

ANALYST FORECAST OPTIMISM AND MARKET REACTION: *Australian Evidence*

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This paper examines whether earnings forecasts within the Australian context suffer from analysts' optimism and under- or overreaction to new information in forecast revisions, and also whether and how investors respond to analysts' bias in a given forecast. Our findings indicate that Australian analysts are optimistic and underreact both to positive and negative forecast revisions. We also find that when making investment decisions, investors are unable to distinguish the predictable component of forecast bias from the unpredictable component, although they are aware of the overall optimism in analysts' forecasts and adjust for that.

It is a common phenomenon that firms (media) mention in their earnings release (news reports) whether earnings of the firm have met or beaten analysts' forecasts. Depending on the overall market expectations, claims made in these communications affect company stock prices. That is, investors also pay attention to such claims and reward those firms whose earnings meet or beat analysts' estimates (Bartov et al. 2002). Given the importance attached to such claims by the company, the media and investors, it is natural to ask how reliable these forecasts are. Extant empirical evidence suggests that analysts are generally reluctant to issue negative recommendations for the firms they follow and their earnings forecasts are typically above the actual earnings.

Related literature suggests both strategic and behavioural (cognitive) reasons for such optimistic analyst bias. The strategy-related explanations indicate that the analysts tend to be optimistic to foster a cozy relationship with the companies they follow to enable easy access to management information and future investment banking business (Francis and Philbrick 1993; Eames et al. 2002). The behavioural explanations, on the other hand, posit that analysts' under- and overreaction to predictive new information may also bias their earnings forecasts (Amir and Ganzach 1998; Easterwood and Nutt 1999).¹ Motivated by these findings, this study examines potential bias in analysts' earnings forecasts and its impact on marginal investors' decision making within the Australian context.

Examining forecast bias is important for a number of reasons. First, recent studies indicate that market participants place substantial value on analysts' forecasts. Viewing stock price as a function of future earnings, Beaver et al. (2008) show that analysts' forecast errors and forecast revisions serve as proxies for market expectations. In addition, upgrades (downgrades) in analyst recommendations are associated with positive (negative) abnormal returns (Goff et al. 2008). From this viewpoint, an understanding of forecast bias is important to researchers who use analysts' earnings forecasts as a proxy for the market's expectation of earnings. Second, regulatory bodies may be interested in an analysis of forecast bias as it will help them frame appropriate rules and regulations in order to improve the quality of analysts' forecasts and help restore investor confidence in them. They may also be interested in determining the extent to which the market is aware of forecast bias and whether investors can beat the market by adopting an earnings strategy based on this bias. Third, existing empirical evidence on analyst forecast bias in Australia is limited; relevant studies have only considered issues such as analyst optimism, anchoring² and adjustment, and leniency³ heuristics (e.g. Aitken et al. 1996;

Ho 1996; Marsden et al. 2008). Fourth, most of the related studies focus on US markets. These US findings, however, might not hold in Australia because of country-specific differences (Allen et al. 1997, 1999).⁴

An understanding of forecast bias is important to researchers who use analysts' earnings forecasts as a proxy for the market's expectation of earnings. Regulatory bodies may be interested in an analysis of forecast bias as it will help them frame appropriate rules and regulations in order to improve the quality of analysts' forecasts and help restore investor confidence in them.

Using data for Australian Securities Exchange (ASX) firms, we find that Australian analysts are optimistic in their earnings forecasts and they underreact to new information. Our findings indicate that Australian analysts underreact both to positive and negative forecast revisions. We also find that when making investment decisions, investors are unable to distinguish the predictable component of forecast bias from the unpredictable component, although they are aware of the overall optimism in analysts' forecasts and adjust for that.

Methodology

Analyst forecast bias

Analysts' forecast bias is usually characterised as the difference between the values of actual earnings and analysts' forecasts of those earnings. As mentioned in the previous section, this forecast bias can be attributed to analysts' general optimism about the firms they follow and/or their under- or overreaction to currently available predictive information.

The study by Amir and Ganzach (1998) is the first which emphasises examining the joint effect of optimism and under- or overreaction to news on forecast bias using the following regression framework:

$$Bias_{t-n} = \alpha + \beta FR_n + \varepsilon_n, \quad n = 1, 2, \dots, 10 \quad (1)$$

In the above model, a positive (negative) value for α implies optimism (pessimism) and a positive (negative) value of β implies overreaction (underreaction) to new information. Variables in equation (1) are defined as follows:

- > $Bias_{t-n}$ – Forecast error (overall bias) n months prior to the earnings announcement month in year t , calculated as $FEPS_{t-n} - EPS_t$, where EPS_t and $FEPS_{t-n}$ are actual earnings per share in year t and the monthly consensus forecast (median) of EPS_t n months prior to earnings announcement, respectively.
- > FR_n – forecast revision n months prior to the earnings announcement month in year t , calculated as $FEPS_n - FEPS_{n+1}$.

In order to test whether the pattern of forecast bias is different for positive and negative forecast revisions, Amir and Ganzach (1998) estimate equation (1) separately for subsamples of positive and negative forecast revisions. In this paper, however, we estimate the following specification on the full sample of forecast revisions to test the same predictions as those of Amir and Ganzach:

$$Bias_{t-n} = \alpha_1 d_{1n} + \alpha_2 d_{2n} + \beta_1 d_{1n} FR_n + \beta_2 d_{2n} FR_n + \varepsilon_n, \quad n = 1, 2, \dots, 10 \quad (2)$$

In equation (2), d_{1n} is the dummy variable which takes a value of 1 when forecast revisions (FR_n) are positive and otherwise zero and $d_{2n} = 1 - d_{1n}$ takes a value of 1 when forecast revisions are negative and otherwise zero. In this equation, α_1 and α_2 capture analyst optimism or pessimism and β_1 and β_2 capture under- or overreaction in positive and negative forecast revisions, respectively.

Investor's ability to distinguish between predictable and unpredictable components of bias

Analysts' earnings forecasts are widely perceived to be informative to the market. Therefore, it is important to examine whether and how market participants factor the bias in earnings forecasts into their reaction to actual earnings announcements. For this purpose we divide total forecast bias into two components: predictable and unpredictable. Clearly, investors' reactions to these components of bias would depend on how much earnings information their information set contains. For example, if their information set contains only information from the time series properties of earnings (i.e. past earnings information and earnings forecast), they are expected to react only to the unpredictable component of bias. However, if investors are not efficient, or if they are slow in incorporating information embedded in past earnings and earnings forecasts, they are expected to react to predictable as well as unpredictable forecast bias.

Barnerd and Thomas (1990) show that a nontrivial portion of investors does not incorporate past earnings information and thus ends up reacting to the predictable portion of the bias. Lopez and Rees (2002), on the other hand, find that investors not only react to the unpredictable component of forecast error but also partially react to the predictable portion. More recently, Battallio and Mendenhall (2005) show that, while the investors initiating small trades react to both predictable and unpredictable components of bias, those initiating large trades properly discount predictable bias and only respond to the unpredictable bias. Following Battallio and Mendenhall, we divide analyst forecast error into predictable and unpredictable components as follows:

$$Bias_{t-n} = FEPS_{t-n} - EPS_t = \underbrace{FEPS_{t-n} - EPS_{t-12}}_{\text{Predictable bias}} + \underbrace{EPS_{t-12} - EPS_t}_{\text{Unpredictable bias}} \quad (3)$$

where $FEPS_{t-n}$ is the latest consensus EPS forecasts n months prior to the actual earnings announcements in year t (EPS_t) and EPS_{t-12} is actual EPS 12 months before earnings announcement in year t (i.e. previous year's EPS). The predictable portion of the forecast error represents the amount that an efficient market could reasonably expect to predict given the historical forecast error of the firm. This component of bias should be known with certainty prior to the earnings announcement as it does not depend on announced earnings. The unpredictable portion of forecast error is the 'news' or 'surprise' aspect to which the market is expected to react. If investors are unable to undo the forecast bias, both components of bias should be associated with abnormal returns around the earnings announcement date.

We employ the following regression model to test whether investors can distinguish between the predictable and unpredictable parts of analysts' forecast bias:

$$SCAR_t = \alpha + \beta_1 PB_t + \beta_2 UPB_t + \beta_3 \ln(MV_t) + \beta_4 \ln(TV_t) + \beta_5 ANA_t + \varepsilon_t \quad (4)$$

where $SCAR$ denotes abnormal returns around the earnings announcement date (for the technically minded readers, calculation of $SCAR$ is provided in the footnote of Table 2), PB denotes the predictable component of bias, and UPB denotes the unpredictable portion of bias. If the market responds to both the predictable and unpredictable components of forecast bias, then both PB and UPB should be statistically significant. In model (4), we have controlled for the size of the firm (MV), trading volume (TV), and number of analyst following (ANA). Previous studies report that the firm size (measured as the natural log of the market value of common equity) is related to analyst forecast bias (Lim 2001). From the strategic reporting bias view, since there is less public information available for small firms, analysts have stronger incentives to issue optimistic forecasts for these firms to facilitate management communication. Trading volume (measured as the natural logarithm of annual dollar trading volume) is used to capture analysts' strategic incentive to generate brokerage commissions from increased trading of the stocks they cover (Francis and Willis 2000). Analyst following (measured by the number of analysts making forecasts) is also likely to be related to forecast bias. A greater number of analysts following a firm could lead to less informational uncertainty and thus may lead analysts to produce less biased earnings forecasts (Lim 2001).

Data and empirical results

Data

Our sample of 5,782 firm-year observations comprises 413 firms listed on the Australian Securities Exchange (ASX), spanning the period from 1994 to 2007. To save our results from the effects of unusual market circumstances such as the global financial crisis, we restrict our sample to 2007. While an analysis with special focus on the periods of market stress may itself be an interesting topic of inquiry, our goal in this paper is limited to examining analyst bias and its effects on investor behaviour focusing only on usual market circumstances. A focus restricted to the typical market environment improves the comparability of our results with that of the other related studies. In this study, unadjusted actual and forecasted earnings per share and analyst following data are collected from Institutional Brokers Estimate System (IBES) via Wharton Research Data Services (WRDS). Data for other variables such as share price, firm size and trading volume are collected from Datastream.

Empirical results

Table 1 reports the results of the regression of forecast bias on forecast revisions n months prior to actual earnings announcement. These results indicate that earnings forecasts by Australian analysts suffer from clear biases with a strong tendency towards both optimism and underreaction. Specifically, positive and significant estimates of α_2 suggest that earnings forecasts are generally optimistic for negative forecast revisions. On the contrary, although negative estimates of α_1 suggest pessimism, these estimates are generally statistically insignificant except when $n = 7$. The test results of the hypothesis that $\alpha_1 = \alpha_2$ bolster our finding that analysts are systematically optimistic in relation to negative forecast revisions. In addition, we find that the values of α_2 are generally higher for the longer forecast horizons than for the shorter forecast horizons. This finding supports the idea that analysts tend to show more optimism when issuing their longer-term earnings forecasts. Table 1 also shows that the parameter estimates of both β_1 and β_2 are generally negative and statistically significant.

This finding clearly suggests that, irrespective of the nature of earnings information (good or bad), Australian analysts tend to underreact when revising their previous forecasts. In addition, we observe that the analysts' tendency to underreact gets stronger as the forecast horizon increases, particularly when forecast revisions are negative. It is notable that our evidence of analysts' underreaction in both positive and negative forecast revisions is consistent with extant theory and some experimental research outcomes in behavioural decision making. For example, Amir and Ganzach (1998) argue that, in the presence of a potent anchor upon which to base predictions, it is more likely to observe underreactions than overreactions in forecast revisions. Naturally, in forecast revisions, previous forecasts are likely to serve as a powerful anchor on which to base new forecasts. Czaczkes and Ganzach (1996), on the other hand, experimentally demonstrate systematic underreaction to both positive and negative information signals when there is a salient anchor on which predictions are based. Stevens and Williams (2004) also document similar phenomenon and attribute that to human decision bias.

Having established that Australian analysts are generally optimistic and tend to underreact to new information, we test the hypothesis that they underreact more when processing negative information (negative forecast revisions) as opposed to positive information (positive forecast revisions). Assuming optimism as given, Amir and Ganzach (1998) argue that analysts are less (more) likely to depart from previous forecasts when processing negative (positive) information and, as a result, more (less) underreaction is likely to be observed in negative (positive) forecast revisions. However, our results in Table 1 do not seem to support their prediction. Although the absolute values of most of the β_2 coefficients are higher than that of β_1 coefficients, we fail to reject the null hypothesis that $\beta_1 = \beta_2$ over the forecast horizons considered in the analysis. This finding therefore further corroborates the fact that Australian analysts symmetrically underreact to positive as well as negative forecast revisions.

TABLE 1: Regression of forecast bias on forecast revisions n months prior to actual earnings announcement

$$Bias_{t-n} = \alpha_1 d_{1n} + \alpha_2 d_{2n} + \beta_1 d_{1n} FR_n + \beta_2 d_{2n} FR_n + \varepsilon_n, \quad n = 1, 2, \dots, 10$$

Months prior to actual earnings release (n)	α_1	α_2	F-stat $\alpha_1 = \alpha_2$	β_1	β_2	F-stat $\beta_1 = \beta_2$	R^2	Obs.
1	0.016 (1.49)	0.007 (1.14)	0.46 [0.50]	-2.104 (2.92) [†]	-0.846 (3.02) [†]	2.65 [0.10]	0.18	1129
2	-0.007 (1.04)	0.028 (2.83) [†]	8.54 [0.00]	-0.822 (2.69) [†]	-0.700 (1.29)	0.04 [0.85]	0.05	1181
3	-0.006 (0.91)	0.006 (0.63)	1.08 [0.30]	-0.769 (2.06) [*]	-1.457 (4.57) [†]	1.96 [0.16]	0.07	1144
4	-0.004 (0.57)	0.021 (2.41) [*]	4.70 [0.03]	-1.097 (5.54) [†]	-1.303 (5.17) [†]	0.41 [0.52]	0.07	1181
5	-0.000 (0.06)	0.035 (4.49) [†]	11.54 [0.00]	-1.248 (3.68) [†]	-1.188 (6.72) [†]	0.02 [0.87]	0.13	1303
6	-0.005 (0.55)	0.025 (3.75) [†]	6.54 [0.01]	-1.016 (2.64) [*]	-1.274 (4.92) [†]	0.31 [0.58]	0.16	1668
7	-0.17 (1.96) [*]	0.025 (4.18) [†]	15.66 [0.00]	-0.839 (2.06) [*]	-1.641 (6.50) [†]	2.81 [0.09]	0.23	1237
8	-0.009 (1.01)	0.040 (3.44) [†]	10.77 [0.00]	1.676 (3.03) [†]	-1.725 (4.45) [†]	0.01 [0.94]	0.17	1067
9	-0.007 (0.76)	0.045 (3.27) [†]	9.85 [0.00]	-1.385 (3.25) [†]	-2.022 (2.07) [*]	0.36 [0.55]	0.05	1190
10	0.007 (0.68)	0.031 (1.94) [‡]	1.51 [0.22]	-1.972 (5.95) [†]	-2.454 (1.71) [‡]	0.11 [0.74]	0.07	1089

Significant at: [†]1, ^{*}5, [‡]10 per cent levels, respectively. (.) Indicates robust t-statistics and [.] indicates p-values.

Notes: This table reports the results of the regression of forecast bias on forecast revisions, n months prior to actual earnings announcement. Here d_{1n} and is the dummy variable which takes a value of 1 when forecast revisions are positive and otherwise zero, and $d_{2n} = 1 - d_{1n}$. Zero forecast revisions are not included in the regression.

Table 2 reports the results of the regression of abnormal returns on predictable and unpredictable components of bias and a set of control variables comprising firm size, trading volume, and number of analysts following. Statistically significant coefficients on both predictable and unpredictable bias imply that the investors are unable to distinguish between these two components of bias in earnings forecasts. The finding that investors react to the predictable part of analyst bias suggests that a significant portion of investors do not exploit past earnings information in a timely fashion when making trading decisions. Bernard and Thomas (1990) also report similar findings and show that this type of investor behaviour gives rise to post-earnings announcement drifts in stock prices (see Hong et al. 2003 for Australian evidence on post-earnings announcement drifts).⁵ This result, however, is in contrast with that of Battalio and Mendenhall (2005) who find that a subset of investors correctly distinguishes between the predictable and unpredictable components of the forecast bias and adjusts trading behaviour accordingly. Reported results in Table 2 also show that investors' response to both the predictable and unpredictable components of bias is negative. This may reflect the fact that, despite having difficulty in unwinding the components of forecast bias, investors do perceive the existence of persistent optimism in analysts' forecasts and thus adjust for that with an earnings expectation discount (optimism discount). In other words, although marginal investors are not smart enough to disentangle the predictable component of bias from the unpredictable component, they appear to recognise the overall optimism in analysts' forecasts and reflect this accordingly in their stock price reactions.

TABLE 2: Regressions of abnormal stock returns on predictable bias and unpredictable bias

$$SCAR_i = \alpha + \beta_1 PB_i + \beta_2 UPB_i + \beta_3 \ln(MV_i) + \beta_4 \ln(TV_i) + \beta_5 ANA_i + \varepsilon_i$$

	α	<i>PB</i>	<i>UPB</i>	<i>ln(Size)</i>	<i>ln(TV)</i>	<i>ANA</i>
Coef.	0.734	-3.852	-6.609	0.065	-0.078	-0.011
SE	0.209	1.926	1.768	0.040	0.031	0.014
<i>t</i>	3.51 [†]	-2.00 [*]	-3.74 [†]	1.60	-2.50 [*]	-0.81
$R^2 = 0.012$, Obs. 2612						

Significant at: [†]1, ^{*}5, [†]10 per cent levels, respectively.

Notes: This table reports the pooled regression coefficients of regressing standardised cumulative abnormal returns (SCAR) on various predictive variables. We estimate the model using different standard errors (e.g. White standard errors, standard errors clustered by year and by firm) but report the results only for standard errors clustered by the firm as it provides most conservative results. Here SCAR is defined as the abnormal stock returns cumulated over a three-day window around the earnings announcements. Defining the actual earnings announcement day as $k = 0$, and using the market model as a benchmark, abnormal returns are calculated over the event window $(k - 1, k + 1)$ as $AR_{i,k} = R_{i,k} - \hat{\alpha}_i - \hat{\beta}_i R_{m,k}$ where $R_{i,k}$ and $R_{m,k}$ are the actual returns for firm i and ASX composite index on day k , respectively, and $\hat{\alpha}_i$ and $\hat{\beta}_i$ are estimates from the market model calculated using the data over $(k - 2, k - 126)$. Next, standardised abnormal returns are calculated as $SAR_{i,k} = AR_{i,k} / sd_i$, where sd_i is the standard deviation of $AR_{i,k}$. Finally, standardised cumulative abnormal returns are calculated as $SCAR_i = \sum_{k=-1}^{k=1} SAR_{i,k}$. The predictive variables are: *PB*, the predictable forecast bias, calculated as $FEPS_{i,t-1} - EPS_{i,t}$ and *UPB*, the unpredictable component of forecast bias, calculated as $EPS_{i,t-12} - EPS_{i,t}$. $FEPS_{i,t-1}$ is the latest consensus EPS forecasts n months prior to the actual earnings announcements in year t ($EPS_{i,t}$) and $EPS_{i,t-12}$ is actual EPS 12 months before earnings announcement in year t (i.e. the previous year's EPS). $\ln(MV)$ represents natural log of year-end market value of common equity, $\ln(TV)$ represents natural log of annual dollar trading volume, and *ANA* represents yearly total number of analysts following a firm.

Conclusion

Empirical evidence on analysts' forecast optimism in Australia is limited. This study contributes to the existing literature by providing extra insights into analyst forecast bias in Australia. Specifically, we seek to determine: whether these forecasts are optimistic and whether analysts under- or overreact to forecast revisions; and whether investors are smart enough to distinguish between the predictable and unpredictable components of bias when making investment decisions.

Our results indicate that analysts, on average, issue optimistic forecasts in Australia. Such optimism could originate from the analysts themselves; they could simply be optimistic about the firm they follow or have other motivations for being optimistic (e.g. an investment banking relationship). Our results also indicate that Australian analysts show systematic underreaction to both positive and negative information and, hence, they are less likely to depart from their previous forecasts when processing new information. These results are in line with the existing experimental evidence on behavioural decision theory which suggests that previous forecasts are likely to serve as powerful anchor for new forecasts (Czaczkes and Ganzach 1996; Amir and Ganzach 1998; Stevens and Williams 2004).

Our results also indicate that Australian analysts show systematic underreaction to both positive and negative information and, hence, they are less likely to depart from their previous forecasts when processing new information.

When financial analysts tend to be biased in their earnings forecasts and forecast revisions, it is of great interest to see if investors in the market react rationally to these publicly available pieces of information. One way to judge investors' efficiency in processing such information would be to assess their ability to distinguish between the predictable and unpredictable components of forecast bias. Our analysis indicates that the marginal investors are not able to distinguish between these two components of bias in earnings forecasts. Interestingly, investors' response to both components of forecast bias eventually translates into a negative price reaction around the

earnings announcement period, which may suggest that the investors indeed suspect an element of optimistic bias in earnings forecasts and tend to adjust for that. Given this scenario, it remains an empirical question as to whether investors can beat the market by adopting an earnings strategy based on optimism in analysts' forecasts.

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Notes

1. Overreaction/underreaction results from analysts' disproportionate response to new information in forecast revisions. Analysts are said to overreact when they overrate recent information and neglect or attribute less importance to past information in updating their forecasts. This type of cognitive response leads to excessive optimism over good news and extreme pessimism over bad news. On the other hand, analysts underreact to new information when they fail or are reluctant to set aside their pre-existing perceptions in updating their forecasts. Therefore, underreaction results from overemphasising prior belief and underemphasising new information.
2. Anchoring is a human tendency to make decisions on the basis of the first piece of information. A classic example of anchoring is the case of a used car salesperson who starts negotiating with a high price and then works downwards. As a result, the customer becomes anchored on a high price and when the salesman offers a lower price, the customer thinks that the lower price represents good value.
3. Leniency is the human tendency to be overly optimistic in judgments and hence it leads to positive errors in predictions.
4. The regulatory environment of a market may have a bearing on analysts' forecast bias. For instance, the continuous disclosure regime introduced in Australia in 1994 requires companies to communicate any price-sensitive information to the market through the Australian Securities Exchange (ASX) whenever it becomes available. This requirement is expected to create a better information environment, increasing analysts' ability to accurately project earnings.
5. The tendency for a stock's returns to drift for a long period in the direction of the difference between actual and expected earnings.

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