An Experimental Approach to Assessing the Quantitative and Qualitative Compatibility Management Bias of Investment Managers

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ABSTRACT

Knowledge asymmetries and agency concerns among entrepreneurs, investors, and managers drive the natural evolution of the corporate information environment. Accounting data serves two main purposes in market-oriented economies. By supporting capital providers, like owners and creditors, in evaluating investment prospects and expected returns, accounting information primarily serves the ex-ante or valuation role. Second, accounting data enables capital suppliers to monitor the utilization of their invested capital. Firms frequently present distorted financial data. In this study, we propose and experimentally test the hypothesis that investors find it difficult to identify known biases in management's earnings forecasts, but they are more inclined to make a comprehensive adjustment when presented with quantitative bias information in EPS form, provided that the investor's evaluation aligns with the data. The findings of three experiments show that not all investors can detect managerial bias solely by compatibility and quantification. Furthermore, we show that this result holds even after accounting for other variables common in management earnings estimates. Our research benefits investors, regulators, and corporate leaders alike.

Keywords: Information Asymmetry, Quantitative Compatibility, Qualitative Compatibility, Investor Behavior, Behavioral Finance, Optimism, Pessimism, EPS

1. Introduction

According to this study, management bias is more likely to arise in cases of ‘quantitative compatibility’. Another example involves using bias as a criterion for evaluating investors' viewpoints. Our argument contends that quantitative compatibility enhances investors' capacity to detect bias in earnings projections. Furthermore, we believe that issues related to qualitative compatibility or other forms of incompatibility will hinder the unraveling of bias. Qualitative compatibility refers to a situation where investors' evaluations are qualitative and skewed. Incompatibility occurs when investors base their quantitative forecasts on a qualitative bias. We feel that qualitative data that merely indicating the direction of bias, whether optimistic or pessimistic, will be insufficient for analysis, even if the investor's appraisal is also qualitative in nature. We believe that any mismatch between the bias measure and the investors' assessments will not be sufficient to eliminate bias.

Although it may appear straightforward to detect bias by examining investors' opinions and quantifying bias, we predict significant opposition. Our theory posits that the quantitative nature of the biased information or the investor's assessment is inconsequential, as it relies on the notion that knowledge, once acquired, is irreversible. Eliminating biased information from memory may be difficult. Our research (Baginski, Hassell, and Kimbrough 2004) focuses on quantitative management earnings projections. Once actual earnings are documented, bias can be determined statistically (in cents and whether it's optimistic or pessimistic) or qualitatively (by bias direction, optimistic or pessimistic). Investors can examine possible gains using quantitative approaches (earnings per share forecast) or qualitative procedures. Consequently, in fields like psychology and marketing, this framework allows testing of both unrealistic or purposefully created scenarios. According to Imam and Barker [1], earnings predictions affect management's credibility, market expectations, and the possibility of a lawsuit.

We conducted three consecutive experiments using factorial designs with diverse participants. Our primary choice is to impact the manager's quantitative earnings forecast, which might be optimistic ($2.01) or pessimistic ($1.91). Additionally, we consider bias at three levels: minimal bias versus significant bias at the quantitative level (i.e., optimistic or pessimistic by $0.05), and purely directional bias at the qualitative level. Participants in the study evaluate realized earnings for the year using both qualitative and quantitative criteria, including earnings favourability and earnings per share (EPS). If study participants' ratings, both quantitative or qualitative, are statistically equivalent in both optimistic and pessimistic scenarios, this experimental design indicate significant bias. Experiments 2 and 3 concentrate entirely on quantitatively documented, highly biased earnings estimations. Our goal in conducting these experiments is to identify and address confounding factors in the earnings forecast domain that may amplify the impact of quantitative compatibility on bias resolution. Experiment two directly tests whether participants are more likely to detect data bias when they calculate the quantitative bias using historical data rather than merely reading about it. Depending on whether corporate remarks accompany the earnings forecast (experiment three), investors may pay varying degrees of attention to the bias that requires clarification.

The experiment yielded three key findings. Investors are more likely to accept management's exaggerated earnings predictions, even when provided with data that could clarify erroneous expectations, such as quantitative EPS forecast information and an associated EPS assessment. Secondly, many investors' EPS estimations still exhibit an optimistic or pessimistic bias depending on management's earnings estimates. This is consistent with psychological research demonstrating that individuals struggle to reject intentionally misleading or prejudiced claims [2]. Regardless of this outcome, we find that the greatest degree of bias occur when investors provide their assessments in a quantitatively similar manner and the bias data is also quantitative [3].

Furthermore, investors' behavior remains consistent regardless of whether they are informed about historical managerial bias, required to compute it independently, or instructed to incorporate manager's perspective into their forecast. Nonetheless, we find that the predictive aspect enhance bias resolution. Previous archival research by Radke and Volman [4] demonstrated that bias unraveling is more effective with optimistically biased projections. Lastly, contrary to popular belief, bias unraveling does not occur in situations that are unlikely to cause it. For example, it fails to manifest when qualitative (i.e., directional) bias information is paired with consistent qualitative judgments, or when there is any form of incompatibility (qualitative bias with a quantitative response, or vice versa), bias unraveling does not occur. Our manuscript has several implications. First, our findings offer behavioral explanations for the apparent lack of general managerial bias disclosure. Our findings also validate So and Achar [5] assertion that behavioral variables may contribute to the challenge of overcoming predicted bias. Even in ideal settings, where quantitative bias data and assessments are available, we demonstrate that rejecting the initial biased prediction is not automatic. As a result, we want to contribute to the accounting and finance literature by showing that market participants can occasionally mitigate the effects of bias.

Second, our findings could explain why corporate management continues to use skewed forecasting, despite its apparent irrationality. In essence, corporate leaders may already understand that, even in ideal circumstances, not all market participants completely grasp deceptive valuations. Certain people have compared this approach to individuals who propagate misinformation, believing that the recipients will accept the false information [6],. Given the possible effects of biased forecasts on investment decisions, regulators have a growing responsibility to prevent the dissemination of false information. Following structure will guide the remaining article. .Firstly, we present the theoretical foundation of our study and refine our forecasts. The next three sections show the experimental designs and results from experiments one through three. We conclude with recommendations for future research and a summary of our findings.

2. Literature Review

Security analysts facilitate communication between investment banks and enterprises. Multiple studies have demonstrated that stock prices are proportionate to changes in projections and recommendations [7-9]. Due to the responsiveness of market participants to pricing, analyst estimates impact the value discovery and profit expectations. However, analysts' investment advice is constrained by their inherent biases. A study by [10] found that analysts are incentivized to produce optimistic estimates and recommendations to develop valuable investment banking contacts. Previous research, such as conducted by [11-14], demonstrate that analysts' desire to preserve positive relationships with upper management may impact their projections and recommendations. Knutson and Bossaerts [15] examine confidential data on analysts' annual salaries and conclude that there is no association between erroneous projections and lower wages. Other research has discovered several sources of bias, including asymmetric reactions to positive and negative news (Easterwood and Nutt, 1999), underreaction to previous information [16-18], overextrapolation of past trends, and overweighting of private information. According to Prosad and Kapoor [19], failure to account for analyst biases can result in substantial valuation differences.

Despite the risk of mispricing, several researchers have investigated how investors use analyst data to construct performance expectations. According to Luo and Li [20], returns are lower for smaller investors who adhere to expert advice. While some investors may over-rely on expert-based signals, they discovered that more prominent investors outperform when trading, contrary to analyst advice.

Due to the unpredictability of the market, managers may choose to provide either good or negative information. Managers decide to disclose information depending on their predictions regarding how investors will utilize it. Assuming that management does not always have access to sensitive information that limits full disclosure, Ramnath and Rock [21] argue that investors are typically unaware of management's information endowment [22, 23]. O'Connor and Arnold [24] illustrates that managers' uncertainty on how investors will respond to their disclosures is sufficient to break the result, despite meeting all of the prerequisites for the finding other than investors' uniform response. As the investors sophistication increases, it may become increasingly difficult for businesses to forecast investor reactions to the news. According to [25], companies are more likely to disclose information to well-informed investors when these investors are rational but they receive private information probabilistically. According to Delmar and Shane [26], well-informed investors may appreciate a company's disclosure, but uninformed investors can merely witness it without deriving a meaningful value implications.

Suppose the number of sophisticated investors is small and the number of uninformed investors is significant. In that case, firms should refrain from disclosing sensitive information (since the latter group may believe that only low-valued businesses would reveal it). These models demonstrate how audience characteristics can explain why companies may lack transparency. Managers disseminate knowledge because they believe that their subordinates will value it. Investor information influences the perspectives of management when shareholders possess information that management does not. The stock market's reaction to a company's disclosure can provide valuable insight [27, 28].

2.1 Role of Investment Managers in Investment Decisions

If stock-based compensation schemes motivate managers to declare their plans to buy or sell firm securities or earn stock options, managers may be more likely to do so freely (option grants and restricted stock). Positive events are more likely than adverse developments to induce directors to sell shares [29]. When insiders increase their purchases of business stock in anticipation of negative news, the share price falls [30]. According to the data, CEOs time voluntary disclosure to maximise stock option awards [31]. When a CEO's income and wealth are more sensitive to stock market fluctuations, analysts' subjective evaluations of an organization's transparency policies improve, suggesting that management is more likely to provide realistic profit estimates. Bonuses tied on the company's stock price encourage the disclosure of positive and negative company events. Poor stock performance, which is often linked to executive turnover, may also be "explained" by voluntary disclosures from management [18]. It remains unclear, according to the survey results, how management's career concerns influence their disclosure practices [9].

Security analysts act as intermediaries between companies and investors. It is well proven that analyst upgrades and downgrades are correlated with stock price variations [32-38]. Analysts' forecasts influence price discovery and investor expectations for future profitability. However, the investing advice of analysts may be distorted. Bradshaw and Brown [39] examine the reasons why analysts provide optimistic estimations and recommendations. Various studies, including those by [40, 41], have found that analysts desire to be acknowledged by management results in erroneous projections and proposals. The literature discusses analysts' asymmetric responses to negative and positive news [40], their underreaction to previous information [13, 42, 43], and analysts' overextrapolation of previous trends [39-41]. Several studies have demonstrated that if evaluators overlook the impact of fundamental analyst biases, they can make significant financial errors.

2.2 Investment Behavior and Financial Reports

Several studies have investigated how investors use analyst reports to set performance objectives. According to research by Shu [44], smaller investors lose money when they follow analyst advice. They cannot demonstrate systematic overweighting because their data indicates that prominent investors earn more from trading, regardless of the recommendations of specialists. Due to overconfidence in their abilities or the influence of monetary incentives, managers may overstate the size of their organizations [2]. When matching expectations is crucial, negative projections may be prepared, but optimistic projections may be made when the public perception of the company should be good [45]. According to several studies, investors will abandon a company if they believe it is attempting to manipulate its performance [2]. It may be a convenient assumption, but market prices eventually adjust to their true value when enough rational investors participate.

2.3 Behavioral Aspects of Stakeholder’s Expectations

Shareholders often do not know what to expect from a company's disclosure practices, allowing managers to reveal as much or as little information as they see fit. When determining whether or not to release information, management frequently analyzes the sentiments of investors rather than the facts [46]. According to Gaspar and Massa [47], investors remain skeptical of a manager's information endowment, even though they may not always have access to private information. Tang and Zhang [48] demonstrate that the unwinding result is disrupted even if all other conditions are met, if managers are uncertain how investors will react to their disclosures. Given the diversity of investor expertise, estimating investor responses to company announcements is challenging. Teo and Nishant [49] argue that when firms are more likely to be well-informed, they are more likely to share information with investors, even if the investors are rational but receive private knowledge probabilistically. According to Compen and Pitthan [3], investors who are already well-informed will gain nothing from a company's disclosure, but those who are not should pay attention. It is futile to provide financial information to the public if there are few astute investors and many sceptics (who assume that only firms with low valuations would make a disclosure) [45]. These models demonstrate how some organizations are more reluctant than others to disclose specific information and how this reluctance may be at least partially attributed to the characteristics of the audience. Managers deliver information because they have confidence in their audience's intelligence [50]. A panel of experienced investors evaluates management's explanation. Indicating that disclosures serve more purposes than just public education, the stock market's reaction to a company's disclosure can teach management when investors know something they don't [51, 52].

2.4 Intentions and Investment Behavior of Managers

After receiving options or restricted stock, managers may feel compelled to disclose their intentions to purchase and sell company shares. Managers are statistically more likely to sell shares in response to favorable news and more likely to buy shares in response to negative information [53]. Expectations decline when insiders reduce a stock's price [3]. Furthermore, evidence suggests that CEOs carefully time voluntary disclosures to maximize stock option grants [54]. Nadler and Jiao [53] found that when the CEO's income and wealth are more volatile due to stock price fluctuations, management provides profit forecasts more frequently, and analysts' subjective evaluation of firms' disclosure practices improve. According to them, equity-based incentives promote both positive and negative press releases. Due to the correlation between stock performance and executive turnover, managers may "explain" bad performance through voluntary disclosures [32]. Healy and Palepu [55] discovery of a gap in management's disclosure of career concerns calls for further study. Recent research examined whether bias unwinding is more significant in specific instances or sufficient on average for market efficiency. According to Ruggeri and Alí [56], market participants can distinguish between biased optimistic and pessimistic news projections.

2.5 Overconfidence Bias

The most influential psychological component of administrative behavior is overconfidence. Confident leaders tend to overestimate their competence and the monetary advantages of their decisions, while underestimating the probability of failure [57, 58]. This cognitive bias may influence decisions related to organizational change. As part of its transformation, a company must establish a new core business focuses on developing strength rather than size [59]. The quality of an organization improves when resources are allocated more judiciously. The company's organizational structure, operational procedures, resource allocation, and culture are determined by its core business. The entire organization will undergo change and reform as a result of the transformation [60, 61]. Failure to succeed during a shift might impede future growth and place a business at risk. Due to their delusions of knowledge, self-assured managers often inflate the trustworthiness and certainty of data. When presented with potentially lucrative investment prospects, this mentality drives individuals to pursue business transformation despite the inherent risks and objective circumstances.

Financial specialists routinely warn of the dangers of overconfidence [62]. It would be unwise for overzealous managers to place all of their eggs in the stock market or the macroeconomy. This cognitive bias may influence the digital transformation decisions of an organization. The desire to develop a privately held empire may drive managers to become even more arrogant. Whether the economy is a free market or highly regulated, investment decisions and behavior are driven by business and industry growth possibilities [60].

According to research, to assess the reliability of management's quantitative earnings estimate, investors would be best served if they had access to quantitative information about bias and investor assessments that align with that information [57]. Any efforts to overcome bias must begin with scientific data. Due to the magnitude of bias, investors are unlikely to adjust for the discrimination based on qualitative information, such as whether it is optimistic or pessimistic [5]. Because of this, predicting whether investors would over- or under-adjust their projections to account for qualitative biases is challenging. [63] use possible conflict of interest disclosure as an example. In this case, the evidence of bias is qualitative, but the biased data is numerical. Researchers struggled to make sense of the problem due to bias in the data [3]. Positive responses are equally significant. Evidence that supports the response and utilizes the same units of measurement is given higher weight in decision-making based on the compatibility principle [64]. Collaboration can help people uncover their latent biases more quickly, accelerating the process. Based on a review of the psychological literature by [65] complete unwinding is unlikely to occur if compatibility is insufficient.

2.6 Research Hypothesis

Based on the in-depth review of literature following research hypothesis are formulated:

1. We hypothesize that the best opportunity for bias unraveling will occur when information about managerial forecast bias is quantified.
2. Investors' judgments are also compatible with that information (i.e., quantitative EPS judgments).
3. We further hypothesize that qualitative compatibility (i.e., qualitative bias and qualitative responses) and any incompatibility (qualitative bias/quantitative response, or vice versa)—will not lead to reliable bias unraveling.

The hypothesis stated above were tested using following research framework.

3. Research Design

3.1 Materials & Methods

3.1.1 Participants

We met the criteria outlined by Elliott et al. The exploratory experiment included 200 individuals with a total of ten years of experience in the field. Participants must be alumni of GCC-affiliated business schools. Eighty-one percent of the participants had previous experience acquiring common stocks. Participants typically completed four finance and accounting courses. Because of their accounting and financial competence, the participants can act as investors in the experiment.

3.1.2 Research design

To validate or invalidate our research hypothesis, we conducted three distinct experiments. Each experiment is different in nature and pertains to a specific aspect of the present research. Details of each are provided in Section 4 along with their results and implications.

4. Results and Discussion

4.1 Experiment One

In the first test, a 2X3 between-subjects layout was employed. In this role-playing game, three participants assume the roles of stockbrokers in a financial services organization. One factor they consider when determining whether or not to invest in the CEO's press release. This news release includes the optimistic and pessimistic forecasts for the upcoming year, developed by local polling specialists. Additionally, we provide three distinct methods for evaluating bias variance. If there is a slight bias, investors will be presented with evidence that the CEO's projections have a strong history of accuracy. In this case, the investors are informed that the CEO has a track record of making inaccurate forecasts and are given enough data to assess if the CEO is biased toward optimism or pessimism. Each of these severe biases, whether applied to qualitative (positive or negative direction) or quantitative (positive and negative value) data, appears to be exceptional (i.e., direction and magnitude in cents). All participants in the sample must complete two crucial dependent measures. On a scale from 0 (extremely poor) to 100 (outstanding), how optimistic are they about the company's profitability in the following year? (very good).. A free-response question on the candidate's projected EPS for the current fiscal year might appear on a quantitative exam.

We will test our hypothesis using the following iterations of the i and j variables. We may determine whether or not individuals in high-bias scenarios can make directionally adjusted decisions by comparing their performance in the two high-bias settings to their performance in the two low-bias settings. Additionally, we may evaluate the success of anti-discrimination programs by exposing participants to highly biased environments. Strong bias would be entirely eliminated if qualitative or quantitative assessments in high-bias scenarios converged on a midway ground between optimistic and pessimistic expectations. A thorough breakdown is suggested if average qualitative or quantitative evaluations under optimistic and pessimistic high-bias situations are statistically similar. Compatibility or incompatibility may result from high levels of bias (both qualitative and quantitative). Dependent measures may take various forms (i.e., qualitative and quantitative). However, we anticipate the greatest reduction of bias in the quantitative compatibility criterion. The qualitative compatibility criterion and the two incompatible criteria are still significant because they allow us to rule out the possibility of bias reduction in other contexts.

4.1.1 Checks for avoiding manipulation

We asked participants to score the company's press release as positive or negative to identify instances of forecast distortion. To accurately respond to this question, participants needed to choose the relevant condition 97% of the time, with a chi-square value of 188.46 and a p-value of 0.01. The manipulation probe addressed whether the CEO anticipated the share price to be \$2.01 or \$1.96, and 99% of the participants correctly answered this question. The revisions to the projections had positive results.

We'd like to know whether individuals believe the CEO has made mistakes in the past, and if so, how significant they are. The first question had 91% right answers, and the second question had 95%

accuracy. ($p < 0.01$, $\chi2> 100.00$). Our efforts influenced the bias.
This situation met the criteria established by Elliott et al. The study's pilot trial included 200 participants with a combined ten years of industry experience. To be eligible, applicants must have graduated from a business school in one of the GCC member countries. 80% of the participants have prior experience buying ordinary stock. Typically, the participants has completed four accounting and finance courses. Because of their accounting and financial expertise, the participants were well-suited to act as investors in the experiment.

We use a two-by-three between-subjects ANOVA and planned comparisons to test our hypotheses. The model calculates qualitative (earnings favorability) and quantitative judgments (ROI and EPS). For clarity, Table 1, Panel A, contains mean, standard deviation, and medians for condition-organized determinations. Panel B shows ANOVA results, whereas Panel C shows the pre-set comparison tests.

To detect forecast manipulation, participants were asked if the CEO's press release was positive or negative for the company. Nearly 95% of respondents correctly identified the condition ($\chi2=$ 138.46, p 0.01). The CEO's per-share projection of $1.96 to $2.01 was another problem. 99% of the participants answered correctly.

Users are asked to rate the CEO's historical accuracy and whether they know how much the CEO has erred (i.e., whether the CEO's profit projections have always been off by $0.05). After getting the first question right (91% accuracy), over 95% of participants answered the second question right. Correct answers correlate with appropriate experimental design ($\chi2> 100.00$, p 0.01). Our actions effectively reduced bias.

A two-way ANOVA with three groups and preset comparisons was used to test our hypothesis. This approach assesses EPS and earnings favorability. Panel A of Table 1 shows each condition's medians, means, and standard deviations. Panel B shows the analysis of variance, while Panel C outlines the planned comparison tests.

A statistically significant interaction for forecast-bias and independent factor supports our hypothesis. Both of the dependent measure ANOVAs in Panel B of Table 1 demonstrate statistically significant interactions (p-values 0.05). Panel C displays the comparisons we have prepared to analyze these interactions. This involves two comparisons. We adjust the directional bias by testing investors' responses to three bias scenarios. Additionally, we compare the mean responses to the second test between optimistic and pessimistic investors within each bias group. These assessments reveal bias.

Table 1. Statistics of Experiment One

Table 1= Panel A: Descriptive Statistics				
Quantitative Judgment regarding earnings			**Qualitative Judgment regarding earnings**	
	Forecast (optimistic)	**Forecast (pessimistic)**	**Forecast (optimistic)**	**Forecast (pessimistic)**

Lower Bias for Qualitative information	1.95	1.83	75.21	45.59
	[1.94]	[1.81]	[80]	[46]
	-0.02	-0.02	-14.74	-19.14
	n=51	n=51	n=51	n=51
High Bias for Qualitative information	1.93	1.84	69.17	49.18
	[1.91]	[1.82]	[74]	[57]
	-0.03	-0.03	-14.74	-18.14
	n=51	n=51	n=51	n=51
Lower Bias for Quantitative information	1.93	1.84	69.17	56.31
	[1.91]	[1.83]	[80]	[46]
	-0.02	-0.04	-14.54	-21.14
	n=51	n=51	n=51	n=51

Source	**Quantitative Judgment regarding earnings**			**Qualitative Judgment regarding earnings**		
	df	Statistics	Two-tailed p-value	df	Statistics	Two-tailed p-value
Forecast	1	F=159.30	<0.01	1	F=70.01	<0.01
Bias	2	F=0.51	0.590	2	F=0.89	0.49
Forecast X Bias	2	F=4.02	0.029	2	F=6.00	<0.01

Panel C: Planned contrast tests on mean judgments						
	Quantitative Judgment			**Qualitative Judgment**		
Optimistic/Pessimistic Forecasts	**df**	Statistic	p-value	df	Statistic	p-value
X Low Bias/Two High Bias conditions averaged	1	F=10.75	<0.01	1	F=6.75	0.01
X Low Bias Qualitative/High Bias Qualitative	1	F=6.76	0.06	1	F=3.00	0.23
X Low Bias Qualitative/High Bias Quantitative	1	F=10.01	<0.01	1	F=7.37	<0.01
X High Bias Qualitative/High Bias Quantitative	1	F=1.41	0.40	1	F=0.48	0.71
Planned Simple Main Effect and Interaction Contrasts:	**Quantitative Judgment**			**Qualitative Judgment**		
Optimistic vs. Pessimistic Forecasts at:	**df**	Statistic	p-	df	Statis	p-

			value		tic	value
Low Bias	1	F=96.8 1	<0.01	1	F=46. 81	<0.01
High Bias/Qualitative	1	F=24.8 2	<0.01	1	F=21. 02	<0.01
High Bias/Quantitative	1	F=9.83	<0.01	1	F=8.1 3	<0.01

Source: Present research

We employ the same analyses described above to derive our quantitative (EPS) verdict. First, we contrasted the two low-bias conditions (means of $1.95 and $1.83) with the mean of the two high-bias conditions (means of $1.93 and $1.84, respectively, not tabulated). As expected, the results revealed that investors can adjust bias in the right direction (F = 10.75, p 0.01). However, in cases of quantitative compatibility, the crucial test is whether there is more unwinding in the quantitative high-bias situation compared to the quantitative Judgment. Surprisingly, there was no larger unwinding in the former when reaching the two projected means in the quantitative high-bias cases (means of $1.95 and $1.83) to those of the qualitative high-bias conditions (means of $1.95 and $1.83) (F = 1.41, p = 0.40). Contrary to the expectation, we anticipated more unraveling with quantitative scale compatibility but observed the opposite.

4.1.2 Results for the qualitative judgments

There are two methods for distinguishing between the different types of bias. First, we evaluated investors' ability to change their directional preferences in the absence of input by comparing low-bias settings to the average of two high-bias scenarios. In this case of minor bias, the difference between optimistic and pessimistic estimates is greatly overstated (75.21 vs. 45.59; F = 10.75, p < 0.01). However, when incorporating the two high-bias data—the unrecorded means of 63.24 and 47.44—reduces the result. As anticipated, investors successfully overcome their bias. In the second experiment, we compared the means of statistically biased assessments (56.31 and 69.17) to those of qualitatively biased judgments (69.17 and 49.02). There were no statistically significant changes seen when testing the hypothesis that compatibility among qualitative characteristics would result in quantitative bias or qualitative assessment (F = 1.41 and p = 0.40).

The qualitative dependent variable is significantly influenced by all three types of bias (p < 0.01). Finally, the majority of qualitative wage judgments are positive when bias is low. The means of 75.21 and 45.59 (F = 45.91, p = 0.01) did not differ significantly.

Both scenarios exhibit significant bias due to their underlying assumptions. After eliminating qualitative bias, the means for optimistic and pessimistic forecast conditions differed (75.21 vs. 45.59, F=40.82, p<0.01). Sharing similar preferences was not sufficient to eliminate bias. Despite the considerable bias, the means of the two projected scenarios differ (69.17 and 56.31, respectively; F = 9.83, p < 0.01). This discrepancy indicates that the difference between quantitative bias and qualitative responses does not inherently indicate bias.

4.2 Experiment Two

The second set of tests, known as within-bias comparisons, assess investors' ability to fully disentangle bias. The tests reveal substantial main effects for all three bias scenarios, indicating incomplete unwinding (p-values < 0.01). Without bias, quantitative assessments were more beneficial in the optimistic earnings scenario than in the pessimistic one (means of \$1.95 versus \$1.83; F = 96.81; p < 0.01). However, the presence of significant bias does not result in total unwinding (means of \$1.28 vs. \$1.23; F = 42.04, p < 0.01). Even after controlling for the quantitative-compatibility scenario, which quantifies the investor's reaction and excess bias, a large direct primary influence remained. In conclusion, investors' quantitative estimates of earnings per share (EPS) are different in both optimistic and pessimistic scenarios, even though there is a lot of bias in the numbers (means of \$1.93 and \$1.84, F = 24.82, p < 0.001). This resource gap shows that investors are unable to completely eradicate managerial bias.

When analyzing our projections, we considered the number of participants that changed their earnings per share expectations to \$1.96, as the unwinding metric may have impacted these results. We focused the total number of investors who entirely disengaged rather than the average number who unwound.

We expect earnings per share to drop to \$1.86 or higher. Pessimistic and optimistic high-bias scenarios require complete unwinding, with adjustments exceeding five cents. If a participant's bias adjustment exceeds five cents, we may exclude them from these tests. We believe that the inclusion of these participants in the table helps the reader comprehend the magnitude of under-correction due to bias. However, robustness tests reveal that their inclusion makes no difference to the conclusions. This assures that a small number of participants who may have failed to overcome the bias had a significant impact on the mean differences found in our earlier tests. This alternative metric illustrates that changes in the frequencies of the two projected scenarios correspond to differences in total unraveling between the two forecast types, rather than the absence of full unraveling. To test our hypothesis using this frequency data, we employed either a primary bias effect or a bias by forecast interaction (Panel A, Table 2). Nonetheless, because none of the frequencies exceed 100% (all p-values from binomial tests are less than 0.01 in each test), our methodology helps determine the impact of the modified variables.

Table 2. Full bias unraveling: Frequency data for all experiments

Panel A: Frequencies of whole unraveling		
Experiment One		
	Qualitative Low Bias	**Qualitative High Bias**
Optimistic Forecast	0%	37%
	(0/30)	(11/30)
Pessimistic Forecast	5%	20%
	(1/20)	(5/30)

Average Across Forecasts	2%	32%
	(1/60)	(16/60)
Experiment Two (Quantitative High Bias only)		
	Quantitative High Bias	**Read about Bias**
Optimistic Forecast	53%	47%
	(16/30)	(14/30)
Pessimistic Forecast	44%	46%
	(11/30)	(11/27)
Average Across Forecasts	54%	51%
	(27/60)	(25/60)

Experiment Three (Quantitative High Bias only)			
	Calculate Bias	**Commentary**	**No Commentary**
Optimistic Forecast	57%	20%	43%
	(17/30)	(16/30)	(13/30)
Pessimistic Forecast	32%	42%	44%
	(8/25)	(10/25)	(10/25)
Average Across Forecasts	50%	53%	48%
	(25/60)	(26/60)	(23/58)

Panel B: Categorical analysis of variance			
Experiment 1			
	df	**Statistic**	***p*-value**
Forecast	1	$X^2=4.01$	0.05
Bias	2	$X^2=70.02$	<0.01
Forecast X Bias	2	$X^2=7.03$	0.04
Experiment 2			
	df	**Statistic**	***p*-value**
Forecast	1	$X^2=6.01$	0.01
Bias Disclosure	1	$X^2=0.01$	0.83
Forecast X Bias Disclosure	1	$X^2=2.01$	0.21
Experiment 3			
	df	**Statistic**	***p*-value**
Forecast	1	$X^2=1.95$	0.17
Commentary	1	$X^2=0.21$	0.71
Forecast X Commentary	1	$X^2=0.72$	0.5

Source: Present research

Investors struggle with comparing intragroup biases. The unwinding is incomplete since all three bias conditions have significant main effects ($p = 0.01$). Positive quantitative evaluations are more common under the optimistic earnings condition compared to the pessimistic earnings condition. However, both scenarios have significant bias (means of \$1.95 vs. \$1.83; $F = 96.81$; $p < 0.01$). The table does not provide a detailed explanation for the significant difference in mean quality between the two groups (\$1.28 vs. \$1.23; $F = 42.04$, p 0.01). The quantitative compatibility dilemma has major and evident implications. Investors respond quantitatively to measurable representations of minor bias in this situation. Investors' EPS expectations differ between optimistic and pessimistic projection scenarios (means of \$1.93 and \$1.84, $F = 24.82$, $p < 0.01$), indicating a quantitative bias. This methodological difference demonstrates that, contrary to popular belief, investors are not intrinsically adept at detecting managers' biases.

Given the likelihood of fluctuation in the second round of results, we evaluate our forecasts further by counting the number of people who revised their EPS projections to \$1.96. Our key concern is not the average unraveling rate but rather the proportion of investors who experienced a complete unraveling.

When pessimistic or optimistic high biases raise their EPS predictions to \$1.86 or higher, the bias is erased (i.e., they change their EPS forecasts by five cents or more). We believe that the need to correct several inaccuracies may leave certain individuals incapable of carrying out these tests. The table used a small sample size to illustrate the extent of participant bias under adjustment, even though robustness tests indicated that it did not affect the results (one less than the specified frequency).

This ensures that a small proportion of participants, who may have no bias, have not influenced the results of previous experiments. This alternative statistic examines differences in the rate of complete unwinding rather than occurrences of failure to unwind. Panel A, Table 2, shows that a bias-by-forecast interaction and a primary bias effect are the most basic ways to test our hypothesis with these frequency data. All frequencies are statistically lower than 100% (all binomial test p-values are less than 0.01); nonetheless, our tests demonstrate the impact of numerous variables on the results.

4.2.1 Results for the qualitative judgments

The bias affects the forecast in two ways, as shown in Table 2, Panel B. In low-bias settings, only 2% of participants fully adjusted to \$1.96. In both high-bias scenarios, 43% were successful on average (untabulated main effect contrast: = 61.92, $p < 0.01$). This and the intermediate solution are strikingly similar. During the follow-up analysis, we will see if quantitative compatibility boosts the number of responders who can totally unwind in high-bias settings. Investors can detect bias in data more accurately (54% versus 32%) than through verbal communication . This demonstrates how quantitative compatibility, defined as the fraction of people capable of dissociating their biases, leads to positive outcomes. The results show a significant main impact (= 4.01, $p = 0.04$), as shown in Table 2. The findings indicate that predictions characterized by extreme optimism were more susceptible to bias. Rogers and Stocken's 2005 study found that optimistic predictions are easier to understand.

As the first study showed, investors who know their quantitative or qualitative biases can mitigate them. Investors often encounter disagreements due to ideological differences and other issues.

Investors may find it easier to adapt their profit projections to account for bias in circumstances where the quantitative scales are compatible. A sizable fraction of investors selling their assets suggest a shift in market behaviour. We carry out two additional experiments that alter environmental variables within the prediction domain, aiming to gain insight into the potential for participants to completely disentangle their biases under quantitative compatibility. The extra experiments primarily address difficulties associated with high-bias quantitative data.

To help participants calculate and demonstrate historical bias independently, we provide actual profit realizations and estimates from previous years during the second experiment. In the first experiment, we provided a summary estimate of quantitative tendency to the participants. Kusev and Purer [66] revealed that when people produce their own content rather than simply reading it, they learn, absorb, and retain it better. We hypothesized, based on the their findings, that our investment participants would respond differently if asked to calculate the bias using historical data. If people are more aware of historical bias, they may be less likely to rely on the initial skewed earnings forecast, as they will be more critical of it than if they were only given a summary of bias.

4.2.2 All stakeholders, components, and schematics

The second experimental design involved a 2 × 2 between-participants manipulation. We calculated the five cents of historical bias using data from the previous year, considering whether participants receive it as a summary statistic for review, and the degree of optimism or pessimism in the CEO's forecast. As in the first experiment, we inform participants in the read-about-bias condition that the historical forecast error has been five cents per share, depending on the forecast condition. This error has shown both optimistic and pessimistic tendencies. During the calculate-bias step, we compare six years of historical earnings projections to actual results, emphasizing both the optimistic and pessimistic aspects of the forecasts as needed. The forecasting error varies annually between four and six cents, with an average of five cent (So 2013). Both trials used the same research apparatus as the initial investigation. To avoid subject overlapping in our second experiment, we used the same population for both samples. The tenure of employment (5.8 years) and the proportion of those who had invested (63%) nearly matched the results of the first experiment.

4.2.3 Checks for avoiding manipulation

We asked participants to determine whether the CEO's press statement portrayed the company positively or negatively, to assess if the forecast had been updated. Ninety-six percent of participants correctly answered the question, and accurate responses were exclusively linked with the appropriate condition ($\chi2 = 550.05$, $p < 0.01$). A subsequent question inquired about participants' memories of times when the CEO supplied them with erroneous or misleading information. Participants may even claim to have forgotten unreliable projections that are negatively skewed or overly optimistic. A substantial majority of participants (89%) accurately answered this question. Once again, the appropriate responses are linked to the accurate experimental condition ($\chi2 = 154.08$, $p < 0.01$). The queries show that our modified forecast was successful.

Table 3. Experiment two results.

Panel A: Descriptive statistics—Mean [Median] (Standard deviation)				
Quantitative Judgment about future earnings			**Qualitative Judgment about future earnings**	
	Optimistic forecast	*Pessimistic forecast*	*Optimistic forecast*	*Pessimistic forecast*
Read about Bias	1.81	1.99	63.65	52.00
	[1.63]	[151]	[70]	[60]
	(0.02)	(0.07)	(18.56)	(16.16)
	(n=30)	(n=29)	(n=30)	(n=28)
Calculate Bias	1.41	1.39	62.52	61.45
	[1.36]	[1.34]	[70]	[62]
	(0.03)	(0.03)	(17.20)	(15.12)
	(n=30)	(n=29)	(n=30)	(n=30)

Panel B: ANOVA of Judgement						
Source	**Quantitative Judgement**			**Qualitative Judgement**		
	Df	**Statistic**	**Two-Tailed p-Value**	**df**	**Statistic**	**Two-Tailed p-Value**
Forecast	1	F=12.71	<0.01	1	F=0.71	0.51
Disclosure of Bias	1	F=0.30	0.49	1	F=0.20	0.54
Forecast X Disclosure of Bias	1	F=2.01	0.3	1	F=6.01	0.02

Panel C: Planned Contrast test of Judgment						
	Quantitative Judgement			**Qualitative Judgement**		
Optimistic VS Pessimistic Forecast @	**df**	**Statistic**	**Two-Tailed P-Value**	**df**	**Statistic**	**Two-Tailed P-Value**
Read about Bias	1	F=11.91	<0.01	1	F=6.01	0.04
Calculate Bias	1	F=2.99	0.21	1	F=1.30	0.31

Source: Present research

Our experiments analyzed the primary dependent, qualitative, and quantitative variables, independently, just as the previous experiment did. Table 3 shows the full set of results.

4.2.4. Insights gained from our qualitative assessments

Note that there is an incompatibility between the quantitative forecast information and the judgment; therefore, we anticipate an imperfect resolution of these judgments.

There is a substantial interaction between forecast and bias disclosure, despite neither component exerting a dominant influence on the overall ANOVA ($p > 0.40$). It was found that the interaction happened because there was no total bias in the read-about-optimistic condition (means of 63.16 and 51.33; $F = 6.01$; $p = 0.02$). In contrast, there was no significant difference between the two calculate-optimistic conditions (means of 56.22 and 62.30; $F = 2.29$, $p = 0.21$). Even with the incompatibility, the calculate-bias scenario resulted in complete disintegration. This finding will be revisited in the discussion and conclusions section after the results of the three incompatibility experiments are received.

4.2.5. Results from the quantitative research

Quantitative EPS evaluations with quantitative compatibility show a significant main impact in the ANOVA ($F = 13.70$, $p < 0.01$). Nonetheless, there is no indication of an interaction effect or a significant main effect of bias disclosure (p-values > 0.20). If participants' assessments of bias had revealed unraveling, we would have observed a forecast-bias interaction with higher levels of unraveling in the calculate-bias conditions. Post-hoc simple effect tests show significant differences between the two forecast means in the read-about-bias conditions (means of \$1.27 and \$1.24; $F = 12.19$, $p < 0.01$), but only minor differences in calculate-bias conditions (means of \$1.96 and \$1.25; $F = 3.00$, $p < 0.09$).

Table 2 shows how many people altered their estimates to \$1.96 to better understand the results. The unreported binomial test p-values (< 0.01) indicate that none of the frequencies were near 100 percent, similar to the initial experiment. Consistent frequencies are seen regardless of the bias-disclosure condition ($\chi 2 = 0.01$, $p = 0.93$), consistent with expected average results. The proportion of participants who fully acknowledged the CEO's bias did not differ significantly between the read-about-bias condition (51 percent) and the calculate-bias condition (50 percent).

The second experiment found that educating participants to compute the quantitative bias rather than simply reading about it did not significantly improve their ability to detect it in their compatible EPS judgments. The finding suggests that it is difficult to eliminate biased information about future revenues generated from the past.

4.3 Experiment Three

In the third experiment, we removed the associated management statement from the forecast. This was done to test the hypothesis that investors perceived the remarks as lacking significant future insights, thereby preventing a complete collapse. Do you recall the CEO's appraisal of the company's forecast from the news releases in experiments one and two? The participants' belief in the legitimacy of management's perspective may explain the insufficient evaluation of historical bias. Psychological research suggests, reading about or attempting to explain a future event increases an individual's sense of its possibility [67, 68]. Such explanations help us understand some circumstances more efficiently. However, we propose that explanations may improve the retention of incorrect information while simultaneously decreasing the likelihood of bias emergence.

To address this possibility, we include or exclude the CEO's perspective in our third experiment.

Examining a situation in which a forecast is supplied without management commentary may appear arbitrary; however, prior empirical studies show that management earnings forecasts vary when accompanied by explanations [69]. We altered two aspects of our experimental three-study design: (1) the inclusion of management commentary in the earnings forecast; and (2) the nature of the CEO's forecast, whether optimistic or pessimistic. The experiment's between-participants design consists of two equal groups. Similar to the second experiment, all participants must identify management's bias by comparing profit predictions with actualizations during the previous six years. In experiment three, we quantified the average bias at five cents as a summary metric. Furthermore, the experiment closely mimics earlier experiments.

All three experiments used the same population, ensuring no overlap. Like those in the previous two experiments, participants in this experiment, had an average of 5.9 years of professional experience, with 63% of them having made prior investments. Seven approaches were employed to detect any tampering.

To confirm the change in the forecast, we first asked participants to identify the CEO's forecast ($2.01, $1.96, or no recollection). 97% of respondents correctly answered the question and properly identified the appropriate experiment ($p < 0.01$). A later question asked participants if the CEO had previously made exact, optimistic, or retroactive estimates. Participants also had the option to express their inability to recall. Ninety percent of participants properly answered this question. The forecast modification proved effective, as evidenced by the connection of specific reactions with appropriate experimental conditions ($\chi2 = 37.19$, $p < 0.01$).

To ensure transparency and avoid any deception, we asked a cannot-recall question to see if the CEO had mentioned the results forecast in the press release. The manipulation was effective, as 90% of participants correctly answered the question and were linked to the proper experiment ($\chi2 = 34.29$, $p < 0.01$).

Table 4. Experiment three results

Panel A: Descriptive statistics - Mean median SD				
	Quantitative Judgment about future earnings		**Qualitative Judgment about future earnings**	
	Optimistic forecast	**Pessimistic forecast**	**Optimistic forecast**	**Pessimistic forecast**
Management Commentary	1.81	1.99	68.56	67.9
	[1.30]	[1.40]	[71]	[70]
	(0.01)	(0.02)	(17.01)	(14.31)
	(n=30)	(n=29)	(n=30)	(n=29)
No Management Commentary	1.31	1.29	51.81	73.29
	1.30	1.20	52.7	73.41
	[1.34]	[1.29]	[55]	[74]

	(0.03)		(0.06)		(23.01)		(19.21)
	(n=30)		(n=29)		(n=30)		(n=29)
Panel B: Analysis of variance (ANOVA) on mean judgments							
	Quantitative Judgment			**Qualitative Judgment**			
Source	*df*	Statistic	Two-tailed p-value	*df*	Statistic	Two-tailed *p*-value	
Forecast	1	F=16.62	<0.01	1	F=10.62	<0.01	
Management Commentary	1	F=0.623	0.67	1	F=0.73	0.41	
Forecast X Management Commentary	1	F=1.61	0.32	1	F=1.64	0.30	
Panel C: Planned Contrast test on mean judgment							
	Quantitative Judgment			**Qualitative Judgment**			
Optimistic vs. Pessimistic Forecasts with:	*df*	Statistic	*p*-value	*df*	Statistic	*p*-value	
Management Commentary	1	*F=4.12*	0.08	1	*F=0.12*	0.81	
No Management Commentary	1	*F=13.43*	<0.01	1	*F=0.13*	<0.01	

Source: Present research

Similar to the first two experiments, we independently estimate our statistical model for each of the two judgment metrics. Table 4 presents the findings.

4.3.1 Results for the qualitative judgments

The forecast variable had a significant main effect ($F = 10.62$, $p < 0.01$) on qualitative evaluation outcomes, which is expected given the lack of unraveling in cases of qualitative incompatibility. The statistics ($F = 8.64$, $p < 0.01$) reveal an interesting forecast based on the interaction of comments. After doing some simple effect analyses, we found that there wasn't a significant difference between the two predictions for the commentary conditions (means of 68.56 and 67.9; $F = 0.623$, $p = 0.67$). This indicates that there was unexpected total unraveling behavior when there was a mismatch between the biased information and the judgment.

4.3.2 Should investors take managerial biases into account?

Biased information permeates financial records in business. This study posits and empirically evaluates the hypothesis that investors, when informed of bias in the form of quantitative EPS, are more likely to fully adjust their judgement, even though they may struggle to notice acknowledged errors in management's profit forecasts. The investor's perspective aligns with the biased information, and EPS quantitatively reflects this perspective. Despite the importance of compatibility and quantification in explaining management bias, the results of three experiments reveal that not all investors can do so even in such circumstances. We further validate this finding by comparing it with other moderator factors that represent management profit forecasting characteristics. Our results are beneficial to investors, regulators, and business executives.

The qualitative earnings response varies between optimistic and pessimistic scenarios in no-commentary conditions, as expected (means of 52.7 and 73.41, 50.68 and 71.33, respectively; $F = 13.43$, $p < 0.01$). The average judgments in the pessimistic condition were unexpectedly higher than those in the ideal condition, indicating that participants overcompensated for forecast bias. The publication's discussion and conclusions section discusses the unexpected findings from the qualitative assessments of experiments two and three.

4.3.3 Results for the quantitative judgments

Consider that we expected management feedback to be inadequate, resulting in bias. This suggests that quantitative assessment requires a strong interplay between prediction and analysis. The ANOVA results indicate a significant main effect for the predictor variable ($F = 10.62$, $p < 0.01$). The primary effect of management remarks ($F = 0.73$, $p = 0.41$) and the forecast-commentary interaction ($F = 1.64$, $p = 0.30$) did not appear to influence investors' unraveling behavior.

Without the CEO's comments, the difference between the two projections is significant (means of \$1.99 and \$1.81; $F = 13.43$, $p < 0.01$), but with his commentary, it is marginally significant ($F = 4.12$, $p = 0.81$). In both cases, we observe that total unraveling does not occur, demonstrating the intricacies of this behavior, even in seemingly simple contexts.

Table 2 demonstrates that the number of participants who completely compensated for bias did not differ between commentary settings ($\chi2 = 0.21$, $p = 0.71$), and there was no interaction impact ($\chi2 = 0.72$, $p = 0.51$). This supports earlier mean quantitative estimates of earnings per share (EPS). According to the findings, 53 percent of participants completely compensated for the forecast bias, with those in the commentary condition statistically comparable to those in the no-commentary condition (48 percent). None of the frequencies neared 100 percent, as expected based on previous experiments. Despite the absence of a CEO remark accompanying the forecast, the results of experiment three show that this was not the case. This finding underscores the psychological impact of initial, incorrect assumptions about the company's future revenues.

5. Conclusions, Implications and Future Research

According to the findings of this study, response compatibility (EPS) and bias quantification are the most effective approaches for investors to identify bias in management's quantitative earnings forecasts. However, when we compare the results of Experiment One, which used mean EPS judgments as a measure of bias unraveling, we find no evidence to support this claim. This contrasts with using the percentage of participants who totally unwound as a criterion for bias. Our additional tests show that when there is quantitative compatibility, the unraveling behavior of the participants remains consistent, whether they are asked to identify the historical bias or exclude management's comments from their predictions. Our results show that, while quantitative compatibility has advantages, entrenched biases are difficult to eliminate and will continue to influence evaluations, despite efforts to improve investors' ability to mitigate them.

We did not find consistent unraveling when there was qualitative consistency or incompatibility between the bias measure and the judgment. In our three experiments, which included seven assessments of qualitative compatibility or incompatibility, we observed four instances of partial unraveling, two instances of complete unraveling, and one instance of extreme unraveling. When we expressed the bias quantitatively, the most noticeable characteristic was the complete and dramatic breakdown. However, investors may perceive this situation as exceptionally challenging, as evidenced by the qualitative response measure from experiments two and three. Despite our expectations, we rarely observed investors engaging in unraveling behavior in circumstances of qualitative compatibility or incompatibility. Maintaining consistent action in such circumstances appears to be a significant challenge for investors.

5.1 Implications and future direction of research

Our discovery has opened up numerous new study areas. Although we focus our research on profit projections, we anticipate that our findings will apply to a broad spectrum of quantitative data used in financial scenarios. In situations where sell-side analysts have an incentive to bias the profits and target prices of the companies they cover; further research may investigate whether our hypotheses are correct. How does compatibility influence this behavior, and how do the buy-side and other investors adjust for this bias? Similarly, future studies could explore if market mechanisms can increase the ability to unravel biased data. The efficiency of market systems in enabling such behavior is debatable, given that our data did not reveal systematic, complete unraveling behavior. Further research into the boundary conditions of unraveling behavior is required.

Another promising area for future research could be to investigate the consequences of bias unraveling. We argue that educating investors about management's history of skewed forecasts will enhance their ability to counteract the biased predictions. Researchers have conducted extensive studies on immunization and its capacity to instill resistance to persuasive messages, with implications for marketing, politics, education, and health. In this context, current disclaimers on mutual funds' past performance and future prospects have little effect on investors' behavior. Nonetheless, it is believed that using a distinct language for releases could be effective. It appears that this study could greatly benefit from deeper exploration into the topic of profit forecasts.

References

[1] Imam, S., Barker, R. and Clubb, C. The use of valuation models by UK investment analysts. European Accounting Review, 2008, 17.

[2] Zahera, S.A. and Bansal, R. Do investors exhibit behavioral biases in investment decision making? A systematic review. Qualitative Research in Financial Markets, 2018, 10.

[3] Compen, B., Vermeir, J. and Van Kenhove, P. How to elicit and cease herding behaviour? On the effectiveness of a warning message as a debiasing decision support system. Decision Support Systems, 2022, 152.

[4] Radke, S., Volman, I., Nockur, L., Reuter, M., Koch, S., van Rooij, D., Toni, I. and Roelofs, K. Testosterone biases

the amygdala toward social threat approach. Science Advances, 2015, 1.

[5] So, J., Kuang, J. and Cho, H. The psychology of appraisal: Specific emotions and decision-making. Journal of Consumer Psychology, 2015, 25.

[6] Lazer, D.M.J., et al. The Science of Fake News: Addressing Fake News Requires a Multidisciplinary Effort. Science, 2018, 359(6380), 1094.

[7] Reniers, R.L., Murphy, L., Lin, A., Bartolomé, S. and Wood, S.J. Risk perception and risk-taking behaviour during adolescence: The influence of personality and gender. PLoS ONE, 2016, 11.

[8] Geniole, S.N., Bird, B.M., Ruddick, E.L. and Carré, J.M. Effects of competition outcome on testosterone concentrations in humans: An updated meta-analysis. Hormones and Behavior, 2017, 92.

[9] Vanacker, T., Forbes, D.P., Knockaert, M. and Manigart, S.. Signal Strength, Media Attention, and Resource Mobilization: Evidence from New Private Equity Firms. Academy of Management Journal, 2020, 63.

[10] Johnson, D.D. and Tierney, D. Bad world: the negativity bias in international politics. International Security, 2019, 43.

[11] Tversky, A. and Kahneman, D. Judgment under uncertainty: Heuristics and biases. Science, 1974, 185.

[12] Busenitz, L.W. and Barney, J.B. Differences between entrepreneurs and managers in large organizations: Biases and heuristics in strategic decision-making. Journal of Business Venturing, 1997, 12.

[13] Martino, B., Kumaran, D., Seymour, B. and Dolan, R.J. Frames, biases, and rational decision-making in the human brain. Science, 2006, 313.

[14] Putman, P., Hermans, E.J. and Honk, J. Exogenous cortisol shifts a motivated bias from fear to anger in spatial working memory for facial expressions. Psychoneuroendocrinology, 2007, 32.

[15] Knutson, B. and Bossaerts, P. Neural antecedents of financial decisions. Journal of Neuroscience, 2007, 27.

[16] Statman, M. Behavioral finance: Past battles and future engagements. Financial Analysts Journal, 1999, 55.

[17] Steinberg, L. A social neuroscience perspective on adolescent risk-taking. Developmental Review, 2008, 28.

[18] Stevenson, R.M., Kuratko, D.F. and Eddleston, K.A. Out of control or right on the money? Funder self-efficacy and crowd bias in equity crowdfunding. Journal of Business Venturing, 2019, 34.

[19] Prosad, J.M., Kapoor, S. and Sengupta, J. Behavioral biases of Indian investors: A survey of Delhi-NCR region. Qualitative Research in Financial Markets, 2015, 7.

[20] Luo, X., Zhang, J., Duan, W. and Hu, J. Predicting stock price movements with social media sentiment indices: A comparative study. Journal of Electronic Commerce Research, 2017, 18.

[21] Ramnath, S., Rock, S. and Shane, P. The financial analyst forecasting literature: A taxonomy with suggestions for further research. International Journal of Forecasting, 2008, 24.

[22] Myers, S.C. and Majluf, N.S. Corporate financing and investment decisions when firms have information that investors do not have. Journal of Financial Economics, 1984, 13.

[23] [23] Wei, F., Zhang, X., Li, Y. and Wang, J. Nexus of economic policy uncertainty, economic expansion and clean energy consumption and their role in carbon neutrality of emerging economies. Geological Journal, 2023.

[24] O'Connor, K.M., Arnold, J.A. and Maurizio, A.M. The prospect of negotiating: Stress, cognitive appraisal and performance. Journal of Experimental Social Psychology, 2010, 46.

[25] DeWitt, S.J., Aslan, S. and Filbey, F.M. Adolescent risk-taking and resting state functional connectivity. Psychiatry Research, 2014, 222.

[26] Delmar, F. and Shane, S. Does Experience Matter? The Effect of Founding Team Experience on the Survival and Sales of Newly Founded Ventures. Strategic Organization, 2006, 4.

[27] Ding, J., Zhang, Y., Liu, H. and Wang, X. Role of climate fund raising under fiscal balance on climate change mitigation: An analysis from Pareto optimality. Environmental Science and Pollution Research, 2023, 30.

[28] Drover, W., Wood, M.S. and Corbett, A.C. Toward a cognitive view of signalling theory: Individual attention and signal set interpretation. Journal of Management Studies, 2018, 55.

[29] Gleason, C.A., Johnson, W.B. and Li, H. Valuation model use and the price target performance of sell-side equity analyst. Contemporary Accounting Research, 2013, 30.

[30] Asquith, P., Mikhail, M.B. and Au, A.S. Information content of equity analyst reports. Journal of Financial Economics, 2005, 75.

[31] Bonini, S., Zanetti, L., Bianchini, R. and Salvi, A. Target price accuracy in equity research. Journal of Business Finance and Accounting, 2010, 37.

[32] Xie, W. and Karan, K. Predicting Facebook addiction and state anxiety without Facebook by gender, trait anxiety, Facebook intensity, and different Facebook activities. Journal of Behavioral Addictions, 2019, 8.

[33] Xiuzhen, X., Zheng, W. and Umair, M. Testing the fluctuations of oil resource price volatility: A hurdle for economic recovery. Research Policy, 2022, 79.

[34] Xu, B. A re-estimation of the Evans-Jovanovic Entrepreneurial Choice Model. Economic Letters, 1998, 58.

[35] Y, Z. and M, U. Examining the interconnectedness of green finance: An analysis of dynamic spillover effects among green bonds, renewable energy, and carbon markets. Environmental Science and Pollution Research, 2023, 30, 77605–77621.

[36] Yonelinas, A.P., Ranganath, C., Ekstrom, A.D. and Wiltgen, B.J. A contextual binding theory of episodic memory: Systems consolidation reconsidered. Nature Reviews Neuroscience, 2019, 20.

[37] You, S. Valuation-driven profit transfer among corporate segments. Review of Accounting Studies, 2014, 19.

[38] Yu, M., Li, Z., Chen, J. and Zhang, W. Exploring the nexus between monetary uncertainty and volatility in global crude oil: A contemporary approach of regime-switching. Research Policy, 2023, 85.

[39] Bradshaw, M.T., Brown, L.D. and Huang, K. Do sell-side analysts exhibit differential target price forecasting ability? Review of Accounting Studies, 2013, 18.

[40] Groysberg, B., Healy, P. and Chapman, C. Buy-side vs sell-side analysts' earnings forecasts. Financial Analysts Journal, 2008, 64.

[41] Demerens, F., Le Manh, A. and Paillart, T. The use of segment information by financial analysts and forecast accuracy: A study on European intermediate-size companies. Thunderbird International Business Review, 2017, 59.

[42] Martino, B., Camerer, C.F. and Adolphs, R. Amygdala damage eliminates monetary loss aversion. Proceedings of the National Academy of Sciences of the United States of America, 2010, 107.

[43] Sial, M.S., Zheng, C., Khuong, N.V. and Khan, T. Impact of female directors on the board and foreign institutional investors on earning manipulation of Chinese listed companies. Asia-Pacific Journal of Business Administration, 2019.

[44] Shu, H.-C. Investor mood and financial markets. Journal of Economic Behavior & Organization, 2010, 76, 267-282.

[45] Vamossy, D.F. Investor emotions and earnings announcements. Journal of Behavioral and Experimental Finance, 2021, 30.

[46] Chatterjee, D., Pacini, C. and Sambamurthy, V. The shareholder-wealth and trading-volume effects of information-technology infrastructure investments. Journal of Management Information Systems, 2002, 19.

[47] Gaspar, J.-M., Massa, M. and Matos, P. Shareholder investment horizons and the market for corporate control. Journal of Financial Economics, 2005, 76(1), 135-165.

[48] Tang, D.Y. and Zhang, Y. Do shareholders benefit from green bonds? Journal of Corporate Finance, 2020, 61, 101427.

[49] Teo, T.S., Nishant, R. and Koh, P.B. Do shareholders favor business analytics announcements? The Journal of Strategic Information Systems, 2016, 25.

[50] Griffith, J., Najand, M. and Shen, J. Emotions in the stock market. Journal of Behavioral Finance, 2020, 21.

[51] [51] Gompers, P.A., Gornall, W., Kaplan, S.N. and Strebulaev, I.A. How do venture capitalists make decisions? Journal of Financial Economics, 2020, 135.

[52] Cao, P., et al. Eco-engagement: Tracing CSR communication's ripple effect on consumer hospitality loyalty. Journal of Retailing and Consumer Services, 2024, 79, 103879.

[53] Nadler, A., Wu, H., Huber, J. and Levy, O. The Bull of Wall Street: Experimental analysis of testosterone and asset trading. Management Science, 2018, 64(9), 4032-4051.

[54] Pan, Z. A review of prospect theory. Journal of Human Resources and Sustainable Studies, 2019, 7.

[55] Healy, P.M. and Palepu, K.G. Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. Journal of Accounting and Economics, 2001, 31.

[56] Ruggeri, K., Alí, S. and Berge, M.L. Replicating patterns of prospect theory for decision under risk. Nature Human Behaviour, 2020, 4.

[57] MacKinnon, D.P., Lockwood, C.M. and Williams, J. Confidence limits for the indirect effect: Distribution of the product and resampling methods. Multivariate Behavioral Research, 2004, 39.

[58] Meyer, K.E. Asian management research needs more self-confidence. Asia Pacific Journal of Management, 2006, 23.

[59] Greenland, S., et al. Statistical tests, P values, confidence intervals, and power: A guide to misinterpretations. European Journal of Epidemiology, 2016, 31.

[60] Moslehi, F. and Haeri, A. A genetic algorithm-based framework for mining quantitative association rules without specifying minimum support and minimum confidence. Scientia Iranica, 2020, 27.

[61] Tiep, N.C., Wang, M. and Mohsin, M. An assessment of power sector reforms and utility performance to strengthen consumer self-confidence towards private investment. Economic Analysis and Policy, 2021.

[62] Ahmad, M. Does under confidence matter in short-term and long-term investment decisions? Evidence from an emerging market. Management Decision, 2020, 59.

[63] McCann, B.T. and Vroom, G. Opportunity evaluation and changing beliefs during the nascent entrepreneurial process. International Small Business Journal, 2015, 33.

[64] [64] Sonnemann, U., Camerer, C.F., Fox, C.R. and Langer, T. How psychological framing affects economic market prices in the lab and field. Proceedings of the National Academy of Sciences of the United States of America, 2013, 110.

[65] Imam, S., Chan, J. and Shah, S.Z.A. Equity valuation models and target price accuracy in Europe. International Review of Financial Analysis, 2013, 28.

[66] Kusev, P., et al. Understanding risky behavior: The influence of cognitive, emotional and hormonal factors on

decision-making under risk. Frontiers in Psychology, 2017, 8.

[67] Lee, H. and Kim, Y. Social media use, financial literacy, and financial behavior: Evidence from Korea. Journal of Consumer Affairs, 2019, 53.

[68] Bhatia, A., Chandani, A. and Chhateja, J. Robo advisory and its potential in addressing the behavioral biases of investors—a qualitative study in Indian context. Journal of Behavioral and Experimental Finance, 2020, 25.

[69] Chaudhary, A.K. Impact of behavioral finance in investment decisions and strategies–a fresh approach. International Journal of Management Research and Business Strategy, 2013, 2.