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Impact of Biases on Analyst´s Accuracy: a Cluster-Based Analysis

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Abstract

Objective: This study investigates the impact of biases on the accuracy of financial analysts by distinguishing between analysts with higher and lower levels of accuracy through cluster analysis.
Method: The analysis encompassed publicly traded companies in Brazil and the USA during the quarters of 2019, comprising 840 observations from 76 Brazilian firms and 16,402 observations from 880 U.S. firms. The cognitive biases examined included: anchoring, optimism, overconfidence, communal bias, representativeness, and realism, measured using Diction®. Data analysis was conducted using STATA® and SPSS®, employing analysis of variance (ANOVA), post-hoc ANOVA test, cluster analysis and multiple regression models.
Results: Among the biases analyzed, anchoring—defined as the tendency to rely on past earnings as a reference point for future forecasts, was the only bias to exhibit consistent patterns across both accuracy groups and countries. This finding suggests that the stochastic effect of past profitability contributes positively to earnings forecasting accuracy. In the U.S. sample, cognitive biases were more strongly associated with analyst accuracy than in the Brazilian sample. Overconfidence and realism were particularly salient among the higher accuracy groups in the U.S. In Brazil, the only statistically significant result indicated a negative effect of optimism on forecasts issued by analysts in the higher accuracy group. The communal bias was found to negatively affect analyst accuracy in the U.S., regardless of accuracy level. Representativeness bias also had detrimental effect on analyst with lower accuracy in the U.S.
Contributions: This study emphasizes the relevance of considering biases in the evaluation financial analysts and suggests that awareness of such biases may enhance investment decision-making. Specifically, analysts with overconfidence and realism in the U.S. tend to produce more accurate forecasts, whereas those influenced by optimism in Brazil, and communal or representativeness biases in the U.S., should be approached with caution.
Keywords: Analyst accuracy. Behavioral biases. Clustering.

How to Cite:

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Introduction

The capital market plays a fundamental role in a country's economic development by facilitating the efficient allocation resources. Through this mechanism, companies are able to secure financing to expand their operations, invest in innovation, and generate employment. At the same time, investors can allocate their savings to stocks and other financial instruments, thereby contributing to economic growth. The capital market is strongly influenced by corporate information disclosure, a phenomenon extensively examined in financial literature. Fama (1970) discusses the efficiency of capital markets in relation to information disclosure, while Eachempati et al. (2021) explore how information affects the market behavior using deep neural networks.

However, information is not limited to financial data; it also encompasses the overall performance of companies (He et al., 2022). Investors rely on such information to make investment decisions, often guided by analyses conducted by financial analysts (analysts) (Eliwa et al., 2021). In less transparent and more uncertain markets, however, companies tend to disclose limited information (Hou & Gao, 2021). This practice contributes to information asymmetry between investors and managers (BC & Esfahani, 2020), thereby complicating the decision-making process (Chang et al., 2016).

To support more informed investment decisions, financial analysts process and interpret both quantitative and qualitative data (Machado & Lima, 2021), as well as information obtained from company managers or other analysts. Their objective is to publish reports that include recommendations to buy, hold, or sell an asset (Brown et al., 2022). In addition, analysts provide forecasts of companies' future earnings, which influence stock prices, making forecast accuracy a critical component of their relevance. Furthermore, the speed at which stock prices incorporate available information is often regarded as an indicator of market´s level of development (Wisniewski & Yekini, 2015; Chang et al., 2016; Martins et al., 2016; Chourou et al., 2021; Eliwa et al., 2021).

Nonetheless, the information disclosed is subject to interpretation by analysts, who are susceptible to behavioral biases when formulating investment recommendations. These biases can influence the content of their reports, and, consequently, affect investors' choices. Human rationality is inherently limited and represents a simplification of reality (Simon, 1955). The assumption that individuals are utility maximizers who make rational decisions was challenged by Kahneman & Tversky (1979).

Given the relevance of the topic, studies on analysts' forecasts - whether from a financial or behavioral perspective- have examined various markets. Examples include the U.S markets (Ho et al., 2020; Sinha, 2021; Yang & Chen, 2021); European markets (Aboud et al., 2018), Eastern European markets (Chang et al., 2016), the South African market (Bernardi & Stark, 2018), and the Brazilian market (Martins et al., 2016). However, there remains a gap in the literature regarding cross-country comparison of the factors influencing analysts' forecasts, particularly behavioral bias. Such comparative analyses – spanning countries like U.S, where modern financial theory originated, to less developed markets such as Brazil- remain scare, especially when multiple biases are considered within a unified analytical framework.

Furthermore, although research on the behavioral aspects of financial analysts has gained prominence in recent years (Nguyen et al., 2021), there remains a gap in studies that investigate the underlying factors influencing analysts' forecasts (BC & Esfahani, 2020; Ho et al., 2020; Iqbal et al., 2021). This gap indicates that behavioral biases remain an underexplored area, particularly considering that cultural context influences the development and interpretation of theories (Hofstede, 1980). Therefore, it is important to assess whether findings on analysts accuracy can be generalized to political, economic, and cultural environments different from that of the U.S. (Basu et al., 1998). This comparison is particularly relevant given that culture, defined as the collective programming of the mind (Hofstede, 1980), shapes behavioral patterns.

In this context, the present study aims to analyze whether the presence of biases influences analysts' accuracy, considering both high and low accuracy levels in samples from the U.S. and Brazil. The study focuses on six specific biases: commonality, overconfidence, optimism, anchoring, representativeness, and realism. Previous literature has identified relationships between analysts' errors and certain biases such as anchoring, representativeness, overconfidence, and optimism. Two considerations are worth emphasizing in this regard. First, these biases are often examined using a quantitative approach, which typically involves calculating average values for groups of analysts. However, a qualitative individualized assessment of such biases for each analyst may enhance the robustness of the analysis and contribute to a deeper understanding to the relationships under investigations. Second, biases such as commonality and realism remain underexplored in this context, offering the potential to generate new evidence for the literature. Additionally, adopting a multi-bias perspective may improve forecasting models by identifying novel explanatory variables and enhancing their predictive accuracy.

For instance, commonality may enhance analysts' projections by encouraging alignment with peer perspectives (Kumar et al., 2021). Overconfidence is one of the most well-defined biases in the literature (Bregu, 2020), and is considered among the most influential in decision-making

(Friehe & Pannenberg, 2019). Optimism affect how analysts process and interpret market signals, shaping their earnings forecasts (Davis & Lleo, 2020). This bias may result from unconscious psychological mechanisms (Clarke & Shastri, 2001; Hou et al., 2021) or represent deliberate, rational behavior aimed at market signaling (O'Brien et al., 2005; Krolikowski et al., 2016). Anchoring has been widely studied in finance (Marsden et al., 2008; Campbell & Sharpey 2009; Cen et al., 2013; Silva Filho et al., 2018; Peña & Gómez-jía, 2019; Li et al., 2021) because it reflects a natural human tendency to rely on initial information when making decisions (Hirshleifer & Teoh, 2003). Representativeness also affects analysts´ forecast by leading them to assign disproportionate importance to specific cues or past patterns (Tversky & Kahneman, 1974). Realism, in contrast, is a constructive characteristic that brings balance to forecasts. It is associated with the capacity of market participants to appropriately recognized and respond to negative information (Bénabou, 2009), as well as to integrate non-financial disclosures from corporate reports-often enabling analysts' forecasts to outperform statistical models (Linnainmaa et al., 2016). These relationships present intriguing opportunities for empirical research, particularly in understanding how such biases manifest across different institutional and cultural environments.

Another recurring feature in the literature is the predominance of international studies, whose conclusions are largely drawn for North American context (Lim, 2001; Ciccone, 2003; Gu & Wu, 2003; Hilary & Menzly, 2006; Campbell & Sharpe, 2009; Cen et al., 2013; Broihanne et al., 2014; Galanti & Vaubourg, 2017; Du & Budescu, 2018; Ashour & Hao, 2019). However, expanding research to include diverse environments is essential, as cultural, institutional, and economic contexts can significantly shape behavior and decision-making (Corredor et al., 2013). In this regard, studies conducted in different settings may yield complementary insights to those derived from the U.S. context. Culture is a key variable in studies of economic phenomena, as it helps to explain the actions of individuals (Illiashenko, 2019), who often make different choices when confronted with the same situation, a divergence shaped by cultural conditioning, life experiences, and education (Hofstede, 1980).

When considering cultural differences between Brazil and the U.S., Brazil is characterized as more collectivist, while the U.S. is more individualistic (Hofstede, 1980). This variation in individualism may help explain the greater incidence of certain biases, since individuals may consider more private opinions when making decisions, which increases the range of approaches and aspects considered in these decisions (Saad & Samet, 2020). This would imply different results for commonality when considering the environment. In this sense, more individualistic cultures may present greater overconfidence among individuals (Schmitt & Allik, 2005), leading to errors in the interpretation of information (Deaves et al., 2010). From a cultural perspective, optimism should also be considered cautiously, since classic market indexes used to predict future profits tend to be less reliable in developing economies compared to developed ones (Akhtar, 2021). Thus, optimism in developing markets may contribute to less accurate forecasts.

Similarly, financial analysts incorporate information about the economy and the sector in which a company operates (Hou et al., 2021). Developing countries tend to experience greater political and economic instability (Liu & Sheng, 2019), resulting in more volatile prices that complicate future forecasting (Garcia & Liu, 1999) compared to developed countries (Mensi et al., 2021). Moreover, in countries with weaker accounting standards, companies are more susceptible to earnings management, which diminishes the quality of accounting information (Novaes et al., 2020). Consequently, biases such anchoring, representativeness, and realism are expected to exert a more positive influence on analysts' forecasts in developed countries. Realism, in particular, is shaped by the learning process involved in information processing, enabling individuals more accurate in their analyses (Linnainmaa et al., 2016). This suggest that the relationship between biases and decisions-making varies across different institutional economic environments.

This research differs from Nardi et al. (2022) in the technique applied, the separate analysis by clusters, and the consideration of two distinct environments. Consequently, it contributes to a better understanding of the relationship between biases and analyst´s accuracy in both higher and lower accuracy groups. This approach helps identify determinants of analysts' accuracy that may vary between markets, which should be considered when developing forecasting models of these countries.

Consequently, this research enriches the discussion of the analyst's role as an informational intermediary and contributes to a better understanding of the so-called "black box" of the analyst's decision-making process (Machado & Lima, 2018). As a secondary objective, we aim to assist banks and securities brokers by providing insights into analysts´ profiles for recruitment purposes, enabling the incorporation of these attributes into models that evaluate the accuracy of analysts' forecasts. In the long term, this contribution is expected to improve the precision of forecasts presented by brokers, thereby reducing investors´ exposure to risk when making investments decisions.

2 Theoretical Framework

2.1 The capital market: rationality and irrationality

Classical economic theories were developed under the premise of unlimited rationality (Arnott & Gao, 2022). Within this context, the capital market functions as a mechanism for efficient resource allocation and, theoretically, should fully reflect all available information, enabling investors to make confident decisions (Fama, 1970). This rational perspective is central to classical finance theory, which views analysts as intermediaries of information who operate under the assumptions of unlimited rationality (Fama, 1970; Brauer & Wiersema, 2018).

However, when examining how external environments and executive behaviors influence profit forecasts, the field of behavioral finance emerges. In this perspective, rationality is limited (Simon, 1955, 1986), and psychological biases (Kahneman & Tversky, 1979; Tversky & Kahneman, 1974) along with social factors (Brauer & Wiersema, 2018) significantly affect decision-making. Behavioral finance emphasizes that individual choices are not purely rational but are influenced by heuristics and cognitive limitations, as illustrated by Tversky and Kahneman (1974). Incorporating psychological concepts, behavioral scientists have tested the predictive capabilities of utility theories (Fishburn, 1968). By observing irrational behaviors, economists, sociologists, and psychologists have contributed to the development of this field (Vila-Henninger, 2021). As pioneers, Tversky and Kahneman revelated that decisions are often based on subjective beliefs and personal experiences rather than purely rational analysis (Tversky & Kahneman, 1974).

Furthermore, theories such as Prospect Theory (Kahneman & Tversky, 1979) challenge the notion of utility maximization by arguing that individuals evaluate gains and losses relative to reference points. Additionally, Social Choice Theory (Arrow, 1951), Satisfaction Theory (Simon, 1956), and Adaptive Choice Theory (Lam & White, 1999) emphasize the dynamic and evolving nature of decision-making processes. Collectively, these theories highlight how cognitive constraints, environmental factors, and behavioral patterns choices.

Biases in profit forecasts, as highlighted in studies (Machado & Lima, 2021), require further investigation, particularly concerning differences between analysts operating in developed and developing markets. Cultural factors play a critical role in shaping these behaviors, as demonstrated by Hofstede's cultural dimensions framework (1980). Hofstede defined culture as a "collective programming of the mind," emphasizing the shared experiences and education within society. This framework provides a valuable lens through which to examine how cultural variables, such as power distance and individualism versus collectivism, influence decision-making and the manifestation of biases.

For example, Brazil, characterized as a collectivist society (Hofstede, 1980), contrasts with the U.S., which is known for its individualistic culture. In Brazil, the emphasis on group dynamics may lead to greater conformity in decision-making, as individuals tend to prioritize collective opinions (Saad & Samet, 2020). Furthermore, Brazil's higher power distance index may result in increased reliance on senior analysts, potentially amplifying biases due to hierarchical influences.

Legal systems also intersect with cultural dimensions, influencing the quality of information available to analysts. Countries with common law systems generally demonstrate higher standards in law enforcement and accounting practices (La Porta et al., 1997; Silva & Nardi, 2018), which enhances analysts' confidence and the accuracy. In contrast, Brazil´s civil law system presents challenges, such as decision fatigue, as analysts must process a larger volume of less reliable information.

Thus, cultural and institutional factors-including legal systems- significantly shape the decision-making environment for analysts. Behavioral studies must consider these variables to offer a more nuanced understanding of the differences in forecast accuracy across diverse cultural contexts (Illiashenko, 2019; Eliwa et al., 2021; Iqbal et al., 2021). Hofstede's cultural dimensions, particularly collectivism and power distance, remain essential frameworks for analyzing such variations.

In addition to behavioral factors established in the literature, unconscious biases and lifelong cultural conditioning also play a significant role. Lived experiences and the education received within a given environment contribute to shaping these individual differences (Hofstede, 1980). This “collective programming of the minds” does not refer to individuals in isolation, but rather to a groups that share similar educational and experiential backgrounds. Thus, groups from specific regions develop mental frameworks that differ from those of groups in other locations. Consequently, as individuals adopt ways of thinking, behaving, and acting that align with their social environment, it is reasonable to expect that behavioral studies conducted in culturally distinct countries, such as Brazil and the U.S., will yield different results.

Studies in psychology identify a key dimension of cultural variability as the degree of collectivism versus individualism in a society (Lu et al., 2021), which is defined by the importance individuals place on other members of their community (Hofstede, 1980). Research has further explored the psychological impact of these cultural orientations, showing that collectivist societies tend to emphasize emotional regulation strategies that conform to group norms, whereas individualist cultures prioritize personal autonomy (Ford & Mauss, 2021). Additionally, recent discussions in cross-cultural psychology highlight the need for more inclusive methodologies, as Western-dominated research frameworks often overlook important regional cultural nuances (Arnett, 2009).

According to Hofstede (1980) cultural dimensions, Brazil (a collectivist society) and the U.S. (an individualist society) belong to culturally distinct group. The level of collectivism may help explain the higher incidence of biases in countries like Brazil, as individuals tend to consider others´ opinions more heavily in decision-making, often imitating the decisions of the group to which they belong (Saad & Samet, 2020). Similarly, the power distance index, described by Hofstede (1980)-which reflects a greater dependence on authority figures- is higher in Brazil and may lead Brazilian analysts to be more deferential to the opinions of more experienced colleagues.

This circumstance reflects broader discussions in cross-cultural research, including insights into self-enhancement and in group biases that shape cognitive behaviors worldwide (Chiu et al., 2022). Cultural characteristics- such as legal system- influence societal development. The strength of the legal system is a relevant factor in determining the quality of the information that analysts use to issue profit forecasts. Nations with common law legal systems tend to have higher quality in law enforcement (La Porta et al., 1997) compared to countries with civil law systems, which results in better applicability of accounting standards (Silva & Nardi, 2018).Consequently, higher-quality accounting information provides analysts with greater confidence, leading to more accurate forecasts (Eliwa et al., 2021; Iqbal et al., 2021). However, this context of improved information quality may also contribute to decision fatigue among Brazilian analysts, who must process a larger volume of data to make decisions or may rely more heavily on observing the forecasts of their peers. In this sense, the origin of the legal system can be seen as a cultural component that may help explain why profit forecasts made by Brazilian analysts tend to be less accurate than those made by U.S. analysts' forecasts.

Behavioral finance research further underscores the influence of cultural factors on financial decision-making. For instance, a study on financial behaviors in Ghana illustrates how communal traditions and societal expectations shape investment and savings decisions (Opoku-Okuampa, 2024). Similarly, research in behavioral economics highlights how cultural difference affect framing effects and group membership, which in turn influence financial judgments in countries such as China and the U.S. These findings reinforce the notion that cultural conditioning plays a crucial role in shaping financial decision-making processes.

2.2 Predictors of Analyst Accuracy

2.2.1 Behavioral Biases

Optimism is characterized by an unrealistic overestimation of future outcomes (Mohamed et al., 2019; Tversky & Kahneman, 1974). Among financial analysts, this phenomenon is manifested as excessive optimism (Hou et al., 2021) regarding the future performance of companies, leading to systematically upward-biased forecast that inaccurately reflect the available information. Therefore, a negative relationship between optimism and analyst accuracy can be expected. Giving the limited usefulness of macroeconomic information in developing countries (Akhtar, 2021) and its effects on price volatility and the predictability of corporate earnings (Garcia & Liu, 1999), optimism is expected to have a more detrimental impact on analysts' forecasts in Brazil compared to the U.S. Furthermore, Brazil´s higher power distance the more pronounced power distance (Hofstede, 1980) may cause analysts to be more deferential to the views of more experienced peers, who are typically optimistic (Hou et al., 2021) - that is, upwardly biased in their forecasts (Ernstberger et al., 2008).

Overconfidence, one of the central concepts in behavioral finance (Mousavi, 2020), is characterized by behavior similar to optimism (Mohamed et al., 2019). This bias involves the overestimation of an analyst´s own abilities, knowledge, and the accuracy of their information (Mohamed et al., 2019). As a result, individuals tend to place greater weight on their private information than on publicly available information (Friesen & Weller, 2006), due to increased confidence in their own judgments. Unlike optimistic analysts, who typically overestimate company performance, overconfident analyst my produce forecast that deviate from actual results in either direction- including underestimation- depending on their subjective interpretation of information (Nardi et al., 2022).

According to Hofstede (1980), the culture of the U.S. is 139.47% more individualistic and 26.53% more masculine than that of Brazil. Additionally, it exhibits 42.03% lower power distance and 39.47% less uncertainty avoidance. Collectively, these cultural dimension suggest that individual in the U.S may have greater independence and a strong tendency toward individualized decision-making compared to Brazilians. Given that people from different countries exhibit varying levels of overconfidence (Dessí & Zhao, 2018)-a tendency by societal levels of individualism and collectivism (Illiashenko, 2019) - it is expected that more individualistic cultures are generally more prone to overconfidence. Consequently, this bias may have a stronger negative impact on analyst´s forecasts in the U.S. than in Brazil. It is important to note that overconfidence has both exogenous components (which vary from person to person) and endogenous components (which vary across countries), underscoring the need to examine this phenomenon at both the individual and context levels.

Therefore, when incorporating a variable that reflects political and economic instability into the experiment, the result may differ- showing higher confidence levels in countries where greater expectation of change in the economic and political spheres exist (Dessí & Zhao, 2018). This scenario supports the notion that analysts in the U.S. may be more confident than those in Brazil.

Anchoring is another bias that can influence analysts' forecasts. Individuals exhibiting this bias begin with an initial, readily available value, which they then adjust toward a final estimate (Tversky & Kahneman, 1974). However, this revision process may be inadequate or insufficient, as individuals tend to keep their estimates close to the initial anchor (Cen et al., 2013). This tendency may lead to the neglect of external factors, such as political, economic, legal events, etc. Although anchoring can erroneously influence the analysts´ forecast, past corporate performance- often used in profit projections- may not necessarily serve as an inefficient anchor (Kajimoto et al., 2019). This is partly due to the practice of earnings smoothing, the tendency to keep net income variability as low as possible (Leuz, 2003; Mirzajani & Heidarpoor, 2018), which is adopted to enhance the clarity of profit communication and may become a standardized practice among firms (Kajimoto et al., 2019). Consequently, a stochastic relationship may exist between the past profits and future earnings, potentially justifying a positive correlation between analysts' anchoring on past profits and their future projections. Even when considering factors such as the quality of accounting information, the use of macroeconomic and sector-specific information by financial analysts (Hou et al., 2021), and the increased difficulty of forecasting difficult due to greater political and economic instability (Garcia & Liu, 1999), anchoring may still be viewed as a valuable heuristic. Based on this assumption, anchoring should not be interpreted as a deterministic source of forecasting error but rather as a potentially useful parameter for profit prediction by analysts in both the U.S. and Brazil.

Communality is a behavioral trait in which individuals' values and ideas originate from the shared experience of a social group (Nardi et al., 2021). This behavior often leads to a pattern of decision-making, among members of a group or society, as a balance tends to emerge between the individual preferences, beliefs, and actions of those involved (Picavet, 2015). As a result, greater importance is placed on the survival and well-being of the group rather than on its individual members. In contrast, individualistic cultures emphasize personal autonomy, wherein individuals are view as independent units. In such context, the survival unit is the individual.

However, individuals with more accumulated knowledge or expertise regarding the subject of their decisions tend to form their own opinions based on this background. In contrast, those with less experience and knowledge often rely on group-defined norms- that is collective- to support their decision, in part to share the associated risks. From this perspective, it can be inferred that in environments where capital market are less developed, analysts tend to base their decisions on communality. Conversely, in more developed markets characterized by individualistic culture- such as the U.S. - analysts who rely on communality may be those with less experience and knowledge. This is because the U.S. tends to exhibit a more dominant culture in individual decision-making when compared to Brazil (Hofstede, 1980), thereby reducing the influence of commonality-related biases. Therefore, it is reasonable to expect a more negative effect of communality bias on the forecasts of U.S. analysts compared to those in Brazil.

In addition, one can consider the scenario in which, based on experience, human beings tend to more easily recall situations that are more frequent and have a greater impact than those that occur less incidence. Similarly, highly probable events are easier to imagine than the unlikely ones (Tversky & Kahneman, 1973). This bias, known as representativeness, leads individuals to assume that an event resembles a previously known one, thus judging it to be more likely to occur again (Kahneman & Tversky, 1973; Tversky & Kahneman, 1974). This often results in serious and systematic errors (Kahneman & Tversky, 1972; Tversky & Kahneman, 1971, 1973). Given that memory plays a crucial role in shaping beliefs that deviate from rationality (Bordalo et al., 2021), representativeness is one of the factors that may influence analysts´ forecast. If an analyst gives disproportionate weight to an event or information that is more easily remembered (Tversky & Kahneman, 1973), while neglecting other relevant elements due to the cognitive limitations in processing large volumes of information (Li et al., 2021), and considering that economic instability may cause analysts to emphasize recent or widely reported events that are not aligned with the company´s future outlook, it is reasonable to expect that analysts´ forecasts in Brazil are more negatively affected by representativeness than those in the U.S.

Finally, realism is associated with temporal awareness and concreteness, bringing individuals closer to the facts as they exist in the present and enabling more accurate analyses (Wisniewski & Yekini, 2015). This characteristic is also shaped by the learning process involved in information processing, leading individuals to be more assertive in their evaluations (Linnainmaa et al., 2016). Realism contributes to balance forecasts, as it is linked to the ability of market participants to recognize and respond appropriately to negative news. Moreover, the capacity to incorporate non-financial information enhances the accuracy of analyst´s forecasts compared to those generated by statistical models (Linnainmaa et al., 2016).

Thus, realism- reflected in the ability to accurately interpret the tone of reports- helps identify pessimistic disclosures that are intended to lower expectations so that actual earnings surpass forecast, thereby creating a favorable impression on the market (Iatridis, 2016). Similarly, realism aids in recognizing favorably biased disclosures designed to positively influence performance evaluations (Iatridis, 2016) and attract new investors (Wisniewski & Yekini, 2015).

There may be a mistaken expectation that realism serves to neutralize the undesired effects of other biases, as this behavior is assumed to make the analysts more aware of the context surrounding the data being analyzed. However, the impact of this attribute may vary across cultures. Being realistic in an environment with unreliable information can still lead the analysts to incorporate inaccurate data into their decision-making. In this regard, developing countries tend to exhibit more unstable market information behavior, as corporate profitability is more sensitive to shifts in economic policy and subject greater government interference (Garcia & Liu, 1999). Therefore, considering that the environment of developing countries- characterized by higher political and economic instability (Garcia & Liu, 1999)- tend to foster the disclosure of less accurate information, realism is expected to have a more positive impact on the accuracy of analysts' forecasts in the U.S. than on the projections analysts in Brazil.

2.2.2 Other Predictors

Financial factors and company characteristics are widely examined in the literature as predictors of the accuracy of analysts' profit forecasts. One such characteristic is company popularity, which can play an important role in forecast accuracy (Ho et al., 2020). Previous studies have found a positive relationship between the number of analysts covering a company and the accuracy of their earnings forecasts (Ho et al., 2020; Dai et al., 2021). Therefore, it is reasonable to expect that the greater a company´s popularity, the higher the accuracy of analysts' forecasts.

Company-incurred losses are also a relevant factor in studies of analyst accuracy, as analysts tend to exhibits different behaviors when predicting the performance of firms expected to report losses (Das, 1998). Since such scenarios complicate the forecasting process, it is reasonable to expect that losses negatively affect the accuracy of earnings forecasts (Coën et al., 2009; Nardi et al., 2021).

On the other hand, profitability can serve as a motivation for market disclosure (Nardi et al., 2022), as companies in profitable scenarios may seek to boost investor confidence by positioning themselves as attractive investment opportunities. In such cases, information asymmetry is reduced, contributing to a more transparent informational environment. This enhanced transparency provides greater support for analysts in making their forecasts, and therefore, a positive relationship is expected between company profitability and forecast accuracy (García-Meca & Sánchez-Ballesta, 2006).

Another factor is company growth, which can positively influence the informational environment, as firms may seek to highlight their expansion and its potential impacts (Hu et al., 2021). However, growing companies often generate a greater volume of information, demanding increased effort and analytical capacity from forecasters (Nardi et al., 2022), which may negatively affect the accuracy of analysts´ forecasts (Nardi et al., 2021).

Earnings volatility refers to the variation in a company's financial results (Nardi et al., 2022). This measure reflects the difficulty analyst face when making projections, as higher volatility is associated with greater uncertainty, which is likely to negatively affect forecast accuracy (Nardi et al., 2021).

Financial leverage is a variable related to unexpected accruals, reflecting greater management discretion over reported earnings through discretionary accruals (Brown et al., 2022), which can affect the quality of the disclosed profits. This complexity can make analysts' forecasting tasks more challenging, and thus, a negative impact on forecast accuracy is expected.

Finally, company age can represent maturity in terms of its informational environment (Nardi et al., 2022). Research has consistently demonstrated a positive relationship between company age and the accuracy of analysts' forecasts (Bradshaw et al., 2012). In a context where the quality information provided by firms is crucial for analyst's work, it is expected that company age are positively influences analysts' accuracy.

3 Methodology

3.1 Data and research methods

The study uses the Accounting and Biases database (2023), using its most recent updated from 2023. The data required to construct the variables were obtained from the Thomson Reuters® and S&P Capital® databases, covering the quarterly periods of 2019 for publicly traded companies in Brazil and the U.S. The choice to use a single year for the sample is justified by the time-intensive nature of the database construction. A portion of the data was manually collected for each analyst in order to capture individual-level bias and characteristic measures, making this a unique and original dataset. However, the excessive time required for its development limited the composition the dataset to the year 2019.

The sample comprised 840 observations from 76 Brazilian companies and 16,402 observations from 880 U.S. companies. Behavioral variables were derived from a textual analysis of analyst´s reports, conducted using Diction® software. Statistical analyses were performed using STATA® and SPSS®, applying analysis of variance (ANOVA) and the post-hoc ANOVA test.

Cluster analysis was employed as the statistical method in the first stage, enabling of the identification of the influence of analysts' profiles and other variables on forecast accuracy. This technique allowed for the grouping of similar observations based one variables that affect analysts' forecasts, forming clusters characterized by internal homogeneity (Fávero & Belfiore, 2017).

Cluster analysis was conducted using the k-means method, which is considered the most appropriate for analyzing large databases (Fávero & Belfiore, 2017). This analysis grouped analysts´ profiles based on behavioral variables, financial factors, and levels of forecast accuracy. Clusters were selected according to the optimal distribution of observations and greatest variation in mean forecast accuracy across cluster. Subsequently, analysis of variance (ANOVA) with Tukey´s post-hoc test was applied to the selected clusters to confirm the robustness of the process. The use of the cluster analysis enables the identification of relationships within the dataset by the observations of interest and reducing the influence of control variables.

In the second stage, multiple regression analysis was applied to the clusters that exhibited the highest and lowest levels of forecast accuracy, with the principal identifying the explanatory power of the clusters on analysts' accuracy.

3.2 Definition of variables and econometric model

To measure analysts´ accuracy, the forecast error variable was used, obtained by the ratio of the absolute difference between the actual earnings per share (EPS) and the analyst's forecast EPS to the actual EPS (Coën & Desfleurs, 2016, 2017; Nguyen et al., 2021). This value was then subtracted from 1 (one) (Dai et al., 2021; Nardi et al., 2021), as shown in Equation 1:

$$AC = 1 - \left|\left(\frac{EPS_{real} - EPS_{prev}}{EPS_{real}}\right)\right| \quad (1)$$

Where:
AC= analyst's accuracy;
EPSreal= earnings per share actually reported by the company;
EPSprev= earnings per share forecasted by individual analyst.

The econometric model used to analyze the influence of behavioral and financial factors on accuracy is presented in Equation 2:

$$AC_{i,t} = \alpha_0 + + \beta_1 Behav_{i,t} + \beta_2 Popul_{i,t} + \beta_3 Loss_{i,t} + \beta_4 Profit_{i,t} + \beta_5 Growth_{i,t} + \beta_6 Volat_{i,t} + \beta_7 Lev_{i,t} + \beta_8 Age_{i,t} + \varepsilon_{i,t} \quad (2)$$

Where:
ACi,t is the dependent variable in the model and is calculated by Equation 1;
Behavi,t represents the behavioral variables, namely: Optim (optimism); OverC (overconfidence); Ancor (anchoring); Comun (communality; Repre (representativeness) and, Real (realism). Anchoring is a dummy variable that take the value 1 (one) when the analyst's forecast lies between the actual earnings per share and the anchor based on previous period´s earnings per share, and value 0 (zero) otherwise. Using the dictionary, five main variables were identified: a) Optimism, which reflects support, conviction or event, or highlights effective achievements. For this purpose, expressions involving praise and satisfaction are weighted positively, while terms related to guilt and denial; b) overconfidence, which suggests determination, inflexibility, integrity and a propensity to speak with authority, where terms such as tenacity and insistence are emphasize, while aspects involving ambivalence and variety are subtracted; c) commonality, which emphasizes share precepts within a community and excludes particular characteristics of engagement. Expressions related to diversity and exclusion are subtracted from terms indicating centrality and cooperation; d) representativeness, which indicates mobility, modification, concretization of ideas and the prevention of inactivity. Word associated with passivity and subtracted from those indicating aggression and movement; e) realism, which portrays concrete, immediate and knowable themes related to individuals´ daily lives. Terms expressing past concern and complexity are subtracted from those representing familiarity, temporal and spatial awareness.
Populi,t= variable representing the company's popularity, measured by the number of analysts following the company;
Lossi,t-1= dummy variable indicating periods of uncertainty, which assumes 01 (one) if the company has a loss, 0 (zero) otherwise;
Profiti,t-1= variable representing the company's profitability, calculated as the ratio of Earnings Before Interest, Taxes, Depreciation and Amortization (EBITDA) to Total Assets;
Growthi,t-1= variable that indicating the company's growth, measured by the change in revenue;
Volati,t-1= volatility of earnings per share;
Levi,t-1= variable representing that demonstrates the company's leverage, calculated as a ratio of total debts to net assets;
Agei,t= is a variable representing the age of the company, calculated by the difference between the year 2019 and the year the company went public.

Bias measurements using Diction® are performed by analyzing analysts' reports with a specialized dictionary, designed to calculate the frequency of words occurrences by categorizing them (Wisniewski & Yekini, 2015) through lexical analysis (Oliveira et al., 2021). Further methodological details about the software can be found in the literature (Hart & Carroll, 2015).

The model presented in Equation 2 demonstrates robustness by incorporating multiple independent variables, encompassing both behavioral and financial factors. The strengths of this approach can be summarized as follow: i. The inclusion of both behavioral and financial variables allows for a comprehensive analysis, capturing important nuances that affect analysts' forecasts; ii. Previous studies (Coën & Desfleurs, 2016, 2017) have highlighted the relevance of these variables in forecasts evaluating. For example, overconfidence can lead to systematic errors in estimates; iii. The inclusion of dummy variables, such as "Ancor" variable mentioned in Equation 2, enables modelling specific conditions, including periods of uncertainty, thereby adding flexibility to the model; iv. cluster analysis that allows: a) Identification of Non-Linear Patterns: it uncovers complex, non-linear relationship within the data by considering natural groupings. For instance, different clusters of companies- based on behavior, size, sector etc.- may exhibit varying levels of forecast accuracy; b) Segmentation of Observations: cluster analysis segments the dataset, facilitating a better understanding of how distinct subgroups behave. In this study, clusters can represent different company profiles (e.g., technology vs. manufacturing), aiding in the capture of specific nuances; c) Dimensionality Reduction: it reduces the dimensionality of variables by focusing on the most relevant characteristics, which is particularly beneficial when dealing with numerous behavioral and financial variables. This simplification maintains important information while improving model manageability; d) Internal and External Validation: the method allows evaluation of clusters quality to ensure robustness; e) Contextual Interpretation: clusters have practical meaning, representing groups of companies with similar traits. In this study, clusters can be interpreted in terms of analysts' behavior, financial characteristics and business strategies.

4 Results

The descriptive statistics of the observations from the U.S. and Brazil are presented in Tables 1 and 2, respectively.

Table 1 - Descriptive Statistics for the U.S. sample

Variable	Mean	Median	Standard Deviation	Minimum	Maximum
AC	0.74	0.88	0.32	-0.23	1.00
Optim	48.76	48.81	1.08	45.85	51.97
OverC	44.11	46.33	8.58	23.59	54.21
Comun	50.37	50.23	1.55	46.31	55.80
Repre	48.59	48.61	1.55	45.23	51.24
Real	40.20	40.41	2.06	33.65	44.40
Popul	10.37	10.00	5.47	1.00	23.00
Profit	0.03	0.03	0.02	-0.01	0.07
Growth	0.04	0.03	0.14	-0.23	0.37
Volat	1.73	1.69	0.74	0.13	3.56
Lev	0.78	0.56	0.77	0.00	2.84
Age	60.32	44.00	41.87	10.00	173.00

Table 2 - Descriptive Statistics for the Brazil sample.

Variable	Mean	Median	Standard Deviation	Minimum	Maximum
AC	0.39	0.73	0.72	-1.51	1
Optim	48.62	48.66	0.98	46.56	50.81
OverC	48.97	50.42	5.18	35.59	55.12
Comun	50.81	50.61	1.69	47.46	54.41
Repre	49.13	49.47	1.44	46.09	51.60
Real	40.51	40.78	1.66	36.92	42.95
Popul	6.35	6.00	2.58	1	13
Profit	0.03	0.03	0.02	0.00	0.06
Growth	0.14	0.10	0.19	-0.12	0.69
Volat	0.50	0.41	0.65	-0.99	1.70
Lev	0.61	0.46	0.63	0	2.01
Age	57.15	57.00	33.87	9	147

Table 3 presents the frequency distribution of the dichotomous variables: anchoring and loss.

Table 3 – Frequency Distribution of the Ancor and Loss variables for the U.S. and Brazil.

Value	USA		Brazil	
	Absolute Frequency	Relative Frequency	Absolute Frequency	Relative Frequency
Anco (0)	11,439	0.6974	566	0.6738
Anco (1)	4,963	0.3026	274	0.3262
Loss (0)	12,722	0.7756	752	0.8952
Loss (1)	3,680	0.2244	88	0.1048

The accuracy of Brazilian analysts was found to be significantly lower than that of their American counterparts, with U.S. analysts exhibiting an accuracy rate 20.63% higher. Moreover, the minimum accuracy observed among Brazilian analysts was 84.69% lower than that of U.S. analysts. These findings are consistent with existing literature, which suggests that more developed markets foster greater competitiveness and social learning, thereby enhancing forecasts precision and reducing dispersion (Kumar et al., 2022). The lower forecast dispersion in the U.S. may also be attributed to the maturity and stability of its financial environment, where higher-quality accounting information and regulatory consistency contribute to more reliable analyses. Additionally, cultural differences- such as Brazil´s collectivism versus the U.S.´s individualism- may influence financial decision-making, shaping how analysts interpret and process information, as discussed in behavioral finance literature.

Given that the data did not follow a normal distribution- as indicated by the Kolmogorov test- the Spearman correlation analysis was conducted (Table 4).

Table 4 - Correlation for U.S. and Brazil.

	USA	Brazil
	AC	
Optim	0,02(**)	-0,02
OverC	0,06(***)	0,00
Comun	-0,03(***)	0,04
Repre	0,01	-0,05
Reali	-0,04(***)	-0,01
Popul	0,15(***)	-0,09(***)
Profit	0,33(***)	0,25(***)
Growth	0,08(***)	-0,04
Volat	0,04(***)	-0,36(***)
Lev	0,07(***)	0,00
Age	0,12(***)	-0,12(***)

Being, ***, **, significant at 1% and 5%, respectively.

The results presented in Table 4 further indicate that the influence of biases on forecast accuracy is more pronounced in the U.S. context. This supports the notion that collectivist societies, such as Brazil, tend to emphasize group consensus, thereby reducing the prominence of individual biases. In the Brazilian sample, anchoring was the only bias that showed a significant correlation with forecast accuracy. Notably, this bias was measured quantitatively, without accounting for the analysts´ individual behavioral characteristics. The findings suggest that anchoring—where past earnings influence future profit estimates—may function as a positive bias in forecasting, as it offers a structured reference point for analysts' predictions across different environments.

Moreover, optimism and overconfidence appear to be positively correlated with forecast accuracy, particularly in the more developed U.S. market, where competitive pressures and a structured regulatory frameworks may enhance analysts´ confidence in financial projections. The communality bias also aligns with theoretical expectations, reinforcing the role of shared decision-making in collectivist cultures. Interestingly, preliminary evidence suggests that the realism bias may negatively impact accuracy, highlighting the need for further empirical testing to confirm this relationship and to better understand its implications across different financial environments.

Based on the cluster analysis results, a regression was conducted for the clusters with the lowest and higher average accuracy. The objective was to identify the factors influencing accuracy by examining distinct analyst profiles- those who demonstrate higher assertiveness and those whose forecast are less accurate (Table 5).

Table 5 - Regression analysis of clusters with lower and higher forecast accuracy in the U.S. and Brazil

	U.S.				Brasil			
	Lower Acur.		Higher Acur.		Lower Acur.		Higher Acur.	
Variables	Coef.	t	Coef.	t	Coef.	t	Coef.	t
Optim	-0.004	-0.48	0.00	0.59	0.04	1.34	-0.03	-1.95*
OverC	-0.002	-1.23	0.00	2.7***	0.00	0.34	0.00	0.87
Ancor	0.14	4.61***	0.05	8.02***	0.80	8.73***	0.00	Omitida
Comun	-0.02	-2.22*	-0.004	-1.95*	0.01	0.68	0.01	0.79
Repre	-0.01	-2.12*	0.00	0.97	-0.02	-0.85	-0.02	-1.51
Reali	-0.002	-0.4	0.00	2.96***	0.03	1.43	-0.02	-1.32
Popul	0.01	2.43**	-0.003	-3.74***	-0.09	-2.15**	-0.02	-2.16**
Loss	0.32	6.76***	0.08	3.51***	-0.02	-0.13	0.00	omittid
Profit	-5.73	-8.21***	-0.57	-2.88***	-8.17	-2.68***	3.68	2.18**
Growth	0.32	5.11***	-0.12	-4.33***	-2.76	-6.61***	-0.47	-4.76***
Volat	-0.14	-8.5***	-0.06	-9.14***	-0.48	-3.64***	-0.27	-6.34***
Lev	-0.05	-3.63***	0.06	7.64***	0.18	1.13	-0.13	-2.38**
Age	-0.002	-5.15***	0.00	11.79***	-0.001	-0.33	-0.002	-2.82***
Constant	2.06	2.91***	0.74	3.37***	-2.78	-1.00	3.57	2.3**
F	45.64***		19.38***		103.06***		7.73***	
R2	0.2		0.19		0.72		0.4	
VIF	1.17		1.16		3.16		1.29	
White Test	358.36***		352.14***		68.90		101.5**	

Being, ***, **, *, significant at 1%, 5% and 10%, respectively

4.1 Analysis of results

Overall, the test results suggest that analysts in the USA market are subject to a higher incidence of bias, which aligns with expectation from the literature based on cultural differences, as these societies tend to be more individualistic (Hofstede, 1980). This individualism may explain the greater prevalence of biases in analysts' decisions.

The results presented in Table 5 indicate that, contrary to previous literature suggesting that optimism negatively affects financial analysts´ forecast (Davis & Lleo, 2020), there was no statistical evidence of a relationship between optimistic bias and forecast accuracy in either of the U.S. clusters. This may be explained by the competitive nature of the market and the role social learning in promoting more accurate forecasts (Kumar et al., 2022), which could discourage U.S. analysts from exhibiting optimism driven by economic incentives.

In Brazil, optimism negatively influences the profit forecasts of analysts who demonstrate higher accuracy. This finding aligns with the literature, which predicts a negative relationship between optimism and forecast accuracy (Davis & Lleo, 2020; Nardi et al., 2021), and confirms the study´s hypothesis that optimism would have a more detrimental effect on Brazilian analysts´ forecast compared to those of their U.S. The collectivist nature of Brazilian society may lead analysts to be more influenced by the opinions of more experienced colleagues, causing them to align their forecasts with the consensus, which tends to be optimistic (Hou et al., 2021). Consequently, in seeking greater conformity with the forecasts of these experienced analysts, Brazilian analysts may be affected by the optimism embedded in their peers´ more accurate forecasts.

Regarding overconfidence in the U.S., although the data indicate statistical significance and a positive effect, the magnitude of this impact was very close to zero. Therefore, despite the significance, no meaningful influence on the forecasts of U.S. analysts with higher accuracy was observed, as the practical effect is negligible. This finding contrasts with the existing literature, which generally suggested a negative relationship between overconfidence and earnings forecast accuracy, as analysts tend to overestimate their abilities (Mohamed et al., 2019) and produce erroneous estimate (Deaves et al., 2010). The observed result may be linked to the high accuracy of U.S. analysts, as professionals tend to become more confident in their beliefs when consistently delivering accurate forecast (Aragón & Roulund, 2020).

For Brazil, however, overconfidence was not significant factor for either the group of analysts delivering higher accuracy forecasts or those with lower accuracy, which aligns with the findings of Nardi et al. (2022), who did note distinguish between groups based on accuracy levels. Regarding anchoring, the results support the notion that this bias- anchored on past profits- has a positive effect on analyst´s earnings forecast, likely due to the stochastic influence of past profits on future earnings. This is evidenced by the significant and positive results observed in both countries and across groups with higher or lower accuracy. This finding confirms the theory that companies exhibit consistent earnings disclosure pattern (Kajimoto et al., 2019), which analysts use as a bias for their forecasts (Low & Tan, 2016), thereby enhancing the quality of forecasts grounded in historical profit data. Moreover, anchoring appears to be the most influence bias in determining analysts´ forecast, compared to the other biases considered.

It is noteworthy that, among U.S. analysts with lower forecast accuracy, the influence of anchoring was 1.8 times greater than that observed for analysts with higher accuracy. This finding suggests that U.S. professionals with lower quality forecast may rely more heavily on past earnings as an anchor, potentially using it as a compensatory mechanism to offset limitations in their analytical and forecasting abilities.

In Brazil, anchoring was significant for the group of analysts delivering lower-accuracy profit forecast. However, for the cluster of analysts with higher forecast accuracy, the regression did not show statistical significance or a clear direction of the bias´s impact. This is likely because all observations within this group exhibited anchoring when making their estimates. Although the regression analysis could not statistically measure the impact of anchoring in this cluster, due to the clustering method grouping only perfectly uniform observations that consistently displayed anchoring, it can be concluded that anchoring played an important role in achieving forecast accuracy among Brazilian analysts.

When comparing the effects of anchoring on analysts´ forecasts, it is evident that the bias has a positive influence for both American and Brazilian professionals. However, the anchoring coefficient for analysts with lower accuracy in Brazil was 4.74 times higher than in the U.S., indicating that this bias plays a more significant role in the accuracy of Brazilian analysts. Therefore, the results for anchoring across both countries and accuracy groups align with the initial expectations.

Regarding the bias of commonality, a stronger effect was expected in Brazil; however, this was not observed. Conversely, negative effect was confirmed in the U.S. In the U.S., the coefficient for commonality bias was four times higher among analysts with lower forecast accuracy compared to those with higher accuracy. This suggest that U.S. analysts who rely more heavily on their colleagues´ opinions tend to have a reduced ability to interpret available information- whether financial data from companies, sector economic indicators, or peer forecasts. If commonality ideally facilitates better information interpretation, the issue may lie in the analyst's capacity to utilize this information effectively rather than in the data itself. Supporting this, the literature indicates that analysts tends to exhibit stronger commonality bias in situations where they must issue negative predictions, which heightens their insecurity (Jegadeesh & Kim, 2010). In such scenarios, analysts often engage in herd behavior, relying on the consensus opinions of their peers (Jegadeesh et al., 2004; Jegadeesh & Kim, 2010).

Representativeness was significant only for U.S analysts with lower forecast accuracy, showing a negative relationship with forecast accuracy. This finding aligns with the literature describing representativeness as a bias that leads to systematic errors in judgment (Kahneman & Tversky, 1972; Tversky & Kahneman, 1971, 1973), as memory used tends to be selective and deviates from rationality (Bordalo et al., 2021). For instance, relying on recent profits as representative for forecasts can undermine the accuracy of estimates (Tversky & Kahneman, 1974) if other relevant factors are not simultaneously.

In Brazil, however, representativeness did not show significance in any cluster. One possible explanation is that Brazil´s economic and political instability leads analysts to place less reliance on information unrelated to past profits. Given the limitations individuals face when processing large volumes of information (Li et al., 2021), a more unstable environment may prompt defensive behavior among analysts. To avoid incorrectly selecting information from memory (Bordalo et al., 2021), analysts might rely more heavily on historical profit data rather than on recent events stored in individual memory.

In the U.S., realism exhibited statistical significance and a positive coefficient in the cluster of analysts with higher forecast accuracy. This result aligns with theoretical expectations, as realism enables individuals to interpret facts objectively (Wisniewski & Yekini, 2015), thereby enhancing the precision of earnings forecasts. In this context, the realism bias contributes to more balance projections by allowing analysts to respond appropriately to unfavorable information (Bénabou, 2009). Consequently, it may mitigate unconscious optimistic, a common behavioral tendency in which analysts overreact to positive signals and underreact to negative company news (Clarke & Shastri, 2001; Silva Filho et al., 2018). Notably, optimism was not statistically significant for the most accurate analysts in the U.S., which supports the realism theory within the North American context when these two behavioral dimensions- optimism and realism- as jointly considered.

In Brazil, however, realism did not exhibit significance in any of the analyst clusters. This result may be explained by the political and economic context of the country, which appears influence analyst´s behavior by encoring them to disregard available information that is not directly related to historical earnings. In environments marked by higher uncertainty and institutional fragility, such as developing economies (Akhtar, 2021) may adopt a more cautions and defensive stance, relying predominantly on historical finance data to avoid potential distortions in their forecasts caused by volatile or ambiguous market and political information.

Thus, the results suggest that anchoring, representativeness and realism had a more pronounced effect on U.S. analysts, as anticipated by the literature. This can be attributed to the country´s greater political and economic stability, as well as its lower market volatility (Mensi et al., 2021), which create a more conducive environment for the emergence and measurement of behavioral biases in analysts' forecasts.

5 Final considerations

The objective of this research was to identify the bias profiles of financial analysts who demonstrate higher and lower levels of forecast accuracy. The study aimed to uncover behavior patterns across distinct societal contexts, taking into account cultural influences, the origin of legal systems, and the stage of market development in the countries analyzed.

The study highlighted the significant impact of behavioral factors on the analysts' accuracy. Among the biases examined- optimism, overconfidence, anchoring, communalism, representativeness and realism- each demonstrated statistical relevance in at least one of the analyst groups evaluated in this research, whether among American or Brazilian professionals, or among those with higher or lower forecast accuracy.

The findings demonstrated that individuals from countries with distinct cultural backgrounds exhibit different behaviors patterns, which, in turn, influence their decision-making processes. With the expectation of anchoring- whose impact was consistently positive across both context- all other biases affected analysts´ forecasts differently when comparing the results between the U.S. and Brazil.

The results indicated a greater number of significant biases among U.S. analysts compered to their Brazilian counterparts. This disparity may be attributed to the forecasting approach adopted by Brazilian professionals, who tend to rely more heavily on historical profits rather than subjective assessment of the companies under evaluation. This behavioral aligns with the theory of profit smoothing, which is especially prevalent in countries where accounting information is of lower quality- often a consequence of weaker enforcement mechanisms and the historical foundations of their legal systems.

Furthermore, in the U.S., a greater incidence of positive biases was observed among the most accurate analysts, whereas more negative biases were associated with less accurate professionals. This finding supports the notion that increased market competitiveness positively influences the quality of analysts' forecasts. In such an environment, the most skilled analysts appear to leverage biases as analytical tools to enhance the precision on their forecasts, while less accurate professionals seem unable to mitigate or neutralize the distorting effects of these biases.

Among the analyzed biases, commonality stands out, as it is generally considered a positive attribute for enhancing forecast accuracy. However, form Americans analysts, it behaved contrary to the expectations established in the literature. This result aligns Hofsted's cultural dimensions, which characterize American society as more individualistic- suggesting that analysts in the U.S. are less likely to subordinate their decisions to group consensus and more inclined to rely on their own judgments. This cultural trait may limit the effective use of commonality as a cognitive tool in that context. Secondly, optimism was found to negatively affect the forecast of Brazilian analysts with higher accuracy, a result consistent with prior studies. Conversely, optimism did not influence the accuracy of U.S. analysts. This may reflect the greater competitiveness and accountability present in the U.S. market, where analysts are more likely to engage in social learning and adopt a more cautions stances to preserve the quality of their forecasts- and, by extension, their professional credibility and job security. Additionally, Brazil´s considerably smaller and less mature market may impose limitations on the availability and diversity of data for analysis. This constraint may help explain certain findings, such as the homogeneity observed in anchoring among the more accurate group of Brazilian analysts, which limited the statistical capacity to identify variation in the impact of this bias.

This research incorporated several non-behavioral control variables commonly used in academic studies. However, without aiming to exhaustively explore all possible combinations of control variables, future research could benefit from incorporating additional variables to further enrich and refine the findings presented here. Moreover, the inclusion of a larger number of variables- whether behavioral or not-behavioral- opens up opportunities for employment advances multivariate techniques. These techniques could facilitate the grouping of variables and, subsequently, the clustering of similar factors, thereby enhancing the robustness and interpretability of the analyses.

Furthermore, the groupings examined in this study focused on evaluating the profiles of analysts with lower and higher forecast accuracy. Future research could explore additional clusters generated through data-driven grouping methods. Such an approach would enable the analysis of whether descriptive statistics and regressions results within these alternative clusters provide further relevant insights to the literature on the accuracy of the analysts' earnings forecasts.

This research identified heuristics that influence analysts' decision-making patterns in relation to the most critical aspect of their work: the accuracy of earnings forecasts. These findings can contribute to the refinement of company valuation models (Nardi et al., 2021) used by brokerages and financial institutions, by incorporating behavioral factors aligned with profiles of individual analysts. Consequently, such institutions may include these behavioral attributes in their models for assessing forecast assertiveness. Moreover, if forecast accuracy proves to be predictable, it becomes possible to develop more precise proxies for earnings expectations. These proxies could apply appropriate weights to analysts' forecasts based on their behavioral tendencies, thereby reducing investor exposure to risk in their investment decisions.

Analyzing the information produced by financial analysts is essential for the efficient functioning of capital markets. Understanding the behavioral aspects that influence analysts´ decisions can assist investors in minimizing errors during the asset allocation process. Recognizing how behavior impacts forecast accuracy enable investors to identify specific behavioral patterns and better assess the likelihood of higher or lower precision in the forecast that inform their investment choices. Additionally, by examining how different variables affect analysts' accuracy across diverse market environments, investors can access more robust insight to support strategic decisions- particularly in scenarios involving portfolio diversification.

Finally, this research was limited to data from the year 2019. Although it allowed the identification of individual analyst observations, the study did not capture the influence of different economic contexts, cyclical fluctuations, or exogenous shocks- such as the COVID-19 pandemic- which may significantly alter analysts' behavior. Future studies could extend the temporal scope of analysis to include periods marked by economic crisis, thereby enabling the evaluation of behavioral and forecasting dynamics under stress conditions. Furthermore, the application of alternative methodological approaches, such as structural equations and machine learning techniques, may offer a broader and more nuanced understanding of the relationships between behavioral biases and forecast accuracy.

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