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Analysis of the relationship between temporal and behavioral aspects of the analyst's forecasting accuracy

Análise da relação entre aspectos comportamentais e temporal com a acurácia da previsão do analista

Análisis de la relación entre los aspectos conductuales y temporales de la precisión del pronóstico del analista

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Abstract
The study analyzed the relationship between optimism, anchoring, overconfidence, representativeness, realism, commonality and time, with the accuracy in the profit forecast of analysts. Publicly traded Brazilian companies were considered in 2019, and correlation tests, mean differences and multiple regression analyses were applied. The results indicated that accuracy is negatively influenced by optimism and positively by anchoring and commonality. In addition, the uncertainty present in the distance between the forecast issued and the disclosure of earnings per share also negatively influences the accuracy of analysts. Additionally, it was found that fair value, profitability, issuing ADRs and self-regulated sector, are aspects related to greater accuracy. Thus, the research contributes to the literature by linking behavioral and temporal aspects to financial ones, as well as by signaling the importance of analysts' forecasting models to consider behavioral aspects in their information technologies.
Keywords: Analyst's forecast; Behavioral biases; Forecast time

Resumo
O estudo analisou a relação entre otimismo, ancoragem, excesso de confiança, representatividade, realismo, comunalidade e tempo, com a acurácia na previsão de lucro de analistas. Foram consideradas empresas brasileiras de capital aberto em 2019, aplicando teste de correlação, diferença de média e regressão múltipla. Os resultados indicaram que a acurácia é influenciada negativamente pelo otimismo e positivamente pela ancoragem e comunalidade. Ademais, a incerteza presente na distância entre a previsão emitida e a divulgação do lucro por ação também implica negativamente na acurácia dos analistas. Adicionalmente, constatou-se que o valor justo, lucratividade, emissão de ADRs e setor auto regulamentado, são aspectos relacionados com maior acurácia. Desse modo, a pesquisa contribui com a literatura para reflexão quanto à necessidade de concatenar aspectos comportamentais e temporais aos financeiros, bem como para sinalizar a importância de que os modelos de previsão dos analistas considerem os aspectos comportamentais em suas tecnologias de informação.
Palavras-chave: Previsão do analista; Vieses Comportamentais; Tempo de previsão

Resumen
El estudio analizó la relación entre optimismo, anclaje, exceso de confianza, representatividad, realismo, concordancia y tiempo, con la precisión de las previsiones de los analistas. Se consideraron las empresas brasileñas que cotizan en bolsa en 2019, aplicando la prueba de correlación, diferencia de medias y regresión múltiple. Los resultados indicaron que la precisión está influenciada negativamente por el optimismo y positivamente por el anclaje y la similitud. La distancia entre el pronóstico emitido y la divulgación de ganancias por acción también afecta negativamente la precisión de los analistas. Se encontró que el valor razonable, la rentabilidad, la emisión de ADR y el sector autorregulado son aspectos relacionados con una mayor precisión. La investigación contribuye a una reflexión sobre la necesidad de concatenar aspectos conductuales y temporales a los financieros, y señalar la importancia de los modelos de pronóstico de los analistas considerando aspectos conductuales en sus tecnologías de la información.
Palabras clave: Pronóstico del analista; Sesgos de comportamiento; Tiempo de previsión

1 Introdution

The capital market has a unique importance for the economic development of a country. It is responsible for channeling society's savings towards more efficient allocation of resources, in order to guarantee a better return on investments. In addition, it is able to favor corporate governance by encouraging transparency in the disclosure of information by companies, leading to greater economic growth, more jobs, innovation, reduced cost of capital, increased availability of resources, greater liquidity for companies and investors (ANBIMA, 2018). This represents improvements in resource allocation efficiency (Wang, Hou & Chen, 20182).

However, the functioning of this market takes place through relations between agent and principal, which, as recommended by the Agency Theory of Jensen and Meckling (1976), are subject to a series of conflicts of interest potentiated by the condition of asymmetry of information between those involved.

In this context, financial analysts play an important role in brokering and monitoring information for investors (Brauer & Wiersema, 2018), able to assist investment decisions and reduce this informational asymmetry between companies and investors (Bildstein-Hagberg, 2003; Dalmácio, Lopes, Rezende & Sarlo Neto, 2013), via profit forecast and disclosure of their reports. In addition, financial analysts, when providing investment advice, influence the demand for a company's shares and, therefore, its price (Brauer & Wiersema, 2018), further evidencing its importance in the capital market.

However, analysts do not have access to the same information at the same time, and yet, there are different individual interpretations for the same information, which produces different results to the point of recommending or not investing in a particular company. This means that the analysts' analysis is individual, although based on a network of relationships, their risk assessment is particular and stems from their perception. And, this diversity is the result of the analyst's cognitive capacity (Boff, Procianoy & Hoppen, 2006).

Therefore, the view that analysts know companies, analyze and disclose information about future scenarios, being considered intermediaries of information, places it in a perspective that is not subject to cognitive biases or social context. But analysts operate in a social context that influences behavior making them subject to behavioral biases (Brauer & Wiersema, 2018).

Given this context, and considering the seminal work of Simon (1955), which discusses concepts of bounded rationality and simplifying approaches to rationality, some research has sought to observe the relationship between behavioral biases and analysts' accuracy, such as: a) optimism (Gervais & Odean, 2001; Kafayat, 2014; Galanti & Vaubourg, 2017); b) overconfidence (Gervais, Heaton & Odean, 2002; Hilary & Menzly, 2006; Du & Budescu, 2018); c) anchoring (Brown, 2001; Campbell & Sharpe, 2009; Silva Filho, Miranda, Lucena & Machado, 2018); d) representativeness (Marsden, Veeraraghavan & Ye, 2008); e) time (Amiran, Landsman, Ownes & Stubben, 2017; Muslu, Mutlu, Radhakrishnan & Tsang, 2019), etc.

Despite this research, Brauer and Wiersema (2018) state that research with analysts is still far from maturity and, in fact, holds strong promise for future growth, as we do not have a coherent understanding of the extent and nature of the various influences of analysts in executive and investor decision making and the context in which analysts operate.

Therefore, what is perceived in these researches is the observation of the analysts' accuracy by an average of forecasts of a group of analysts. In addition, behavioral factors tend to be observed by quantitative techniques. However, there is the possibility of ascertaining this relationship considering these main variables individually, that is, by analyst, and not by a concentrated data set. In addition, it is understood from the previous literature that there is an advance in discussions in international works, and a slower pace for national ones. Thus, the reflection on the relationship between accuracy and cognitive biases in a different context from those in which most research is carried out can reveal different results, which must be analyzed in order to better contribute to the academy.

It was also possible to identify that there is room for the development of research that considers in their forecast models a concatenation of financial aspects with behavioral and temporal aspects, highlighting

biases little explored in this relationship, such as commonality, and comparing with others more worked on by the literature, such as the bias of optimism, anchoring, representativeness, overconfidence and realism.

Therefore, this study aimed to analyze the relationship between behavioral biases, such as optimism, anchoring, overconfidence, representativeness, realism, commonality, in addition to time with analysts' profit forecast accuracy.

Thus, it is understood that, as the human factor is composed of behavioral heuristics that can help to explain part of the predictions made by analysts, such aspects, if identified, can compose the models and technologies of prediction and decision. This is capable of helping in forecasts that are closer to the real economic-financial performance of companies, in turn, indicating more efficient investment decisions. In this sense, the purpose of this project to contribute with models and technologies for evaluating companies is to relate to analysts' forecasts, not only economic and financial factors, but also behavioral ones.

In addition, we emphasize that the research builds the database by collecting data from analysts manually, unlike previous studies. This allowed us to consider the accuracy and cognitive biases per individual, whereas most studies use the average of a group of analysts. Therefore, observing a larger set of cognitive biases, identified by individual, is an advance of this research in the academic environment of Brazil.

2 Theoretical Framework

Traditional finance theories focus on the rationality of economic agents and the existence of efficient markets (Barros & Felipe, 2015), explaining the functioning of markets under the assumption of the agents' unlimited rationality, in which they, in possession of new information, make use of their ability to think and act in deciding correctly, so that information is instantly shared and incorporated by all agents, without privileged information (Markowitz, 1952; Fama, 1970). It was also considered that the individual is a rational and efficient being, who decides in a consistent way, maximizing its usefulness. Therefore, without taking into account the biases regarding the interpretation of information (Byrne & Brooks, 2008).

However, Simon (1955) already criticized economic theories and the consideration of rational behavior, arguing that learning theories better explained the observed behavior. Then, Kahneman and Tversky (1979) impact the literature of the area, defending the irrational behavior of investors. Under the Prospect Theory, these authors consider the presence of behavioral biases in the decision-making process. Thus, a line of research is developed that considers the perspectives of the social sciences, with sociology and psychology (Shiller, 2003), considering that the markets are, to a certain extent, inefficient (Oliveira & Krauter, 2015).

Therefore, more emphasis is given to research in finance that considers behavioral biases and the aspect of time and uncertainty in decisions. Along these lines, some of these biases can be considered, such as: optimism, anchoring, time, overconfidence, representativeness, realism and commonality.

Optimism, according to Tversky and Kahneman (1974), is understood by overestimating the probability of succeeding in future events, so that, in the context of the capital market, it is the bias that influences the analyst to overestimate profits (Shefrin , 2007). In this context, the need for analysts to maintain good relations with the management of companies, as well as due to the commissions they receive from brokerage firms, means that there is an incentive to issue optimistic reports and investment recommendations, even if biased (Sedor, 2002; Irvine, 2004). Therefore, according to Corredor, Ferrer and Santamaria (2013), optimism calls into question the analyst's objectivity, in order to be able to reduce the analyst's precision.

It is noteworthy that these aspects capable of explaining reasons that lead analysts to be optimistic in their forecasts were built on research that analyze the market in countries such as the USA and China. However, if we consider Brazil, and the uncertainties inherent to the economy, politics and performance of its institutions and enforcement power, it may be appropriate to expect that the relationship between the analyst's optimistic behaviors, given the aforementioned conjuncture, may lead to a lower accuracy of the profit forecast.

Therefore, it is possible to propose the following research hypothesis:

H_1: The optimistic bias negatively impacts the accuracy of the analysts' profit forecast.

Tversky and Kahneman (1974) highlight that anchoring bias is a psychological phenomenon that explains how people tend to form an estimate starting with an initial number and adjusting it to reflect new information or circumstances. However, Campbell and Sharpe (2009) point out that this bias ends up leading to forecasts that underlie new information, which may generate forecast errors.

Although the literature considers that there are flaws in the adjustments of reference values, which is why the use of anchoring is considered a bias, other literature, based on the concept of smoothing and earnings management, considers that past earnings tend to be the basis for future earnings, even due to the need to disclose greater volatility by companies. In this case, observing previous earnings as an anchor can mean a positive relationship with analysts' accuracy. Linked to this and to the fact that the stock market in Brazil is not one of the most developed and with a significant volume of trades, it makes sense to think that

the use of the anchor based on the previous result can signal a positive relationship with accuracy. So that the second hypothesis is proposed:

H_2: The anchoring bias negatively impacts the accuracy of the analysts' profit forecast.

Possible errors in analysts' forecasts occur due to human limitations in decision-making processes, which may be linked to emotion, such as the case of overconfidence (Tversky & Kahneman, 1974), which is considered as a big mistake by analysts (Plous , 1993). According to Pimenta, Borsato and Ribeiro (2012), the overconfidence of analysts is related to the fact that they consider the information they use to be better and more reliable than that of other professionals. Thus, Kafayat (2014), Bosquet, Goeji and Smedts. (2015), Du and Budescu (2018) point out that overconfidence can harm financial decisions, which may indicate less accurate forecasts and higher risk investments (Barber & Odean, 2001).

In addition, studies have found that the degree of expected stability of the environment, with a greater capacity for change giving rise to more confident beliefs, is a determinant of differences in overconfidence (Dessí & Zhao, 2018). Brazil, specifically, is not classified as a relatively stable country.

This scenario allows us to propose the following research hypothesis:

However, considering that Schmitt and Allik (2005) found that, although overconfidence is a universal characteristic, it may have a more neutral response in collectivist cultures, as is the case in Brazil, a possible insignificance of this bias in terms of accuracy analysts may not come as a surprise.

H_3: The overconfidence bias negatively impacts the accuracy of the analysts' profit forecast.

Tversky and Kahneman (1974) highlighted that representativeness occurs when one event is considered to be similar or representative of another. If so, the probability of an event occurring can be captured by the occurrence of the representative event, otherwise the probability is considered low. This approach to judgment leads to serious errors, since similarity or representativeness is not influenced by several factors and ends up affecting judgments.

Furthermore, Bordalo, Coffman, Gennaioli, Schwerter and Shleifer (2021) also consider that the recall of an event is driven by how similar it is to the data of another event, so that the existence of analogous information prevents other information from coming to mind when analyzing the probabilities of an event occurring. Thus, the memory access process is selective and ends up dependent on the decision-maker's experience (Bordalo, Conlon, Gennaioli, Kwon, & Shleifer, 2021), underestimating reliability in representative facts (Tversky & Kahneman, 1974).In this sense, considering Brazil as a country in which the capital market is not so developed and where the volume of negotiations and forecasts is also lower compared to other countries, then the bias of representativeness may be present, however, carrying with it all the fundamentals that would justify greater error in their forecasts.

Therefore, it is expected that there is a negative relationship with the analyst's accuracy, making it possible to establish the following research hypothesis:

H_4: The representativeness bias negatively impacts the accuracy of the analysts' profit forecast.

Realism, within discourse analysis, is highlighted by psychology as the ability to feel the environment around, interpret it and react accordingly. Bénabou (2009) states that realism is defined by the absorption and interpretation of news, including bad news, by the participants. Thus, based on McDonald et al. (2015), it can be considered that realism is not a cause, but a consequence of the experiences and individual personality. In this context, Piotr and Sina (2015) state that the realistic characteristic can help in the prediction of the returns of an action, since in being realistic the analyst has greater capacity to observe the real situation of the company. Nevertheless, given the instability of the environment in Brazil, including aspects of a political and economic nature, it is understood that the competence to consider the environment and interpret it well to reflect on a decision such as profit forecasting can be a challenge.

Therefore, the following hypothesis is proposed:

H_5: The realism bias negatively impacts the accuracy of analysts' profit forecasting.

There is also a commonality bias. According to Brah (2006), commonality is characterized by the existence of values and ideas that originated from the shared experience of a social group, being a characteristic present in speeches that highlights the agreed values of a group and rejects idiosyncratic modes of involvement (Short & Palmer, 2008). It should also be considered that the relationship between commonality bias and analysts' accuracy may be different from the point of view of cultural origin. In this sense, for example, according to Hofstede's scores (Beckmann, Menkhoff & Suto, 2008; Chui, Titman & Wei, 2010), the USA is characterized as an individualist country and Brazil as a collectivist.

Thus, considering that the Brazilian analyst tends to have a stance that considers the idea of the groups, such as the analyzes of other colleagues, it is possible to expect that there is a positive result with his prediction of results. Thus the following hypothesis emerging:

H_6: The commonality bias has a positive impact on the accuracy of analysts.

Finally, Prelec and Loewenstein (1991) observed that time and uncertainty are correlated, so that behavioral violations occur given the inherent connection between intertemporal choices and uncertainty. In addition, Laverty (1996) states that a forecast closer to the announcement of the results reduces the uncertainty environment in the analyst, who will have more time to gather a larger set of information about a company, in order to reduce the probability or size of the error of the forecast.

H_7: Estimated profit forecast time has a negative relationship with analysts' profit forecast accuracy.

3 Methodology

3.1 Study delimitation and methods

The survey was conducted considering the year 2019 for publicly traded Brazilian companies, whose accounting and financial information was obtained from the S&P Capital and Thomson Reuters® databases. Financial analyst reports were obtained from the Thomson One® database. From these reports, data such as: estimated earnings per share, date of estimate, analyst name and brokerage name were collected. This entire collection process took place manually, which implied the construction of a single database. However, due to the time required for data collection, this study was limited to the year 2019. It is noteworthy that the consideration of the year 2019 was also due to the greater volume of data, since the Brazilian capital market is still does not present a significant volume of negotiations and profit forecasts, if compared to the North American market, for example, so that the most lagged years have a lower volume of data for the research. In addition, financial companies were disregarded from the sample, due to their normative peculiarities and accounting structure, which could bias the tests.

It is noteworthy that, for some variables, based on variations between periods, such as Surprise, Growth and Volatility, other years were considered in the collection, such as 2018 and 2017. Details on how these variables are calculated are described in section 3.2

Thus, the final sample consisted of 94 companies, whose history is shown in Table 1.

Table 1
Definition of the final sample

Procedures for selecting the final sample	**Brazil**
Initial sample	338
(-) Financial	34
(-) Without estimated LPA	181
(-) Lack of accounting data	29
(=)Final number of companies	**94**

The reports of the collected financial analysts took place for each quarter of the year 2019. As a characteristic of the database, it is emphasized that the companies are followed by a number of different financial analysts and brokers, so that the final database made up a total of 1,026 observations, that is, an average of 10.9 reports per company.

In terms of methods, the Kolmogorov-Smirnov test was initially applied to analyze the normality of each variable. Given that the result indicated for rejection of the null hypothesis of normality, the correlation test applied was Spearman's. Then, a study of difference of means was made, using the Mann-Whtiney U nonparametric test. Finally, for multiple regression analysis, the Shapiro-Francia test was applied to verify the normality of residues, VIF test for multicollinearity analysis and White test for heteroscedasticity analysis.

3.2 Definition of variables and econometric model

The accuracy of the analyst's forecast was calculated based on previous research (García-Meca & Sanchez-Ballesta; 2006; Coën, Desfleurs & L'Her, 2009; Saito, Villalobos & Benetti, 2008, Dalmácio et al., 2013). The difference is that, in order to facilitate the interpretation of the results, the value 1 was subtracted from Equation 1, as used by Abernathy, Heremann, Kang and Krishnan (2013) and Lang and Lundholm (1996):

$$Err\,\Pr ev = 1 - \left| \left(\frac{EPS_{real} - EPS_{prev}}{EPS_{real}} \right) \right| \quad (1)$$

Where:
EPS_{real}= corresponds to realized earnings per share;
EPS_{prev}= corresponds to the predicted earnings per share, based on the analysts' consensus (average).

To analyze the influence of behavioral and temporal aspects on the forecast accuracy of analysts, the econometric model presented in Equation 2 was considered:

$$\begin{aligned} AC_{i,t} = {} & \alpha_0 + \beta_1 Behav_{i,t} + \beta_2 FV_{i,t-1} + \beta_3 Loss_{i,t-1} + \beta_4 Profit_{i,t-1} + \beta_5 Surp_{i,t} + \beta_6 Growth_{i,t-1} + \\ & + \beta_7 Volat_{i,t-1} + \beta_8 Indeb_{i,t-1} + \beta_9 Roa_{i,t-1} + \beta_{10} Age_{i,t} + \beta_{11} ADR_{i,t} + \beta_{12} Sector_{i,t} + \beta_{13} SizeBrok_{i,t} + \\ & + \beta_{14} Popul_{i,t} + \beta_{15} SpecAna_{i,t} + \beta_{16} ExperAna_{i,t} + \beta_{17} Size_{i,t} + \beta_{18} CG_{i,t} + \varepsilon_{it} \end{aligned} \quad (2)$$

Where:
AC = analyst's forecast accuracy, calculated according to Equation 1;
Behav = Variables representing behavioral and temporal biases, the ones used here:

a) Optim: dummy variable representing the analyst's optimism, with 1 when the analyst's forecast extrapolates the average consensus of the other analysts, 0 (zero) the opposite;
b) Ancho: dummy variable representing the anchoring effect, being 1 (one) if the analyst's forecast is between the real earnings per share and the anchor, 0 (zero) the opposite. For this study, the real earnings per share in t-1 was used as an anchor;
c) Overconf: variable representing the analyst's overconfidence, obtained through the software Diction®, which considers the language used in the analysts' reports, more specifically the use of terms that indicate trust, such as “always”, “totally”, “Absolute”, etc., reduced terms of hesitation, such as “maybe”, “supposedly”, etc.;
d) Repres: variable related to the analyst's representativeness aspect, calculated by analyzing the discourse of the analysts' report, via Diction®, which considers expressions such as “challenging”, “dominated”, “motivated”, “influencing”, etc., reducing terms such as “examine”, “reasonable”, “indifferent”, etc.;
e) Real: variable related to the aspect of realism in the discourse of the analysts' report, obtained via Diction®, which considers terms that describe tangible, immediate and recognizable issues that affect people's daily lives, such as “local”, “municipality”, “Instant”, “obsolete” etc. and disregards others related to the past or abstract;
f) Common: variable representing a discourse focused on centrality and cooperation, obtained via Diction®, considering terms such as “standardized”, “conformity”, “alignment”, “equivalent”, etc. and disregarding others that represent diversity and exclusion as “inconsistent”, “extremist”, “self-sufficient”, etc.;
g) Time: represents the distance between the date on which the forecast was made and the date of the earnings release, considering here the end of 2019;

FV = dummy variable, indicating 1 (one) if the company has assets or liabilities at fair value, 0 (zero) otherwise. Since fair value represents a possibility to measure and disclose assets and liabilities in a way that is closer to their reality, it is a method that allows companies to disclose their economic and financial conditions also closer to reality. Therefore, this information becomes more useful (Kajimoto & Nakao, 2018; Black & Nakao, 2017; Barth, Landsman & Lang, 2008; Bahadır, Demir, & Öncel, 2016), including to financial analysts, being able to have a positive impact in the accuracy of its predictions, since it allows greater comparability, comprehensibility and relevant information (Milburn, 2008; Ayres, Huang & Myring, 2017).

Loss = dummy variable, being 1 (one) if the company has a loss, 0 (zero) otherwise. Companies with reported losses signal times of uncertainty and distress (Ayres et al., 2017), and may also generate negative fluctuations in the estimates of corporate profits and earnings for shareholders (Coën et al., 2009; Rahman, Zhang & Dong, 2019), consequently, negatively impacting the accuracy of analysts.

Profit = company's profitability, calculated by the ratio between Ebitda and Total Assets. Profitability tends to be a way of motivating the company's disclosure to the market, given the positive aspect that this represents in terms of investment. In turn, increased disclosure provides more support for analysts to make their predictions (García-Meca, Parra, Larrán & Martinez, 2005), in order to expect a positive and accurate relationship.

Supr = surprise of the company, estimated through the ratio between the variation of the profit between two periods and the profit in t-1. A surprise effect represents something unexpected, which implies a scenario of greater uncertainty. Given this, although the existing literature (Abernathy et al., 2013, Magnan, Menini & Parbonetti, 2015) did not directly relate this variable to the analyst's accuracy, it is possible to expect that the relationship between the variables is negative.

Growth = growth of the company, as measured by the variation in sales revenue. Growing companies tend to have a greater amount of information that the analyst needs to consider (Silva, Pletsch & da Cunha, 2018). Given this complexity, the analyst's effort tends to be greater (Barth, Beaver & Landsman, 2001), which can negatively imply the accuracy of his results forecasts. In addition, growing companies may have a greater volume of funds raised from financial institutions, which implies a greater need for attention by analysts. Lehavy, Li and Merkley (2011) also state that companies with high growth tend to attract more analysts, due to investor interest and potential as an investment. However, they corroborate the idea that it is more difficult to predict the profits of such companies with greater precision, causing more disagreement among analysts and less accuracy, unlike the scenario of a stable company.

Volat = volatility of the company's results, estimated by the logarithm of the ratio between the standard deviation of profit of the previous five quarters and the average profit module. Companies with greater volatility in results may make it difficult for analysts to predict (Saito et al., 2008) due to the increase in uncertainties in the reported information (Behn, Choi & Kang, 2008; Ayres et al., 2017), so expect a negative relationship with accuracy.

Indeb = corporate indebtedness, calculated by the ratio between total liabilities and total assets. The high indebtedness implies a greater number of variables that need to be taken into account by analysts, such

as debt contracts and their clauses, interest rates and covenants, among other aspects. Thus, the scenario is representative of greater complexity for monitoring analysts (Saito et al., 2008), which may imply greater difficulties in determining profit forecasts.

ROA= variable representing the company's performance, estimated by the ratio of net profit and total assets. It is expected that companies with better performance will disclose more information and better quality to the market, allowing analysts to have better conditions to determine their results forecasts.

Age = age of the company, is the difference between the year of opening of the company and the year of 2019. Older companies have a longer disclosure history, allowing analysts to have better monitoring of this company (Bradshaw, Drake, Myers & Myers, 2012). Therefore, it is expected that the relationship between the variables will be positive.

ADR = dummy variable, 1 (one) for companies that issue ADRs, 0 (zero) the opposite. Companies that trade stocks in North American markets must follow certain information disclosure rules that make them more transparent (Leuz, 2003), which, in turn, can positively imply in the forecasting of results by analysts.

Sector = dummy variable, 1 (one) for companies belonging to the self-regulated sector, 0 (zero) the opposite. The self-regulated sector has additional regulatory aspects, which are monitored by additional regulatory bodies to the Securities and Exchange Commission (CVM), which can positively imply the quality of the information disclosed (Malaquias & Lemes, 2013), in turn, in the forecast of result in the analyst. However, it is noteworthy that no studies were found in the literature that directly related these two variables.

SizeBrok = variable representing the size of the broker, calculated according to the number of companies followed by the broker. Jacob, Lys and Neale (1999) pointed out that analysts at large brokerage firms have access to more resources, more sophisticated forecasting models, which contributes to the quality of their forecasts. Therefore, a positive relationship with the accuracy of the forecasts is expected.

Popul = variable representative of the company's popularity, calculated by the number of analysts who follow the company. Although no studies were found that considered popularity in relation to analysts' accuracy, it is expected that companies followed by a greater number of analysts have a greater basis for the analysts themselves, contributing to the accuracy of their forecasts.

SpecAna = variable that represents the analyst's specialization, found by the number of sectors followed by the analyst. The lesser specialization of the analyst can increase the complexity of his analyzes (Bolliger, 2004) and not have similarity gains in the analyzes (Martinez, 2007). Thus, and, given that the higher this variable, the lower the specialization, the expected relationship in this study is negative between the variables.

ExperAna = represents the analyst's experience in a given company, calculated by the analyst's forecast volume in a given company. It is expected that the greater the analyst's experience in a given company, the greater his knowledge of it and the greater the chance of accuracy in his predictions (Clement, 1999; Martinez, 2007; Wang et. al, 2012).

Size = variable representing the size of the company, calculated by logging the value of Total Assets. A positive relationship with accuracy is expected, as larger companies have experience and technologies that enable better collection, forecasting and dissemination of reliable information to the market (García-Meca & Sanchez-Ballesta, 2006; Saito et al., 2008; Ayres et al., 2017; Gazzoni Junior, Simões, Brandão & de Souza, 2019).

CG = dummy variable, being 1 (one) for companies belonging to the differentiated levels of corporate governance of B3, 0 (zero) otherwise. The corporate governance levels established by B3 can be called Level 1, Level 2 and New Market, in ascending order of informational quality. These levels of governance require greater disclosure of companies and capital dispersion, compared to the traditional market, greater visibility is expected of companies classified at these levels, in order to have an incentive for the quality of the disclosure of information to the market. Therefore, it is expected that there will be a positive relationship with the accuracy of the analysts' forecast (Bhat, Hope & Kang, 2006; Byard, Li & Weintrop, 2006; Dalmácio et al., 2013).

4 Presentation and Analysis of Results

4.1 Results presentation

Initially, there is the descriptive statistics of the variables, shown in Table 2. Descriptive statistics allow us to observe that, with the exception of binary variables, accuracy and time, the mean and median of the other variables are close, indicating that the data are not strongly impacted by extreme values. However, the data show variability, if you observe the difference between the minimum and maximum values. With regard to data dispersion, emphasis can be placed on accuracy, time, age, popularity, specialization and experience of the analyst. These results indicate, mainly, that there is a great dispersion and variability in the forecasts of the analysts' results for the Brazilian market, indicating heterogeneity in the values of these forecasts.

Table 2
Descriptive Statistics

Variables	Mean	Median	SD	Min	Max
Ac	0.168	0.663	1.109	-4.925	1
Time	189.207	225	100.332	2	333
Overconf	48.232	50.28	7.931	0.730	59.950
Repres	49.017	49.43	2.015	30.280	54.030
Real	40.220	40.78	4.098	0	60.290
Common	50.376	50.53	4.792	0	57.1
Size	3.658	3.683	0.498	2.003	4.497
Profit	0.027	0.024	0.021	-0.042	0.086
Surp	0.251	0.148	0.763	-0.966	2.411
Growth	0.143	0.107	0.202	-0.398	0.726
Volat	-0.303	-0.331	0.439	-1.106	1.050
Indeb	0.613	0.643	0.223	0.109	1.464
ROA	0.013	0.014	0.021	-0.127	0.103
Age	57.089	54	33.917	9	147
Popul	6.289	6	2.576	1	13
SpecAna	3.950	4	2.080	1	9
ExperAna	2.979	3	1.374	1	7

It is worth mentioning that, of the total number of observations, 45.7% have the optimistic characteristic, 33.3% anchoring, 90.2% using fair value, 12.3% with loss, 45.8% of ADR, 23, 6% in the regulated sector, 41.6% forecasts made by major brokerage firms.

Then, after observing that the variables did not follow a normal distribution, the Spearman correlation test was applied for continuous variables and the Point Biseral Correlation test for dummies variables, shown in Table 3.

Table 3
Spearman correlation between each variable and Accuracy (AC)

Variables	Correlation	Variables	Correlation	Variables	Correlation
Otim	-0.1150***	Size	0.0014	Age	-0.0542*
Ancho	0.1197***	Loss	-0.0851***	ADR	0.0405
Time	-0.0751**	Profit	0.2671***	Sector	0.1254***
Overconf	0.0248	Surp	0.3421***	SizeBrok	0.0203
Repres	-0.0235	Growth	-0.0626**	Popul	-0.0711**
Real	0.0283	Volat	-0.1736***	EspecAna	0.0577*
Common	0.0840***	Indeb	-0.2565***	ExperAna	-0.0371
FV	0.0181	ROA	0.2774***		

Being ***, ** and * the statistical significance at 1%, 5%, 10%, respectively.

Then, the mean difference test was performed, so that each independent variable was ordered from the lowest to the highest value, separated into four quartiles, with quartile 1 (Q1) being defined as having the lowest values and quartile 4 (Q4) those with the highest values. This classification of the variables guided the classification of the variable of interest, accuracy, so that the averages of their values were calculated for the Q1 and Q4 of each independent variable and used for the analysis of the mean difference. The results are shown in Table 4.

Table 4
Average test considering continuous variables

Variables	Q1	Q4	t	Variables	Q1	Q4	t
Otim	0.0038082	-1.016502	3.844***	Growth	0.2945034	-0.432873	2.537**
Ancho	-0.835499	0.2881412	-4.763***	Volat	-0.801231	-1.680348	4.426***
Time	0.0576168	-0.869354	2.432**	Indeb	0.4125048	-1.747029	6.096***
Overconf	-0.575285	-0.919997	-0.129	ROA	-0.742273	0.1560476	-0.248***
Repres	-0.435015	-0.838285	-0.248	Age	-0.243136	-1.178277	3.362***
Real	-0.612802	-0.870838	0.033	ADR	-0.626583	-0.264549	0.706
Common	-1.195958	-0.249375	-2.091**	Sector	0.1368658	-1.367621	-5.856***
FV	-0.705004	-0.435785	0.738	SizeBrok	-0.579049	-0.297539	-0.648
Size	0.0700983	0.055894	0.566	Popul	-0.071039	-1.357508	4.530***
Loss	-0.321292	-1.46635	11.272***	SpecAna	-0.305933	-0.737391	0.067
Proft	-1.975307	-0.275518	-8.223***	ExperAna	-0.388592	-1.067343	1.748*
Surp	-2.056117	0.0957183	-9.633***				

Being ***, ** and * the statistical significance at 1%, 5%, 10%, respectively.

Finally, the multiple regression test with Generalized Least Squares was carried out, the results of which are reported in Tables 5 and 6. Regarding the tests of regression assumptions, for all models, the hypothesis of homoscedasticity was not rejected, but it was rejected the hypothesis of normality of the residues. As for multicollinearity, the highlights were the variables of size and corporate governance, which needed to be removed from the models to avoid multicollinearity problems.

Table 5
Multiple Regression Results

Variables	Coef.	z	Coef.	z	Coef.	z	Coef.	z
Otim	-0.905	-3.41***						
Ancho			1.154	3.95***				
Overconf					-0.014	-0.87		
Repres							-0.076	-1.15
FV	1.238	2.52**	1.332	2.72***	1.265	2.56***	1.239	2.51**
Loss	-1.090	-1.87*	-0.993	-1.70*	-1.055	-1.79*	-1.122	-1.91*
Profit	28.676	3.56***	31.780	3.97***	30.891	3.82***	30.596	3.79***
Surp	-0.003	-0.34	-0.002	-0.24	-0.004	-0.41	-0.004	-0.43
Growth	-1.060	-1.42	-0.882	-1.19	-1.012	-1.35	-1.002	-1.34
Volat	0.139	2.49**	0.141	2.53**	0.148	2.63***	0.149	2.65***
Indeb	-5.146	-7.63***	-5.121	-7.61***	-5.231	-7.72***	-5.228	-7.72***
ROA	-25.376	-2.32**	-26.677	-2.44**	-27.194	-2.47**	-27.682	-2.51**
Age	-0.009	-1.89*	-0.009	-1.99**	-0.008	-1.78*	-0.009	-1.86**
ADR	0.731	2.41**	0.431	1.38	0.727	2.38**	0.714	2.34**
Sector	0.558	1.46	0.672	1.76*	0.60	1.56	0.595	1.55
SizeBrok	0.221	0.74	0.235	0.79	0.152	0.51	0.1446	0.48
Popul	-0.102	-1.58	-0.049	-0.74	-0.102	-1.57	-0.104	-1.60
SpecAna	-0.015	-0.19	0.008	0.11	-0.008	-0.10	-0.010	-0.13
ExperAna	0.049	0.49	0.014	0.14	0.049	0.49	0.048	0.48
Constant	2.294	2.70***	1.103	1.28	2.48	2.28**	5.636	1.67*
F	7.65***		7.08***		6.90***		6.94***	
R^2	0.1083		0.1068		0.0988		0.0992	
Shapiro-Francia	11.004***		11.012***		11.017***		11.015***	
VIF	1.52		1.55		1.52		1.52	
White Test	156.08		110.97		121.11		126.53	

Being ***, ** and * the statistical significance at 1%, 5%, 10%, respectively

Table 6
Multiple Regression Results - Continued

Variables	Coef.	z	Coef.	z	Coef.	z
Real	0.049	1.47				
Common			0.063	2.21**		
Time					-0.003	-2.08**
FV	1.306	2.64***	1.315	2.67***		
Loss	-1.106	-1.88 **	-1.101	-1.88*	1.275	2.59***
Profit	30.215	3.75***	30.546	3.79***	-1.019	-1.74*
Surp	-0.003	-0.35	-0.003	-0.38	30.191	3.75***
Growth	-1.070	-1.43	-1.073	-1.44	-0.003	-0.31
Volat	0.148	2.64***	0.148	2.64***	-0.948	-1.27
Indeb	-5.358	-7.85***	-5.416	-7.95***	0.142	2.54**
ROA	-26.913	-2.45**	-27.286	-2.49**	-5.179	-7.65***
Age	-0.009	-2.00**	-0.009	-2.03**	-24.682	-2.24**
ADR	0.679	2.22**	0.655	2.14**	-0.008	-1.78*
Sector	0.514	1.33	0.474	1.22	0.686	2.25**
SizeBrok	0.158	0.53	0.158	0.53	0.607	1.58
Popul	-0.098	-1.50	-0.098	-1.51	0.104	0.35
SpecAna	-0.015	-0.19	-0.025	-0.32	-0.101	-1.55
ExperAna	0.051	0.51	0.045	0.44	-0.001	-0.01
Constant	0.025	0.02	-1.047	-0.67	0.034	0.33
F	7***		6.4***		7.15***	
R^2	0.10		0.0976		0.1019	
Shapiro-Francia	11.023***		11.021***		11.019***	
VIF	1.53		1.53		1.52	
White test	127.34		119.19		117.49	

Being ***, ** and * the statistical significance at 1%, 5%, 10%, respectively.

4.2 Analysis of results

As a general result, it is observed that the findings in correlation, mean test and regression were consistent for most variables, diverging to surprise, volatility, ROA, sector and analyst's experience. Therefore, consistent results were obtained, in the face of different research methods.

Descriptive statistics indicated that almost 50% of the forecasts were classified as optimistic, and that this bias, observing all other tests, is negatively related to the accuracy in the analysts' profit forecast. This result corroborates with the literature (Kothari, 2001; Galanti & Vaubourg, 2017). Therefore, hypothesis 1 of the study is confirmed.

With regard to anchoring, although research has indicated that this bias is related to the accuracy of analysts, the relationship found was contrary to what was expected by the literature (Campbell & Sharpe, 2009; Kratz, 2016, Silva et al., 2018). In this research, the analysis of correlation, mean difference and regression indicated that the use of anchoring bias ends up having a positive effect on the analyst's accuracy, thus indicating that the fact that analyst base themselves on, previously reported earnings per share, may contribute to accuracy of your predictions. Thus, hypothesis 2 of the research was not confirmed.

We emphasize that the anchoring was obtained considering past earnings per share and future earnings per share, as used in the literature (Amir & Ganzach, 1998; Marsden et al., 2008; Campbell & Sharpe, 2009; Kratz, 2016; Silva Filho, et al., 2018; Ashour & Hao, 2019), whose result was positive with the analysts' accuracy, contrary to what was theoretically expected. However, we understand that past earnings tend to be a natural predictor of future earnings, based on reasons exposed by research on earnings management and smoothing, so that a positive relationship between analysts' accuracy and anchoring can be justified.

The results for biases of overconfidence, representativeness and realism, were found to be consistent with the relationship expected by the literature (Piotr & Sina, 2015; Du & Budescu, 2018), however, the results were not statistically significant, which also differs from previous research (Mokoteli, Taffler & Ryan, 2006). Therefore, hypotheses 3, 4 and 5 of this research could not be confirmed.

Regarding the commonality bias, all tests indicate that the cases in which this bias is present tend to be more accurate. This positive relationship between the variables does not allow us to reject hypothesis 6 of this study, and it signals that the consideration of shared experience, that group considerations, therefore cooperation and relationship can contribute to the accuracy in the analysts' forecast.

With regard to the time factor, the literature highlights that there is a correlation between time and uncertainty (Prelec & Loewenstein, 1991), so that the forecast closer to the disclosure of the company's results reduces the analyst's uncertainty environment (Laverty, 1996) In addition, forecasts further away from the announcement date are more subject to uncertainty and over-optimism (García-Meca & Sánchez-Ballesta, 2006), which in turn tends to negatively impact the accuracy of analysts, as identified in this research. Therefore, the results found here are consistent with these notes, so it is not possible to reject hypothesis 7 of this research.

The results also indicate the set of financial factors that were related to the accuracy of the analyst's forecast. More specifically, it was found that the use of fair value, profitability, the issuance of ADRs and companies in self-regulated sectors have a positive and significant relationship with accuracy. These findings are in agreement with that found by García-Meca et al. (2005), Saito et al. (2008), and Ayres et al. (2017). However, it was found that for companies with losses, greater surprise in the results, in growth and with greater indebtedness, the relationship with accuracy is negative. The previous literature already indicates that the loss indicates uncertainty scenarios, in the same way as a considerable variation in the result between the periods, and that growing and more indebted companies may have a higher degree of complexity and factors that must be monitored by analysts, in order to make a forecast error more susceptible. Therefore, the result corroborates Byard et al. (2006), Tong (2007), Saito et al. (2008), Xie, Zhang and Zhou (2012), Abernathy et al. (2013) and Ayres et al. (2017).

Three results that draw our attention concern the control variables such as: volatility, ROA and age of the companies, as the findings were contrary to what was expected in the literature. It is noteworthy that the base literature for the definition of such variables is predominantly international, with national ones tending to observe only performance more frequently.

The findings of this research indicated that companies with greater volatility have greater accuracy and companies with younger age and lower ROA have greater accuracy. Such results, in Brazil, can be explained by the possibility of indications that, in the face of greater volatility of results, analysts tend to dedicate themselves more to these companies, which may imply in lower forecast errors. On the other hand, they devoted less effort to older and older companies, probably because they felt more secure in the information disclosed in these cases. However, such results need to be explored in future research.

Finally, although the results indicate an alignment with what was expected, the results were not statistically significant for variables related to the size of the broker, specialization and experience of the analysts. It drew attention that, the fact that the company is followed by a greater number of analysts, indicated that the accuracy is lower, although the regression model did not indicate significance for this

variable, the correlation analysis and average test confirmed this relationship, which goes against what was expected.

Therefore, the study brings models that try to relate a larger set of financial variables, with emphasis on behavioral variables, when trying to identify factors that are related to the accuracy in the analysts' forecast, confirming, in most cases, what the theory has been sustained.

5 Final Considerations

In order to contribute to research and to discuss how human and psychological factors, more specifically behavioral biases and uncertainty measured over time, are related to decisions in financial and business environments, this research analyzed the relationship between some of these biases with the accuracy of the financial analysts' profit forecast. Along with a set of financial aspects and characteristics of the analysts, the biases were considered as: optimism, anchoring, overconfidence, representativeness, realism and commonality, plus the condition of uncertainty established by time.

Overall, the results confirmed that, in the Brazilian context, these biases are related to the accuracy of analysts, more specifically, optimism, commonality and the time factor, so that hypotheses 1, 6 and 7 were not rejected. It is noteworthy that the anchoring bias also showed a relationship with accuracy, but in the opposite direction to that expected by the literature. Indicating that the use of anchor measures benefits the analysts' forecast, increasing its accuracy. While optimism and time are negatively related to accuracy and commonality, it has a positive effect.

Although the results have not been significant for the other biases, the tendency that can be indicated is that overconfidence and representativeness imply less accuracy, while the characteristic of realism suggests greater accuracy.

Thus, the study considered a set of variables, which can be related with accuracy, in a broader way than that already addressed in previous research. He managed to prove that there is an impact on the accuracy of analysts by some behavioral biases, not yet observed in the literature. These aspects differentiate the study from other international ones, but mainly from national research.

In addition, it reaffirms that heuristics can affect, and therefore, should be considered by information technologies, as they are present in the interface of decision-making processes. And, this happens because, according to central cognitive theory, based on the concept of human agency, the human factor directs and regulates its own experiences and can intentionally influence the functioning and immediate circumstances (Bandura, 2001, 2006).

In this way, this research contributes to the interdisciplinary literature dedicated to deepening studies on the areas of psychology and financial behavior, especially in the context of Brazil, whose research is still incipient compared to the US and China.

If compared with existing research, this study differs by observing the cognitive aspects through the analysis of texts. Furthermore, the study considered a set of variables, which can be related to accuracy, in a broader way than that already addressed in previous studies. He managed to prove that there is an impact on analysts' accuracy by some behavioral biases, not yet observed in the international and national literature, such as commonality and realism. Thus, it signals for future research that, in order to better establish an accuracy prediction model, they should consider behavioral biases, whether they are: optimism, anchoring, commonality, in addition to the time factor.

In practical terms, it signals to investors the profile of reports that they should observe to follow the orientation in the decision of their investments, noting that the reports of Brazilian analysts with anchoring and use of commonality terms are related with greater accuracy, but that, the reports with a tendency to optimistic writing have a negative relationship with accuracy.

Due to some results obtained that are different from what was theoretically expected, this study indicates that future research should be carried out to better understand how cultural, legal and institutional aspects can shape biases, which in turn can have a different impact on analysts' accuracy. Also, future research can expand this database, in addition, use differentiated analysis methods, mainly with the prerogative of a possible non-linear relationship between these sets of factors regarding the accuracy of the analysts.

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