Heuristics of Representativeness, Anchoring and Adjustment, and Leniency: Impact on Earnings' Forecasts by Australian Analysts

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This paper investigates analysts' earnings forecasts for equities listed on the Australian Stock Exchange. Recent research shows that heuristics may influence analysts' decision making (Amir and Ganzach 1998); however, most of the evidence is limited to US and European markets. We provide further international evidence by examining the power of representativeness, anchoring and adjustment, and leniency heuristics on analysts' forecast errors using Australian data. Our findings show that analysts in Australia make forecasts optimistically—supporting the leniency hypothesis. We also find that analysts tend to overreact when forecast revisions and changes are positive and underreact when forecast revisions and changes are negative.

Introduction

This paper examines how analysts react to new information and use different heuristics in their decision making. Heuristics are rules of thumb or strategies that often deviate from normative statistical rules but enable individuals to simplify complex tasks of assessing subjective probabilities.[1] In this paper we test if the heuristics

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[1]Shanteau (1989) reviews the concept of heuristics in his discussion of limited rationality. Tversky and Kahneman (1974) also show that to simplify complex tasks of assessing

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of representativeness, anchoring and adjustment, and leniency impact on errors in analysts' forecasts of earnings using Australian data.

The accuracy of analysts' forecasts has been subject to much debate in the economic literature (for example, Cragg and Malkiel, 1968). Typically, analysts review financial information provided by companies and spend significant effort in forecasting future earnings. Despite this, it is not possible to obtain and process all the relevant information before making a forecast decision (Duru and Reeb, 2002).

A large body of research suggests analysts are overly optimistic in their predictions. For example, Crichfield et al. (1978) document positive analyst forecast errors in the 1970s. This tendency for observed positive analyst forecast errors has persisted in the 1980s, 1990s, and early 2000s (O'Brien, 1988; Butler and Lang, 1991; Brous, 1992; Brous and Kini, 1993; Kang et al., 1994; Duru and Reeb, 2002; Beckers et al., 2004; and Ding et al., 2004). To explain this positive forecast bias Schipper (1991) argues that analysts' forecasts are influenced by their incentives. Analysts are cognisant that their forecasts are biased upwards, but they wish to maintain good relationships with managers of the companies they follow. Hong et al. (2000) suggest that analysts' concerns about their careers influence their forecasts. Forecasts from inexperienced analysts are more likely to be close to consensus analysts' forecasts and less timely.[2]

Researchers also have found that analysts are subject to underreaction in their forecast modifications of earnings for companies (Mendenhall, 1991; Mande and Kwak, 1996; Ramnath, 2002; Constantinou et al., 2003). Chan et al. (1996) find that although analysts incorporate earnings news in their forecasts, earnings revisions are often slow or delayed, especially for stocks with earnings well below expectations. Similar to Schipper (1991), Chan et al. attribute their results to analysts' reluctance to alienate management.

In contrast, other research suggests that analyst tend to overreact in their predictions of future earnings. For instance, DeBondt and Thaler (1985) find evidence that investors tend to overreact to unexpected and dramatic news events. In a subsequent paper DeBondt and Thaler (1987) argue that mean reversion in stock prices is consistent with evidence that investors overreact to new information.[3]

To explain the conflicting empirical evidence of analysts' under- and overreaction in their forecasts of earnings, Abarbanell and Bernard (1992) argue that inefficiencies in analysts' forecasts can be explained partially by anomalous stock price behavior. Easterwood and Nutt (1999) suggest that negative earnings informa-

subjective probabilities and predicting values, people usually rely on a limited number of heuristic principles.

[2]Individual characteristics also may systematically influence the forecast accuracy of analysts' earnings. For instance, Clement (1999) suggests that analysts' experience, employer size, and the number of firms and industries followed by the analyst can impact their forecast accuracy of earnings.

[3]Also see De Bondt and Thaler (1990) and Bauman et al. (1999).

tion results in underreaction by analysts while positive earnings information results in overreaction, suggesting analysts are systematically overly optimistic.

Related research by Amir and Ganzach (1998) suggest heuristics or peoples' adaptive strategies to cope with limitations on their ability to process information may explain both analysts' overreaction and underreaction in their earnings forecasts. The three heuristics examined by Amir and Ganzach are the representativeness heuristic, the anchoring and adjustment heuristic, and the leniency heuristic. Under the representativeness heuristic individuals predict outcomes that appear most representative of the evidence (Kahneman and Tversky, 1972, 1973).[4] Amir and Ganzach (1998) argue that this leads to extreme predictions. Under the anchoring and adjustment heuristic individuals anchor on prior outcomes (initial values) or starting points.[5] Under the leniency heuristic individuals are more likely to attribute desirable traits to things they know or like (Schriesheim et al., 1979) and usually make overly optimistic predictions.

This paper replicates the methodology of Amir and Ganzach (1998) to investigate if the heuristics of representativeness, anchoring and adjustment, and leniency can explain forecast errors by Australian analysts. Specifically, we seek to answer the following research questions:

1. Do Australian analysts forecast future earnings optimistically?
2. How do Australian analysts react to new information when using different anchors?
3. Does forecast quality decrease as the forecast horizon increases?

The study of the Australian market is interesting for the following reasons. First, most research on the accuracy of analysts' forecasts of earnings relates to the US and European markets, and there is less evidence from markets outside these countries. Second, in the Australian market companies only are required to report semi-annual profit and loss announcements, compared to the US that has quarterly reporting requirements. Australian companies also must comply with Australian GAAP that may use different levels of accruals, accounting policies, and different choices of accounting methods compared to US GAAP. In this respect Alford et al. (1993) concludes that Australian GAAP generated information is at least as informative and timely as US reported accounting earnings.

Third, since 1994 the Australian market has adopted a continuous disclosure regime. Under the Australia's continuous disclosure regime, the Australian Stock

[4]Kahneman and Tversky (1972, 1973) suggest that representativeness refers to making an uncertain judgment on the basis of the degree to which (1) it is similar in essential properties to its parent population; and (2) reflects the salient features of the process by which it is generated.

[5]Tversky and Kahneman (1974) argue that anchoring and adjustment involves starting from an initial value that is adjusted to yield the final solution. They also find that the starting point may be suggested by the formulation of the problem or the result of a partial computation and that adjustments are typically insufficient.

Exchange (ASX) listing Rule 3.1 provides that listed companies immediately must disclose to the market any information that likely would have a material effect on the company's share price. The ASX's listing rules have statutory backing through the Corporations Law Reform Act 1994 and the Corporations Act 2001, and there are significant civil and criminal penalties for breach of the requirements to disclose price sensitive information in a timely manner. The Surveillance Division of the ASX monitors compliance by companies of their continuous disclosure obligations and also monitors market activity for signs of unusual trading and volume disclosure.

There are only limited exemptions to the continuous disclosure requirements under ASX Listing Rule 3.1.[6] The rules are designed to improve the fairness and efficiency of the Australian stock market by ensuring that all investors have equal access to all available information in making their investment decisions (Neagle and Tsykin, 2001). Continuous disclosure of price sensitive information may improve analysts' forecasts of earnings particularly as the actual company earnings announcement day approaches. A study by Higgins (1998) found that, for seven countries that included US, Japan, and several European countries,[7] analysts' forecasts of earnings were more accurate and less optimistic when relatively more disclosure was mandated.

Our study on the accuracy of analysts' forecasts of earnings therefore will be of interest to those markets that do not have a continuous disclosure regime. For instance, the US market has not adopted a continuous disclosure regime; instead, US companies must comply with Regulation Fair Disclosure (Reg FD). This prohibits US companies from disclosing price sensitive information to professional financial analysts without simultaneously releasing the same information to the market. An interesting study by Heflin et al. (2003) reports no reliable evidence of any change in analysts' forecast errors or forecast dispersion post the introduction of Reg FD. Bailey et al. (2003), however, report an increase in analysts' forecast dispersion following the introduction of Reg FD, suggesting that analysts have greater difficulty in forming forecasts.

Similar to research by Aitken et al. (1996) and Ho (1996) the results for our sample of analysts' forecast errors show that Australian analysts have a tendency to be too optimistic. We also find that analysts tend to overreact when forecast revisions and changes are positive and underreact when forecast revisions and changes are negative. Overall our evidence is broadly consistent with analysts being subject to the anchoring and adjustment and leniency heuristics.

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[6]These exemptions are designed to protect legitimate commercial interests of listed companies and apply when (1) a reasonable person would not expect the information to be disclosed; (2) the information is confidential, and (3) at least one of the following holds: it would be a breach of the law to disclose the information; the information comprises matters of supposition; the information is generated for internal management purposes of the entity; or the information is a trade secret.
[7]These were the United Kingdom, Netherlands, France, Germany, and Switzerland.

Data, Hypotheses & Methods

Data

Data are obtained from the Institutional Brokers Estimate System (IBES) database. Our sample comprises all Australian companies recorded on the IBES database over the period 1993 to 2004 with at least two years of earnings data and a minimum of one analyst following. The variables collected included the IBES industry company classification, market capitalization, mean and median monthly annual earnings' forecasts by analysts for the year, the reporting date of the actual annual profit announcement, and the actual annual earnings per share ($ value). We require at least two years of earnings data to calculate the forecast changes in earnings by analysts used in our empirical analysis.

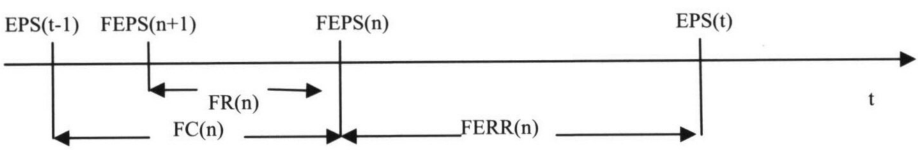
Following, Amir and Ganzach (1998) we define:

- EPS(t) – the actual $ value of the annual earnings per share in year t;
- FEPS(n) – the median analyst forecast of EPS(t) n months before EPS(t) was actually announced (n = 1,2 … 11);
- FERR(n) – the forecast error n months prior to the earnings announcement month of EPS(t), i.e., FEPS(n) – EPS(t);
- FC(n) – the forecast change n months prior to the earnings announcement month of EPS(t), i.e., FEPS(n) – EPS (t-1);
- FR(n) – the forecast revision n months prior to the earnings announcement month of EPS(t), i.e., FEPS(n) - FEPS(n+1).

Figure 1 shows the relationship between the above variables. For illustrative purposes we assume EPS(t) > FEPS(n) > FEPS(n+1) > EPS(t-1).

Figure 1—Relationship between $ Value of Annual Earnings per Share (EPS), Median Analysts' Forecast Earnings per Share (FEPS), Forecast Errors (FERR), Forecast Revisions (FR), and Changes (FC)

The time period equal to n is the number of months prior to the earnings announcement month of ESP(t).



For illustrative purposes we assume EPS(t) > FEPS(n) > FEPS(n+1) > EPS(t-1)

Table 1 provides a breakdown of the 1003 companies in the sample according to the IBES industry classification and the market capitalization of the companies in the fiscal year they first were included in the sample. The greatest number of companies in the sample were drawn from the finance, real estate and insurance sectors (225 companies) and from the steel, mining, forest products, miscellaneous materials, and chemicals sectors (191 companies). The mean (median) market capitalization of the

Table 1—Descriptive Statistics of the Sample of Australian Companies

Industry Classification	Number of Companies	Mean Market Capitalization ($Million)	Median Market Capitalization ($Million)	Max. Market Capitalization ($Million)	Min. Market Capitalization ($Million)
Finance, Financial Services, Real Estate, Insurance	225	575.1	229.5	20,786.7	4.6
Steel, Mining, Forest Products, Misc. Materials, Chemicals	191	595.5	176.8	8,465.0	2.5
Broadcasting, Publishing, Leisure, Tourism, Merchandising	167	361.4	97.7	10,567.8	1.5
Building Materials, Construction, Electrical and Engineering	88	419.9	115.0	6,220.2	6.6
Food, Beverage, Textiles, Recreation, Household	77	539.6	80.5	6,794.7	3.7
Healthcare, Biotechnology	64	170.2	97.4	1,386.4	6.9
Electronics, Data Processing	63	227.1	96.3	3,284.1	2.9
Energy, Oil, Energy Equipment	52	743.3	188.8	20,902.9	12.5
Telecommunications, Gas, Electricity	29	1,975.0	148.8	27,673.9	3.3
Automobiles, Appliances	21	153.3	47.8	793.3	9.4
Transportation	16	470.4	235.6	2,549.2	9.9
Miscellaneous	10	111.9	76.6	365.3	32.2
Total	1003	513.4	139.1	27,673.9	1.5

companies was $513.4 million ($139.1 million), with a maximum capitalization of $27,673.9 million and a minimum market capitalization of $1.5 million.

Table 2 provides descriptive statistics of the median and mean analysts' forecast errors, forecast revisions, and forecast changes. To mitigate the undue influence of outliers, we winsorize the sample by setting the upper and lower percentiles for each variable to the values of the first and 99th percentiles, respectively.[8] The mean (median) FERR is 0.040 (0.002), the mean (median) FR is -0.002 (0.000), and the mean (median) FC is 0.044 (0.016).

Hypotheses and Methods

Amir and Ganzach (1998) suggest that two main types of prior information are used when analysts forecast company earnings. These are their previous forecasts and the previously announced earnings. Analysts usually base their forecasts on this prior information set, combined with current (new) information predict future company earnings. Following, Amir and Ganzach (1998), we seek to investigate whether the pattern of analysts' forecast errors or the difference between forecast or actual earnings depends on (1) the sign (positive or negative) of the forecast modification (being either a forecast revision or a forecast change); and (2) the type of the prior information, i.e., whether it is a forecast revision or a forecast change.

[8] This is similar to the approach adopted in prior literature by Guay (1999), Core and Guay (1999) and Coles, Daniel and Naveen (2006). Amir and Ganzach (1998) delete observations in their paper that were in the upper or lower 1 percent of the variables' distribution.

Table 2—Descriptive Statistics of the Sample of Australian Analysts' Forecast Errors of Earnings (FERR), Forecast Revisions (FR), and Forecast Changes (FC)

	Number of Observations.	Min $	Max $	Mean $	Median $	25 Percentile $	75 Percentile $	Std. Deviation $
FERR	43,721	-0.340	1.426	0.040	0.002	-0.012	0.034	0.197
FR	36,701	-0.107	0.076	-0.002	0.000	-0.002	0.000	0.019
FC	36,088	-0.420	1.152	0.044	0.016	-0.004	0.052	0.176

The number of observations includes measures with a zero value. All figures are expressed in $ value
In the empirical analysis we only consider cases where FR and FC are other than zero

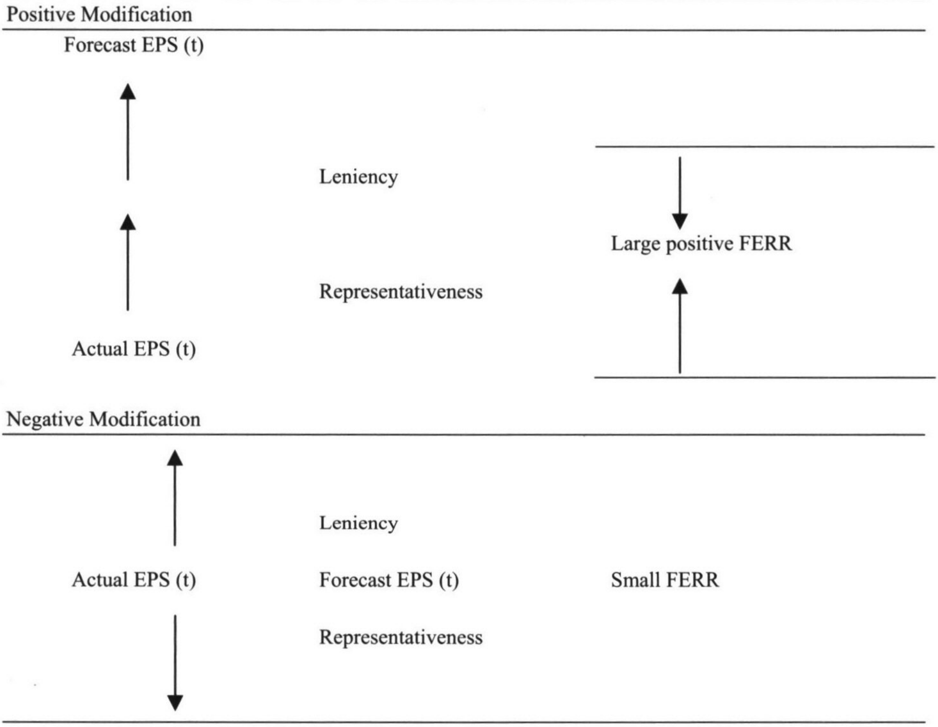
Figure 2 considers the impact of the representativeness and leniency heuristics on analyst forecast modifications.[9] When the forecast modification (i.e., either a forecast revision or a forecast change) is positive, the representativeness heuristic pushes analysts' forecast earnings above the actual earnings. Because the leniency heuristic also leads to optimism, it pushes analysts' forecast earnings even higher. The forecast error (FERR) is the total of these two effects, and it would be positive and large. In contrast, while leniency causes a positive error when the forecast modification is negative, representativeness leads to overreaction or analysts being too pessimistic in their earning forecasts. The forecast error is the difference between these two effects and thus the forecast error is smaller compared to those forecast errors with positive modifications. Amir and Ganzach (1998) suggest that under this joint effect of representativeness and leniency we would observe more positive forecast errors when there are positive forecast modifications compared to when there are negative forecast modifications.

If the anchoring and adjustment (instead of representativeness) and leniency heuristics govern forecast earnings by analysts, however, the predicted results would be the exact opposite. When the forecast modification is positive, leniency drives analysts to make forecasts higher than actual earnings. Anchoring and adjustment means analysts, however, put more weight or anchor on their prior earnings' forecasts and the prior announced earnings by the company. This joint effect leads to a small forecast error. (See Figure 3.) On the other hand, when the forecast modification is negative, both the leniency and anchoring and adjustment heuristics pushes forecast earnings higher than the actual earnings. In this context Amir and Ganzach (1998) suggest that there should be more positive forecast errors with negative forecast modifications compared to when there are positive forecast modifications.

Following, Amir and Ganzach (1998), we first divide the whole sample into two parts according to the sign of the forecast modifications by analysts and report the number of positive forecast errors in each group. Second, we undertake regression analysis using the following models:

[9]Also see Amir and Ganzach (1998, Figure 1, p. 335).

Figure 2—The Combined Effect of the Representativeness and Leniency Heuristics on Forecast Errors for Positive and Negative Forecast Modifications (Either a Forecast Revision or a Forecast Change)



$$\text{FERR}(n) = \alpha(n) + \beta(n)\text{FR}(n) + \varepsilon, \quad n = 1 \text{ to } 10 \tag{1}$$

$$\text{FERR}(n) = \alpha(n) + \beta(n)\text{FC}(n) + \varepsilon, \quad n = 1 \text{ to } 10 \tag{2}$$

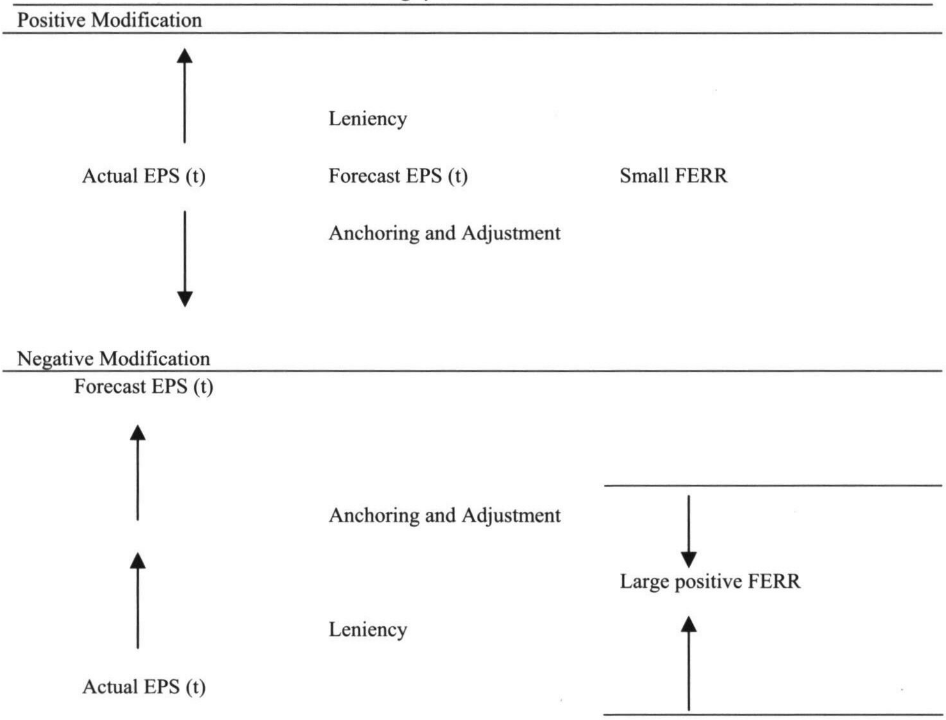
$$\text{FERR}(11) = \alpha(11) + \beta(11)\text{FC}(11) + \varepsilon \tag{3}$$

where n is the number of months prior to the annual earnings announcement by the company.

In equations (1) to (3) the intercept, $\alpha(n)$, is a measure of analysts' degree of optimism or pessimism. If it is positive, it means analysts' forecasts of earnings are more likely to exceed the actual earnings of the company and analysts are overly optimistic; if it is negative, it indicates that analysts are pessimistic.

The slope, $\beta(n)$, is a measure of analysts' tendency to under- or overreaction. A positive $\beta(n)$ implies overreaction due to analysts revising upwards their forecast modifications leading to positive forecast errors, while a negative $\beta(n)$ implies under-reaction. If the coefficients for both $\alpha(n)$ and $\beta(n)$ are zero and not significant, this indicates that analysts' earnings forecasts are without bias.

Figure 3—The Combined Effect of the Anchoring and Adjustment, and Leniency Heuristics on Forecast Errors for Positive and Negative Forecast Modifications (Either a Forecast Revision or a Forecast Change)



In equation (1) analysts' forecast errors are regressed against forecast revisions for the sample of companies over the periods n = 1 to 10 months. We also regress forecast errors separately for both positive and negative forecast revisions. This is to test if there is less overreaction with negative forecast revisions compared to positive forecast revisions.

In equation (2) analysts' forecast errors are regressed against forecast changes over the periods n = 1 to 10 months. DeBondt and Thaler (1990) and Amir and Ganzach (1998) argue that uncertainty is greater the longer the time horizon and this increases the level of any prediction bias. Hence, the degree of analysts' over- and underreaction and the level of optimism increase as the length of time horizon or n increases. Comparing the results in equations (1) and (2) also enables us to test if analysts use different heuristics in making forecast revisions and forecast changes. Amir and Ganzach (1998) argue analysts are more subject to the anchoring and adjustment heuristic with respect to forecast revisions as opposed to forecast changes.

Last, in equation (3) the forecast error is regressed against analysts' forecast change in month 11 prior to the annual earnings announcement. In period n = 11

Amir and Ganzach (1998) suggest that anchoring and adjustment will have a weaker effect on analysts' predictions and representativeness a stronger effect, given that analysts have not yet made a prediction of next years' earnings.

Empirical Findings

In this section we first examine the relationship between analysts' forecast revisions and forecast errors. We then examine the relationship between analysts' forecast changes and forecast errors.

Results for Forecast Revision

Nonparametric Results

Table 3 reports the mean and the percentage of positive analysts' forecast errors (FERR) when forecast revisions (FR) are *positive* (third and fourth columns) and when forecast revisions are *negative* (sixth and seventh columns). For positive forecast revisions and for periods n = 1 to 9, (i.e., one to nine months prior to the actual company earnings announcement date), there are fewer positive forecast errors than negative forecast errors. These results suggest that analysts are subject to anchoring and adjustment, and leniency. For example, at two months (n = 2) prior to the earnings release date, the percentage of positive (negative) forecast errors is 42.9 percent (57.1 percent), significantly different from 50 percent under the sign test. Only for the period n = 10 is the number of positive forecast errors (52.6 percent) greater than 50 percent (but not significant under the sign test). At n = 10 our results show that analysts may be subject to the representativeness heuristic as opposed to the anchoring and adjustment heuristic.

Table 3—Mean and Percentage of Positive Forecast Errors when Forecast Revisions are Positive and Negative

This table shows the mean and the percentage of positive forecast errors when forecast revisions (FR) are positive (FR > 0, columns 3-4) and when forecast revisions are negative (FR < 0, columns 6-7). We define forecast errors (FERR) as the difference between the actual $ value of earnings per share ("EPS") and the $ value of the forecast EPS

Months Prior to Earnings Release (n)	No. of Obs.	Mean FERR when FR > 0	FERR > 0 (%) when FR > 0	No. of Obs	Mean FERR when FR < 0	FERR > 0 (%) when FR < 0
1	984	0.0194	43.5%***	1150	0.0305	52.6%*
2	784	0.0140	42.9%***	1165	0.0279	52.2%
3	773	0.0124	44.0%***	1091	0.0348	55.1%***
4	785	0.0158	43.9%***	1131	0.0369	59.3%***
5	1062	0.0159	42.5%***	1276	0.0424	62.5%***
6	901	0.0069	42.6%***	1294	0.0458	63.5%***
7	733	0.0080	45.3%**	1067	0.0609	66.8%***
8	731	0.0175	46.9%*	1084	0.0578	65.3%***
9	802	0.0157	46.9%*	1095	0.0702	66.3%***
10	944	0.0336	52.6%	1015	0.0644	66.3%***

* Significant at the 10 percent level
** Significant at the 5 percent level
*** Significant at the 1 percent level

In contrast, when analysts' forecast revisions are negative, there are more positive analysts' forecast errors than negative forecast errors in all periods. For example, when n = 3 there are 55.1 percent positive forecast errors compared to 44.9 percent negative forecast errors, significantly different from 50 percent under the sign test. In general when forecast revisions are negative and the months prior to the earnings release (n) increases, there is a corresponding increase in the mean FERR and the percentage of positive analysts' forecast errors.

The mean FERR is also greater in each period n =1 to 10 when the forecast revisions are negative compared to the mean FERR when forecast revisions are positive.

Overall our results in Table 3 suggest analysts are subject to the anchoring and adjustment, and leniency heuristics. That is, when there is negative information, analysts are reluctant to revise their forecasts downwards as a result of the combined effect of anchoring on prior forecasts and analysts' tendency to leniency. This results in a greater likelihood of positive forecast errors. With good news and when analysts revise their earnings forecasts upwards, however, the anchoring and adjustment heuristic neutralizes the effect of the leniency heuristic—this leads to less positive and smaller forecast errors by analysts.

Regression Analysis

We next undertake regression analysis on the entire sample where forecast revisions are either positive or negative. Table 4 shows the regressions of forecast errors on forecast revisions for our sample. The table shows that all the intercept terms, α(n), are positive and significant at the 1 percent level which suggests that analysts are overly optimistic in their earnings forecasts. In general, the longer the time period (n) to the actual company earnings announcement date, the bigger is the intercept term α(n).[10] For example, one month before the company's earnings announcement date, α(1) is 0.0251 with a t-value of 7.38. Ten months before the earnings announcement date, α(10) is 0.0499 with a t-value of 10.39. Our findings suggest that the longer the prediction period prior to the earnings' announcement date, the greater is the tendency for analysts to be too optimistic.

Table 4 also indicates that analysts underreact in their forecast revisions by using prior forecast earnings as their anchors. All the slope coefficients, β(n)s, are negative and significant at the 5 percent level or better except β(1) and β(2). Our results suggest that as the actual company earnings announcement date approaches, analysts are more cognisant of potential biases in their forecasts. A possible reason is that companies may have announced their interim profits and are more likely to have released any price-sensitive information under the Australian continuous disclosure

[10]Note that FR(11) equals to FC(11) (Amir and Ganzach, 1998). Thus, we do the analysis on n = 11 separately in Tables 6 to 8.

Table 4—Regression Results of Forecast Errors on Forecast Revisions

In this table forecast errors (FERR) are regressed on forecast revisions (FR) n months prior to the earnings release. We test the model: FERR(n) = α (n) + β(n)FR(n) + ε. The model includes all observations where there was a positive or negative forecast revision. The values in parentheses are White's (1980) t-statistics

n	α	β	Adjusted R^2	Number of Observations
1	0.0251	-0.2393	0.002	2134
	(7.38)***	(-0.83)		
2	0.0201	-0.5559	0.008	1949
	(5.46)***	(-1.48)		
3	0.0214	-1.0399	0.024	1864
	(5.85)***	(-2.50)**		
4	0.0236	-1.0295	0.021	1916
	(5.97)***	(-2.45)**		
5	0.0275	-0.8689	0.018	2338
	(8.09)***	(-2.69)***		
6	0.0262	-1.1154	0.029	2195
	(7.51)***	(-3.34)***		
7	0.0303	-1.9621	0.079	1800
	(7.88)***	(-4.93)***		
8	0.0330	-2.0539	0.072	1815
	(8.09)***	(-5.12)***		
9	0.0430	-1.6272	0.036	1897
	(9.38)***	(-3.95)***		
10	0.0499	-0.7664	0.012	1959
	(10.39)***	(-2.11)**		

* Significant at the 10 percent level
** Significant at the 5 percent level
*** Significant at the 1 percent level

rules that provide guidance on the annual earnings and profits. Despite this, analysts still anchor and are reluctant to change their prior forecasts.

We next divide the entire sample into two groups, one with positive forecast revisions and the other with negative forecast revisions. According to the sign of forecast revisions we then regress forecast errors on forecast revisions. The results are shown in Table 5.

For the groups with negative forecast revisions, the findings are broadly similar to those for the whole sample—apart from α(3) all the intercepts, α(n)s, are positive and significant for α(1), α(6), α(9), and α(10), while all the slope coefficients, β(n)s, are significantly negative. Our results are consistent with Nutt et al. (1999), who argue that optimism causes analysts to underreact to bad news, and with Amir and Ganzach (1998) who posit that when information is negative, analysts are less likely to make a pessimistic forecast and deviate from the anchoring and adjustment heuristic.

In contrast, for the group with positive forecast revisions, the intercept, α(n), is only positive when n = 8 but not significant. The slope coefficients, β(n)s, are all positive and (apart from when n = 7 and 8) are significant at the 10 percent level or

Table 5—Regression Results of Forecast Errors on Positive and Negative Forecast Revisions

In this table forecast errors (FERR) are regressed on forecast revisions (FR) n months prior to the earnings release. We test the model: FERR(n) = α (n) + β(n)FR(n) + ε. The model separates positive forecast revisions from negative forecast revisions. The values in parentheses are White's (1980) t-statistics

	Positive Forecast Revisions				Negative Forecast Revisions			
n	α	β	Adjusted R^2	No. of Obs.	α	β	Adjusted R^2	No. of Obs.
1	-0.0049	1.6784	0.055	984	0.0116	-1.2934	0.034	1150
	(-1.05)	(3.59)***			(2.09)**	(-2.94)***		
2	-0.0152	2.6988	0.098	784	0.0030	-1.8115	0.070	1165
	(-2.44)**	(3.19)***			(0.61)	(-4.05)***		
3	-0.0095	1.8887	0.058	773	-0.0002	-2.3362	0.087	1091
	(-1.81)*	(2.91)***			(-0.03)	(-3.86)***		
4	-0.0099	2.6668	0.071	785	0.0028	-2.3703	0.102	1131
	(-1.35)	(2.58)***			(0.54)	(-4.73)***		
5	-0.0020	1.3552	0.025	1062	0.0106	-1.9142	0.070	1276
	(-0.37)	(2.30)**			(1.89)*	(-3.96)***		
6	-0.0123	1.4427	0.032	901	0.0136	-2.1681	0.076	1294
	(-1.87)*	(2.14)**			(2.37)**	(-4.57)***		
7	-0.0023	0.8195	0.011	733	0.0116	-3.0138	0.129	1067
	(-0.36)	(1.28)			(1.64)	(-5.17)***		
8	0.0066	0.9252	0.010	731	0.0074	-3.3884	0.147	1084
	(0.98)	(1.37)			(1.17)	(-6.00)***		
9	-0.0007	1.2480	0.019	803	0.0272	-3.0643	0.080	1095
	(-0.09)	(1.80)*			(3.51)***	(-4.89)***		
10	-0.0031	2.0097	0.049	944	0.0191	-2.8154	0.108	1015
	(-0.49)	(3.98)***			(2.65)***	(-4.55)***		

* Significant at the 10 percent level
** Significant at the 5 percent level
*** Significant at the 1 percent level

are *positive* (third and fourth columns) and when forecast changes are *negative* (sixth and seventh columns). The number of observations in the positive forecast change better. These results suggest that when forecast revisions are positive analysts are more likely to overreact to new information rather than to underreact.

Results for Forecast Change Period over the Months Subsequent to the Month of the Earnings Release

In this section we investigate the relationship between analysts' forecast changes (positive or negative) and forecast errors in the months subsequent to the month of the earnings release.

Table 6—Mean and Percentage of Positive Forecast Errors when Forecast Changes are Positive and Negative

This table shows the mean and the percentage of positive forecast errors when forecast changes (FC) are *positive* (FC > 0, columns 3-4) and when forecast changes are *negative* (FC < 0, columns 6-7). Forecast errors (FERR) are defined as the difference between the actual $ value of EPS and the $ value of the forecast EPS

Months Prior to the Earnings Release (n)	No. of Obs	Mean FERR when FC > 0	FERR > 0 (%) when FC > 0	No. of Obs	Mean FERR when FC < 0	FERR > 0 (%) when FC < 0
1	2092	0.0271	47.2%**	1159	0.0390	50.0%
2	1979	0.0233	45.7%***	1100	0.0431	53.6%**
3	1990	0.0251	46.9%***	1051	0.0468	57.0%***
4	2014	0.0312	49.6%	1006	0.0475	58.2%***
5	2095	0.0369	52.0%*	950	0.0511	60.3%***
6	2144	0.0383	52.9%***	879	0.0560	62.8%***
7	2209	0.0449	55.2%***	807	0.0503	60.8%***
8	2276	0.0485	56.9%***	743	0.0516	59.5%***
9	2325	0.0543	58.5%***	674	0.0419	56.5%***
10	2343	0.0573	60.4%***	581	0.0384	54.6%**
11	2174	0.0627	61.8%***	490	0.0342	50.2%

* Significant at the 10 percent level
** Significant at the 5 percent level
*** Significant at the 1 percent level

Nonparametric Results

Similar to the tests on forecast revisions, we divide the whole sample into positive and negative groups according to the sign of the forecast change. Table 6 shows the mean and the percentage of positive forecast errors when forecast changes (FC) group exceeds by approximately 100 percent or more the number of observations in the negative forecast change group. When the forecast change is positive the percentage of positive forecast errors also tends to fall as the actual earnings announcement date approaches (i.e., n becomes smaller). The percentage of positive FERRs reduces from 60.4 percent when n = 10 to 52.9 percent when n = 6, all significantly different from 50 percent under the sign test. Between n = 1 to 3, however, the percentage of positive FERRs varies between 45.7 percent and 49.6 percent (significantly different to 50 percent under the sign test).

When the forecast change is negative the percentage of positive forecast errors is significantly greater than 50 percent for all periods n = 2 to 10. The total number of observations in the negative forecast change group increases as the actual earnings announcement month approaches (for example, from 581 observations when n = 10 to 1159 observations when n = 1). As already noted, as the company annual earnings announcement date approaches, analysts will be aware of the semi-annual profits announced by the company and any other price-sensitive information that the company may have disclosed under Australia's continuous disclosure regime. The evidence suggests that over time as more information is available on the likely earnings for the company, greater numbers of analysts modify their forecasts downwards

Table 7—Regression Results of Forecast Errors on Forecast Changes

In this table forecast errors (FERR) are regressed on analysts' forecast changes (FC) n months prior to the earnings release. We test the model: FERR(n) = α (n) + β(n)FC(n) + ε. The model includes all observations where there was a positive or negative forecast revision. The values in parentheses are White's (1980) t-statistics

n	α	β	Adjusted R^2	Number of Observations
1	0.0282	0.1061	0.010	3251
	(9.03)***	(2.02)**		
2	0.0272	0.1042	0.011	3079
	(8.47)***	(1.80)*		
3	0.0283	0.1243	0.015	3039
	(8.30)***	(2.15)**		
4	0.0304	0.1621	0.024	3020
	(8.70)***	(2.81)**		
5	0.0326	0.2077	0.037	3045
	(9.00)***	(3.54)***		
6	0.0324	0.2502	0.050	3023
	(8.63)***	(4.02)**		
7	0.0317	0.3068	0.069	3014
	(8.49)***	(4.94)***		
8	0.0308	0.3602	0.091	3019
	(8.01)***	(5.74)***		
9	0.0294	0.3984	0.109	2999
	(7.56)***	(6.36)***		
10	0.0292	0.4148	0.121	2924
	(7.32)***	(6.61)***		
11	0.0300	0.4497	0.137	2664
	(7.01)***	(6.96)***		

* Significant at the 10 percent level
** Significant at the 5 percent level
*** Significant at the 1 percent level

and this leads to more negative forecast changes. The results are consistent with expectations of analysts' earnings that are initially overly optimistic. Analysts who make positive forecast changes switch to the negative forecast change group, albeit analysts are still slow to correct for their positive bias. The evidence is consistent with Amir and Ganzach (1998) who also suggest that US analysts reduce their degree of optimism over time.

Overall the evidence in Table 6 suggests analysts are still subject to the anchoring and adjustment and to the leniency heuristics when making negative forecast changes. For positive forecast changes there is some evidence analysts are more subject to the leniency and representativeness heuristics for periods n = 6 to 10 prior to the earnings announcement date.

Regression Results

Our regression model takes the following form:

$$FERR\ (n) = \alpha(n) + \beta(n)FC(n) + \varepsilon,\ \ n = 1 \text{ to } 10$$

We first regress forecast error on forecast changes for the full sample. The results are shown in Table 7. Consistent with our regression results for forecast revisions, we find analysts are overly optimistic (all the intercepts, α(n)s, are significantly positive). Unlike our results in Table 4 the slope coefficients, β(n)s, are all significantly positive at the 10 percent level or better, suggesting analysts' overreaction. The values of the β(n)s decrease as n approaches one, suggesting overreaction declines as the company earnings announcement date approaches.

We also undertake regressions of the forecast errors against the sub-samples of positive and negative forecast earnings changes. The results (Table 8) show that the slope coefficients, β(n)s, are all significantly positive for the positive forecast change group, consistent with analyst overreaction. The intercepts, α(n)s, are, however, only positive and significant for the positive forecast change group when n = 9 and 10.

Table 8—Regression Results of Forecast Errors on Positive and Negative Forecast Changes

In this table forecast errors (FERR) are regressed on forecast changes (FC) n months prior to the earnings release. We test the model: FERR (n) = α (n) + β(n)FC(n) + ε. The model separates positive forecast changes from negative forecast changes. The values in parentheses are White's (1980) t-statistics

	Positive Forecast Changes				Negative Forecast Changes			
n	α	β	Adjusted R^2	No. of Obs.	α	β	Adjusted R^2	No. of Obs.
1	0.0018	0.2878	0.098	2092	0.0003	-0.4958	0.068	1159
	(0.42)	(4.45)***			(0.05)	(-4.24)***		
2	-0.0037	0.3085	0.119	1979	-0.0043	-0.6421	0.105	1100
	(-0.83)	(4.48)***			(-0.62)	(-4.89)***		
3	-0.0031	0.3122	0.123	1990	-0.0002	-0.6687	0.096	1051
	(-0.70)	(4.69)***			(-0.03)	(-4.44)***		
4	0.0007	0.3356	0.123	2014	0.0013	-0.6828	0.098	1006
	(0.15)	(5.11)***			(0.17)	(-4.36)***		
5	0.0016	0.3858	0.150	2095	0.0015	-0.7396	0.112	950
	(0.37)	(5.90)***			(0.19)	(-4.56)***		
6	0.0004	0.4288	0.169	2144	0.0062	-0.7883	0.115	879
	(0.08)	(6.26)***			(0.74)	(-4.41)***		
7	0.0057	0.4483	0.159	2209	0.0142	-0.5950	0.069	807
	(1.25)	(6.48)***			(1.61)	(-3.23)***		
8	0.0061	0.4881	0.183	2276	0.0217	-0.5136	0.044	743
	(1.36)	(7.12)***			(2.15)**	(-2.44)**		
9	0.0103	0.5004	0.177	2325	0.0155	-0.4645	0.044	674
	(2.19)**	(7.33)***			(1.60)	(-2.15)**		
10	0.0131	0.5021	0.183	2343	0.0129	-0.4292	0.037	581
	(2.83)***	(7.38)***			(1.23)	(-1.88)*		
11	0.0155	0.5360	0.201	2174	0.0027	-0.5318	0.055	490
	(3.23)***	(7.73)***			(0.25)	(-2.22)**		

* Significant at the 10 percent level
** Significant at the 5 percent level
*** Significant at the 1 percent level

For the negative forecast change group the intercepts, $\alpha(n)$s, apart from $\alpha(2)$ and $\alpha(3)$ are positive but only significant at the 5 percent level where n = 8. This weakly suggests that analysts are overly optimistic. The slope coefficients, $\beta(n)$s, are significantly negative when forecast changes are negative at the 5 percent level or better for periods n = 1 to 9. Compared to our results in Table 5 for forecast revisions, our results in Table 8 suggest greater levels of overreaction for positive forecast earnings changes. For negative forecast changes analysts still exhibit underreaction, suggesting that when information is negative analysts are more likely to anchor on prior forecasts.

Specific Period

Month Immediately after an Earnings Announcement

In the absence of a previous forecast in the month immediately after the company's annual earnings announcement (n = 11), Amir and Ganzach (1998) hypothesize that the representativeness heuristic would be used more frequently. In this month analysts make their forecasts of next year's earnings in the absence of any anchor based on their prior earnings' forecasts that incorporates information contained in the most recent earnings announcement by the company. This would lead to a greater tendency to analyst overreaction instead of underreaction for month n = 11. We test this hypothesis using Australian data in this subsection.

We separate the whole sample into positive and negative forecast changes in earnings. The results in Table 6 (last row, column 4) show that when forecast changes are positive 61.8 percent of the forecast errors are also positive (significantly greater than 50 percent under the sign test), consistent with analyst overreaction and the representativeness and leniency heuristics (Figure 2). The mean FERR is also larger than for any other months n = 1 to 10. When forecast changes are negative (Table 6, last row, column 7), only 50.2 percent (not significantly different to 50 percent) of the forecast errors are positive, contrary to the predictions of the anchoring and adjustment and leniency heuristics (Figure 3). Overall the evidence provides support to analysts being more subject to representativeness in their earnings' forecasts at time period n = 11.

We also examine analysts' overreaction in this particular month by regressing the forecast error (FERR) against the forecast change (FC) for month n = 11. Our model takes the following form:

$$FERR\,(11) = \alpha(11) + \beta(11)FC(11) + \varepsilon$$

For the whole sample the intercept, α, is positive (0.0300) with a t-value of 7.01 (last row, Table 7). The slope coefficient, β, is also positive (0.4497) with a t-value of 6.96. The evidence is consistent with optimism and overreaction by Australian analysts in their forecast of the company's annual earnings per share in the month immediately following the earnings' announcement.

We also separately regress the positive and negative groups based on forecast changes. For the positive forecast change group we find a significant positive intercept and slope. The α is 0.0155 with a t-value of 3.33, and the β is 0.5360 with a t-value of 7.73 (Table 8, last row). For the negative forecast change group the intercept, α, is still positive (0.0027) but not significant (t value of 0.25). The slope coefficient, β, is negative (-0.5318) and significant (t-value of -2.22). Thus, when analysts make either positive or negative forecast changes in the month immediately following the most recent annual earnings announcement by the company, there is a tendency for analysts to be overly optimistic. For positive (negative) forecast changes analysts are also more likely to exhibit overreaction (underreaction).

Conclusions and Implications

Amir and Ganzach (1998) argue that three heuristics—representativeness and anchoring and adjustment, and leniency—all affect US analysts when making earnings forecasts. The purpose of this study is to investigate whether these heuristics also affect analysts' forecasts in Australia. Australia is a market that has a continuous disclosure regime for all listed ASX entities and where most companies only report their earnings semi-annually.

In summary, the results for our sample of forecast errors by Australian analysts are broadly consistent with the results of Amir and Ganzach (1998). We show that Australian analysts have a tendency to be too optimistic. The evidence suggests analysts are subject to the anchoring and adjustment and leniency heuristics. We also find that analysts tend to overreact when forecast revisions and changes are positive and underreact when forecast revisions and changes are negative.

Amir and Ganzach (1998) indicate that the extremity of predictions is influenced by the representativeness and anchoring and adjustment heuristics. Consistent with their results, we find that analysts' prior forecasts are a more powerful anchor than prior announced earnings. When the weak anchor—the prior announced earnings by the company—is used, analysts are more likely to use the representativeness heuristic in decision making and appear to overreact (underreact) to information when making positive (negative) forecast changes. Our results also provide some evidence that suggests analysts' optimism decreases over time closer to the actual annual earnings announcement date.

While this paper examines the reaction of analysts when making forecasts using different heuristics, the cause of the differences in Australian analysts' tendency to overreact and underreact when making positive and negative modifications warrants further consideration. As already noted, one possible explanation is the different incentives faced by analysts (Schipper, 1991). Beckers et al. (2004) also suggest that industry and company characteristics (such as the volatility of earnings and market capitalization) may influence the accuracy of analysts' forecasts. This is left for future work.

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