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Accuracy of brokers' consensus earnings forecasts: The South African case

1. INTRODUCTION

In an extensive survey of hundreds of individual investors, institutional investors and financial analysts, Chang and Most (1979) find that earnings forecasts are considered by respondents in the United States to be the most important expectational data in selecting stocks. As, Givoly and Lakonishok (1984:1) remark, *"No better proof exists for the important role that earnings play in financial markets than the handsome livelihood derived by many professionals from the production, analysis and forecasting of earnings numbers".*

This paper investigates the accuracy of security analysts' consensus earnings forecasts of companies listed on the JSE Securities Exchange (JSE) of South Africa. The extent of the systematic error or bias inherent in these earnings forecasts is determined. The accuracy of analysts' earnings forecasts is compared as the earnings announcement date approaches. Thereafter, the accuracy of analysts' forecasts is compared to those derived from a first order auto regressive model. Should the earnings forecasts made by analysts be more accurate than those estimated using the naïve time series model, this would partially justify their popularity among investors. In addition, analysts' earnings forecasts are decomposed to ascertain whether their expectations fully reflect the history of the systematic error of their previous forecasts. Based on Muth's (1961) criteria, for a forecast to be rational: (i) it must not contain a systematic error and (ii) it cannot be improved by studying past forecasts and realisations.

This paper is organised as follows. In Section 2 a detailed review of the prior research on the accuracy of analysts' earnings forecasts is presented. Section 3 provides an overview of the data and methodology employed in this study. In Section 4 the results of the empirical analysis are presented and discussed. Section 5 concludes the paper.

2. PRIOR RESEARCH

The properties of security analysts' earnings forecasts have been subject to extensive research in the United States. The focus of the early research concerning security analysts' earnings forecasts has been on the issue of accuracy. However, contemporary research on the accuracy of analysts' earnings forecasts is conflicting in its findings.

Cragg and Malkiel (1968) compared the five-year earnings growth rates forecasted by five investment houses for 185 companies for the years 1962-1963 with two sets of naïve models: one predicting no change and the other a change in growth rate equal to past changes in growth rate. They conclude, *"...forecasts based on perceived past growth rates....do not perform much differently from the analysts' predictions".* In their study Elton and Gruber (1972) examined annual earnings forecasts made by analysts in a large pension fund, an investment advisory service and a large brokerage house and reached the same conclusion. They were unable to find any significant difference in accuracy between the best naïve model (an exponential smoothing model) and each of the three groups of analysts' forecasts.

Although these early results cast doubt on the usefulness of analysts in formulating forecasts, later studies resulted in different findings.

Brown and Rozeff (1978) examined two sets of quarterly earnings forecasts for 50 firms over the period 1971 to 1975. The first set was obtained through the application of Box-Jenkins (1970) models to each firm's previous earnings history. The second set was obtained from the earnings forecasts of security analysts as reported in the Value Line Investment Survey. The results suggested that the Value Line Investment Survey consistently makes better earnings forecasts than the Box-Jenkins time-series models.

Crichfield, Dyckman and Lakonishok (1978) investigated the ability of security analysts to provide 'rational' estimates of earnings per share. Besides concluding that analysts' forecasts become more accurate as the reporting date approaches, the study found that the predictions of changes in earnings per share data contain no significant systematic bias.

Givoly and Lakonishok (1984) found that analysts' earnings forecasts do incorporate the past history of realisations and predictions in an unbiased manner and, as such, can be classified as being rational.

Conroy and Harris (1987) studied how the accuracy of forecasts made by analysts, time-series models or combinations of the two are affected by forecast horizon, number of analysts and the dispersion of analysts' forecasts. It was found that the average of

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analysts' forecasts is a more accurate predictor of corporate earnings per share than forecasts from the time-series models. However, this superior forecasting ability appears largely for forecast horizons of less than a year and declines steadily as the forecast horizon increases. Furthermore, for predictions in the first half of the fiscal year, the study demonstrated that forecasting benefits could be achieved by combining time-series and analysts' forecasts, especially if there are few analysts' forecasts available.

O'Brien (1988) compared the accuracy of three composite analysts' earnings per share forecasts: the mean, the median and the most current forecast. Quarterly time-series models of earnings were used as benchmarks, against which analysts' forecasts were compared. The primary result was that the most current forecast available is more accurate than either the mean or the median of all available forecasts. Consistent with previous research, it was also found that analysts are generally more accurate than time-series models. Consistent with Stickel (1992), the study found that security analysts' forecasts tend to be too optimistic, i.e. are upwardly biased.

De Bondt and Thaler (1990) reached the conclusion that predictions of stock market professionals show a pattern of overreaction and that forecast changes are too extreme to be considered rational. De Bondt and Forbes (1999) empirically analysed the herding behaviour in analysts' forecasts of earnings per share. They defined herding as *'excessive agreement'* among predictions, i.e. a surprising degree of consensus relative to the predictability of corporate earnings. In agreement with prior research, evidence of excessive optimism in consensus forecasts and herding behaviour among analysts was found. Furthermore, the study pinpointed that as more analysts produce forecasts, disagreement rises, but only up to a point. Once they had 8 predictions, additional forecasts do not add to the forecast dispersion.

More recently, measuring the earnings surprises of international firms in 40 countries from the Asia/Pacific and Europe regions, Hsu (2001) found that financial analysts were not accurate in forecasting and that they tended to over-estimate earnings more often over the sample period considered. Black and Carnes (2002) investigated the determinants of the accuracy of analysts' earnings forecasts in the larger economies of the Asian/Pacific region. Besides exhibiting an optimistic bias on average, analysts' forecasts were shown to be more accurate in those nations with higher overall competitiveness rankings. Countries using British-based accounting methods were found to have smaller forecast errors. Firms with a larger difference between market and book value of equity were typified with a larger optimistic bias in the analysts' forecasts. It was found that the lower the book-to-market ratio, the greater the earnings forecast error, which implies that analysts generally make less accurate forecasts for companies with higher risk and growth opportunities. da Silva (2002) demonstrated that the accuracy of a particular industry's earnings forecasts can be improved by taking into consideration information from other industries. More specifically, by incorporating inter-industry linkages information into both the raw analysts' forecasts and forecasts obtained using the time-series models, the adjusted-analysts' forecasts were found to be unbiased and significantly more accurate.

To summarise the prior literature, first, earnings forecasts of security analysts appear to be significantly better than those estimated by time-series models. Second, it has been found that the accuracy of security analysts' earnings forecasts declines steadily as the forecast horizon increases. It has further been shown that timely composites of analysts' forecasts are superior to the mean forecast in terms of predictive ability. However, there have been mixed findings as to whether analysts' forecasts can be classified as being rational. While some concluded that earnings forecasts of analysts contain no significant systematic bias, others have rejected analysts' earnings forecasts as being rational especially due to the upward bias they tend to demonstrate. Recent studies have observed that analysts also appear to have intrinsic herding behaviour. Finally, analysts' earnings forecasts are more accurate if they are (i) of firms with a modest difference in their market and book value of equity (ii) adjusted to include inter-industry linkages information and (iii) from countries that utilise British-based accounting methods and have a good standing in the global competitiveness rankings of the World Economic Forum. The accuracy of earnings forecasts remains an uninvestigated avenue of enquiry in the South African literature.

3. DATA AND METHODOLOGY

Reported interim and final earnings figures and their respective earnings announcement dates were obtained from I-Net Bridge. The monthly consensus analysts' earnings forecasts for the current financial year were sourced from the I/B/E/S summary database. I/B/E/S, a product of the New York based brokerage firm of Lynch, Jones and Ryan, has available in both manual and computer-readable form, consensus earnings estimates for the current and next fiscal year. The I/B/E/S data is updated once a month with new forecasts. The original data contained monthly earnings forecasts of 167 firms listed on the JSE for the period January 1990 until April 2002. Unfortunately, not all the firms listed on the JSE are covered by analysts and those with analysts' earnings forecasts, only 30 have them at the start of 1990.

Out of the 167 firms for which analysts' earnings forecasts were available, 114 were considered in analysing the accuracy of these forecasts. Only those firms for which reported earnings data are available on the I-Net Bridge were retained. Companies that make quarterly earnings announcements were also disregarded[1]. Additionally, the sample period was restricted to 1990-2002 since analysts' earnings forecasts are only available from the year 1990. Moreover, to be included in the study, a firm must have monthly forecasts during the twelve months prior to the actual announcement.

Testing for the relative accuracy of analysts' earnings forecasts requires a benchmark for comparative purposes. This study opts to make use of a semi-annual time-series model, which has been adapted by Liu, Strong and Xu (2001) to the United Kingdom setting of interim and final earnings announcements after Foster, Olsen and Shevlin (1984) utilised it to estimate quarterly expected earnings previously in their research. Time-series models have often been used in prior research to provide earnings expectations. O'Brien (1988) describes univariate models as a common means of generating earnings expectations with relative ease and simplicity.

Applied to a semi-annual structure of earnings announcement, the model becomes:

$$E\left[X_{jt}\right] = \delta_j + X_{jt-2} + \phi_j\left(X_{jt-1} - X_{jt-3}\right) \qquad \ldots (1)$$

where X_{jt} = half-year earnings of the j th firm in period t and δ_j is a drift term. Equation (1) is calculated for each share successively over the sample period, using a minimum of nine semi-annual observations and adding to the number of observations as data become available. For example, the first half-year expected earnings for the firm for 1995 would equal (i) the firm's first half-year earnings in 1994, plus (ii) the change in the second half-year earnings for 1993 to the second half-year earnings of 1994 times the parameter ϕ_j, plus (iii) the parameter δ_j. The values of ϕ_j and δ_j are determined by regression analysis of the behaviour of earnings prior to the first half-year of 1995. As such, this study uses the above semi-annual time-series model, which is a first-order auto regressive process in first difference with a drift to generate earnings estimates.

Firms for which earnings forecasts are estimated under the time-series model are restricted to those which have at least ten semi-annual earnings per share figures available on the I-Net Bridge reported earnings database. Again, only shares of firms which announce semi-annual earnings are considered. Companies with quarterly or in some cases yearly announcement of earnings per share are discarded as this hampers the estimation of semi-annual earnings forecasts. For comparative purposes, earnings forecasts are estimated using the auto regressive model only as from the year 1990. Satisfying these criteria results in only 237 firms being retained, for which semi-annual earnings forecasts are estimated. Note that the sample of firms for which earnings forecasts are estimated by the time-series model is larger than that of the forecasts made by analysts.

A breakdown of the number of firms for which analysts' earnings forecasts are observed at the end of each year is provided in Table 1. Similarly, the number of firms in each year for which earnings forecasts are estimated using the auto regressive time-series model is shown.

Table 1 shows that in the early 1990s only a few firms were subject to analysts' earnings forecasts. In the late 1990s the number of firms with analysts' earnings forecasts more than doubled, and in the year 2001, 119 firms had analysts' earnings forecasts. Likewise, the number of firms for which earnings are econometrically estimated increased considerably from 88 in 1990 to 208 in 2001. The availability of at least ten semi-annual earnings per share figures from the I-Net Bridge reported earnings database for more firms in the 1990s explains the increase.

Past studies have widely used two average error measures in assessing the accuracy of earnings forecast: the average absolute percentage error of the form $\frac{\left|Y_{jt}^s - Y_{jt}^a\right|}{Y_{jt}^a}$, and the average square percentage error $\frac{\left(Y_{jt}^s - Y_{jt}^a\right)^2}{Y_{jt}^a}$, where Y_{jt}^s and Y_{jt}^a are the predicted and realised earnings variables for firm *j* respectively. Which of the error measures is selected may not be important because of the very similar information content contained within the measures. This study opts to make use of the average (mean) absolute percentage error measure in assessing the accuracy of earnings forecasts.

Theil (1966) proposed the U statistic for the evaluation of economic forecasts. Some studies have relied exclusively on Theil's U for evaluating analysts' forecasts. Theil's U statistic has been improved over time and this study prefers to use the more sophisticated Theil's inequality coefficient, which is defined as:

$$U = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(Y_t^s - Y_t^a\right)^2}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(Y_t^s\right)^2} + \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(Y_t^a\right)^2}}$$

where, Y_t^s = forecasted value of earnings

Y_t^a = actual value of earnings

T = number of periods

[1]Many mining companies in South Africa have the norm of reporting quarterly earnings.

Table 1: Number of firms with earnings forecasts for each year from January 1990 until April 2002

Year ending:	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
Analysts' earnings forecasts:	30	31	39	39	46	53	60	64	84	97	113	119	38
Earnings forecasts from time-series model:	88	99	121	140	150	154	163	167	166	171	189	208	144

The number of firms with analysts' earnings forecasts as well as the number of firms for which earnings forecasts have been estimated using a first-order auto regressive time-series model are shown. The year 2002 reflects analysts' earnings forecasts until the 30th of April.

The numerator of U is the RMS (root-mean-square) forecast error and the scaling of the denominator will always result in U falling between 0 and 1. As such, Theil's inequality coefficient measures the RMS error in relative terms. Comparing U between forecasting models provides a way of determining the relative accuracy of each model, where U=0 will imply a perfect fit while U=1 indicates that the predictive performance of the model is as bad as it could possibly be.

Theil's inequality coefficient can be decomposed into the bias (U^M), the variance (U^S) and the covariance (U^C) proportions of U respectively. The decomposition of Theil's inequality coefficient provides a powerful means of analysing each component of the error in assessing the relative accuracy of the analysts' earnings forecasts and the forecasts estimated using the first-order auto regressive model. The proportions of the inequality can be defined as follows:

$$U^M = \frac{\left(\bar{Y}^s - \bar{Y}^a\right)^2}{\left(\frac{1}{T}\right)\sum\left(Y_t^s - Y_t^a\right)^2}$$

$$U^S = \frac{\left(\sigma_s - \sigma_a\right)^2}{\left(\frac{1}{T}\right)\sum\left(Y_t^s - Y_t^a\right)^2}$$

$$U^C = \frac{2(1-\rho)\sigma_s\sigma_a}{\left(\frac{1}{T}\right)\sum\left(Y_t^s - Y_t^a\right)^2}$$

where $\bar{Y}^s$, $\bar{Y}^a$, σ_s and σ_a are the means and standard deviations of the earnings forecasts and the actual earnings respectively, and ρ is their correlation coefficient.

The bias proportion (U^M) is an indication of the systematic error, since it measures the extent to which the average values of the simulated and actual series deviate from each other. Whatever the value of the inequality coefficient U, it is hoped that U^M will be close to zero. The variance proportion (U^S) indicates the ability of the model to replicate the degree of variability in the variable of interest. If U^S is large, it means that the actual series has fluctuated considerably while the simulated series shows little fluctuation, or vice versa. Finally, the covariance proportion (U^C) measures the unsystematic error. It represents the remaining error after deviations from average values have been accounted for. Since it is unreasonable to expect predictions to be perfectly correlated with actual outcomes, this component of error is less worrisome than the other two. Since the bias, the variance and the covariance are just proportions of the U value, this implies that $U^M+U^S+U^C=1$.

The empirical analysis begins with a comparative investigation of the accuracy of analysts' earnings forecasts as the announcement date approaches. It is presupposed that as the earnings announcement date approaches, analysts should be able to provide forecasts that are more accurate since the information on which they base their forecasts becomes more timely. The absolute percentage error is computed for each consensus analysts' earnings forecast (annual) for different horizons prior to the earnings being announced. Then, the average absolute percentage error for each horizon is calculated and the pattern in forecast accuracy of analysts is investigated. A n-month time or forecast horizon represents a period of n months prior to the earnings announcement date, with the exception of the 12-month time horizon. It is observed that analysts' consensus earnings forecasts for certain firms are only updated to reflect the next announcement within a period of 1-3 months since the last announcement was made. As such, the 12-month time horizon represents only the updated analysts' earnings forecasts. In addition, Theil's inequality coefficient is computed for each of the forecast horizons and its decomposition allows the analysis of each component of the forecast error as the earnings announcement date approaches.

For the purpose of testing for their relative accuracy, the relevant set of analysts' consensus earnings forecasts is compared to earnings forecasts estimated by the time-series model. In order to maintain consistency in our comparison, the semi-annual earnings estimated by the time-series model are utilised to obtain annual forecasts. To calculate the forecast of the annual earnings per share using the semi-annual earnings estimated by the time-series model, the first actual semi-annual earnings per share of the year is added to the estimated second semi-annual forecast[2]. A sample of 669 earnings forecasts of analysts were considered, whereas 1693 annual earnings forecasts were estimated under the first-order auto regressive model. This full set of earnings forecasts is referred as *"Sample 1"*.

Since there are considerably more firms with earnings forecasts in the late 1990s under both models, the analysis has also been conducted on the sub period which is restricted from the year 1997 to the year 2001 (referred as *"Sample 2"*). This resulted in a total of 419 earnings forecasts of analysts that are considered and 779 earnings forecasts of firms estimated using the first-order auto regressive model.

Finally, 460 earnings forecasts of analysts were matched up with 460 econometric earnings forecasts of the same announcement events. This set of matched earnings forecasts is referred as *"Sample 3"*. This sample represents the union of the sets of 669 earnings forecasts of analysts (sample 1) to the 1693 annual earnings forecasts (sample 1) estimated by the time-series model.

In summary, three samples (Sample 1, Sample 2 and Sample 3) are considered in comparing the accuracy of analysts' earnings forecasts and those estimated using the first order auto regressive time-series model. Each error measure (average absolute percentage error and Theil's inequality coefficient) is calculated for the three samples described above and for each of the two earnings forecast approaches (analysts' earnings forecasts and forecasts estimated using the time-series model).

4 RESULTS

Table 2 displays the pattern of increasing forecast accuracy observed in analysts' earnings forecasts as the reporting date approaches. Both measures of error decline uniformly as the announcement date approaches. The average absolute percentage error, which amounts to 23,62% 12-month prior to the reporting date, decreases to 16,66% in the 6-month horizon and further to 7,95% 1-month prior to the reporting date. Theil's inequality coefficient, for the 12,6 and 1-month earnings forecast horizon gradually declines from 0,17 to 0,1 and 0,07 respectively. This pattern of convergence towards the announced earnings per share number is consistent with either the information on which their forecasts are based becoming more accurate or the incorporation of some new information by analysts relevant to the predicted earnings per share over the course of the year. This finding corresponds to the pattern that Crichfield, Dyckman and Lakonishok (1978) and O'Brien (1988) find in their respective research.

In Table 3, the bias (U^M), the variance (U^S) and the covariance (U^C) components of the forecast error for each of the forecast horizons are obtained by the decomposition of Theil's inequality coefficient. It is noticed that the bias (U^M) proportion in the analysts' earnings forecasts initially increases from 0,16% in the 12-month forecast horizon to 0,58% in the 6-month forecast horizon, before decreasing considerably to a state of no systematic error at all in the 1-month forecast horizon. In other words, as the announcement date approaches, the extent to which the average value of analysts' earnings forecasts deviates from the average value of the actual earnings diminishes. Although there are grounds to suggest that over-optimism is inherent in analysts' earnings forecasts, it appears to fade away as the announcement date approaches. This observation is further supported in considering the declining mean percentage forecast error as the earnings announcement date approaches. The mean percentage forecast error at the 12, 6 and 1-month horizon is 9,40%, 6,46% and –1,85% respectively. Although the 1-month mean percentage forecast error is negative, it is not significant enough to affect the above implication.

As the announcement date is approached, the variance (U^S) proportion of Theil's inequality coefficient is found to gradually decline. Table 3 shows that the variance (U^S) proportion decreases from 25,54% and 6,27% in the 12 and 6-month forecast horizon respectively to 1,20% in the 1-month forecast horizon. This implies that analysts demonstrate greater ability to replicate the degree of earnings variability in their forecasts as the announcement date approaches.

Therefore, as analysts' earnings forecasts become more accurate, i.e. Theil's U becomes smaller, the proportions of the error representing the systematic bias (U^M) and the level of variability (U^S) eventually decrease. This implies that analysts' earnings forecasts become increasingly rational as the earnings announcement date approaches. More precisely, analysts' earnings forecasts display the highest degree of rationality one month prior to earnings announcement. Figure 1 provides a graphical display of the trend in Theil's inequality coefficient and its characteristic sources as the announcement date approaches. To be noted that the characteristic sources of Theil's inequality coefficient in the 1-month forecast horizon approach largely the ideal distribution of inequality of the three sources, i.e. $U^M = U^S = 0\%$ and $U^C = 100\%$.

As mentioned earlier, three samples were considered whereby in each one the relevant set of analysts' earnings forecasts, with a 6-month horizon, was compared to the estimated earnings forecasts from the

[2]Since semi-annual realised earnings have been used to compute the semi-annual forecasts from the time-series model and these forecasts do not change until the next realised semi-annual earning is known, it is assumed that the computed semi-annual forecasts have a 6-month forecast horizon.

auto regressive time-series model. Table 4 summarises the average absolute percentage error under each of the three samples for both the analysts' earnings forecasts and the forecasts estimated using the time-series model. The mean forecast value and the mean actual value are also disclosed for each earnings forecasts model under the three samples.

The results tabulated reveal that analysts' earnings forecasts are on average more accurate than earnings forecasts estimated by the time-series model. In the first sample considered, over the years 1990-2002, the average absolute percentage error reflected by analysts' earnings forecasts is 16,66%, compared to a considerably higher 98,96% achieved by the earnings forecasts which were estimated by the first-order auto regressive model over the same years. The notably higher level of error computed for the time-series model, which reflects very poor performance, can be partially explained by the fact that 1693 earnings forecasts were used for the time-series model compared to a mere 669 analysts' earnings forecasts.

Table 2: The trend of the error in analysts' earnings forecasts as the earnings announcement date approaches

Time horizon:	12-month	6-month	5-month	4-month	3-month	2-month	1-month
Mean forecast error (%)	9,40	6,46	4,65	2,27	0,85	-0,25	-1,85
Mean absolute percentage error (%)	23,62	16,66	14,29	11,75	9,81	9,16	7,95
Theil's inequality coefficient (U)	0,17	0,1	0,09	0,08	0,08	0,07	0,07

A 1-month time horizon represents a period of 1 month prior to the earnings announcement date. The mean absolute percentage error and Theil's inequality coefficient are calculated for each time horizon prior to the announcement date, from the year 1990 until the year 2002. Theil's inequality coefficient measures the RMS (root-mean-square) in relative terms, where U=0 will indicate a perfect fit while U=1 will imply that the model is as bad as it could possibly be. Sample 1, which has 669 analysts' earnings forecasts is used.

Table 3: Decomposed Theil's inequality coefficient of the analysts' earnings forecasts as the earnings announcement date approaches

Time horizon:	12-month	6-month	5-month	4-month	3-month	2-month	1-month
U	0,17	0,10	0,09	0,08	0,08	0,07	0,07
U^M	0,16%	0,58%	0,50%	0,42%	0,24%	0,04%	0,00%
U^S	25,54%	6,27%	3,90%	2,03%	1,29%	1,62%	1,20%
U^C	74,46%	93,31%	95,76%	97,70%	98,62%	98,49%	98,95%

A 1-month time horizon represents a period of 1 month prior to the earnings announcement date. U is Theil's inequality coefficient and U^M, U^S and U^C are the bias, the variance and the covariance proportions of U respectively. Theil's inequality coefficient U is decomposed into its characteristic sources for each horizon prior to the announcement date, from the year 1990 until the year 2002. Sample 1, which has 669 analysts' earnings forecasts is used.

Table 4: Comparison of the average absolute percentage error between analysts' earnings forecasts and forecasts estimated using a time-series model (6-month time horizon)

Sample:	1 (1990-2002)		2 (1997-2001)		3 (1990-2002)	
Model:	**Analysts**	**Time-series**	**Analysts**	**Time-series**	**Analysts**	**Time-series**
Mean absolute percentage error (%)	16,60	98,96	9,53	65,81	11,79	14,59
Mean forecast value (cents)	225,90	124,85	241,74	148,91	247,47	248,48
Mean actual value (cents)	218,95	125,74	240,72	148,28	246,40	246,66

In calculating the Mean absolute percentage error in the earnings forecasts provided by analysts and estimated using the first order auto regressive time-series model, three samples are considered. Sample 1, with 669 analysts' earnings forecasts and 1693 earnings forecasts estimated using a time-series model, is for the years 1990-2002 and is the original sample resulting from the sample requirements. Sample 2, with 419 analysts' earnings forecasts and 779 earnings forecasts estimated by the time-series model, concentrates on the years 1997-2001 and is considered since more firms had an analysts' earnings forecast over this period. And finally, sample 3 has 460 analysts' earnings forecasts and 460 estimates using the time-series model. Sample 3 is constructed with the aim of comparing similar number of earnings forecasts, pertaining to the same firms and earnings announcement dates. The mean forecast value and the mean actual value are the arithmetic means of all the forecast earnings and reported earnings considered under each model and for each sample. The comparison is performed using earnings forecasts estimated 6 months prior to the announcement date.

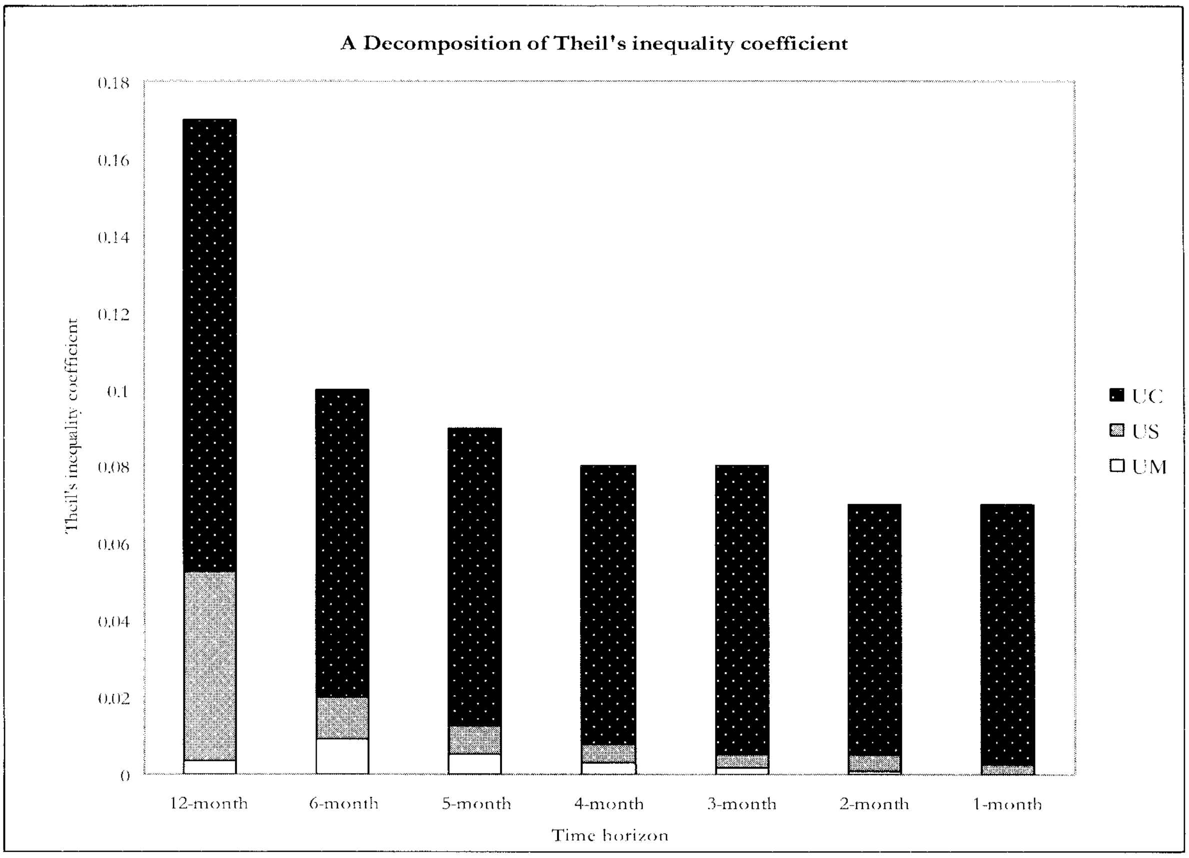

Figure 1: The trend of the decomposed Theil's Inequality Coefficient as the earnings announcement date approaches

A 1-month time horizon represents a period of 1 month prior to the earnings announcement date. Sample 1, which has 669 analysts' earnings forecasts is used. Theil's inequality coefficient U is decomposed into its characteristic sources for each horizon prior to the announcement date, from the year 1990 until the year 2002. U^M, U^S and U^C are the bias, the variance and the covariance proportions of U respectively. The proportion of U^M, U^S and U^C is graphically adjusted in each horizon so that the trend can be viewed successfully.

Restricting the time horizon over the period where more firms had earnings forecasts (i.e. Sample 2 with forecasts from years 1997 to 2001) shows little change from the previous results. In this case, the analysts' earnings forecasts reflect an average absolute percentage error of 9,53% compared to the figure of 65,81% that is observed in the earnings forecasts estimated by the time-series model. This again implies that analysts provide more accurate forecasts than the time-series model.

When the accuracy is evaluated using matched observations (Sample 3), the forecasts made by analysts again show a lower average absolute percentage error than that returned by the first-order auto regressive model (11,79% vs. 14,59%). This confirms that analysts' earnings forecasts are more accurate than those estimated by the time-series model. Interestingly, matching the number of observations in each model has resulted in bringing the level of error more in line, although analysts still outperform the time-series model. The lower level of error calculated for the time-series model is partly due to the removal of highly dispersed earnings forecasts with regard to the actual mean values of earnings.

As a means of corroborating the result discussed above, the relative accuracy of the two sources of earnings forecasts is further evaluated using Theil's inequality coefficient (U). Table 5 displays over each period, Theil's inequality coefficient for analysts' earnings forecasts and forecasts estimated by the time-series model. The bias (U^M), the variance (U^S) and the covariance (U^C) proportions of U for each model are compared over each sample.

Theil's inequality coefficient also reveals that the earnings forecasts estimated by the time-series model lead to more error than analysts' earnings forecasts. In each of the samples considered, the analysts' earnings forecasts achieved a less significant value of U relative to the value of U attained by the time-series model. Theil's inequality coefficient was thereafter decomposed into its respective bias, variance and covariance proportions and compared across the two forecasting approaches.

The bias proportion (U^M) is larger for the analysts' earnings forecasts than for the time-series model. This is the case within each sample. Although, for the analysts' earnings forecasts, the 0,01% of bias proportions is acceptable in sample 2 and 3, a 0,58% of bias proportion in sample 1 is somewhat high[3]. But, it was observed earlier from Table 3 that as the reporting date approaches, the bias component in the analysts' earnings forecasts decreases considerably from 0,58% in the 6-month horizon to no systematic bias at all in the 1-month horizon. The time-series model achieves the ideal proportion of bias (close to 0%) and this may be explained by the fact that it is a mechanical model.

The analysts' earnings forecasts resulted in lower values of the variance (U^S) proportion in each of the three samples, i.e. 6,27% vs. 28,09%, 9,25% vs. 23,60% and 7,93% vs. 39,24% respectively. Finally, the value of the covariance proportion (U^C) for the analysts' earnings forecasts is closer to 100% than for the time-series model and this observation is true in each of the three samples. Indeed, for any value of U > 0, the ideal distribution of inequality over the three sources is $U^M = U^S = 0\%$ and $U^C = 100\%$.

As such, except for the first sample in which a considerably high systematic bias level was detected, analysts' earnings forecasts appear to be derived from a better model than earnings forecasts estimated using the first order auto regressive time-series model.

Coupled with the above assessment, a popular method of evaluating a forecast is to regress the actual changes to forecast changes. This approach also breaks down the MSE (mean square error) of the forecast into three parts, namely, the bias proportion (reflected by the extent to which the intercept term is non-zero), the regression proportion (reflected by the extent to which the slope coefficient differs from one) and the disturbance proportion (measures by the variance of the residuals from the regression analysis). It is interesting to note the similarity of these three parts of the MSE to the decomposed proportions of Theil's inequality coefficient. Regressing the percentage growth in analysts' 12, 6 and 1-month earnings forecasts against the percentage growth in reported earnings results in declining values of the intercept (approaching zero) and values of the slope closer to one as the earnings announcement date gets closer. This is evidence of increasing accuracy as the earnings announcement date approaches.

The percentage growth in the forecasts estimated by the auto regressive time-series model is also regressed against the percentage growth in reported earnings. The intercepts and slope coefficients of the percentage growth in analysts' 6-month earnings forecasts and the percentage growth in the forecasts estimated by the auto regressive time-series model are tested to see how different they are from zero and one respectively. Testing the values of the intercept in each case reveals that they are significantly different from zero. Similarly, testing for the slope coefficients shows that they are significantly less than one in each scenario. The implication is that both analysts and the auto regressive time-series model used fail to significantly forecast the exact change in the reported earnings. It is difficult to differentiate which is a better predictor using regression analysis.

The results reported in Table 6 focus on the relative frequency of cases of underestimation or overestimation in the number of analysts' earnings forecasts. Within each forecast horizon investigated there are more overestimates than underestimates of analysts' earnings forecasts. In addition, as the forecast horizon decreases, the number of overestimated and underestimated forecasts converges, implying that on average, as overestimates cancel underestimates, analysts' forecasts tend to become more accurate. This observation confirms that the over-optimism in analysts' earnings forecasts weakens as the reporting date is approached. It also confirms the pattern of increasing accuracy in analysts' earnings forecasts as the earnings announcement date approaches.

5. CONCLUSION

The investigation of the accuracy of security analysts' earnings forecasts of firms listed on the JSE demonstrates that analysts display a pattern of increasing accuracy as the announcement date approaches. A declining trend in the level of error, using both the average absolute percentage error and Theil's inequality coefficient methods, is observed. A 1-month forecast horizon displays a 7,95% of average absolute percentage error and 0,07 Theil's inequality coefficient, while a 6-month horizon results in 16,66% average absolute percentage error and 0.1 Theil's inequality coefficient. The 12-month horizon depicts a 23,62% of average absolute percentage error and 0,17 Theil's inequality coefficient. This result is consistent with findings of prior international research.

[3]According to common convention, a U^M value greater than 0.1% or 0.2% is considered to be high [Pindyck and Rubinfeld (1998)].

Table 5: Comparison of Theil's inequality coefficient between analysts' earnings forecasts and forecasts estimated under a time-series model (6-month time horizon)

Sample:	1 (1990-2002)		2 (1997-2001)		3 (1990-2002)	
Model:	Analysts	Time-series	Analysts	Time-series	Analysts	Time-series
U	0,1000	0,2141	0,0970	0,1379	0,1014	0,1104
U^M	0,58%	0,00%	0,01%	0,00%	0,01%	0,02%
U^S	6,27%	28,09%	9,25%	23,60%	7,93%	39,24%
U^C	93,31%	71,99%	90,98%	76,53%	92,27%	60,95%

U is Theil's inequality coefficient and U^M, U^S and U^U are the bias, the variance and the covariance proportions of U respectively. Theil's inequality coefficient is computed for the analysts' earnings forecasts and forecasts estimated using a first order auto regressive time-series model. Sample 1, with 669 analysts' earnings forecasts estimated using a time-series model, is for the years 1990-2002 and is the original sample resulting from the sample requirements. Sample 2, with 419 analysts' earnings forecasts and 779 earnings forecasts estimated by the time-series model, concentrates on the years 1997-2001 and is considered since more firms had an analysts' earnings forecast over this period. And finally, Sample 3 has 460 analysts' earnings forecasts and 460 estimates using the time-series model. Sample 3 is constructed with the aim of comparing similar number of earnings forecasts, pertaining to the same firms and earnings announcement dates.

Table 6: Relative frequency of cases of underestimation or overestimation in analysts' earnings forecasts

Time horizon:	12-month		6-month		5-month		4-month		3-month		2-month		1-month	
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%
Forecast>Actual	384	57,4	371	55,5	371	55,5	370	55,3	366	54,7	355	53,1	334	49,9
Forecast<Actual	283	42,3	296	44,2	295	44,1	295	44,1	299	44,7	310	46,3	329	49,2
Forecast=Actual	2	0,3	2	0,3	3	0,4	4	0,6	4	0,6	4	0,6	6	0,9
Total	669	100	669	100	669	100	669	100	669	100	669	100	669	100

A 1-month time horizon represents a period of 1 month prior to the earnings announcement date. Sample 1, which has 669 analysts' earnings forecasts for the years 1990-2002, is used for this analysis. The figures in the column entitled No. represent the number of overestimates or underestimates whereas the percentages of the number of overestimates or underestimates are exhibited under the column entitled %.

In addition, Theil's inequality coefficient is decomposed into its bias, variance and covariance components. Analysing each element of error in Theil's inequality coefficient shows that the systematic bias in analysts' earnings forecasts initially increases before declining considerably as the earnings announcement date approaches. More precisely, the 1-month forecasts prior to the announcement date have no significant systematic bias, although the 12 and 6-month forecasts reflect a mild level of bias, i.e. 0,16% and 0,58% respectively. The mean percentage forecast error declines as the earnings announcement date approaches from 9,40% and 6,46% in the 12 and 6-month horizons to –1,85% in the 1-month horizon. The implication is that although over-optimism is inherent in analysts' earnings forecasts, it fades away as the reporting date approaches. It is noticed that the variance component of Theil's inequality coefficient decreases as the earnings announcement date approaches. Moreover, it has been observed that earnings forecasts produced by analysts are more accurate than those estimated using a first order auto regressive time-series model. A possible area for further research is to attempt to estimate superior econometric models that are able to augment the explanatory power of analysts' earnings forecasts.

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