“Unpacking analyst forecast bias: The role of optimism and sequence in shaping earnings predictions”

AUTHORS	Yuki Gong Hideyuki Hao Sun Sing Lui So Zehua Chen Ruixue Sun
ARTICLE INFO	Yuki Gong, Hideyuki Hao Sun, Sing Lui So, Zehua Chen and Ruixue Sun (2025). Unpacking analyst forecast bias: The role of optimism and sequence in shaping earnings predictions. *Investment Management and Financial Innovations*, *22*(1), 324-338. doi:10.21511/imfi.22(1).2025.25
DOI	http://dx.doi.org/10.21511/imfi.22(1).2025.25
RELEASED ON	Monday, 03 March 2025
RECEIVED ON	Thursday, 14 November 2024
ACCEPTED ON	Thursday, 20 February 2025

JOURNAL	"Investment Management and Financial Innovations"
ISSN PRINT	1810-4967
ISSN ONLINE	1812-9358
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
30	0	3

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine
www.businessperspectives.org

Yuki Gong (USA), **Hideyuki Hao Sun** (USA), **Sing Lui So** (USA),
Zehua Chen (Hong Kong SAR), **Ruixue Sun** (China)

UNPACKING ANALYST FORECAST BIAS: THE ROLE OF OPTIMISM AND SEQUENCE IN SHAPING EARNINGS PREDICTIONS

Abstract

Earnings forecasts by financial analysts are critical to guiding investment decisions and corporate valuations. This study examines how forecast sequence (disaggregation vs. aggregation) interacts with initial optimism (presence vs. absence) to shape the accuracy of earnings predictions. A 2×2 between-subjects experimental design was employed, involving 97 professional financial analysts from leading U.S.-based brokerage firms with extensive experience in equity research. These analysts, representative of the target population making critical market forecasts, were tasked with predicting the annual earnings per share (EPS) of a hypothetical global hospitality firm, Firm X, listed on the New York Stock Exchange. The sample was chosen to ensure high external validity by mirroring real-world practices and decision contexts in financial forecasting. Initial optimism was manipulated using "strong-buy" and "neutral" stock recommendations, while forecast sequence was adjusted by requiring updates either after each management announcement (disaggregation) or collectively (aggregation). Results demonstrate that disaggregation amplifies optimistic bias in the presence of initial optimism, resulting in inflated earnings forecasts. This effect is attributed to confirmation bias. In contrast, no significant differences in forecasts were observed between sequences in the absence of initial optimism. These findings offer practical insights into mitigating cognitive biases in financial analysis, emphasizing the dual-edged role of disaggregation. Future research may extend these findings across diverse industries and forecasting contexts to further refine strategies for enhancing decision-making accuracy and investor trust.

Keywords analyst forecasting, earnings predictions, forecast sequence, initial optimism, cognitive biases, disaggregated forecasting, confirmation bias, behavioral finance

JEL Classification G17, G41, M41

Received on: 14th of November, 2024
Accepted on: 20th of February, 2025
Published on: 3rd of March, 2025

Yuki Gong, Postgraduate Student, College of Computing, Georgia Institute of Technology, USA.

Hideyuki Hao Sun, Postgraduate Student, College of Computing, Georgia Institute of Technology, USA.

Sing Lui So, Postgraduate Student, College of Computing, Georgia Institute of Technology, USA. (Corresponding author)

Zehua Chen, Audit Intern at Klynveld Peat Marwick Goerdeler (KPMG), Hong Kong SAR.

Ruixue Sun, Analyst at Global Law Office, China.

Conflict of interest statement:
Author(s) reported no conflict of interest

INTRODUCTION

The accuracy of financial analysts' earnings forecasts is a cornerstone of effective capital market functioning, shaping investment decisions, corporate valuations, and resource allocation (Mikhail et al., 1999). Reliable forecasts reduce information asymmetry, yet analysts' predictions are frequently subject to errors. For instance, a study by Beyer et al. (2010) reported that the mean absolute forecast error for S&P 500 companies can range between 5% and 20% of actual earnings, depending on market conditions. Such inaccuracies not only undermine investor confidence but also distort market efficiency.

These errors are often rooted in cognitive biases, with confirmation bias being particularly prominent. Confirmation bias – the tendency to seek and interpret information in ways that align with pre-existing beliefs – can significantly impair analysts' objectivity, especially when they hold optimistic expectations (Kunda, 1990; Thayer, 2011). This

http://dx.doi.org/10.21511/imfi.22(1).2025.25

bias is not merely theoretical; research shows that 70% of professional analysts admit to overemphasizing favorable information when making forecasts (Libby et al., 2008).

Forecasting itself is a complex process that requires synthesizing large amounts of conflicting data under uncertain conditions (Hales, 2007). Analysts adopt varying approaches to mitigate this complexity, such as disaggregation (breaking tasks into smaller components) and aggregation (holistically synthesizing data). Disaggregation has been shown to reduce cognitive load and enhance attention to detail (Ravinder et al., 1988; Chen et al., 2015). However, its benefits may come with risks; disaggregation can amplify biases like optimism by providing more opportunities for selective information processing. On the other hand, aggregation, while reducing such opportunities, can lead to cognitive overload, increasing the likelihood of errors (Bonner, 2008).

Despite these known dynamics, little is understood about how these methodological choices interact with cognitive biases like confirmation bias. Addressing this gap is essential, given that analysts' recommendations influence trillions of dollars in global investments annually. By examining the interplay between forecast sequence (disaggregation vs. aggregation) and initial optimism (presence vs. absence), this study provides critical insights into the cognitive and methodological factors shaping earnings forecasts. These findings have the potential to improve forecast accuracy, enhance market transparency, and bolster investor trust.

1. LITERATURE REVIEW AND HYPOTHESIS

Disaggregation is widely acknowledged as a technique that reduces cognitive load, allowing forecasters to better process and consider available information. However, one stream of prior research also suggests that preparing disaggregated forecasts is *not* necessarily always beneficial to forecasters' judgment quality especially when there are other factors that interact with disaggregation (e.g., Henrion et al., 1993; Chen et al., 2015; Lee & Siemsen, 2017). This section reviews prior studies examining the influence of forecast sequence and initial optimism on analyst forecast properties and introduces the predication.

1.1. Forecast sequence and information consideration

Prior studies suggest that disaggregation reduces the cognitive load of forecasters, enabling them to pay *greater* attention to all available information when forecasting each component (Ravinder et al., 1988; Henrion et al., 1993; Lee & Siemsen, 2017). This is much aligned with the argument in *support theory* which indicates that unpacking an event into multiple components helps individuals to think about the details of this event more carefully, making it easier to generate evaluative evidence mentally and increasing their rated likelihood of the event occurring (Tversky & Koehler, 1994; Van Boven & Epley, 2003; Beck et al., 2023). In contrast, a holistic forecast is more complex than disaggregating one forecasting problem into its component parts and then combining these parts to generate an aggregate forecast (Ravinder et al., 1988; Henrion et al., 1993; Lee & Siemsen, 2017). With such increased task complexity, individuals have incentives to reduce their cognitive costs, and they tend to choose a *non-compensatory* decision-making strategy in which they do *not* collect and/or consider all relevant information (Bonner, 2008). Consequently, their decision quality will be reduced. Consistent with the above arguments, in business contexts, Zimbelman (1997) documents that auditors will improve their abilities of fraud detection when they separately assess the risk of intentional and unintentional misstatements rather than making risk assessments holistically.[1] Similarly, Chen et al. (2015) find that preparing disag-

1 In the condition of holistic risk assessments, participants were required to assess misstatement risk without documenting whether an expected misstatement is intentional (e.g., financial statement fraud or excessively biased reporting) or unintentional (e.g., an error). In the condition of decomposed risk assessments, they were required to separately assess the risk of intentional and unintentional misstatements.

gregated forecasts (relative to preparing aggregated forecasts) enhances management forecast accuracy.[2]

1.2. Initial optimism and confirmation bias

Individuals tend to succumb to subconscious biases during their information-searching process, which may result in biased judgments. One of these biases is confirmation bias, which suggests that individuals selectively seek the information consistent with their *previously* held beliefs (e.g., Lowin, 1967; Frey, 1986; Spohr, 2017). Such bias exists even when decision-makers have economic incentives to be accurate (Arkes, 1991). This is consistent with motivated reasoning theory which indicates that an individual's initial belief constructs a directional preference that will affect one's information-acquisition process (Kunda, 1990; Douglas & Sutton, 2022). In other words, one will *not* consider a balanced set of reasons for the desired outcome consistent with his/her previous belief during the information-acquisition process (Ditto & Lopez, 1992; Oeberst & Imhoff, 2023).

Consistent with the above argument, previous experimental studies in accounting contexts provide evidence indicating that market participants are susceptible to the effects of confirmation bias. For example, Tan (1995) shows that auditors with prior involvement with a client, relative to auditors new to the client, pay more attention to the facts consistent with their *prior* expectations. Thayer (2011) finds that investors tend to conduct a biased information search to confirm their initial beliefs in investment positions, even though such supportive information may lack a certain amount of credibility.

In the presence of initial optimism, analysts have a *directional* preference for positive future performance. As guided by motivated reasoning, they may subconsciously pay disproportionately more attention to positive information that is consistent with their starting expectations in this firm, and these analysts, relative to their "neutral" peers, may therefore make *higher* estimates and exhibit *greater* optimistic bias. Specifically, initially-optimistic analysts, though compensated based on their recommendation accuracy, may 'work backward' by looking for preference-consistent (i.e., positive) evidence to justify their desired belief rather than performing their analysis first and then using the results to derive a forecast or recommendation. Conversely, these optimistic analysts are likely to discount disconfirming (i.e., negative) information, though they may already "see" warning signals about future performance from such information. To make it even worse, initially-optimistic analysts may begin to interpret ambiguous or negative information as positive. For example, they may introduce uncommon valuation metrics and/or re-interpret traditionally negative indicators in a positive way to justify their initial beliefs. Anecdotal evidence of such reasoning appeared during the 1990s dot-com bubble when some analysts introduced new valuation metrics such as the number of page views and revenue per subscriber, and re-interpreted traditionally negative factors (e.g., a high "cash burn" rate) as positive factors to justify high valuations for Internet stocks (Nocera & Maroney, 1999; Veverka, 1999; Koonce & Mercer, 2005). Undoubtedly, these analysts' opinions eventually proved to be extremely optimistic. Drawing on prior literature, analysts with initial optimism towards one firm are expected to issue *higher* earnings forecasts (which may potentially lead to greater optimistic bias) for the firm than their peers with initial "neutral" expectations.[3]

1.3. The interaction between disaggregation and initial optimism

As noted, preparing a disaggregated forecast reduces cognitive workload (Ravinder et al., 1988; Henrion et al., 1993; Lee & Siemsen, 2017; Arvan et al., 2019), enabling analysts to process more detailed information when forecasting individual components. However, the benefits of disaggregation in improving forecast quality are likely to depend on the presence of initial optimism about the firm being evaluated.

2 Chen et al. (2015) used an abstract experimental task (i.e., completing an SAT-type test). Different to their design, the paper adopted a true experimental design by presenting the research instrument that describes a global hospitality company (see Appendix A) to participants.

3 It is noted that, forecast optimism (i.e., higher estimates) does not necessarily lead to optimistic bias. That is, a higher estimate does not mean that it is wrong/biased. Some papers use the two words, "optimism" and "optimistic bias" interchangeably, but this paper would not agree with it. In this study, what is examined is forecast optimism.

http://dx.doi.org/10.21511/imfi.22(1).2025.25

In situations where initial optimism is present, disaggregated forecasting is expected to amplify this optimism, resulting in higher earnings estimates than aggregated forecasting. This effect arises because optimistic analysts, driven by confirmation bias, tend to focus more on positive, preference-consistent information that aligns with their expectations (Kunda, 1990; Douglas & Sutton, 2022). The reduction in cognitive load offered by disaggregation provides analysts with more opportunities to interpret detailed information in ways that confirm their pre-existing beliefs. However, this advantage may be diminished or even negated by the bias introduced through selective attention. In contrast, aggregated forecasting, while limiting opportunities for biased interpretation, may help mitigate the effects of confirmation bias, even if analysts are motivated to issue optimistic forecasts.

In the absence of initial optimism, the relationship between forecast sequence and forecast optimism is expected to be less pronounced. Neutral analysts, who lack strong initial beliefs, are less motivated to focus on preference-consistent information. Consequently, their forecasts, whether based on disaggregated or aggregated approaches, are less susceptible to confirmation bias. As such, no significant difference is anticipated between the two forecasting methods in the absence of initial optimism.

H1: *The difference in forecast optimism between disaggregated and aggregated analyst forecasts will be greater when initial optimism is present than when it is absent.*

2. METHODOLOGY

2.1. Participants

This study conducts a 2×2 (forecast sequence × initial optimism) between-subjects experiment and recruits ninety-seven *real* analysts taking the role of professional financial analysts.[4] The responses from all participants were usable, given their instrument completion. Each participant is compensated with a $10 coupon as an incentive, encouraging them to thoroughly read the instructions and respond to the questions with greater attention and care.

Table 1 presents participant demographic data. Of these participants, 62.89 percent were female, and the median age range was 30-39 years. Participants, on average, have high levels of forecasting experience and financial knowledge, evidenced by high mean values for their self-ratings on their working experience (4.72 out of 5) and knowledge of financial concepts and principles that they have (4 out of 5).

Table 1. Participant demographic data (N = 97)

Description	Std. Deviation	Mean	Number	Percent
Age				
30-39			61	62.89%
40-49			36	37.11%
Gender				
Male			38	39.18%
Female			59	60.82%
Analyst forecasting experience	0.45	4.72	97	
Financial knowledge[5]	0.88	3.94	97	

2.2. Experimental task

The research instrument (see Appendix A) describes a hypothetical global hospitality company, Firm X, listed on the New York Stock Exchange (NYSE). It operates a chain of full-service hotels and resorts, extended-stay suites, and focused-service hotels. Choosing a firm in the hospitality industry for this study provides a relevant setting to observe analyst forecast behaviors due to the industry's unique characteristics. The hospitality sector is highly sensitive to economic shifts, seasonal demand, and global events, which often leads to fluctuations in performance metrics such as occupancy rates and revenues. This variability makes it an ideal context for studying how initial optimism and the sequence of forecasts (disaggre-

4 Before formally testing the hypothesis, the paper conducted a pilot study involving 17 Ph.D. students from a Top 50 business school who voluntarily participated in the experiment. This preliminary test helped refine this experimental design. The consent of participants (including those involved in the pilot test) to engage in the experiment has been documented and is available upon request.

5 To understand the level of participants' financial knowledge, they were asked to report the level of knowledge of financial concepts and principles they have, on a five-point scale with endpoints of 1 = "No Knowledge" and 5 = "High Knowledge".

gated versus aggregated) can influence analysts' earnings predictions. Furthermore, since hospitality firms regularly release updates that impact future projections (e.g., announcements related to occupancy rates or new management hires), this industry offers practical and frequent opportunities for analysts to revise and test their forecasting approaches based on real-time information.

Participants assume the role of a professional financial analyst at XYZ Securities, a Wall Street brokerage firm. They are assigned to make the 2021 annual EPS forecast for Firm X after reading four announcements issued by the top management of Firm X. Additionally, this study *randomizes* the placement of the four management announcements across participants, to prevent the potential sequencing effect. Table 2 presents a timeline of the experimental task.

Table 2. Timeline of experimental task

Procedure	Task(s)
Introduction	Participants are provided with task instructions.
Background information	Firm background information and recent financial information is provided.[a] The last-term consensus analyst forecast of $1.48 is presented.[b]
Initial stock recommendation	Participants are provided with their last-term stock recommendations ("Strong Buy" or "Neutral"). Initial optimism is manipulated between participants.
Preliminary EPS Forecast	Participants are asked to make a preliminary forecast of the firm's annual EPS.
Additional information[c] and forecast revision	Participants are asked to either revise their EPS forecasts holistically after viewing four management announcements or update their forecasts when viewing each announcement. Forecasting sequence is manipulated between participants.
Post-experiment questionnaire	Manipulation success is checked. Demographic information is collected.

Note: [a] The financial information (on sales, gross profit, net income, and earnings per share) is calculated after averaging the corresponding values in a given year (i.e., 2018, 2019, or 2020) for all firms (available in Compustat) in the Restaurants, Hotels & Motels Industry (SIC = 44) and adding two standard deviations because the hypothetical Firm X is described as a global leader in its industry. [b] The last-term consensus analyst forecast is presented to give an initial reference point for participants to make an EPS estimate. Without such information, there might have been a large variance of participants' forecasts. The number, $1.48, is calculated after taking one-year-ahead analyst forecasts for the year ending 2021 (available in I/B/E/S) for all firms in the Restaurants, Hotels & Motels Industry (SIC = 44), averaging these numbers out, and adding two standard deviations because the hypothetical Firm X is described as a global leader in its industry. [c] The four management announcements are adapted from the announcements frequently released by the five dominant firms occupying the largest market share in the Restaurants, Hotels & Motels Industry during 2021. The announcement data are obtained from the Factiva news database.

2.3. Study design

This study employs a 2 (Forecast Sequence: Disaggregation versus Aggregation) ×2 (Initial Optimism: Presence versus Absence) between-participants experiment to investigate how the extent of disaggregation in analyst forecasts interacts with initial optimism to influence analysts' earnings estimates. In other words, initial optimism and forecasting sequence are manipulated between participants. Specifically, investors' initial optimism is manipulated by providing participants with their initial stock recommendations for Firm X issued at the beginning of 2021 (i.e., for the end of which year they need to make EPS forecasts). Participants are randomly assigned with the presence or absence of initial optimism, by telling them that the most recent stock recommendation issued by them for Firm X is of "STRONG BUY" or "NEUTRAL".

The forecasting sequence is manipulated by showing participants how to document their forecasts.[6] Specifically, participants are randomly assigned to make either disaggregated forecasts or aggregated forecasts. Participants in the disaggregated condition are told:

"*There were four announcements that might be useful for updating your EPS forecast. You are required to update your forecast number after reading EACH announcement.*"

On the other hand, participants in the aggregated condition are told:

"*There were four announcements that might be useful for updating your EPS forecast. You are required to update your forecast number after reading ALL announcements.*"

Participants are required to update their forecasts for Firm X's annual EPS in the year ending 2021

6 In the disaggregated condition, the paper put each management announcement on an individual page. Participants need to turn the page to view the next announcement. This prevents participants from viewing four announcements all at once before being informed of how to document their forecasts.

http://dx.doi.org/10.21511/imfi.22(1).2025.25

after reading four management announcements.[7] A higher EPS estimate indicates greater optimism, but it is noted that greater optimism does not necessarily lead to more errors.

To control for the effect of analysts' general forecasting experience[8] on their forecasting behavior, this paper considers this factor as a covariate in the statistical analysis. It is documented that overoptimism is lower for analysts with greater general experience because these analysts have a superior capacity to *efficiently* incorporate all available information (Drake & Myers, 2011).[9] The experienced analysts, relative to their inexperienced peers, are less likely to have a differing response to the forecasting sequence even when they hold initial optimism. Therefore, an analyst's general experience needs to be controlled to avoid any potential bias.[10] Specifically, this paper asks participants to indicate the level of their forecasting experience (*Experience*) on a five-point scale, where 1 is "very inexperienced" and 5 is "very experienced". This study includes their *Experience* as a covariate because individuals who have longer forecasting experience can better incorporate information into their forecasts, enhancing accuracy. Specifically, participants are required to indicate their analyst forecasting experience *after* they are exposed to the manipulated variables and respond to the study's dependent measure.[11] Table 1 shows that participants on average report a relatively high level of forecasting experience, with the mean to be 4.72.

3. RESULTS

This section presents the findings of the study, starting with manipulation checks to ensure the validity of the experimental design, followed by the analysis of primary hypotheses.

3.1. Manipulation checks

This study incorporated post-experimental questions to evaluate participants' ability to recall each manipulation. Regarding the forecast sequence manipulation, participants were prompted to answer the following question: "*How did you update your EPS estimate?*". Possible responses were "*Update my estimate each time I read a management announcement*" or "*Update my estimate only after I read all management announcements*". For the initial optimism manipulation, this study asked participants to respond to the following question: "*What stock recommendation did you release in early 2021?*". Possible responses were "*STRONG BUY*" and "*NEUTRAL*". Around 97 percent of participants responded correctly to the two questions. Additionally, participants were required to provide their preliminary EPS estimates after being informed of the stock recommendation ("*STRONG BUY*" or "*NEUTRAL*") issued by them in early 2021. Participants with *STRONG-BUY* stock recommendations (mean = 1.54) reported a significantly higher EPS estimate ($t = 4.27$; $p < 0.01$) than participants with *NEUTRAL* stock recommendations (mean = 1.49), indicating that participants assigned with *STRONG-BUY* stock recommendations exhibited initial optimism for Firm X's future profitability. In summary, participants successfully recalled the manipulations related to report type and confrontation, indicating their engagement with these elements.

3.2. Main results

This study tested *H1* using a 2×2 between-participants ANCOVA, where *Forecast Sequence* (disaggregated versus aggregated) and *Initial Optimism* (presence versus absence) were the two independent variables. *Experience*, measured as the participants' level of forecasting expertise, was included

7 In the disaggregated condition, though participants are required to update their forecasts after acquiring each announcement, only their *final* estimates are used for statistical analysis.

8 To clarify, "general forecasting experience" is different to "firm-specific forecasting experience" which cannot be controlled because Firm X is a hypothetical firm in the research instrument.

9 This can be explained by the learning-by-doing theory predicting that the cost of performing a task decreases as experience with the task increases, resulting in improved performance (Arrow, 1962; Anzai & Simon, 1979).

10 This paper does *not* make any predictions on the relation between participants' general experience and their EPS estimate because it uses EPS forecast rather than forecast accuracy as the dependent variable.

11 It is noted that the participants are required to indicate their forecasting experience in the *post*-experiment question rather than before their exposure to the experiment. Otherwise, participants without longer work experience might have been more careful with their EPS estimates because admitting/realizing the lack of experience may make "novice" participants feel less confident in their financial knowledge and potential forecasting abilities. Therefore, they might have spent more time on the details of the research instrument.

as a covariate. The dependent variable was analysts' 2021 annual EPS estimates. *H1* posits that the increase in earnings estimates between aggregated and disaggregated forecasts will be greater in the presence of initial optimism compared to its absence. As reported in Panel A of Table 3, a significant interaction between *Forecast Sequence* and *Initial Optimism* was observed ($F = 3.50$, $p = 0.06$), supporting this prediction.

Panel B of Table 3 provides information on cell sizes, means, standard deviations, and the results of simple effects analyses. The findings from these tests support the interaction effect predicted by *H1*. Specifically, in the presence of initial optimism, analysts are more likely to make high EPS estimates when preparing disaggregated forecasts (mean = 1.452) relative to preparing aggregated forecasts (mean = 1.413) ($F = 4.79$, $p = 0.03$). There is *no* significant difference in EPS estimates between disaggregated forecasting (mean = 1.353) and aggregated forecasting (mean = 1.358) in the absence of initial optimism ($F = 2.54$, $p = 0.12$).

Lastly, a custom contrast test was conducted to examine the expected pattern of means while accounting for the effect of the *Experience* covariate. This test assigned a weight of –3 to the disaggre-

Table 3. Effects of forecast sequence and initial optimism on analyst EPS forecast

Panel A: ANCOVA model[a,b]

Source	SS	Df	MS	F-Statistic	p-value (two-tailed)	Partial η^2[c]
Forecast Sequence	0.015	1	0.015	2.41	0.12	0.08
Initial Optimism	0.151	1	0.151	25.13	<0.01	0.34
Forecast Sequence × Initial Optimism	0.021	1	0.021	3.50	0.06	0.27
Experience	0.018	1	0.018	2.99	0.08	0.13
Error	0.552	92	0.006			
Total	0.757	96	0.008			
R^2=0.824 (Adj. R^2=0.766)						

Panel B: Estimated marginal means (standard error) and tests of simple main effects

Initial Optimism	Forecast Sequence		Total	Simple Effects
	Disaggregation	Aggregation		
Presence	1.452	1.413	1.434	F=4.79
	(0.015)	(0.010)	(0.024)	(p=0.03)
	n=24	n=25	n=49	
Absence	1.353	1.358	1.356	F=2.54
	(0.006)	(0.036)	(0.027)	(p=0.12)
	n=24	n=24	n=48	
Total	1.415	1.382		
	(0.052)	(0.039)		
	n=48	n=49		
Simple Effects	F=6.15	F=4.15		
	(p=0.02)	(p=0.05)		

Panel C: Custom Contrast Test (Adjusted for Experience)

Contrast weight[d]	Estimate	F-Statistics	p-value
–3, 1, 1, 1	0.003	9.37	<0.01

Note: [a] The dependent variable is the 2021 annual EPS forecast for Firm X given by participants after reading four management announcements made in the first two quarters of 2021. *Forecast Sequence* is an experimental manipulation of whether a participant disaggregates his/her forecast by updating the forecast after acquiring each management announcement (=1) or makes his/her aggregated EPS forecast holistically after acquiring all management announcements (=0). *Initial Optimism* is an experimental manipulation of whether a participant released a "Strong Buy" (=1) or "Neutral" (=0) stock recommendation for Firm X in his/her last report. [b] Results are statistically similar when *Experience* was excluded as a covariate. [c] Partial measured on a scale of 0 to 1, indicates the proportion of the variance in the dependent variable explained by the independent variable. [d] Contrast coefficients are -3 for the disaggregation/the presence of the initial optimism condition (i.e., *Forecast Sequence* = 1 and *Initial Optimism* = 1), and +1 for the remaining conditions.

http://dx.doi.org/10.21511/imfi.22(1).2025.25

gation/presence of initial optimism condition and +1 to the aggregation/presence of initial optimism, disaggregation/absence of initial optimism, and aggregation/absence of initial optimism conditions. As detailed in Panel C of Table 3, the results of this contrast analysis confirm the hypothesized pattern of means ($F = 9.37$, $p < 0.01$).[12] These findings provide robust support for H1, indicating that analysts respond differently to forecasting sequences when they possess initial optimism about the firm compared to when they lack such optimism.

3.3. Analysis of covariate

Experience, serving as a proxy for general forecasting expertise, was included as a covariate in the analysis. As shown in Panel A of Table 3, this covariate demonstrates marginal statistical significance ($F = 2.99$; $p = 0.08$), indicating that experienced analysts might have a differing response to the forecasting sequence even when they hold initial optimism.

To further analyze the effect of general experience on analysts' forecasting abilities, this study first limits the sample to the participants assigned with the presence of initial optimism ($n = 49$) and employs a 2×2 ANOVA analysis in which *Forecast Sequence*, *Experience*, and *Forecast Sequence ×Experience* served as the independent variables and EPS estimate as the dependent variable. The un-tabulated results indicate a significant forecast sequence and forecasting experience interaction ($F = 4.89$, $p = 0.03$). This indicates that experienced analysts, relative to their inexperienced peers, are less likely to be affected by forecast sequence in the presence of initial optimism. Also, the same test is re-run for the subsample consisting of participants assigned with the absence of initial optimism ($n = 48$). The un-tabulated results indicate an insignificant interaction ($F = 1.75$, $p = 0.19$). This indicates that there is no significant difference in experienced analysts' and inexperienced analysts' responses to forecast sequence in the absence of initial optimism. Combined, the above analysis supports the necessity of including *Experience* as a covariate in the main ANCOVA analysis.

4. DISCUSSION

The findings suggest that, in the presence of initial optimism, disaggregated forecasting significantly amplifies forecast optimism, leading analysts to issue higher earnings estimates compared to aggregated forecasting. This result supports the idea that disaggregation, by reducing cognitive load, provides more opportunities for analysts to selectively focus on information that aligns with their initial beliefs, thereby intensifying the effects of confirmation bias.

These findings align with and extend previous research on the impact of disaggregation on judgment and decision-making. Prior studies (e.g., Ravinder et al., 1988; Henrion et al., 1993) have shown that disaggregation reduces cognitive load, enabling better processing of detailed information. This study further illustrates that, while this reduction in cognitive load can enhance information processing, it can also create conditions where confirmation bias is exacerbated, particularly when analysts start with an optimistic outlook. In contrast, when initial optimism is absent, the difference in earnings estimates between disaggregated and aggregated forecasts is minimal, suggesting that confirmation bias has a more pronounced effect when analysts are motivated by pre-existing positive beliefs.

This study also makes an important contribution to the literature on confirmation bias and motivated reasoning in financial forecasting. Previous research has documented that analysts are susceptible to confirmation bias (Tan, 1995; Thayer, 2011), but this study goes a step further by illustrating how the combination of forecast sequence and initial optimism creates a potent environment for biased forecasting. Specifically, this study demonstrates that analysts, driven by an initial optimistic outlook, may "work backward" to find preference-consistent evidence, a process further facilitated by disaggregated forecasting. This insight contributes to the growing body of literature on how cognitive biases can influence decision-making processes in financial settings.

From a practical standpoint, these results have significant implications for the financial industry.

12 The results of the contrast test excluding the Experience covariate also support the hypothesized interaction ($F = 9.44$, $p < 0.01$).

First, they suggest that disaggregation, while generally beneficial for reducing cognitive load, may inadvertently amplify optimism bias under certain conditions. This could lead analysts to overestimate company performance, potentially misleading investors and other stakeholders. As a result, firms and financial institutions should be aware of the cognitive biases that may influence analysts' judgments and take steps to mitigate these biases in their forecasting processes. One possible solution could be to incorporate safeguards such as structured decision-making frameworks or systematic checks to counteract the effects of confirmation bias.

Furthermore, this study highlights the importance of initial optimism in shaping analysts' predictions. Since analysts often work with limited information and under time constraints, their initial beliefs can have a disproportionate influence on their forecasts. In this context, it may be valuable for analysts to engage in more critical reflection about their initial assumptions and to challenge their own biases more actively.

CONCLUSION

This study investigates how the extent of disaggregation in analyst forecasts interacts with initial optimism to affect earnings estimates. The results show that disaggregated forecasts lead to higher earnings estimates compared to aggregated forecasts, but only when initial optimism is present. In this case, disaggregation reduces cognitive load and amplifies analysts' tendency to focus on information that supports their optimistic expectations, thus increasing forecast optimism. In contrast, when initial optimism is absent, analysts are less likely to exhibit biases, leading to similar earnings estimates regardless of the forecast method.

This study opens several avenues for future research. First, while this study focused on the hospitality industry, it would be valuable to investigate whether the interaction between forecast sequence and initial optimism produces similar effects across other industries with varying levels of volatility. Future studies could also explore how different types of analysts (e.g., equity analysts vs. credit analysts) might be more or less susceptible to these biases, depending on the nature of their tasks and the information they use.

Additionally, the role of external factors, such as market trends or economic conditions, could be examined to determine if these factors moderate the effect of initial optimism and disaggregation on forecast optimism. Given that analysts often work in dynamic and complex environments, understanding how external cues interact with cognitive biases could provide deeper insights into how analysts form their predictions under uncertainty.

However, this study, like all experimental studies, is subject to some limitations. The controlled setting may not reflect real-world complexity, and external validity is limited by industry-specific factors and reliance on management announcements. Other analyst incentives, such as client relationships, were also not considered. Future research could explore how disaggregation interacts with these factors in earnings estimates.

AUTHOR CONTRIBUTIONS

Conceptualization: Yuki Gong, Hideyuki Hao Sun, Sing Lui So.
Data curation: Yuki Gong, Hideyuki Hao Sun, Sing Lui So.
Formal analysis: Yuki Gong.
Funding acquisition: Yuki Gong, Hideyuki Hao Sun, Sing Lui So.
Investigation: Yuki Gong, Hideyuki Hao Sun, Sing Lui So, Zehua Chen, Ruixue Sun.
Methodology: Yuki Gong.

http://dx.doi.org/10.21511/imfi.22(1).2025.25

Project administration: Yuki Gong, Hideyuki Hao Sun, Sing Lui So, Zehua Chen, Ruixue Sun.
Resources: Zehua Chen, Ruixue Sun.
Software: Yuki Gong, Hideyuki Hao Sun, Sing Lui So.
Supervision: Yuki Gong, Sing Lui So.
Validation: Yuki Gong, Hideyuki Hao Sun, Sing Lui So, Zehua Chen, Ruixue Sun.
Visualization: Hideyuki Hao Sun.
Writing – original draft: Yuki Gong.
Writing – review & editing: Yuki Gong, Zehua Chen, Ruixue Sun.

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http://dx.doi.org/10.21511/imfi.22(1).2025.25

APPENDIX A. Research instrument

GENERAL TASK INSTRUCTIONS

This study focuses on analysts' decisions. There are ***NO*** correct/expected answers, and the researcher is solely interested in your most likely forecasting number given the facts provided in this case study.

With your newly-granted postgraduate degree, you decided to take a position as a professional financial analyst at XYZ Securities, a Wall Street brokerage firm. You have been assigned to issue forecasts for ***Firm X***'s earnings-per-share (EPS), as well as recommendations since 2018.

Over the next few pages, you will be provided the information pertaining to your forecast-making, and you will be asked to respond to a series of questions. Your responses to the questions in this case should reflect the information provided in the case.

Response measures:

- You will be asked to record your responses using both qualitative and numerical measures.
- Where qualitative responses are required, you will be provided with several choices, and you will be asked to ***TICK*** the box that best represents your response.
- For the numerical responses, you are expected to round your forecasting number to ***TWO*** decimal places.
- Once you have provided responses in a particular section and moved to the next section, please *do not* change your earlier responses.
- Please note that all the responses that you provide will be kept confidential and will be used only for the purpose of this research.
- If you have any questions while completing this study, please do not hesitate to ask.
- This case study should take 10 minutes to complete. Please kindly return your response by 9 am May 5, 2023. Thank you very much for your involvement in this research.

PART A – BACKGROUND INFORMATION

The following information is background information on Firm X. Please read the following information carefully and respond to the questions on the next page.

Firm X is a global hospitality company listed on the New York Stock Exchange (NYSE). It operates a chain of full-service hotels and resorts, extended-stay suites, and focused-service hotels. Firm X makes its fiscal year the same as the calendar year for convenience's sake. You are now assigned to forecast Firm X's annual EPS for the year ending December 31, 2021, based on the below information.

The historical financial performance of Firm X in the last three years is given as follows:

Last three years' financial data (in millions except per share data)			
	2020	**2019**	**2018**
Sales	$4,307	$9,452	$8,906
Gross profit	3,687	8,198	7,574
Net income	(715)	881	764
Earnings per share	(2.58)	3.04	2.50

The consensus one-year-ahead analyst forecast for Firm X's 2021 annual EPS was calculated as $1.48 at the end of 2020.

In your last report (issued on 6 January 2021), you held a strong positive belief in Firm X's performance in 2021, and therefore you issued a stock recommendation of "***STRONG BUY***" for Firm X.

Please record your earnings forecast here:

Your current 2021 annual EPS forecast ($): _________________

PART B – ADDITIONAL INFORMATION

After six months, your superior asked you to *revise* your preliminary forecast for Firm X's 2021 annual EPS in response to a series of management announcements made in the first two quarters of 2021. Specifically, there were ***FOUR*** announcements that might be useful for updating your EPS forecast. You are required to update your forecast number after reading each announcement. Please note that your new forecast number can be the same as or different from any of your earlier answers.

(1) Announcement 1

"Some of our international hotels were damaged by natural disasters in the last three months, and these hotels are currently under repair."

Please record your earnings forecast here:

Your current 2021 annual EPS forecast ($): _________________

(2) Announcement 2

"Our hotel occupancy rate has increased to 53% in the first two quarters of 2021 from 41% in 2020. We expect that the occupancy rate will rise to 60% by December 2021."

Please record your earnings forecast here:

Your current 2021 annual EPS forecast ($): _________________

(3) Announcement 3

"China's zero-Covid policy requires strict lockdowns (even if just a handful of cases are reported), and this policy has forced us to temporarily close some hotels in China in the past six months."

Please record your earnings forecast here:

Your current 2021 annual EPS forecast ($): _________________

http://dx.doi.org/10.21511/imfi.22(1).2025.25

(4) Announcement 4

"Thomas Pryde, who has an MBA degree in hotel management as well as over ten years of relevant working experience, joined our top management team in March 2021."

Please record your earnings forecast here:

Your final 2021 annual EPS forecast ($): ________________

Follow-Up Questions:

(1) How did you update your 2021 annual EPS estimate?

- ☐ Update my estimate each time I read a management announcement
- ☐ Update my estimate only after I read all management announcements

(2) What stock recommendation did you release in early 2021?

- ☐ STRONG BUY
- ☐ NEUTRAL

When you are ready, please proceed to the next page.

PART C – DEMOGRAPHICS

The following questions are designed to enable the researcher to gain a better understanding of the information that you have provided.

All the information you provide will be strictly CONFIDENTIAL and used solely for the purpose of this study.

Please answer the following questions:

(1) Please indicate your age range:

- ☐ Under 30
- ☐ 30 – 39
- ☐ 40 – 49
- ☐ 50 – 59
- ☐ Over 60

(2) Please indicate your gender:

- ☐ Female
- ☐ Male
- ☐ Other
- ☐ Prefer not to say

(3) What is your highest level of education?

- ☐ Secondary
- ☐ Undergraduate degree
- ☐ Postgraduate degree
- ☐ Other (please specify)

(4) Do you have any personal share investing experience?

- ☐ Yes
- ☐ No

(5) On average, how often do you trade?

- ☐ Daily
- ☐ Weekly
- ☐ Monthly
- ☐ Yearly
- ☐ When necessary

(6) How do you rate the level of your forecasting experience?

1	2	3	4	5
Very Inexperienced				Very Experienced

(7) Do you think it is important to consider EPS when making your investment decisions?

1	2	3	4	5
Not Important at all				Extremely Important

(8) 8. How do you rate your knowledge of financial concepts and principles?

1	2	3	4	5
No Knowledge				High Knowledge

THANK YOU FOR YOUR PARTICIPATION IN THIS PROJECT

http://dx.doi.org/10.21511/imfi.22(1).2025.25