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Overreaction and underreaction in analysts' forecasts

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Abstract

We examine hypotheses derived from behavioral decision theory regarding conditions that lead to overreaction and conditions that lead to underreaction in analysts' earnings forecasts. We argue that three heuristics jointly influence earnings forecasts: leniency, representativeness and anchoring and adjustment. We present a model for the concurrent influence of these heuristics on forecast errors, and examine three predictions of this model: (1) that there is a tendency towards overreaction in forecast changes and underreaction in forecast revisions, (2) that there is overreaction to positive forecast modifications and underreaction to negative forecast modifications, and (3) that these biases increase with the forecast horizon.

JEL classification: C44; M10; M40

Keywords: Analysts' earnings forecasts; forecasts errors; Overreaction; Underreaction; Optimism

1. Introduction

A large body of laboratory research in behavioral decision making has shown that peoples' intuitive predictions are governed by heuristics, or rules of thumb, that deviate systematically from normative statistical rules (e.g. Tversky and Kahneman, 1974). These studies have inspired researchers in financial economics to investigate whether such heuristics influence the predictions of important financial variables, such as earnings (DeBondt and Thaler, 1990; Klein, 1990; Abarbanell and Bernard, 1992), and as a result

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affect the subsequent behavior or financial markets (DeBondt and Thaler, 1985, 1987; Bernard and Thomas, 1989).

Research in financial economics has usually concentrated on the study of a single heuristic operating in isolation. However, as recent developments in behavioral decision theory indicate, intuitive predictions are often influenced by various heuristics that operate concurrently (Ganzach and Krantz, 1990, 1991; Czaczkes and Ganzach, 1996). The purpose of this paper is to investigate the combined influence of various heuristics on the prediction of earnings by financial analysts. In particular, we examine the influence of three heuristics: *representativeness*, *anchoring and adjustment*, and *leniency*.

The first two heuristics, representativeness and anchoring and adjustment, influence the extremity of predictions. The *representativeness heuristic* leads to excessively extreme predictions, or overreaction. When using this heuristic, people choose a prediction value whose extremity matches the extremity of the predictive information (Kahneman and Tversky, 1973). Such predictions are excessively extreme, since normative predictions are regressive – the extremity of the prediction is a fraction of the extremity of the predictor: The lower the validity of the predictor, the less extreme the prediction. Note that excess extremism (i.e. excess volatility) associated with representativeness is systematic. When the value of the predictor is low, predictions are excessively low, and when the value of the predictor is high, predictions are excessively high. Thus, the volatility associated with reliance on representativeness should be distinguished from volatility associated with a response to useless information.

The *anchoring and adjustment* heuristic leads to excess moderation (i.e. underreaction). When using this heuristic, people anchor at some salient outcome value, and adjust based on predictive information. Since adjustment is often insufficient, predictions by this heuristic are excessively moderate (Slovic and Lichtenstein, 1971; Kahneman and Tversky, 1973).

The third heuristic, *leniency*, leads to lenient (overly optimistic) predictions. A tendency towards overly optimistic predictions was documented in many domains, including earnings forecasts (Givoly and Lakonishok, 1984; Schipper, 1991). One possible explanation for analysts' optimism may be related to their preference to maintain good relations with management as a primary source of information (Affleck-Graves et al., 1990; DeBondt and Thaler, 1990). In particular, this preference for maintaining good relations by issuing optimistic forecasts may be stronger in the presence of unfavorable stock recommendations (e.g., 'hold,' 'sell'). Francis and Philbrick (1993) provide evidence in support of this argument. Using value-line earnings forecasts, Francis and Philbrick find that average optimism for 'sell' stocks is greater than average optimism for 'hold' stocks, which in turn is greater than average optimism in 'buy' stocks.[2] Whether optimism is a result of a rational economic behavior or a result of irrational forecasting has no direct bearing on our study. We take optimism as given and attempt to detect overreaction/underreaction.

[2] Unlike the IBES database, the Value-Line database includes earnings forecasts made by analysts who do not make stock recommendations. These stock recommendations are made by a separate group in Value-Line but are included in the analysts' reports. For further details, see Francis and Philbrick (1993).

The study is organized as follows. Section 2 presents the underlying theory. Section 3 discusses the data and variables. In Section 4, we report the results of our tests. Section 5 contains some concluding remarks.

2. Theory

In predicting earnings, analysts are likely to use a salient value, such as a previous forecast or previously announced earnings, and modify it on the basis of new information. We distinguish between two types of *forecast modifications*, forecast revision and forecast change. *Forecast revision* is defined as the difference between the prediction of future earnings and the previous forecast. *Forecast change* is defined as the difference between the prediction of future earnings and the previously announced earnings. This study demonstrates that the pattern of forecast errors, defined as the difference between the earnings forecast and the actual earnings, depends on (1) whether forecast modification was positive or negative; and (2) whether it was forecast revision or forecast change. In addition, we trace this dependence to the psychological processes underlying various types of forecast modifications.

Consider the joint effect of representativeness (overreaction) and leniency (optimism) on a forecast modification depicted in Fig. 1. In the following analysis we distinguish between a positive and a negative modification, but we do not yet distinguish between forecast revision and forecast change. When the modification is positive (top part of Fig. 1), both leniency (denoted as $\Uparrow$) and representativeness (denoted as $\uparrow$) lead to a forecast, which is above the actual earnings, causing a large positive forecast error. On the other hand, when the modification is negative (bottom part of Fig. 1), leniency leads to a forecast which is above actual earnings, while representativeness leads to a forecast which is below actual earnings, causing a small forecast error (denoted as $\downarrow$). As a result, an asymmetry should be observed: Forecast errors are more likely to be positive when the forecast modification is positive than when it is negative.

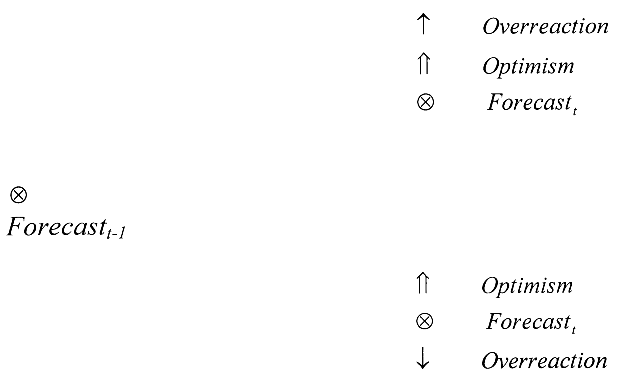

Fig. 1. The joint effect of optimism and overreaction on forecast errors for positive (top) and negative (bottom) forecast modifications.

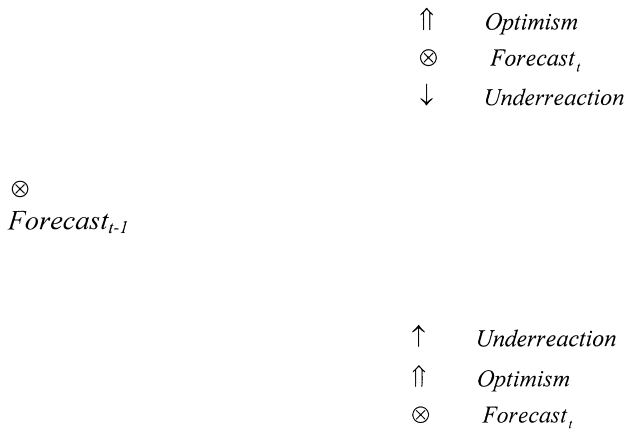

Fig. 2. The joint effect of optimism and underreaction on forecast errors for positive (top) and negative (bottom) forecast modifications.

If the extremity of prediction is governed by anchoring and adjustment (underreaction, denoted as ↑ or ↓), the opposite pattern of forecast errors should be observed (Fig. 2). When forecast modification is negative, both leniency and anchoring and adjustment lead to a forecast which is above actual earnings. On the other hand, when the modification is positive, leniency leads to a forecast above actual earnings, while anchoring and adjustment leads to a forecast below actual earnings. Consequently, we should observe the following asymmetry: Forecast errors are more likely to be positive when forecast modifications are negative than when forecast modifications are positive.

Can we a priori predict the conditions in which representativeness governs earnings forecasts and the conditions in which anchoring and adjustment governs them? We suggest that while representativeness is often the heuristic that governs prediction, when a potent anchor exists, anchoring and adjustment becomes more likely. An experiment conducted by Czaczkes and Ganzach (1996) demonstrates this argument.

In the experiment, subjects predicted the impact of a series of *earnings changes* on simulated share prices. After each prediction, subjects received feedback reflecting a linear relationship between earnings changes and price changes. In one condition subjects were asked to predict the price levels that followed changes in earnings, while in the other condition they predicted price changes that followed the same changes in earnings. In both conditions the subjects were truthfully told that since price reflects earnings, earnings changes cause price changes.

The results of the experiment showed that predictions were less extreme in the ‘price level’ condition than in the ‘price change’ condition. These results are consistent with the notion that anchoring and adjustment is more likely to operate in the price level condition than in the price change condition, since previous price serves as a salient anchor on which predictions are based.

The current study examines two hypotheses concerning forecast modifications. First, while in general both previously announced earnings and previously made forecasts can serve as anchors, we suggest that a previous forecast is a more powerful anchor than previous earnings. People tend to have a strong commitment to a course of action once a choice is made, judgment is expressed, or forecast is communicated (Staw, 1981). Thus, we hypothesize (H1) that there will be a greater tendency for anchoring and adjustment (underreaction) with regard to forecast revisions than with regard to forecast changes. Note that the most dramatic example of this hypothesis is a case in which forecast revisions lead to underreaction and forecast changes lead to overreaction.

Second, leniency also affects the anchor by making it more potent when the forecast is negative than when it is positive. That is, when positive information is processed, analysts are willing to depart from a previous anchor in modifying their forecast positively. On the other hand, when negative information is processed, analysts are less likely to deviate from an established anchor, and to make a pessimistic forecast. Thus, our second hypothesis (H2) is that there will be less overreaction (or more underreaction), for a negative forecast modification than for a positive modification. The most dramatic example of this hypothesis is a case in which negative modification leads to underreaction and positive modification leads to overreaction.

Finally, DeBondt and Thaler (1990) argue that the extent of overreaction in analysts' earnings forecasts increases with the length of the forecast horizon, because overreaction increases with uncertainty and uncertainty is greater over longer horizons. A more general form of this hypothesis is that the longer the prediction horizon, the larger the prediction bias. Thus, a third hypothesis (H3) is that overreaction, underreaction and optimism increase as the prediction horizon increases.

3. Data and variables

Since our tests require analysts' earnings forecasts, our sample firms must be covered by the Institutional Brokers Estimate System (IBES) database. Earnings forecasts are taken from the 1991 summary IBES tape. The median forecasts are determined from the analyst forecasts available on file as of the third Thursday of each month.

All available monthly consensus forecasts (median forecasts) of annual earnings per share between 1976–1990 entered the analysis. We adjusted all observations for stock splits and stock dividends using the IBES adjustment factor. In addition, we deleted from the analysis observations that lie in the upper or lower 1 percent of the variables' distribution. The deletion of these outliers had a minor effect on our results. The following variables were defined:

1) EPS(t) - actual annual earnings per share in year t;
2) EPS($t-1$) - actual annual earnings per share in year $t-1$;
3) FEPS(n) - The consensus forecast (median) of EPS(t) n months prior to the month during which EPS(t) was announced (n=1, 2...,11);
4) FERR(n) - forecast error n months prior to the month of EPS(t), defined as FEPS(n)$-$EPS(t);
5) FC(n) - forecast change n months prior to the month of EPS(t), defined as FEPS(n)$-$EPS($t-1$);
6) FR(n) - forecast revision n months prior to the month of EPS(t), defined as FEPS(n)$-$FEPS($n+1$).

Observe that FR(11), the forecast revision one month after EPS($t-1$) was released (and 11 months prior to the month of EPS(t)), is by design equal to FC(11), the difference between FEPS(11) and EPS($t-1$).

4. Methodology and results

Section 4.1 reports the results of analyses in which the previous forecast is treated as the basis for forecast modification, whereas Section 4.2 reports the results of analyses in which the previously announced earnings are treated as the basis for forecast modification. The analyses are conducted using two methodologies: (1) a nonparametric portfolio analysis, and (2) a regression analysis.

4.1. Analysis of forecast revisions: Previous forecast as an anchor

4.1.1. Nonparametric portfolio analysis

Our first analysis concentrates on the relationship between forecast revisions and forecast errors. Since our theory (Figs. 1 and 2) predicts a different pattern of forecast errors depending on whether the forecast revision is positive or negative, we divided the sample into two groups: observations with positive forecast revisions ('positive group'), and observations with negative forecast revisions ('negative group'). The dependent measure is the percentage of observations with positive forecast errors. Table 1 presents the percentage of positive forecast errors (FERR(n)) for each group by period, where n is the number of months prior to the month of the earnings release. The number of available observations is in parentheses and observations for which the consensus forecast revision is zero were deleted from this analysis.

Table 1
Percentage of positive forecast errors by month when forecast revisions (FR) are positive (left column, FR>0) and when forecast revisions are negative (right column, FR<0)

Months prior to the earnings release (n)	FR>0 (observations)	FR<0 (observations)
1	42.1 (5295)	63.6 (7896)
2	38.8 (5601)	67.7 (8494)
3	37.4 (6102)	71.2 (9434)
4	40.7 (5242)	73.3 (8891)
5	41.1 (5544)	74.2 (8560)
6	40.6 (6070)	75.8 (8796)
7	43.3 (5591)	75.6 (8324)
8	44.6 (5926)	75.9 (7878)
9	44.5 (6322)	76.2 (8165)
10	47.5 (5864)	75.4 (8003)

Note: Forecast revision n months prior to the release of earnings per share, FR(n), is defined as the earnings forecast n months prior to earnings per share release, FEPS(n), minus earnings forecast $n+1$ months prior to the release of earnings per share, FEPS($n+1$).

Results show that when forecast revisions are positive (left side of the table), most of the forecast errors are negative (the percentage of positive errors is less than 50% for all periods). On the other hand, when forecast revisions are negative, most of the forecast errors are positive (the percentage of positive errors is greater than 50% for all periods).[3] This pattern of results is consistent with analysts' underreaction to new information when forecasting earnings, as depicted in Fig. 2 (see also Abarbanell, 1991; Ali et al., 1992).

4.1.2. Regression analysis

An alternative method to examine overreaction/underreaction is by regressing forecast errors on forecast revisions.[4] Unlike the nonparametric analysis, regression analysis takes into account the magnitude of the forecast error as well as its direction. The following equation is estimated:

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

where n is the number of months prior to earnings release, $\alpha(n)$ is an intercept term and $\beta(n)$ is the regression's slope. Lack of bias in prediction implies that both αs and βs equal zero; overreaction implies that βs are positive, while underreaction implies negative βs; optimism implies positive αs, whereas pessimism implies negative αs.

Our results reveal clear biases in analysts' forecasts. The regression results for the entire sample, reported by period, are presented in panel A of Table 2. Consistent with the pattern observed for the percentage of positive forecast errors (Table 1), they reveal a clear tendency towards both optimism and underreaction. The intercepts are positive and the slopes are negative for all 10 periods (both effects are reliably different from zero at the 0.01 level). These findings are consistent with underreaction when previous forecasts are used as the basis for the analysts' forecast. Table 2 also reveals that both $\alpha(n)$ and $\beta(n)$ decrease as n decreases (the forecasting horizon becomes shorter as actual earnings release approaches). This finding is consistent with the hypothesis that forecasting biases increase with prediction horizon (H3).

To examine the hypothesis that there is less overreaction (or more underreaction) in negative forecast modifications than in positive modifications, we regress forecast errors on forecast revisions separately for negative and positive revisions. The results of these regressions, by period, are presented in panel B of Table 2. The differences between the models of the positive and the negative revisions are dramatic. First, βs are positive for positive forecast revisions and are negative for negative forecast revisions in each of the 10 monthly regressions. These findings support our hypothesis about the difference between positive and negative forecast modification (H2). Note also that while forecast revisions are, by and large, characterized by underreaction (Panel A of Table 2), this is

[3] The difference between the percentage of forecast errors and 50% is significant at the 0.01 level for each of the 10 periods, both for positive and for negative forecast revisions. The test statistic, z, is calculated as $z=(P-0.5)/(0.25/nobs)$, where P represents the proportion of forecast errors in our sample, *nobs* is the number of observations and 0.5 is the proportion of forecast errors in the population under the null hypothesis.

[4] DeBondt and Thaler (1990) regress actual earnings changes ($\mathrm{EPS}_t - \mathrm{EPS}_{t-1}$) on forecast changes ($\mathrm{FEPS}_t - \mathrm{EPS}_{t-1}$), where the forecasts are made during April of year t. Like in our study, their purpose is to detect optimism and overreaction/underreaction. In their regression, a negative intercept indicates optimism, a slope coefficient below one indicates overreaction, and a slope coefficient above one indicates underreaction.

Table 2
Regressing forecast errors (FERR) on forecast revisions (FR) n months prior to earnings release (t-statistics below the coefficients)

Panel A: All observations
Model: $\mathrm{FERR}(n) = \alpha(n) + \beta(n)\mathrm{FR}(n) + \varepsilon$

n	α	β	R^2	Obs.
1	0.123	−0.320	0.01	13,164
	(20.2)	(−9.3)		
2	0.129	−0.677	0.03	14,095
	(21.1)	(−20.6)		
3	0.138	−0.655	0.03	15,536
	(23.3)	(−21.7)		
4	0.181	−0.958	0.05	14,133
	(26.3)	(−27.1)		
5	0.206	−1.186	0.06	14,104
	(28.0)	(−29.9)		
6	0.219	−1.265	0.08	14,866
	(29.5)	(−35.1)		
7	0.268	−1.339	0.06	13,915
	(32.4)	(−30.5)		
8	0.303	−1.525	0.07	13,804
	(34.4)	(−31.3)		
9	0.317	−1.415	0.07	14,487
	(36.0)	(−32.8)		
10	0.382	−1.279	0.05	13,867
	(39.8)	(25.6)		

Panel B: Separating positive forecast revisions from negative forecast revisions

	Positive forecast revisions					Negative forecast revisions			
n	α	β	R^2	Obs.	n	α	β	R^2	Obs.
1	0.013	0.686	0.02	5295	1	0.125	−0.658	0.02	7869
	(1.3)	(11.3)				(13.9)	(−13.8)		
2	0.005	0.436	0.01	5601	2	0.122	−1.092	0.06	8494
	(0.6)	(8.5)				(12.9)	(−22.6)		
3	−0.006	0.437	0.01	6102	3	0.165	−0.825	0.04	9434
	(−0.7)	(8.2)				(17.6)	(−19.3)		
4	0.010	0.500	0.01	5242	4	0.181	−1.374	0.08	8891
	(1.0)	(8.7)				(17.5)	(−27.5)		
5	0.014	0.372	0.01	5544	5	0.233	−1.501	0.07	8560
	(1.5)	(6.0)				(19.9)	(−25.9)		
6	0.018	0.291	0.01	6070	6	0.241	−1.595	0.09	8796
	(1.9)	(5.0)				(20.0)	(−30.2)		
7	0.033	0.399	0.01	5591	7	0.319	−1.622	0.07	8324
	(3.1)	(5.8)				(23.7)	(−25.0)		
8	0.044	0.476	0.01	5926	8	0.322	−2.273	0.10	7878
	(4.1)	(7.4)				(21.6)	(−29.0)		
9	0.055	0.395	0.01	6322	9	0.350	−1.969	0.09	8165
	(5.0)	(6.5)				(23.4)	(−29.0)		
10	0.085	0.768	0.02	5864	10	0.337	−2.747	0.12	8003
	(6.3)	(11.8)				(22.1)	(−32.8)		

not the case for positive forecast revisions. These revisions exhibit a tendency towards overreaction.

Note that when forecast revisions are negative, the tendency to underreact diminishes considerably as the earnings release month approaches. However, when forecast revisions are positive, there is little change in overreaction over time. It seems that the tendency to underreact to negative information diminishes in the face of reality, while the tendency to overreact to positive information does not. However, the tendency to underreact to negative information appears to be far stronger than the tendency to overreact to positive information when the realization time is still remote. Another difference between positive and negative revisions is that αs are more positive for negative revisions than for positive revisions in all 10 monthly regressions. This finding suggests that analysts are more optimistic when making negative revisions than when making positive revisions.

4.2. Analysis of forecast changes: Previous earnings as an anchor

4.2.1. Forecast change in the first period following earnings announcements

In the previous analysis, the classification to positive and negative groups was based on the assumption that analysts use their previous forecast as an anchor for their predictions and that the availability of this strong anchor leads to insufficient adjustment. However, in the first month after an earnings announcement, denoted as period 11, analysts have not yet made a prediction of the next year's earnings, and as a result, anchoring and adjustment may have a weaker effect on prediction, while representativeness may have a stronger effect. Therefore, it is possible that overreaction, rather than underreaction, would be observed with regard to forecast changes in the month immediately following earnings announcement (see H1 above).

4.2.1.1. Nonparametric portfolio analysis. To examine the overreaction hypothesis, we divide the sample into two groups based on the sign of the forecast change, and calculate the percentage of positive forecast errors in each of the groups. The results indicate that for the positive group, 63.3 percent of the forecast errors are positive (significantly different from 50% at the 0.01 level with a z-statistic of 35.3). Moreover, only 51.5 percent of the forecast errors are positive for the negative group (z-statistic of 1.46, not significantly different from 50% at the 0.10 level). These findings are consistent with overreaction (see Fig. 1).

4.2.1.2. Regression analysis. The findings concerning the percentage of positive forecast errors essentially replicate the DeBondt and Thaler (1990) results. Indeed, in spite of some methodological differences (e.g., we did not standardize current earnings on the basis of previous earnings in different time periods), when we use their method, and regress forecast errors on forecast changes:

$$\mathrm{FERR}(11) = \alpha(11) + \beta(11)\mathrm{FC}(11) + \varepsilon \tag{2}$$

we obtain a highly significant positive slope (β=0.479, t=27.0), which is consistent with overreaction. In addition, similar to DeBondt and Thaler (1990), the intercept of this regression is positive (α=0.217, t=26.0), consistent with excess optimism.

We extend DeBondt and Thaler's analysis by distinguishing between positive and negative forecast changes, and regressing the forecast error on forecast change separately for positive and negative forecast changes. The results of these regressions are similar to the results of the regression of forecast error on forecast revision. First, forecast changes, like forecast revisions, are characterized by overreaction when forecast changes are positive and by underreaction when forecast changes are negative. When Eq. (2) was estimated separately for positive and negative forecast changes, β was 0.773 (t=39.2) for the positive forecast changes and -0.483 (t=-6.1) for the negative forecast changes. These findings support the second hypothesis regarding the difference between positive and negative forecast modification.

Second, forecast changes, like forecast revisions, exhibit more optimism when the forecast change is negative than when it is positive. The regression intercept in Eq. (2) is 0.087 for the positive forecast changes (t=9.2), and 0.247 for the negative forecast changes (t=7.2).

4.2.2. Forecast changes in periods other the one following the earnings announcement

Forecast changes could also be defined for months other than the month following the (previous) earnings announcement. Although earnings predictions in these months are likely to be based on previous forecasts, the association between forecast changes and forecast errors for these periods is discussed in the literature (e.g. DeBondt and Thaler, 1990; Abarbanell and Bernard, 1992). Therefore, we examine this association below.

4.2.2.1. Nonparametric portfolio analysis. Table 3 presents the percentage of positive forecast errors by period for positive and negative forecast changes. Note that the number of observations in the two groups changes in a systematic manner. In particular, the number of observations in the positive group decreases, while the number of observations

Table 3
Percentage of positive forecast errors by month when forecast changes (FC) are positive (left column, FC>0) and when forecast changes are negative (right column, FC<0)

Months prior to the earnings release (n)	FC>0 (observations)	FC<0 (observations)
1	49.8 (16,196)	60.2 (7600)
2	51.3 (16,173)	63.3 (7181)
3	53.0 (16,346)	65.9 (6725)
4	55.3 (16,805)	67.9 (6156)
5	56.9 (17,128)	68.4 (5577)
6	58.0 (17,500)	68.8 (5001)
7	59.4 (17,923)	68.0 (4306)
8	60.7 (18,105)	66.2 (3732)
9	61.7 (18,236)	62.8 (3243)
10	62.6 (18,325)	58.1 (2719)
11	63.3 (17,554)	51.5 (2359)

Note: Forecast change n months prior to the release of earnings per share, FC(n), is defined as the earnings forecast n months prior to earnings per share release, FEPS(n), minus actual earnings per share released $12-n$ months earlier, EPS($t-1$).

in the negative group increases. The reason for this is that as optimism proves to be unwarranted, the forecast change of many companies moves from positive to negative, causing the number of observations in the positive (negative) group to decrease (increase).

Table 3 shows that the percentage of positive forecast errors in the positive group decreases gradually, until it approaches 50%. The reason for this decline is rather obvious. As both overreaction and optimism prove to be unwarranted, the percentage of forecast errors approaches its optimal level of 50%. On the other hand, the percentage of positive forecast errors in the negative group is close to 50% 11 months prior to realization, but is far from this level just prior to realization (60.2%). In the interim, it increases to 69% and then declines again. These results are clearly driven by observations which 'switch' from the positive to the negative group. Since the excessively optimistic forecasts of these observations are associated with a particular slow correction, these forecasts tend to have a strong positive bias when they move from the positive group to the negative group. This causes the percentage of positive forecast errors in the negative group to increase from period 11 to period 6.

4.2.2.2. Regression analysis. We also regress forecast errors on forecast changes where all variables and notations are as defined above.

$$\mathrm{FERR}(n) = \alpha(n) + \beta(n)\mathrm{FC}(n) + \varepsilon, n = 1 \text{ to } 10 \tag{3}$$

Panel A of Table 4 reports results for the full sample. Consistent with H3, both α and β approach zero as n approaches one. This result suggests that both overreaction and optimism, which are also observed in the 11th period, decline as the forecast horizon is shortened.

To complete the analysis, panel B of Table 4 reports the results of regressions of forecast errors on forecast changes by period and by the sign of the forecast change. Again, consistent with H2, the results reveal overreaction for positive forecast changes and underreaction for negative forecast changes, as indicated by the positive βs for positive forecast changes and by the negative βs for negative forecast changes. Note, however, that this latter underreaction is far weaker than the underreaction observed for forecast revisions (right side of Panel B, Table 2), a finding consistent with H1. The results also reveal that αs are more positive for negative forecast changes than for positive forecast changes, indicating more optimism regarding the former than the latter changes.

4.3. Sensitivity analysis

DeBondt and Thaler (1990, p. 55) among others, have argued that measurement error may have an effect on the results of studies that use the IBES database. In particular, if the consensus earnings forecast, represented here by the median monthly forecast, is measured with error, the regressions' slope coefficients are biased downwards.[5] There are several possible sources of measurement error in the median earnings forecast. First, the median forecast is a random variable with a variance that varies as a function of the

[5] In our case, measurement error would cause the results to look as if underreaction occurs.

Table 4
Regressing forecast errors (FERR) on forecast changes (FC) n months prior to earnings release (t-statistics below the coefficients)

Panel A: All observations
Model: $\mathrm{FERR}(n) = \alpha(n) + \beta(n)\mathrm{FC}(n) + \varepsilon$

n	α	β	R^2	Obs.
1	0.120	−0.012	0.00	23,796
	(28.2)	(−2.2)		
2	0.140	−0.025	0.01	23,354
	(30.9)	(−4.1)		
3	0.161	−0.034	0.00	23,071
	(33.5)	(−5.2)		
4	0.190	−0.030	0.01	22,961
	(36.9)	(−4.1)		
5	0.217	−0.026	0.00	22,705
	(39.5)	(−3.3)		
6	0.235	0.006	0.00	22,501
	(39.8)	(0.7)		
7	0.252	0.062	0.00	22,229
	(39.2)	(6.4)		
8	0.265	0.117	0.01	21,837
	(38.2)	(11.0)		
9	0.260	0.203	0.01	21,479
	(35.2)	(17.7)		
10	0.252	0.303	0.03	21,044
	(32.0)	(24.5)		
11	0.217	0.479	0.07	19,913
	(26.0)	(27.0)		

Panel B: Separating positive forecast changes from negative forecast changes

n	Positive forecast changes				n	Negative forecast changes			
	α	β	R^2	Obs.		α	β	R^2	Obs.
1	0.002	0.201	0.04	16,196	1	0.096	−0.199	0.03	7600
	(0.4)	(27.4)				(8.1)	(−14.3)		
2	0.016	0.194	0.04	16,173	2	0.123	−0.226	0.03	7181
	(3.0)	(25.0)				(9.6)	(−14.8)		
3	0.030	0.195	0.03	16,346	3	0.149	−0.260	0.03	6725
	(5.4)	(24.0)				(10.8)	(−15.2)		
4	0.039	0.239	0.04	16,805	4	0.174	−0.346	0.05	6156
	(6.6)	(27.2)				(11.4)	(−17.5)		
5	0.061	0.250	0.04	17,128	5	0.203	−0.408	0.05	5577
	(9.6)	(26.8)				(12.0)	(−18.0)		
6	0.074	0.284	0.05	17,500	6	0.251	−0.421	0.05	5001
	(11.1)	(28.6)				(13.1)	(−15.6)		
7	0.083	0.348	0.06	17,923	7	0.313	−0.439	0.04	4306
	(11.8)	(32.5)				(14.1)	(−13.5)		
8	0.107	0.388	0.06	18,105	8	0.315	−0.509	0.04	3732
	(14.1)	(33.4)				(12.7)	(−13.3)		
9	0.119	0.443	0.07	18,236	9	0.315	−0.505	0.04	3243
	(14.7)	(35.8)				(11.5)	(−11.2)		
10	0.130	0.504	0.07	18,325	10	0.333	−0.444	0.02	2719
	(15.4)	(38.4)				(10.7)	(−8.0)		
11	0.087	0.773	0.08	17,554	11	0.247	−0.483	0.02	2359
	(9.2)	(39.2)				(7.2)	(−6.1)		

number of analysts that follow the firm. Second, analysts' earnings forecast may not be independent of each other, as these forecasts are issued in different periods during the month. Given that some forecasts precede others, some analysts may choose not to issue forecasts lower than previously issued forecasts. Third, the IBES database contains a self-selection bias as analysts sometimes stop following firms that they perceive as performing poorly.

To assess the effect of measurement error on our results, we repeated the analyses separately for firms that are being followed by at least 12 analysts and for firms that are being followed by at most three analysts. Three and 12 analysts are the 25th and 75th percentiles of the distribution of analyst following, respectively. This analysis is performed under the assumption that measurement error is correlated with the number of analysts following the firm. In particular, we conjecture that observations with many analysts following are more likely to generate measurement error of the kind described above than observations with fewer analysts following.

As for observations with three or fewer analysts following, we find (not reported) results similar to those discussed earlier. Similar to the full sample results, we find overreaction to positive forecast revisions and underreaction to negative forecast revisions. We also find optimism that weakens as the release of actual earnings approaches.

As for observations with at least 12 analysts following, we find (also not reported) underreaction to negative forecast revisions; however, we do not find overreaction to positive forecast revisions. In addition, we find that when positive forecast revisions are made, analysts tend to be optimistic only during the first quarter after the release of actual earnings (n=10, 9, 8). When negative forecast revisions are made, we find strong optimism and strong underreaction. This pattern is consistent with measurement error that is stronger in firms with many analysts following. However, consistency of the results in firms with three or fewer analysts supports our claim that heuristics affect analysts' predictions.

5. Summary and conclusions

Previous studies have documented both overreaction (DeBondt and Thaler, 1990) and underreaction (Abarbanell and Bernard, 1992) in analysts' earnings forecasts. The purpose of this study is to examine hypotheses derived from behavioral decision theory, about the conditions that lead to overreaction and those that lead to underreaction. We argue that there are three heuristics that influence earnings forecasts – leniency, representativeness, and anchoring and adjustment.

Leniency affects both the level of prediction and its extremity. Overall, it leads to overly optimistic prediction; and when the forecast modification is negative, it also leads to excessively moderate predictions. Representativeness and anchoring and adjustment influence only the extremity of predictions. Representativeness leads to excessively extreme prediction, and anchoring and adjustment leads to excessively moderate prediction. Whether representativeness or anchoring and adjustment dominates prediction depends on the salience of the anchor – the value which is used as the basis for forecast modification. The more salient the anchor, the higher the tendency to rely on anchoring and adjustment. We suggest that there are two important factors that influence the salience of the anchor. First, previous forecast is more salient than previously announced earnings; and second, when the anchor is used for negative modification it is more salient than when it is used for a positive modification.

The results of our analyses are consistent with our model. We find a tendency towards overreaction in forecast changes and underreaction in forecast revisions. We also find overreaction for positive forecast modifications and underreaction for negative forecast modifications. Finally, we find that overreaction, underreaction and excess optimism increase with forecast horizon suggesting that the longer the prediction horizon, the larger the prediction bias.

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