excessively pessimistic forecasts—relative to the realised outcome—because it may damage relations with company managers (see O'Brien, 1988: 65). Thus, only when analysts have sufficient segment data to make them confident of their forecasts do they predict earnings reductions; where they are less well informed (e.g. poor segmental data) they may be reluctant to commit themselves to predictions of poor earnings performance.

An important aspect to any empirical analysis is the robustness of the results. The results obtained in this study appear robust to a number of additional tests suggested by colleagues and re-

**Table 8**
**Explaining analysts' forecast errors: additional tests**

$$FE_j = B_1 + B_{D1}.D_{1j} + B_2.EC_j + B_{D2}.[D_{2j}.EC_j] + B_3.[MV_j.\ EC_j] + B_{D3}.[D_{3j}.MV_j.EC_j] + B_4.[QLOB_j.\ EC_j] + B_{D4}.\ [D_{4j}.\ QLOB_j.\ EC_j] + B_5.[QGEO_jEC_j.] + B_{D5}.\ [D_{5j}.\ QGEO_j.\ EC_j] + B_6.[NLOB_j.\ EC_j] + B_{D6}.\ [D_{6j}.\ NLOB_j.\ EC_j] + B_7.[NGEO_j.\ EC_j] + B_{D7}.\ [D_{7j}.\ NGEO_j.\ EC_j] + \varepsilon_j$$

| | *Test 1* | *Test 2* | *Test 3* |
|---|---|---|---|
| *Variable* | *Coefficient* | *Coefficient* | *Coefficient* |
| Intercept | −0.001 | 0.012 | 0.025 |
| $D_1$ | 0.220* | 0.24** | 0.323** |
| EC | 0.816** | 0.384** | 0.477* |
| $D_2$.EC | 2.14** | 5.04** | 5.99** |
| $MV^M$ | −0.00003** | −0.00002** | −0.00003** |
| $D_3.MV^M$ | −0.00007 | −0.00001 | 0.000005 |
| $QLOB^M$ | −0.018 | 0.007 | −0.028 |
| $D_4.QLOB^M$ | −0.21** | −1.33** | −1.28** |
| $QGEO^M$ | −0.037 | 0.088* | 0.023 |
| $D_5.QGEO^M$ | −0.63** | −1.55** | −2.04** |
| $NLOB^M$ | −0.037 | −0.029 | −0.039 |
| $D_6.NLOB^M$ | 0.006 | 0.004 | 0.006 |
| $NGEO^M$ | −0.104 | −0.033 | −0.008 |
| $D_7.NGEO^M$ | 0.011* | 0.004 | 0.002 |
| *Adjusted R-squared* | *0.89* | *0.68* | *0.90* |

$^M$indicates multiplicative variable: $X^M = X\ .\ EC$
**White (1980) t-value significant at 0.05 level (two-tail test)
*White (1980) t-value significant at 0.10 level (two-tail test)

*Definitions:* As for Table 7.

*Test 1:* Eliminating single segment firms (119 observations).
*Test 2:* Eliminating firms with reported earnings <£20m (136 observations).
*Test 3:* Non-linear transformation of segment quality metrics (197 observations).

viewers, and detailed below. The results of these tests are contained in Table 8.

### *5.1. Test 1: Eliminating Single Segment Firms*

This study includes single segment firms: in such cases, the consolidated accounts are treated as a single segment. Such reporting is quite adequate if the company is engaged in a single line-of-business or geographic region. With the aid of *Key British Enterprises*, a judgment is made as to an appropriate quality score for QLOB and QGEO. It could be argued, however, that these firms represent a special sub-set of the data which may have different properties from the rest of the sample. Regression 2 is therefore repeated, excluding all firms with single lines-of-business or geographic regions. This reduces the sample size to 119.

### *5.2. Deflator Choice and Metric Volatility*

The metrics used for measuring forecast error (FE) and earnings change (EC) both use the level of reported earnings as a deflator. Very low values for earnings may result in excessive volatility for both FE and EC. While wishing to retain reported earnings as the deflator (for reasons given earlier), Table 3 shows that the minimum value for reported earnings is 1.97 (i.e. £1.97m). It can also be seen that the EC range is from 0.00649 to 2.507. Both of these extreme observations are for poor earnings performers. It could be that these two extreme EC observations are driving the results. Both are eliminated when a minimum value of £20m is placed on reported earnings; the range of values for both FE and EC are greatly reduced from the values reported for the whole sample, in Table 3. Eliminating observations where earnings are less than £20m reduces the sample to 136, and reduces the range for the FE and EC variables. The FE ranges from zero to 1.864, while the EC variable ranges from 0.0298 to 1.282.

### *5.3. Test 3: The Ordinal Nature of Quality Scores*

The quality scores used for lines-of-business and geographic segments are ordinal in nature. They indicate that one level of detail is superior to another, but do not indicate the magnitude of the superiority. This is unavoidable because of the nature of the study: there is no cardinal measure of quality. However, it may be that by changing the weightings for quality, different results may be obtained. To test this hypothesis, both the QLOB and QGEO scores are transformed thus:

$$NewQLOB = \sqrt{(QLOB+1)}$$

$$NewQGEO = \sqrt{(QGEO+1)}$$

These transformations alter the relative importance of good and bad segmental definitions. Regression 2 is re-estimated with the transformed QLOB and QGEO scores.

The results of these three tests, described in Table 8, indicate that the results are quite robust to a number of sensitivity tests. However, before concluding, a number of possible limitations to this study should be acknowledged.

- The forecasts used in this study are generated by analysts employed by one brokerage house. It could be that the forecasts are not representative of analysts' forecasts as a whole. It should be noted, however, that the brokerage house from which the forecasts originate is one of the largest in the City of London, and has a well resourced equities-research department.
- There is potential measurement error in the metrics for segment quality. However, this is unavoidable; there is no precise measure of segment quality. In addition, the results of this study appear robust to the non-linear transformation of these quality metrics.
- There may be additional explanatory variables omitted from this study. For example, there is no control over analyst-specific factors which may influence forecast accuracy. Technical skill (e.g. use of forecasting tools) and educational background (e.g. knowledge of accounting, statistics, economics) may differ greatly across analysts. However, these data are not readily available to researchers and so cannot be controlled for.
- It is possible that predictive gains resulting from a particular level of segment fineness may differ across firms, because of differences in organisational structure. It may be that an increase in the quality of business segments from, say, QLOB = 3 to QLOB = 6 may have a smaller effect where a company is engaged in a number of distinct but similar activities that respond similarly to economic changes, than where a firm is engaged in a number of very different activities with differing responses to economic changes.

## 6. Conclusion

This study examines UK analysts' forecasts of annual earnings, generated at a 22-month horizon prior to the earnings announcement. The results indicate that a firm size effect occurs in analysts' forecasts, similar to that observed in stock prices. Forecasts for large firms better reflect forthcoming earnings information than forecasts for smaller firms. It is also found that forecast errors are positively associated with the magnitude of the change in earnings that analysts must predict. This association is particularly strong where earnings changes are negative. However, where firms provide good quality segmental disclosure for lines-of-business and geographic regions, the forecast error is reduced. These results provide further evidence of the superior insight that analysts obtain from segmental disclosure.

A possible implication from these findings is that, if the aim of segmental reporting is to provide investors with improved insight into corporate prospects, then accounting standards should concern themselves more with improving the definitions of reported segments, and concern themselves less with attempts to extend existing segmental reporting requirements to a wider range of (possibly) less useful accounting items.

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