On the Performance of South African Equity Analysts

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Introduction

This study compares the consensus earnings forecasts of security analysts and full year company earnings per share for companies listed on the Johannesburg Securities Exchange. The study is based on a sample of 665 paired realized earnings and corresponding earnings forecasts. The period of the study is from January 1990 to December 1999 and covers all shares on the JSE for which consensus forecasts were available.

As it is not possible to test the null hypothesis that forecasts are accurate enough for the purposes of security valuation, this paper seeks to describe the size and direction of the errors, and make some comment on the source of the errors. Two testable hypotheses are considered, first whether analysts forecast become more accurate as the announcement of earnings approaches and second, whether analysts forecast earnings without significant bias.

While earnings forecasts are only part of the output of the security analysis industry, they are important for two reasons. First, expected earnings form the basis of almost all valuation models in the theory of finance[1]. Second, they can be directly compared to realizations.

Weak (circumstantial) evidence of a small optimistic bias is found in the analysts' forecasts. The optimistic bias is consistent with recent international findings. The evidence of the bias is weaker than in most countries. This finding is holds within each of the years of the study and within each of the industry groupings.

Errors more than two standard deviations from the mean occur more frequently than on the optimistic side than the pessimistic side, and have greater absolute values.

A decomposition of the errors suggests that the errors are largely random and based on an inability of forecasters to predict at firm, rather than industry or economy level.

Finally, forecasts are found to become more accurate as reporting date for earnings approaches.

The evidence on forecast errors is similar to the recent international evidence.

The paper proceeds as follows: Prior research is discussed briefly in section 1. The data is described in section 2. Methodology and results are in section 3. Direct comparisons to international findings are discussed in this section. Conclusions are in section 4.

[1] For a discussion of earnings based valuation models the reader is pointed to Copeland and Weston(1988) and Fama and Miller(1972)

1. Prior Research

Analysts' forecasts of future earnings are directly important in almost all firm valuation models. Capstaff, Paudyal and Rees (2001) and Amir, Lev and Sougiannis (1999) have suggested that the mere fact that analysts' forecasts are produced at considerable cost in competitive markets is direct evidence of their value beyond the merely theoretical.

While earnings are not the only information contained in financial statements that may affect share prices, there is substantial evidence that earnings do affect share prices. Niederhoffer and Regan (1972) and Ball and Brown (1968) provide evidence supporting a positive relationship between changes in earnings and share returns. Foster, Olsen and Shevlin (1984) find that earnings surprises (based on time series forecasting methods for determining expected earnings) explain 81% of post earnings announcement drift. Finally, Brown (1997a) provides a survey on the research into standardized unexpected earnings. Of particular interest are the reported findings of Freeman and Tse (1989) who find that post earnings announcement drift is more pronounced when expected earnings are based on analysts' forecasts than on time series forecasting methods.

Most of the early research into the properties of analysts' earnings forecasts was conducted in the USA. One of the earliest studies was by Cragg and Malkiel (1968). They examined the accuracy of five year earnings growth forecasts from five sources (institutions involved in money management in some form) made at the end of 1962 and 1963. They found that analysts underestimated earnings growth, "…a result of the average growth rates being considerably higher than the average expectation of each predictor".

Richards (1976) finds a small pessimistic bias analyzing forecasts from each of five analysts for 1972 earnings for a sample of 93 NYSE listed stocks. He finds significant differences in the errors between different industries but not between individual forecasters. Ultimately he concludes that, "analysts perform reasonably well in forecasting earnings." For the period 1972-76 Richards, Benjamin and Strawser (1977) find an overall pessimistic bias in mean analyst forecasts taken from the Standard and Poor's *Earnings Forecaster*. The bias is however optimistic in three of the five years of the study. Differences in errors between industries were again found to be significant.

Using Standard and Poor's *Earnings Forecaster* data from 1967 – 76 Crichfield, Dyckman and Lakonishok (1978) find that analysts' forecasts improve as the time to earnings announcement approaches. Elton, Gruber and Gultekin (1984) find similar results using I/B/E/S data from 1976 – 1978 - the absolute percentage error decreases as the announcement date for earnings approaches with errors less than 5% in the month before earnings announcement. They do not provide any information on the direction (bias) of the analysts' errors.

On the direction of errors, Crichfield, Dyckman and Lakonishok (1978) regress the natural log of the forecast change in earnings on the natural log of the actual change and find intercepts that are not significantly different from zero. They do however note, “a tendency for α to be negative on average”, indicating weak evidence of an optimistic bias. Their slope coefficients are consistently greater than one – a 1% forecast change resulting in a realized change of greater than 1%.

De Bondt and Thaler (1990) investigate bias in analysts’ forecasts for the period 1976-1984 using consensus IBES forecasts. Regressing the forecast change in cents per share on the actual change they find a significantly negative intercept, with a slope less than one and an R^2 of 21.7%.

Brown, Foster and Noreen (1985) use the IBES database for January 1976 – December 1980 and the Wells Fargo database of individual analysts forecasts for January 1977 – June 1980 to analyze the properties of analysts’ earnings forecasts. Consistent with prior and subsequent evidence they find that the forecast error, regardless of definition, declines as the announcement date for earnings approaches. By number of forecasts they find that analysts are more likely to underestimate than overestimate earnings, and the median forecast is pessimistic. The signed percentage errors are however optimistic in all months except the one immediately preceding earnings announcement, suggesting that the magnitude of optimistic errors is greater than the magnitude of pessimistic errors.

The evidence to this point indicates either a pessimistic bias on the part of analysts, or is mixed as in the case of Brown et al (1985). The evidence to follow typically reports a more recent optimistic bias on the part of analysts, and this finding is repeated around the world.

Dreman and Berry (1995) use the Abel Nosser database of consensus earnings forecasts from 1972 to 1991. They find a significant optimistic bias in the mean forecast for the full sample. Further evidence of the optimistic bias is the number of optimistic and pessimistic errors – they found 26,122 positive surprises and 29,363 negative surprises in a sample of 66,100 observations. Dividing their sample into expansionary and recessionary periods for the economy as a whole, they find that the business cycle does not contribute in a significant way to either the size or the direction of analysts’ errors. Finding that fewer than 30% of all forecasts fell within a ±5% error bandwidth around the actual earnings, they concluded that the size of the forecast errors are, “...too high for investors to rely on consensus forecasts as a major determinant of stock valuation”.

Brown (1996) argues against a number of Dreman and Berry’s (1995) findings, particularly their finding that the mean error is increasing through time. In a more complete paper Brown (1997b) finds similar results to Dreman and Berry (1995) – significant optimistic bias – using the IBES data for the period 1983 – 1996. He however finds smaller errors and bias for firms in the S&P500 than for those not in the index, and that no bias is observable for the S&P500 for the 1993 – 1996 period. While Dreman and Berry (1995) argue that forecast errors have increased through time, Brown (1997) again finds the opposite. In Brown’s sample the last year in which the annual mean bias exceeds the overall mean bias is 1991.

Recent evidence from the European markets comes from Capstaff, Paudyal and Rees (2001). Using individual analysts’ forecasts taken from I/B/E/S their study covers the period from February 1987 to December 1994 for nine countries; Belgium, France, Germany, Ireland, Italy, Netherlands, Spain, Switzerland and the United Kingdom. They find an optimistic bias in each of the nine countries in the percentage errors. Testing the bias more formally they regress the forecast percentage change on the actual percentage change they find significantly negative intercepts for all of the countries except Ireland where the intercept is significantly positive. While these findings on the intercepts are consistent with the findings of Crichfield, Dyckman and Lakonishok (1978), like De Bondt and Thaler (1990) their slope coefficients are consistently less than one.

Higgins (1998) analyses I/B/E/S data for the USA, Japan and five European countries for the period 1991 – 1995. The European countries are the United Kingdom, Netherlands, France, Germany and Switzerland. An optimistic bias was found in the percentage errors of all countries in the sample. The errors for the European countries are larger than those found by Capstaff et al (2001) for a similar period.

Further evidence on Japanese forecasts comes from a number of sources. Perhaps the most interesting is Conroy and Harris (1995) who analyze both individual IBES forecasts from (primarily) sell side analysts and Toyo Keizai forecasts for the period 1988 - 1992. Toyo Keizai is a data provider that does not make stock recommendations. They find an optimistic bias in both sets of forecasts; however the I/B/E/S forecasts were much more optimistic. This difference was attributed to the incentives facing sell side analysts working in firms with underwriting relationships with the firm that they were analyzing.

Higgins (2002) considers the relative performance of American and Japanese analysts forecasting earnings for Japanese companies. The American analysts performed better, with a mean absolute percentage error of 28% (1989-1998) against the 41% (1992-1998) mean percentage error for the Japanese analysts. The American analysts did a better job of forecasting earnings for Japanese firms than for American firms, although the errors made by American analysts forecasting earnings for American firms were found to decline through time. This was found to be the result of a decline in the bias in the forecasts. This corresponds with the findings of Brown (1997). This increasing forecast accuracy was not found in the forecasts for Japanese companies from either set of forecasters.

Allen, Cho and Jung (1997) analyze IBES forecasts for Japan, the USA, Korea Malaysia, the Philippines Taiwan, Thailand, Hong Kong and Singapore for 1989, 1990, and 1991. They find optimistic forecast bias in the percentage errors for all countries in the sample. They find a larger bias and lower forecast accuracy in the USA than in Japan. Their sample period is not long enough to comment on the changes in forecast accuracy over time. Like Elton et al (1984) find that the accuracy of forecasts improves as the announcement date of earnings approaches.

In a study of analyst activity in 47 countries, Chang, Khanna and Palepu (working paper) find South African analysts to rank fourth in accuracy, behind the USA, the United Kingdom and Ireland. Their study is limited in that it considers forecasts in 1996 only, and for at most thirty companies. They consider only the size of the errors, and provide no measure of bias.

The recent international evidence suggests a weak optimistic bias in analysts' forecasts. The institutional environment appears to have an impact on forecast accuracy – this is most visible in the case of Japan where the errors have been found to be small. The errors in the American market appear to be larger on average than in Europe or the (non US) Pacific Rim. These errors are however found to be much smaller for S&P500 companies. It may be then that the American results are less accurate simply because relatively smaller companies are covered in the USA than in other countries.

2. Data

Consensus earnings forecasts are taken from the Institutional Broker Estimation Service (I/B/E/S) database. The database consists of monthly earnings forecasts for Financial, Resources and Industrial firms from January 1990 to December 1999. Actual earnings are taken from I-Net Bridge. Where appropriate the earnings are adjusted for stock splits.

The number of companies for which earnings are forecast is 43 in 1990 and 113 in 1990. The total number of paired forecast and actual earnings is 665.

Table 1: approximately here

Except where otherwise stated the earnings forecast from the month before earnings are announced is compared to the actual earnings.

Inet-Bridge earnings figures are based on headline earnings. Where the reporting period is less than one year, the figure is annualized, with no seasonal adjustment. For goldmines the earnings quoted are “after- capex”.

The consensus forecasts are the median of the individual forecasts. Forecasts lying more than 2.3 standard deviations from the mean are omitted.

A limitation of this study is that the firms did not all have the same year end. The market conditions faced by an analyst forecasting for a January year end may be very different from those for an analyst forecasting for December of the same year. Given the sample size and the lack of uniformity it is not feasible to work with a single year end.

A further limitation is that there is often appears to be a lag in the updating of the I/B/E/S consensus forecasts, and the length of this lag is variable. For the sake of ensuring that there is no overlap in reporting periods, the actual earnings are compared to the recorded consensus forecast from the previous month. Actual announcement months are taken from I-Net Bridge. The forecast used may, depending on the lag, be the most recent forecast, one, two or even three months old. As forecasts improve as the year progresses the accuracy of analysts’ forecasts may be understated. On the other side of the reporting date, the earnings forecasts for 12, 11 and 10 months before next year’s earnings announcement may be for the previous year’s earnings. There is no way of consistently correcting for this error as the lag is variable and does not appear to affect all stocks.

While the three industry split has limitations, the size of the data set makes a finer split impractical. Brown (1997) limits himself to industries with at least fifty firms for which data is available, leaving fourteen industries. By that standard, the industrial grouping used would only be eligible from 1996, and the Resources and Financials would be omitted entirely.

3. Methodology

Size and pattern of errors

In order to test forecast accuracy the earnings announced in month t are compared to the consensus forecast published at the end of month t-1. There is no single best definition of forecast error. Four definitions are used in this study (SURPE and SURPF are taken from Dreman and Berry (1995)):

$$ABSURP = \left| A_{i,t} - F_{i,t-1} \right|$$

$$SURPE_{i,t} = \frac{A_{i,t} - F_{i,t-1}}{\left| A_{i,t} \right|}$$

$$SURPF = \frac{A_{i,t} - F_{i,t-1}}{\left| F_{i,t-1} \right|}$$

$$ABSPER = \left| \frac{A_{i,t} - F_{i,t-1}}{A_{i,t}} \right|$$

where

$\mathrm{SURPE}_{i,t}$ = EPS error for company i for month t scaled by actual earnings.

$\mathrm{SURPF}_{i,t}$ = EPS error for company i for month t scaled by forecast earnings.

$\mathrm{A}_{i,t}$ = Actual earnings for company i for month t.

$\mathrm{F}_{i,t-1}$ = Forecast earnings for company i for month t − 1.

ABSURP is the absolute surprise in cents per share. It offers no guidance as to the direction of the error, and is biased by the level of the earnings. SURPE and SURPF are similar, expressing the forecast error as a percentage of the actual and forecast errors respectively. The absolute value of the denominator corrects for negative earnings. They are signed, and thus provide information on the direction of the error. ABSPER is the absolute value of the forecast error scaled by the actual earnings. All four measures are reported on initially, as they have been used in the literature. The remainder of the paper will focus on ABSPER and SURPE, the two most popular measures.

Descriptive statistics of the errors based on these measures are presented in Table 2. Figures 1 contains a histogram of the mean error.

Table 2: approximately here

Figure 1: approximately here

The signed error scaled by actual earnings, SURPE, is -11.2%. This would appear to be clear evidence of over optimism by analysts. The t-test is significant at the 5% level. SURPF is smaller at –1.3%, which confirms the evidence of over optimism (t-test not significant). Where the forecasts are on average larger than actual earnings, scaling by the forecast will result in a smaller percentage errors. However, the median in both cases is extremely small at – 0.002%.

Evaluating five individual analysts Richards (1976) found a SURPE of between –2.6% and –22.9%. All five having negative SURPE values, this was taken as early evidence of over optimism by analysts. Richards, Benjamin and Strawser (1977) find a SURPE of -12.8% and an ABSPER of 24.1%.

Dreman and Berry (1995) find a mean SURPE of –25%, with a median of zero. Brown (1997) with a different source of forecasts and a slightly different time period to Dreman and Berry (1995) finds a SURPE for the US of –31.6%. Higgins (1998) finds similar results to Dreman and Berry (1995) and Brown (1997) with a SURPE of –29% for the US.

In Europe, Capstaff, Paudyal and Rees (2001) find SURPE values of between -2.4% for the Netherlands and -12.3% for Italy using individual analysts' forecasts. For their sample of nine European countries they find a mean SURPE of -7.5%. Higgins (1998) finds much larger signed errors in Europe, ranging from –16% in France to –55% in Switzerland.

For a sample of South East Asian countries and Japan Allen, Cho and Jung (1997) consistently negative mean SURPE values. The mean SURPE values ranged from –3.7% for Japan and Malaysia to –14.2% for the Philippines. The median errors were again very close to zero. At -5.1%, the Philippines was the only country in their sample with a median error greater than -1%.

Conroy and Harris (1995) find SURPE values of -6.3% using the IBES data, and –1% using Toyo Keizai data for Japan.

The mean and median ABSPER values are 19.3% and 5.3% respectively. The mean value is larger than the 8.6% found for South Africa by Khanna and Palepu (2000). For the year of their study, 1996, we had a sample of 69 firms and an ABSPER of 15.7%. Their study used a smaller sample of thirty companies.

In the USA early evidence on this measure again comes from Richards (1976) – he finds ABSPER values all less than ten percent. Elton, Gruber and Gultekin (1984) find values less than 5%. Dreman and Berry (1995) find an ABSPER of 43.8%, Brown (1997) 59% and Allen, Cho and Jung (1997) 22.7%.

In Europe Capstaff et al (2001) find a mean ABSPER of 16.9%, ranging from 18.6% for the Netherlands to 25% for Italy.

For Japan Conroy and Harris (1995) find an ABSPER of 21% using I/B/E/S data and 14.6% using data from Toyo Kezai (a data provider that does not provide any underwriting services). Allen, Cho and Jung (1997) find an ABSPER for Japan of 14.2% using I/B/E/S data.

For their sample of Pacific Basin countries Allen, Cho and Jung (1997) find ABSPER values ranging from 12.6% in Thailand to 25.5% in Taiwan. Across their full sample of 47 countries Khanna and Palepu (2000) find an ABSPER of 25.5%.

Separating the errors into negative and positive errors provides further evidence of some level of optimistic bias. There were 276 positive surprises (earnings greater than forecast) compared to 353 negative surprises. There were 36 correct forecasts. This is similar to Dreman and Berry (1995) who found 26,122 positive surprises and 29,363 negative surprises.

In splitting the sample in this way the median error for the negative surprises has a larger absolute value than the positive surprises.

Error Bandwidths

The signed percentage errors are divided into bandwidths. By year, industry and for the full sample SURPE and SURPF are divided into ± 5%, ± 10% and ± 15% bandwidths. Table 3 shows the percentage of observations that fall in each bandwidth.

Table 3: approximately here

Slightly less than half of all forecast errors are within ±5% of the actual earnings. For Industrials and Financials the figure is above 50%, while for Resources it is only 34%. Thus, while forecasts for Resources stocks may on average be more accurate than those for Industrials, there is a greater dispersion of errors. With the exception of 1992 the ±15 % bandwidth captured 70% of all forecasts. The distribution for Industrial and Financial stocks was similar, with the Industrial stocks having slightly more stocks in each bandwidth.

Richards (1976) found between 69% and 73% of all signed errors fell within the ± 10% bandwidth. Richards, Benjamin and Strawser (1977) found 32.6% in the ±5% bandwidth, 50% in ± 10% and 61.2% in the ±15%. Two percent of the errors fell outside the 100% bandwidth.

Dreman and Berry (1995) find that regardless of whether the error is scaled by earnings or forecast earnings, fewer than 30% of forecasts fall within a ±5% bandwidth, with fewer than 45% within a ±10% bandwidth. Our results are closer to the older results Richards (1976) and Richards, Benjamin and Strawser (1977).

Source of the errors

In the literature two methods of partitioning the mean squared forecast error are used to determine the source of the errors in earnings forecasts (naming conventions here follow Elton et al (1984)).

The mean squared forecast error is given by:

$$MSFE = \frac{1}{N}\sum_{i=1}^{N}(P_i - R_i)^2$$

P_i Forecast Change in Earnings in CPS for company i

R_i Actual Change in Earnings in CPS for company i

Partition by Level of Aggregation

The first partition, by level of aggregation, divides the MSFE into the portion attributable to an inability to forecast at firm, industry and economy level. The partition by level of aggregation is given by:

$$MSFE = (\overline{P} - \overline{R})^2 + \frac{1}{N}\sum_{i=1}^{N} N_a[(\overline{P}_a - \overline{P}) - (\overline{R}_a - \overline{R})]^2 + \frac{1}{N}\sum_{i=1}^{N}[(P_i - \overline{P}_a) - (R_i - \overline{R}_a)]^2$$

$\overline{P}$ The average value of P_i for all stocks

$\overline{R}$ The average value of R_i for all stocks

N_a The number of stocks in industry a

$\overline{P}_a$ The average value of P_i for all of the stocks in industry a

$\overline{R}_a$ The average value of R_i for all of the stocks in industry a

The first term represents the portion of the squared forecast error attributable to analysts' inability to forecast growth for the full sample of forecasts under consideration. The second term, comparing industry means to the sample mean, is the inability to forecast at industry level. The third term is the portion of the error attributable to an inability to forecast at firm level. The percentage contribution of each of the three to the total error is given by dividing each by the MSFE.

Table 4: approximately here

Financial stocks are included from 1997 when there are seven firms in the industry category. This follows Elton et al. (1984).

The largest part of the error is made at the firm level. The firm specific portion never accounted for less than 90% of the MSFE, and averaged 99.4% for the full sample. Inaccuracies for the sample as a whole accounted for at most 5% of the MSFE, with a mean of 0.3% for the full sample. The portion attributable to industry level errors is smaller for the full sample, but has a wider range of values for the individual range, from 0% to 8.1% of the MSFE.

These finding are consistent with Cragg and Malkiel (1968) who found that the industry level error was the smallest, followed by the full sample error. The largest part of the error for all forecasters, and never less than 50% of the error, was an inability to forecast at firm level. Overall they find that analysts do a poor job of forecasting long term growth rates. More recently Elton et al (1984) find that the inability to forecast at the level of the economy never exceeds 3% in the twelve months prior to the earnings announcement, and declines to 0.8% of the error in the month before the year end. The percentage attributable to the industry accounts for 15.5% in the last month of the firms' financial year, while the firm level accounts for 83.3% of the observed error.

These results are consistent with those of other users of this decomposition in finding that the firm level error is the main contributor to the MSFE, and that this proportion is greater than 50% of the total error.

Partition by Forecast Characteristics

The second partition, by forecast characteristics, is based on the regression of the forecast earnings change on the actual earnings change. If analysts' forecasts are perfectly accurate, the fitted line will have an intercept of zero and a slope coefficient of one. Biased forecasts will have a non zero intercept.

$$MSFE = (\overline{P} - \overline{R})^2 + (1 - \beta)^2 \delta_P^2 + (1 - \rho^2)\delta_R^2$$

β Slope coefficient of the regression of R on P

δ_P^2 Variance of P

δ_R^2 Variance of R

ρ Correlation of Rand P

The first term of the output represents the extent to which the forecasters errors were the result of bias. That is the extent to which the intercept differing from zero is responsible for the squared error. The second term measures the extent to which the squared error is a result of the regression slope differing from one. The last term is the portion of mean squared error attributable to random error. Again, the percentage contribution is calculated by dividing each component by the MSFE.

Table 5: approximately here

For the full sample Bias accounts for 0% of the error, inefficiency for 3% and the random error term for 97%. In seven of the ten years, and for the Industrial and Resources firms the random term accounted for more than 90% of the error.

These results are similar to those of Elton et al (1984) who found that bias accounted for 0.9% of the total error, inefficiency for 3% and the random error term 96.1%. Crichfield, Dyckman and Lakonishok (1978) agree that the random error is the most significant contributor to the total, 82%, but find higher values for bias, 13%, and inefficiency, 4.6%.

Regression analysis

Although they have been used as an input into the partition by forecast characteristics, it is useful to consider the regression output on its own, as it provides evidence on the direction of forecasters' errors.

Table 6: approximately here

The results presented in Table 6 are for the percentage change regressions.

The intercepts are mixed, positive in four years and negative in six. The only intercept significantly different from zero is for the Industrials, where the intercept is negative and significant at the 5% level, indicating a significant optimistic bias.

The slope coefficients are, with the exception of the Financial stocks, less than one. A forecast increase of 1% resulted in an actual increase of less than 1%.

These results are similar to those of Crichfield, Dyckman and Lakonishok (1978) in finding mainly negative (but not significant) intercepts. Their slope coefficients were however consistently greater than one.

They are however consistent with Capstaff, Paudyal and Rees (2001) who found significantly negative intercepts, and slope coefficients less than one (except for Ireland where the intercept was positive). Their R^2 values are much lower, the greatest being in the Netherlands where the R^2 was 33%.

Forecast errors within the reporting year

ABSPER declines monotonically as the time to reporting draws nearer. While the data for months –12 to –10 may be tainted by old forecasts for the previous year this suggests that analysts correctly incorporate new information into their forecasts as the reporting year progresses. While the error does not decline as smoothly for each of the industries, the forecast at t-1 is never less accurate than the forecast in any of the preceding months.

In all years where the data exists, the forecast is always more accurate at t-1 than at t-12. There are only two years, 1992 and 1996, where the t-9 forecast (the first entirely untainted forecast) is on average less accurate than the t-1 forecast.

Table 7: approximately here

These results are consistent with Elton et al (1984) who regress their errors on time to maturity and find that forecasts become more accurate as the time to earnings announcement decreases. More recently Allen et al (1997) find similar results. They present SURPE and ABSPER at 9, 6,3 and 1 months before the reporting of earnings. The errors decline monotonically with the exception of the signed error of Taiwan between t=-9 and t=-6.

4. Conclusions

The South African evidence supports the recent international findings in the analysis of analysts' earnings forecasts. There is a small positive bias in earnings forecasts. This bias is evident in both the mean signed error and the intercept of the regression of the forecast earnings change on the actual earnings change.

It is not possible to determine whether the forecasts are accurate enough to be used for the purposes of share valuation. While more than 200 of the 665 observations fell within a very narrow ±2.5% band around the realized earnings, there are a number of errors greater than ±100% - almost certainly too large for any meaningful attempt at security valuation.

South African analysts appear to do better than many of their international counterparts at forecasting earnings. Chang, Khanna and Palepu (2000) ranked South African analysts fourth, admittedly with a small sample. The evidence of bias in South Africa is also weaker than in many other countries.

Future research includes comparing the analysts' forecasts to mechanical time series forecasts, looking for firm specific characteristics that may predict forecast errors and finally the extent to which analysts' errors predict post earnings announcement drift.

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Tables

Table 1: Paired forecast and actual earnings observations by year and industry.

	Industrials	Financials	Resources	Full Sample
1990	34		9	43
1991	39		11	50
1992	40		11	51
1993	40		11	51
1994	43		11	54
1995	45	2	11	58
1996	52	3	14	69
1997	56	7	15	78
1998	63	19	16	98
1999	75	21	17	113
	487	52	126	665

Table 2: Descriptive Statistics.

Absolute error is the error in cents per share. SURPE and SURPF are the percentage errors scaled by the forecast earnings and the actual earnings respectively. ABSPER is the mean absolute percentage error, where the error is scaled by the actual earnings.

	Absolute Error	SURPF	SURPE	ABSPER
Full Sample	665			
Mean	18.485	-0.013	-0.112	0.193
Std. Dev	44.487	0.449	1.009	0.996
Median	4.486	-0.002	-0.002	0.053
Max	391.368	7.674	1.549	22.269
Min	0	-3.453	-22.269	0
T-test (mean different from zero)		-0.7466	-2.8624	
Positive	276			
Mean		0.159	0.097	
Std. Dev		0.564	0.165	
Median		0.050	0.047	
Max		7.674	1.549	
Min		0.001	0.001	
Negative	353			
Mean		-0.148	-0.287	
Std. Dev		0.299	1.353	
Median		-0.068	-0.072	
Max		-0.001	-0.001	
Min		-3.453	-22.269	

Table 2b: Descriptive stats for the industry split.

Definitions are as Table 2a, the sample is split into the three basic industry groups.

	Absolute Error	SURPF	SURPE	ABSPER
Industrials	487			
Mean	10.203	-0.022	-0.146	0.211
Std. Dev	18.686	0.503	1.165	1.155
Median	3.350	-0.005	-0.005	0.044
Max	183.900	7.674	1.422	22.269
Min	0.000	-3.453	-22.269	0.000
T-test		-0.9652	-2.7656	
Financials	52			
Mean	19.270	0.034	-0.014	0.117
Std. Dev	31.401	0.303	0.191	0.151
Median	5.047	0.006	0.006	0.046
Max	163.400	1.802	0.643	0.643
Min	0.005	-0.338	-0.511	0.000
T-test		0.8092	0.5286	
Resources	126			
Mean	45.041	0.005	-0.024	0.153
Std. Dev	66.685	0.212	0.303	0.262
Median	16.885	0.000	0.000	0.085
Max	391.368	0.733	1.549	1.953
Min	0.010	-0.967	-1.953	0.000
T-test		0.2647	0.8891	

Table 3: Error Bandwidths.

The proportion of errors falling within the given bandwidths.

	SURPE		
	± 5%	± 10%	± 15%
1990	0.535	0.721	0.791
1991	0.640	0.760	0.880
1992	0.471	0.529	0.686
1993	0.510	0.745	0.804
1994	0.426	0.630	0.722
1995	0.448	0.655	0.759
1996	0.536	0.652	0.739
1997	0.449	0.628	0.744
1998	0.480	0.643	0.765
1999	0.442	0.628	0.708
Full Sample	0.486	0.653	0.753
Industrials	0.520	0.680	0.764
Financials	0.519	0.635	0.731
Resources	0.341	0.556	0.722

Table 4: Decomposition by Level of Aggregation

Indicates the percentage of the Mean Squared Forecast Error attributable to an inability to forecast at the level of the full sample, industry and individual firm.

	Full Sample	Industry	Firm	Obs
Full Sample	0.003	0.002	0.994	665
1990	0.004	0.001	0.995	43
1991	0.013	0.081	0.906	50
1992	0.001	0.006	0.993	51
1993	0.005	0.001	0.994	51
1994	0.002	0.045	0.953	54
1995	0.040	0.000	0.960	56
1996	0.037	0.059	0.903	66
1997	0.028	0.026	0.946	78
1998	0.002	0.001	0.998	98
1999	0.001	0.074	0.925	113

Table 5: Decomposition by Forecast Characteristics

Based on the regression of the forecast percentage change in earnings on the actual percentage change in earnings. Bias is the portion of the error attributable the intercept differing from zero, Inefficiency is the portion attributable to the slope differing from one, the third term is the portion attributable to the random error term.

	Bias	Inefficiency	Random Error	Obs
Full Sample	0.00	0.03	0.97	665
Industrials	0.02	0.04	0.94	487
Financials	0.01	0.17	0.82	52
Resources	0.00	0.02	0.98	126
1990	0.00	0.43	0.57	43
1991	0.01	0.01	0.97	50
1992	0.00	0.39	0.61	51
1993	0.01	0.09	0.91	51
1994	0.00	0.00	0.99	54
1995	0.04	0.19	0.77	58
1996	0.04	0.02	0.94	69
1997	0.03	0.07	0.90	78
1998	0.00	0.01	0.99	98
1999	0.00	0.01	0.99	113

Table 6: Regression analysis

The table contains the results of the regression of the forecast percentage growth on the actual percentage growth.

	Intercept	FEPS Coefficient	R-Squared	Obs
Full Sample	-0.0146	0.9406	0.9854	665
p Value	(0.2057)	(0.0000)		
Industrials	-0.0264	0.9050	0.9463	487
	(0.0357)	(0.0000)		
Financials	0.0041	1.1005	0.6030	52
	(0.9598)	(0.0000)		
Resources	0.0300	0.9479	0.9962	126
	(0.2906)	(0.0000)		
1990	-0.0263	0.9762	0.9698	43
	(0.2593)	(0.0000)		
1991	-0.0322	0.9259	0.9853	50
	(0.4175)	(0.0000)		
1992	-0.0349	0.8515	0.9082	51
	(0.1232)	(0.0000)		
1993	-0.0163	0.9414	0.9948	51
	(0.3781)	(0.0000)		
1994	0.0024	0.7747	0.9661	54
	(0.9191)	(0.0000)		
1995	-0.0328	0.8548	0.8845	58
	(0.5343)	(0.0000)		
1996	0.0078	0.6860	0.6913	69
	(0.8204)	(0.0000)		
1997	-0.0279	0.8702	0.7635	78
	(0.5401)	(0.0000)		
1998	0.0364	0.9906	0.8611	98
	(0.1823)	(0.0000)		
1999	0.0399	0.9492	0.9956	113
	(0.2479)	(0.0000)		

Table 7: Changes in forecast accuracy as time to earnings announcement decreases

7a: Error measured as ABSPER

	-12	-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1
Overall Mean	0.49	0.40	0.41	0.36	0.30	0.28	0.25	0.20	0.23	0.22	0.22	0.19
Observations	536	592	609	614	619	627	630	640	650	653	660	665
1990		9.00	1.57	1.19	0.89	0.72	0.36	0.28	0.50	0.47	0.40	0.17
		1	6	8	11	15	17	22	32	35	42	43
1991	0.17	0.14	0.14	0.13	0.10	0.12	0.13	0.10	0.10	0.11	0.10	0.08
	30	47	49	49	49	49	49	49	49	49	49	50
1992	0.16	0.17	0.17	0.12	0.14	0.13	0.13	0.15	0.16	0.16	0.16	0.15
	42	48	50	50	50	50	50	51	51	51	51	51
1993	0.35	0.21	0.18	0.12	0.12	0.12	0.10	0.10	0.11	0.11	0.11	0.09
	47	50	50	50	50	50	51	51	51	51	51	51
1994	0.25	0.19	0.32	0.28	0.28	0.26	0.27	0.15	0.16	0.15	0.15	0.13
	49	52	52	52	53	53	53	54	54	54	54	54
1995	0.25	0.24	0.17	0.18	0.17	0.18	0.19	0.19	0.20	0.13	0.14	0.12
	52	57	57	57	57	58	58	58	58	58	58	58
1996	0.22	0.20	0.16	0.14	0.17	0.13	0.14	0.14	0.15	0.15	0.14	0.16
	62	68	68	68	68	68	68	68	68	68	68	69
1997	0.41	0.37	0.40	0.39	0.25	0.26	0.26	0.25	0.25	0.22	0.20	0.19
	69	73	76	77	77	77	77	78	78	78	78	78
1998	0.70	0.38	0.45	0.31	0.28	0.24	0.20	0.19	0.23	0.16	0.14	0.14
	89	94	94	95	96	97	97	98	98	98	98	98
1999	1.07	1.01	0.96	0.90	0.70	0.64	0.54	0.36	0.37	0.47	0.46	0.45
	96	102	107	108	108	110	110	111	111	111	111	113
Industrials	0.47	0.43	0.43	0.39	0.33	0.31	0.27	0.21	0.24	0.25	0.24	0.21
	391	434	444	447	452	457	460	469	479	481	484	487
Financials	0.18	0.16	0.15	0.15	0.13	0.14	0.15	0.13	0.13	0.12	0.12	0.12
	43	47	50	50	50	52	52	52	52	52	52	52
Resources	0.69	0.36	0.44	0.30	0.27	0.24	0.22	0.21	0.24	0.17	0.15	0.15
	102	111	115	117	117	118	118	119	119	120	124	126

Table 7b: As 7a with error measured as SURPE

	-12	-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1
Overall Mean	-0.24	-0.25	-0.26	-0.22	-0.17	-0.16	-0.14	-0.08	-0.05	-0.10	-0.09	-0.11
Obs	536	592	609	614	619	627	630	640	650	653	660	665
1990		-9.00	-1.53	-1.16	-0.86	-0.56	-0.21	-0.15	0.19	0.17	0.14	-0.11
		1	6	8	11	15	17	22	32	35	42	43
1991	0.007	0.035	0.030	0.020	0.032	0.000	0.005	0.032	0.012	-0.018	-0.013	-0.028
	30	47	49	49	49	49	49	49	49	49	49	50
1992	-0.04	-0.09	-0.08	-0.03	-0.05	-0.03	-0.04	-0.04	-0.04	-0.04	-0.04	-0.07
	42	48	50	50	50	50	50	51	51	51	51	51
1993	-0.26	-0.14	-0.10	-0.04	-0.04	-0.03	-0.01	-0.01	-0.01	-0.01	-0.01	-0.03
	47	50	50	50	50	50	51	51	51	51	51	51
1994	-0.04	-0.05	-0.17	-0.15	-0.16	-0.15	-0.15	-0.07	-0.07	-0.04	-0.04	-0.05
	49	52	52	52	53	53	53	54	54	54	54	54
1995	-0.03	-0.12	-0.06	-0.05	-0.05	-0.06	-0.09	-0.12	-0.12	-0.05	-0.06	-0.08
	52	57	57	57	57	58	58	58	58	58	58	58
1996	-0.03	-0.06	-0.01	0.01	-0.04	0.00	-0.02	-0.03	-0.04	-0.04	-0.04	-0.05
	62	68	68	68	68	68	68	68	68	68	68	69
1997	0.05	-0.28	-0.34	-0.32	-0.18	-0.19	-0.18	-0.18	-0.18	-0.16	-0.13	-0.14
	69	73	76	77	77	77	77	78	78	78	78	78
1998	-0.47	-0.21	-0.28	-0.14	-0.11	-0.07	-0.06	-0.05	0.01	-0.06	-0.01	0.00
	89	94	94	95	96	97	97	98	98	98	98	98
1999	-0.76	-0.74	-0.70	-0.67	-0.53	-0.48	-0.43	-0.12	-0.12	-0.36	-0.37	-0.37
	96	102	107	108	108	110	110	111	111	111	111	113
Industrials	-0.24	-0.31	-0.30	-0.28	-0.21	-0.19	-0.17	-0.09	-0.07	-0.12	-0.11	-0.15
	391	434	444	447	452	457	460	469	479	481	484	487
Financials	0.13	0.08	0.04	0.04	0.02	0.00	0.01	-0.01	-0.02	-0.01	-0.01	-0.01
	43	47	50	50	50	52	52	52	52	52	52	52
Resources	-0.43	-0.15	-0.22	-0.10	-0.11	-0.07	-0.10	-0.08	-0.03	-0.06	-0.04	-0.02
	102	111	115	117	117	118	118	119	119	120	124	126

Figure 1: SURPE Histogram

The first range is from –2.5% to 2.5%. The rest follow in 5% range increments.