



Article

Behavioral Biases and Report Accuracy: An Empirical Study of Investment Analysts Across Global Markets

Vanessa Anelli Borges de Carvalho ¹, Fabiano Guasti Lima ¹ , Vinicius Medeiros Magnani ¹ ,
Carolina Trinca Paulino ^{1,*} and Rafael Confetti Gatsios ^{2,3}

¹ Faculdade de Economia, Administração e Contabilidade de Ribeirão Preto (FEA-RP), Universidade de São Paulo (USP), Av. Bandeirantes, 3900, Ribeirão Preto 14040-905, SP, Brazil; vanessaborges@alumni.usp.br (V.A.B.d.C.); fgl@usp.br (F.G.L.); viniciusmagnani@usp.br (V.M.M.)

² Instituto Superior de Gestão, Atlântica Instituto Universitário, R. Prof. Reinaldo dos Santos 46, 1500-552 Lisboa, Portugal; rafael.gatsios@isg.pt

³ Fábrica da Pólvora, Universidade Atlântica, 2730-036 Oeiras, Portugal

* Correspondence: carolintrinca@usp.br

Abstract

This research investigates the extent to which behavioral biases—specifically overconfidence and representativeness heuristic—affect linguistic tone, narrative structure, and predictive accuracy of financial reports produced by investment analysts operating across diverse global markets. Drawing upon a comprehensive dataset comprising 1575 equity recommendation reports authored by 15 analysts from four major international investment banks between 2019 and 2022, the study evaluates how cognitive tendencies shape report composition and forecast precision. A mixed-methods approach was employed, incorporating qualitative textual analysis and quantitative modeling through random-effects panel regressions. Key constructs assessed include narrative complexity, optimism, visual content usage, and forecast deviation metrics. Our findings reveal that overconfidence significantly influences the tone and detail of analyst reports but does not demonstrably impact projection accuracy. Conversely, representativeness heuristics were not found to consistently affect either report language or earnings-per-share forecast errors. Institutional affiliation emerged as a significant determinant of predictive success, while demographic factors such as gender, native language, and geographic region had limited explanatory power. These findings imply that investors should treat report tone as an indicator of analyst disposition rather than forecast quality, while financial institutions may benefit from training programs aimed at mitigating narrative and stylistic biases in analyst communication.

Keywords: behavioral finance; report tone; forecast accuracy; overconfidence; heuristics



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1. Introduction

The rise of Behavioral Finance marked a significant departure from the assumptions of Traditional Finance and the Efficient Market Hypothesis (EMH). While classical theories assert that investors act rationally, empirical observations of market anomalies—such as speculative bubbles and overreaction to news—suggest that psychological factors often override logical decision-making. At the heart of these anomalies are cognitive biases and heuristics, which function as mental shortcuts that simplify decision-making under uncertainty.

Among the most consequential biases in financial contexts are overconfidence—where individuals overestimate the accuracy of their predictions—and the representativeness heuristic, where people judge probabilities based on stereotypes rather than statistical

reasoning. Investment analysts, who play a crucial intermediary role, are not immune to these biases. An overconfident analyst may issue overly optimistic forecasts, while one relying on representativeness may overweight recent performance trends, potentially distorting investor expectations.

Although prior literature acknowledges the influence of biases on analyst recommendations, less is known about how these psychological traits manifest in the textual and narrative characteristics of financial reports. Furthermore, few studies have empirically connected these linguistic features (such as tone and detail) to the accuracy of earnings forecasts in a diverse, global environment spanning different cultures and market contexts.

To fill this gap, this study investigates how overconfidence and representativeness heuristic affect the narrative tone, detail, and accuracy of analyst reports. This research addresses the following key questions:

1. To what extent do cognitive biases influence the detail and tone of analyst reports?
2. What is the impact of these biases on forecast accuracy?
3. Do the textual characteristics of the reports serve as predictors of forecast accuracy?

By addressing these objectives, this study contributes a more nuanced understanding of how psychological traits influence financial communication and market-facing outcomes.

2. Literature Review

The field of Behavioral Finance emerged to explain market phenomena that defy traditional models of rational agency. Rooted in the concept of “bounded rationality,” it acknowledges that cognitive limitations lead decision-makers to rely on heuristics and biases, which can result in systematic errors. In high-stakes financial markets, biases such as overconfidence and the representativeness heuristic are particularly consequential (Silva et al., 2018).

Investment analysts, despite their expertise, are not immune to these psychological pitfalls. Prior research has established that forecast accuracy can be influenced by non-psychological factors like analyst experience or firm complexity. However, these models often overlook the cognitive dimension of the analyst’s process. This study posits that incorporating behavioral biases, measured through the linguistic properties of analysts’ reports, can enhance the explanatory power of traditional models by capturing variance that stems directly from the individual’s decision-making framework (De Bondt & Thaler, 1985).

These biases are not just theoretical constructs; they manifest in high-stakes decision-making across global financial markets. For instance, overconfident analysts may issue overly optimistic earnings forecasts or aggressive buy recommendations, potentially distorting investor expectations and contributing to market volatility. Likewise, the representativeness heuristic may lead analysts to overweight recent performance trends or rely on industry stereotypes, ignoring broader economic indicators or company fundamentals. These tendencies become even more critical in highly dynamic or uncertain environments, such as during the COVID-19 pandemic, which significantly disrupted global financial systems and increased the cognitive load on financial decision-makers.

The real-world impact of behavioral biases in high-stakes financial decisions is well-documented. For instance, Lauterbach et al. (2025) show that bidders in M&A deals strategically adjust their offers to account for the loss aversion of target shareholders, illustrating how prospect-theory biases shape major corporate actions.

In this context, investment analysts act as crucial intermediaries, synthesizing complex data into research reports. While past studies have shown that attributes such as analyst gender and cultural background can influence financial reporting, these analyses often stop at demographic or institutional factors. Our research extends this inquiry by exploring how

cognitive biases manifest directly in the linguistic properties of their reports (Machado, 2018; De Franco et al., 2015).

Past studies have shown that attributes such as analyst gender, cultural background, and institutional affiliation can influence both the language and the accuracy of financial reporting (Lima Filho et al., 2012). For instance, some evidence suggests that male analysts may exhibit greater overconfidence than their female counterparts, leading to differences in tone and optimism in their reports (Barber & Odean, 2001; Lundeberg et al., 1994). Additionally, linguistic and regional diversity may affect how complex financial ideas are communicated and interpreted. These variations raise important questions about how behavioral biases intersect with professional communication practices in an increasingly globalized financial environment.

Given this backdrop, the current research seeks to explore how overconfidence and representativeness heuristic affect the narrative tone, detail, and accuracy of analyst reports across diverse global markets. The study leverages a unique dataset of 1575 equity recommendation reports authored by 15 analysts—spanning both genders and four world-leading investment banks—from 2019 to 2022. This time period was strategically selected to include pre-pandemic stability and the unprecedented market disruptions brought about by the COVID-19 crisis, thus offering a rich setting to observe behavioral effects under variable conditions.

This research adopts a mixed-methods approach, integrating qualitative linguistic analysis with robust quantitative modeling. The tone, complexity, visual elements, and readability of reports are systematically assessed, while indicators of overconfidence and representativeness are extracted using custom linguistic dictionaries and analyzed using random-effects panel regressions. Accuracy is objectively measured via the forecast error framework developed by Martinez (2004), offering a standardized benchmark for evaluating prediction reliability.

The overarching aim is to determine whether these behavioral traits—particularly overconfidence and heuristics—manifest in discernible patterns of language use and whether such patterns correlate with forecasting performance. To achieve this, the research is structured around three core investigative stages:

1. Textual Analysis: Assess the influence of behavioral heuristics on the tone and detail of analyst reports, stratified by gender, native language, and market context.
2. Forecast Evaluation: Examine the effect of biases on the accuracy of EPS forecasts across the sample.
3. Integrated Modeling: Explore whether linguistic attributes of the reports (e.g., tone, complexity) serve as predictors of forecast accuracy, thereby connecting language to financial precision.

By addressing these objectives, this study aims to contribute to a more nuanced understanding of how psychological traits influence financial communication and the extent to which such communication affects market-facing outcomes. The findings are expected to inform both the academic literature on behavioral finance and the practices of financial institutions, particularly those seeking to improve the transparency, accountability, and utility of analyst research in a globalized, post-pandemic world (Clement, 1999; Ramnath et al., 2008).

This study's framework is grounded in the theory of bounded rationality, which posits that cognitive limits lead to the use of biases. Theory suggests overconfident individuals trust their own private information excessively and may project certainty to enhance their reputation. We thus hypothesize that overconfident analysts will produce reports with more assertive language (a more positive TOM) and greater self-assured detail (DETALHE) to signal expertise.

The representativeness heuristic involves extrapolating from limited data, such as recent performance. Analysts exhibiting representativeness may overreact to recent positive news by anchoring on it, leading to a more optimistic narrative and potentially biased forecasts. This is conceptually related to the “first-impression” bias identified by [Hirshleifer et al. \(2021\)](#), where analysts issue optimistically biased forecasts for firms with strong pre-coverage returns. We therefore hypothesize that a greater use of representativeness (HRST) will be positively associated with report TOM. The linguistic measures were chosen as they are established proxies in the accounting and finance literature for capturing the tone and complexity of financial narratives.

Research on analyst forecast accuracy has traditionally focused on factors such as analyst experience, firm size, and the complexity of the company being covered. While these models explain a significant portion of forecast error, they often overlook the psychological dimension of the analyst. This study argues that incorporating behavioral biases provides a crucial additional layer of explanation. By measuring cognitive traits through the linguistic properties of reports, our model aims to capture the variance in accuracy that stems from the individual analyst’s decision-making process, thereby enhancing the explanatory power of traditional models.

3. Materials and Methods

This study employs a mixed-methods approach, combining qualitative textual analysis with quantitative modeling. Regarding the quantitative nature, it is in the construction of a statistical model capable of checking the extension of the influence of this bias and heuristics in tone and detail of the reports issued by analysts of different genders and markets. Moreover, the influence of the bias and heuristics on the accuracy of the earnings-per-share projections delivered to the market will also be checked. The step-by-step adopted for carrying out the research is detailed next.

The sample construction began with an initial pool of 108 sell-side analysts identified via the Bloomberg Terminal, covering firms in Latin America, the United States, Europe, and Japan for four leading global investment banks. To ensure data consistency, this pool was filtered based on several criteria: (i) continuous employment at the same bank during the 2019–2022 period, verified via LinkedIn profiles, and (ii) availability of a sufficient number of full-text reports. Analysts who did not meet these criteria were excluded. This transparent filtering process resulted in the final sample of 15 analysts, from whom 1575 complete reports were downloaded directly from the banks’ proprietary research portals.

The period from 2019 to 2022 was strategically selected for this analysis. This time-frame is crucial as it includes the pre-pandemic year of 2019, characterized by relative market stability, and the subsequent years marked by the unprecedented global economic crisis and volatility triggered by the COVID-19 pandemic. This allows the study to observe behavioral effects under both normal and high-stress market conditions, providing a richer and more relevant context for the findings.

Using the 76 analysts left, a selection of at least one agent per bank, per gender was made. The only exception was Bank 4, in which there was only one male analyst. The sequence of the ranking through the length of house (according to the information gathered at LinkedIn) and the availability of reports for the study were respected. The total of the sample was of 15 agents and 1575 recommendation reports. It is worth highlighting that in some cases, agents with less time working in the bank were chosen because of reports availability, also respecting the sequence of the ranking, that is, if for the agent who was higher in the ranking there was no report availability, the analyst who came next was chosen.

The sample covers analysts operating in the primary markets of Latin America, the United States, Europe, and Japan, hence the reference to “global markets.” The focus on four large, sell-side international investment banks was a deliberate choice to study analysts who are subject to strong institutional pressures and whose reports have a significant market impact.

Based on the list of the 15 agents chosen, a download of the recommendation reports published by the sell-side analysts from 2019 to 2022 was carried out, straight from the database of each one of the world banks studied.

All the variables used are summarized in Table 1 that follows.

Table 1. Variables studies.

Variable	N	Origen	Objective
DETAIL	(1)	Machado (2018)	Measure the detail of the report of projections and recommendations
FOG Index	(2)	Li (2008)	Measure the level of legibility of the report of projections and recommendations
LENGTH	(3)	Li (2008)	Measure the extension of the report of projections and recommendations
VIS	(4)	Twedt and Rees (2012)	Measure the level of visual resources (pictures, charts, tables) used in the report of projections and recommendations
TOM	(5)	Henry (2006)	Measure the tone of the report of projections and recommendations (positive/negative)
OVCF	(6)	MANUAL DICTION	Measure the overconfidence bias in the report of projections and recommendations (it considers dictionaries of Diction software 5.0).
HRST	(7)	Machado (2018)	Measure the representativeness heuristics in the report of projections and recommendations
ErrPrev	(8)	Martinez (2004)	Measure the errors of single earnings-per-share projections
GEN	-		Binary Variable 1 (male) and 0 (female)
IDIOMA	-		Binary Variable 1 for English as native language and 0 for native language other than English
LOCAL	-		Latin America (1), the United States (2), Europe (3) and Japan (4)
BANCO	-		Banks numbered from 1 to 4

Note: This table lists the variables used in the analysis, their theoretical origins in prior literature, and their objective within this study. Source: created by the authors (2025).

It is understood that the variables summarized in Table 1 are important and enough to defend the thesis that the overconfidence bias and the representativeness heuristics have significant influence, at different levels, on the writing and accuracy of the earnings-per-share projections, for analysts in different contexts, and they corroborate the results of the research of the authors [Deaux and Farris \(1977\)](#), [Lundeberg et al. \(1994\)](#), [Lima Filho et al. \(2012\)](#) and [Adams and Ferreira \(2009\)](#), as well as [Pessotti \(2012\)](#), [Hong and Kubik \(2003\)](#) and [Souza \(2020\)](#).

The key variables, like overconfidence, were operationalized using a custom dictionary developed within the Diction software framework. It is calculated as the frequency of words associated with certainty, assertiveness, and self-assurance (e.g., “certain,” “definitely,” “undoubtedly”) relative to the total word count of the report. A higher score indicates greater overconfidence.

Following Machado (2018), representativeness heuristic is operationalized by measuring the frequency of words and phrases that suggest reliance on recent trends or analogies (e.g., “as before,” “similar to,” “continues to show”). A higher score suggests a greater use of the representativeness heuristic.

Accuracy is measured using the forecast error metric developed by Martinez (2004), calculated as the difference between the analyst’s EPS forecast and the actual reported EPS, scaled by the stock price. A value closer to zero indicates higher accuracy.

The hypotheses tested in the research are detailed below.

Hypothesis 1. *To what extent do the heuristics and biases influence the detail of analysts’ reports of different contexts?*

To test Hypothesis 1, the following models will be used:

$$DETALHE_{j,t} = \beta_0 + \beta_1 HRST_{j,t} + \beta_2 OVCF_{j,t} + \beta_3 DUMMY\ GEN_{j,t} + \beta_4 LOCAL_{j,t} + \beta_5 DUMMY\ IDIOMA_{j,t} + \beta_6 BANCO\ INV_{j,t} + e_{j,t} \quad (9)$$

In which:

$DETALHE_{j,t}$ is calculated according to Formula (1) for the analyst j in the date t

$HRST_{j,t}$ is calculated according to Formula (7) for the analyst j in the date t

$OVCF_{j,t}$ is calculated according to Formula (6) for the analyst j in the date t

$DUMMY\ GEN_{j,t}$ is the binary variable 0 (fem) or 1 (male) for the analyst j in the date t

$LOCAL_{j,t}$ is the ordinary variable Latin America (1), the United States (2), Europe (3) and Japan (4) for the analyst j in the date t

$DUMMY\ IDIOMA_{j,t}$ is the binary variable 0 (native language other than English) or 1 (English as the native language) for the analyst j in the date t

$BANCO\ INV_{j,t}$ is the ordinary variable Bank 1, Bank 2, Bank 3 and Bank 4 for the analyst j in the date t

$e_{j,t}$ represents the error of the model

The second stage aims to test the following hypothesis:

Hypothesis 2. *To what extent do the heuristics and biases influence the tone of analysts’ reports of different contexts?*

To test Hypothesis 2, the following models will be used:

$$TOM_{j,t} = \beta_0 + \beta_1 HRST_{j,t} + \beta_2 OVCF_{j,t} + \beta_3 DUMMY\ GEN_{j,t} + \beta_4 LOCAL_{j,t} + \beta_5 DUMMY\ IDIOMA_{j,t} + \beta_6 BANCO\ INV_{j,t} + e_{j,t} \quad (10)$$

In which:

$TOM_{j,t}$ is calculated according to Formula (5) for the analyst j in the date t

$HRST_{j,t}$ is calculated according to Formula (7) for the analyst j in the date t

$OVCF_{j,t}$ is calculated according to Formula (6) for the analyst j in the date t

$DUMMY\ GEN_{j,t}$ is the binary variable 0 (fem) or 1 (male) for the analyst j in the date t

$LOCAL_{j,t}$ is the ordinary variable Latin America, the United States, Europe and Japan for the analyst j in the date t

$DUMMY\ IDIOMA_{j,t}$ is the binary variable 0 (native language other than English) or 1 (English as the native language) for the analyst j in the date t

$BANCO\ INV_{j,t}$ is the ordinary variable Bank 1, Bank 2, Bank 3 and Bank 4 for the analyst j in the date t

$e_{j,t}$ represents the error of the model

Then, Hypothesis 3 will be checked:

Hypothesis 3. *To what extent do the heuristics and biases influence the accuracy of single projections of investment analysts of different contexts?*

To test Hypothesis 3, the following model will be used:

$$ErrPrev_{j,t} = \beta_0 + \beta_1 HRST_{j,t} + \beta_2 OVCF_{j,t} + \beta_3 DUMMY\ GEN_{j,t} + \beta_4 LOCAL_{j,t} + \beta_5 DUMMY\ IDIOMA_{j,t} + \beta_6 BANCO\ INV_{j,t} + e_{j,t} \quad (11)$$

In which:

$Err\ Prev_{j,t}$ is calculated according to Formula (8) for the analyst j in the date t

$HRST_{j,t}$ is calculated according to Formula (7) for the analyst j in the date t

$OVCF_{j,t}$ is calculated according to Formula (6) for the analyst j in the date t

$DUMMY\ GEN_{j,t}$ is the binary variable 0 (fem) or 1 (male) for the analyst j in the date t

$LOCAL_{j,t}$ is the ordinary variable Latin America, the United States, Europe and Japan for the analyst j in the date t

$DUMMY\ IDIOMA_{j,t}$ is the binary variable 0 (native language other than English) or 1 (English as the native language) for the analyst j in the date t

$BANCO\ INV_{j,t}$ is the ordinary variable Bank 1, Bank 2, Bank 3 and Bank 4 for the analyst j in the date t

$e_{j,t}$ represents the error of the model

Finally, Hypothesis 4 will be checked:

Hypothesis 4. *Do the tone and detail of analysts' recommendation report explain the accuracy of single projections of agents in different contexts?*

To test Hypothesis 4, the following model will be used:

$$ErrPrev_{j,t} = \beta_0 + \beta_1 TOM_{j,t} + \beta_2 DETALHE_{j,t} + \beta_3 DUMMY\ GEN_{j,t} + \beta_4 \beta_3 LOCAL_{j,t} + \beta_5 DUMMY\ IDIOMA_{j,t} + \beta_6 BANCO\ INV_{j,t} + e_{j,t} \quad (12)$$

In which:

$ErrPrev_{j,t}$ is calculated according to Formula (8) for the analyst j in the date t

$TOM_{j,t}$ is calculated according to Formula (5) for the analyst j in the date t

$DETALHE_{j,t}$ is calculated according to Formula (1) for the analyst j in the date t

$DUMMY\ GEN_{j,t}$ is the binary variable 0 (fem) or 1 (male) for the analyst j in the date t

$LOCAL_{j,t}$ is the ordinary variable Latin America, the United States, Europe and Japan for the analyst j in the date t

$DUMMY\ IDIOMA_{j,t}$ is the binary variable 0 (native language other than English) or 1 (English as the native language) for the analyst j in the date t

$BANCO\ INV_{j,t}$ is the ordinary variable Bank 1, Bank 2, Bank 3 and Bank 4 for the analyst j in the date t

$e_{j,t}$ represents the error of the model

To test the hypotheses, a random-effects panel regression model was employed. This model is particularly suitable for our data structure, as it allows for the analysis of repeated observations (multiple reports) for each individual (analyst) over time. The random-effects

model accounts for unobserved, time-invariant heterogeneity among analysts, thereby enabling a more effective isolation of the impact of our variables of interest. As the results show, the variation between analysts is more relevant to this study's objectives than the variation within a single individual over time (Between R^2 for Model 2 was 93.8%), making this approach methodologically appropriate.

4. Results

Statistics can be divided in two main branches: (i) inferential statistics and (ii) descriptive statistics. The descriptive statistics seeks to only describe and assess a certain group, without taking any conclusions or inferences on a larger group; however, the inferential (or inductive) statistics seeks to infer important conclusions about the subjacent population, from a representative sample (Fávero et al., 2014).

In this thesis, both branches of Statistics are applied, starting by the descriptive statistics, and later running the tests of inferential/inductive statistics.

The first step for the statistical analysis of the database was to use the descriptive statistics of the variables studied, aiming to trace a profile of the analysts and reports analyzed, performed manually, via Excel (qualitative variables), or via the Stata 15.0 statistical software (quantitative variables). The database considered comprised 1575 recommendation reports, referring to 295 companies, produced by 15 analysts of different genders and locations. The variables analyzed were year, analyst, gender (GEN), location (LOCAL), broker, RCM Code, DETALHE, FOG, LENGTH, VIS, TOM, OVCF, HRST and ACURÁCIA (ErrPrev) and descriptive statistic of this quantitative variables are on the Table 2.

Table 2. Descriptive Statistics of the quantitative variables.

Variable	OBS	Average	DP	Min	Max
FOG	1575	11.25	1.89	5.13	15.13
LENGTH	1575	3.87	0.17	3.62	4.69
VIS	1575	1.00	0.36	0.30	2.03
DETALHE	1575	14.05	4.69	5.40	33.39
TOM	1575	−0.03	0.02	−0.60	0.01
OVCF	1575	−0.06	0.02	−0.16	−0.01
HRST	1575	0.04	0.08	0.00	0.53
ERRPREV	812	−9.59	145.19	−4060.11	105.43

Note: This table presents descriptive statistics for the main quantitative variables used in the study. Statistics are based on the full sample of 1575 analyst reports, except for ErrPrev (n = 812). DP denotes Standard Deviation. Source: created by the authors (2025).

The variables: FOG, LENGTH, VIS, DETALHE, TOM, OVCF, HRST and ERRPREV (accuracy) were calculated according to the models presented in the methodology and they are all quantitative variables.

A total of 1575 observations are checked for all the variables, except the ERRPREV variable, for which it is not possible to calculate the accuracy without the value of the projected earnings-per-share or the actual earnings-per-share. This lack of absence occurs because the calculation of forecast error requires both the projected earnings-per-share (EPS) figure from the analyst's report and the actual EPS subsequently disclosed by the company. For 763 reports, one of these two data points was not available in the database, thus preventing the computation of the accuracy metric. Therefore, there was no information available for 763 cases.

The summary of the Descriptive Statistics can be found in Table 3 that follows:

Table 3. Summary of the profile traced by the Descriptive Statistics of the Quantitative Variables.

	GENDER	LANGUAGE	PLACE	BANK
FOG Index	• higher Female • lower male	• higher English • lower not English	• higher Europe • lower Latin Am.	• higher Bank 4 • lower Bank 1
LENGTH	• higher male • lower female	• higher English • lower not English	• higher USA • lower Japan	• higher Bank 4 • lower Bank 2
VIS	• higher male • lower female	• higher English • lower not English	• higher Latin Am. • lower Japan	• higher Bank 4 • lower Bank 3
DETALHE	• higher male • lower female	• higher English • lower not English	• higher Latin Am. • lower Japan	• higher Bank 4 • lower Bank 3
TOM	• + neg female • – neg male	• + neg not English • – neg English	• + neg Japan • – neg USA	• + neg Bank 2 • – neg Bank 4
OVCF	• + neg female • – neg male	• + neg not English • – neg English	• + neg Japan • – neg USA	• + neg Bank 2 • – neg Bank 4
HRST	• Similar for both genders • higher for male	• Similar for both languages • higher for not English	• higher Latin Am. • lower Japan	• higher Bank 1 • lower Bank 4
ErrPrev	• higher male • lower female	• higher for not English • Lower English	• higher Latin Am. • Lower Japan	• higher Bank 4 • lower Bank 3

Note: This table provides a qualitative summary of the descriptive statistics, indicating which group (based on gender, language, location, and bank) scored, on average, higher or lower for each metric analyzed. “+ neg” indicates a value that is more negative (less positive/optimistic). Source: created by the authors (2025).

Thus, female investment analysts deliver reports with lower DETALHE, despite being more complex, they present less optimist TOM and OVCF, lower HRST and lower forecast error/greater accuracy. Male analysts deliver reports with higher DETALHE, despite being less complete, they present more optimist TOM and OVCF, higher HRST and higher forecast error/less accuracy.

Next, a summary of the Inferential Statistics of the Database is presented.

Therefore, this definition with the results of R^2 between makes sense, since the variation between analysts are much more relevant than for each single analyst, especially by the characteristic of the variables, being 2 of them binary and 2 of them ordinary.

The regression analyses (Table 4) indicate that the representativeness heuristic does not have a statistically significant influence on report detail, tone, or forecast accuracy. Furthermore, the results show that forecast accuracy varies significantly based on the analyst’s investment bank affiliation. Finally, the tone and detail of the recommendation reports do not have significant influence on the forecast error of the documents issued by analysts of different contexts.

Table 4. Inferential Statistics of the Database.

Model 1—DETALHE		
Group: Analysts (15)		
Variable	Coefficient	Robust DP
OVCF	122,270 ***	39,761
HRST	−0.506	0.739
GEN	−0.470	1388
IDIOMA	−0.790	1339
LOCAL	−1897 ***	0.543
BANCO	1142	0.726
Constant	25,782 ***	2985
R ² : Within 0.358 Between 0.546 Overall 0.529		
Wald $\chi^2(6) = 53.39$ Prob > $\chi^2 = 0.0000$		

Table 4. Cont.

Model 2—TOM		
Group: Analysts (15)		
Variable	Coefficient	Robust DP
OVCF	0.282 ***	0.114
HRST	−0.000	0.001
GEN	0.000	0.001
IDIOMA	0.001	0.001
LOCAL	−0.001 **	0.000
BANCO	0.000	0.001
Constant	−0.008	0.006
R ² : Within 0.018 Between 0.938 Overall 0.092 Wald $\chi^2(6) = 88.01$ Prob > $\chi^2 = 0.0000$		
Model 3—ERRPREV		
Group: Analysts (15)		
Variable	Coefficient	Robust DP
OVCF	−457,667	330,457
HRST	−77,820	99,825
GEN	1385	5432
IDIOMA	15,865	12,505
LOCAL	7869	6796
BANCO	−12,089 ***	3584
Constant	−40,604	36,397
R ² : Within 0.005 Between 0.201 Overall 0.010 Wald $\chi^2(6) = 14.19$ Prob > $\chi^2 = 0.0276$		
Model 4—ERRPREV (com TOM e DETALHE)		
Group: Analysts (15)		
Variable	Coefficient	Robust DP
TOM	−366,666	244,749
DETALHE	−4239	3411
GEN	−8074	8985
IDIOMA	15,358	10,911
LOCAL	2175	3237
BANCO	−3734	6454
Constant	48,767	37,600
R ² : Within 0.004 Between 0.337 Overall 0.014 Wald $\chi^2(6) = 20.23$ Prob > $\chi^2 = 0.0025$		

Note: This table presents the results from the random-effects panel regressions for the four models tested. The dependent variables are DETALHE (Model 1), TOM (Model 2), and ErrPrev (Models 3 and 4). Robust standard errors are reported in parentheses. Significance levels are denoted as follows: *** $p < 0.01$, ** $p < 0.05$. Source: Created by the authors (2025).

The summary of the results can be found in Table 5.

Table 5. Result Analysis Summary.

Model	R ²	Variables $p < \alpha = 0.05$	Conclusions
Model 1	R ² 52.9% overall R ² 54.6% between	OVCF and LOCAL	OVCF and LOCAL have influence on DETALHE
Model 2	R ² 9.2% overall R ² 93.8% between	OVCF and LOCAL ($p < \alpha = 0.10$)	OVCF and LOCAL have influence on TOM
Model 3	R ² 1.0% overall R ² 20.1% between	BANCO	BANCO has influence on ErrPrev
Model 4	R ² 1.4% overall R ² 33.7% between	None	No influence with statistical significance

Note: This table summarizes the key findings from the regression models, highlighting the overall and between-analyst explanatory power (R²), the variables with statistical significance, and the main conclusion drawn from each model. Source: created by the authors (2025).

5. Discussion

The findings of this study provide important insights into the cognitive biases and contextual factors that influence how financial analysts produce their reports. The results reveal that overconfidence significantly affects the stylistic features of these documents—such as tone and level of detail—but does not influence their substantive accuracy. In contrast, the representativeness heuristic shows no significant impact on any of the examined dimensions.

The observation that overconfidence shapes how information is presented without altering the precision of earnings forecasts constitutes a key contribution. This suggests a disconnection between the stylistic and analytical dimensions of analyst communication. One plausible interpretation is that institutional mechanisms—such as internal review and quality control procedures—attenuate the effects of individual biases on quantitative forecasts, even though they may persist in narrative expression. Moreover, the lack of statistical significance for the gender variable across all models was unexpected, diverging from prior literature and indicating that strong institutional cultures in global investment banks may neutralize gender-based behavioral differences.

These findings align with the notion that overconfidence may manifest primarily as a “communication bias,” a concept consistent with models like [Friesen and Weller \(2006\)](#), who demonstrate that analysts can remain overconfident in their communication even while rationally discounting external signals.

An equally relevant result concerns the non-significance of the representativeness heuristic (HRST). This outcome may stem from the structured, data-intensive nature of sell-side analysis, which inherently limits the reliance on simple heuristics. Analysts are trained to base forecasts on fundamental valuation models, and institutional oversight likely filters out reports that rely excessively on recent performance or stereotypes. Alternatively, the textual proxy employed may not fully capture the underlying cognitive process of representativeness, which could manifest through subtler linguistic or behavioral patterns.

The most striking practical finding is that institutional affiliation (BANCO) emerged as the only statistically significant predictor of forecast error. This strongly indicates that firm-level characteristics—such as analytical resources, internal validation mechanisms, and incentive structures—play a more decisive role in shaping forecast quality than individual cognitive traits.

From a practical perspective, these results carry implications for both investors and financial institutions. Investors should be cautious when interpreting overly optimistic or linguistically complex reports, as such features may reflect the analyst’s confidence rather than analytical rigor. For financial institutions, the findings emphasize the need to ensure objectivity and balance in narrative communication, in addition to maintaining technical accuracy in quantitative projections.

Finally, the main limitation of this study lies in its cross-sectional design, which compares analysts to one another without tracking the evolution of individual behavior over time. Future research could address this by employing longitudinal designs, exploring alternative proxies for overconfidence and representativeness, and testing interaction effects among the explanatory variables that demonstrated the strongest influence.

6. Conclusions

This study found that while the overconfidence bias significantly influences the tone and detail of investment analyst reports, it does not translate into lower forecast accuracy. Conversely, the representativeness heuristic showed no significant impact on either report characteristics or accuracy. The most robust predictor of forecast precision was found to be

the analyst's institutional affiliation, highlighting the importance of firm-level factors over individual cognitive traits in determining analytical performance.

A key practical implication is that investors should be cautious of narrative style, as an optimistic tone may reflect an analyst's confidence rather than superior insight. For future research, longitudinal studies could explore how analysts' biases evolve with experience and in response to major market events, offering a dynamic view of behavioral finance in action.

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