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CORPORATE USE OF THE X SOCIAL MEDIA PLATFORM AND ANALYST FORECASTING

MIKAÉLI DA SILVA GIORDANI[1]
Federal University of Santa Maria
https://orcid.org/0000-0002-4871-7858
mikagiordani@hotmail.com

ROBERTO CARLOS KLANN
Regional University of Blumenau
http://orcid.org/0000-0002-3498-0938
rklann@furb.br

ABSTRACT

This study aimed to investigate whether the corporate use of X (formerly Twitter) for disseminating financial information, as well as likes, comments, and retweets related to this information, can improve analysts' forecasting accuracy. The dissemination of information on X signals additional evidence for stakeholders in the organization, such as analysts. Multiple linear regression was employed, with robust standard errors. The analysis consisted of 2,548 observations from the period of 2013 to 2019. The results demonstrate that analysts' forecast error is maximized according to the reactions to the posts. Likes, comments, and retweets from the previous quarter influence the accuracy of analysts' forecasts in the current quarter. A possible explanation for this result may lie in the fact that companies publish excessively optimistic information. This leads to an optimistic reaction from users, consequently inducing analysts to err. Further analysis examined the interaction between profitable companies during the period and the variables from X. The results of the interaction between the variables and the companies' profits indicated that profitable companies that tweet demonstrate a greater forecast error from analysts compared to profitable companies that do not tweet. The research highlighted that social media can be an important channel for companies to disseminate financial information. Furthermore, the interaction between companies and stakeholders, or among stakeholders themselves on X, facilitates communication, information circulation, and enables feedback—factors that, together, influence stakeholders in the company, such as analysts.

Keywords: Social media. X. Analysts' forecasting.

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[1] **Correspondence address:** Av. Roraima, 1000 | Cidade Universitária | Camobi | 97105-900 | Santa Maria/RS | Brazil.

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1 INTRODUCTION

Analysts' forecasts are formed based on financial reports and market economic trends; analysts are trained professionals equipped to issue forecasts about a company's future performance (Tsao et al., 2016). The analyst's ability to accurately predict outcomes is an important issue for achieving an efficient capital market. This fact makes analysts' forecasts of company earnings and earnings per share highly sought after by the market (Embong & Hosseini, 2018).

In addition to the financial information disclosed through reports and market data, other information can also be utilized by analysts to form their forecasts, such as information from social media. Companies are using social media as a viable tool for disseminating important information (Giordani & Klann, 2022; Xiang & Birt, 2021). In this sense, it is crucial to verify whether the dissemination of information on social media affects the performance of analysts' forecasts.

The interactive nature of social media contributes to the high-frequency trading environment, which includes the faster dissemination and capture of information. Social media has increasingly been used by companies to interact with investors (Amin et al., 2020). Unlike traditional media, social media offers a two-way communication channel (Cade, 2018). Thus, it becomes a facilitating medium for investors to follow companies, receiving and reacting to important information in real time and at no cost (Amin et al., 2020).

Previous studies on the corporate use of social media have shown that companies that publish information provide investors with a new source of data, promoting the sharing of opinions and social interaction (Teoh, 2018). Additionally, they have a greater influence on investor decisions (Zhang, 2015) and can maximize their performance through the collection and analysis of information generated on these channels (Giordani et al., 2023; Giordani et al., 2022; Arnaboldi et al., 2017). Specifically regarding the relationship between corporate social media use and analysts' forecasts, companies are increasingly adopting social media platforms to reach relevant audiences actively seeking information about these companies (Parveen et al., 2016), such as analysts.

The dissemination of information and the content of the message can play essential roles in shaping market sentiment (Amin et al., 2020), which can be considered in analysts' forecasts. Analysts can act as intermediaries in the relationship between companies and the market, interpreting the information disclosed by companies and transmitting it to the capital market through their forecasts, and there is a demand for these interpretations. In this sense, more disclosures lead to more accurate and less dispersed forecasts from analysts (Tsao et al., 2016).

Amin et al. (2020) analyzed the relationship between corporate social media use and analysts' forecasts, particularly examining the disclosure of corporate information on Facebook, including comments, likes, and shares among companies listed in the Standard & Poor's 500 index. However, the study by Amin et al. (2020) did not analyze specific types of posts, such as corporate disclosures of financial information and user reactions to that information, and whether they influence analysts' forecasts. It is suggested that information on specific subjects may have an incremental effect on the accuracy of financial analysts' forecasts. This research expands on that literature by specifically investigating the disclosure of financial information on social media, as well as the market's reaction to these posts, measured through likes, comments, and retweets.

Thus, this study seeks to verify whether voluntary corporate disclosure on social media interferes with analysts' evaluations, through the following research question: **What is the relationship between the corporate use of X (formerly Twitter) for disseminating financial information and analysts' forecasts?** This study aimed to investigate whether the corporate use of social media X, for disseminating financial information, as well as comments, likes, and retweets related to this information, can improve the accuracy of analysts' forecasts.

The study is justified by addressing the use of social media in the corporate environment, given the growing number of users connected at both organizational and individual levels (Bartov et al., 2018; Hales et al., 2018). From a theoretical perspective, the research expands the literature on social media use to the context of a developing country, as according to Nerantzidis et al. (2024), research on this topic is concentrated in North America and Europe. Additionally, the study relates social media use to analysts' forecasts in order to provide insights into the utility of the information present on these channels.

The study expands the literature by empirically analyzing financial information published on X (Arnabold et al., 2017), the interaction on this social media platform (Teoh, 2018), how investors react to the information (Zang, 2015), and its relationship with analysts' forecasts (Amin et al., 2020). Specifically, it examines corporate tweets about financial information disclosed on the social media platform X, which differs from the study by Amin et al. (2020), who did not analyze specific information and explored the social media of Facebook. According to Dlamini and Johnston (2018), Jung et al. (2018), and Tumasjan et al. (2021), X is one of the most utilized social media platforms for corporate purposes. Brazil has over 19 million users on the social media platform X, making it the 4th country with the highest number of users on this platform (Statista, 2022).

The study provides evidence of the importance of social media, specifically X, as a channel that enables the sharing of information and interaction. This social media platform facilitates the circulation of corporate information among users, which includes sophisticated users such as financial analysts. Overall, the study contributes to all stakeholders in the organization by empirically confirming the corporate use of X for disseminating financial information. Thus, managers can benefit from using social media by maintaining closer relationships with other stakeholders and receiving feedback through direct and timely communication. Investors can use X to interact, exchange, and gather useful information for their decision-making models.

In summary, by addressing the relationship between the corporate use of social media and analysts' forecasts, the study can provide more direct evidence regarding the usefulness of corporate information disclosed on X for financial analysts. Furthermore, the research contributes to the goal of quality education as understood in the United Nations Sustainable Development Goals (SDGs), by facilitating knowledge for professional development.

2 LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Financial analysts play an important role in the capital market, as they provide earnings forecasts, buy/sell recommendations for stocks, and other useful information for investors and the market at large (Chi & Zierbrt, 2014). While organizational management can also provide earnings forecasts and guidance, the forecasts provided by analysts are generally considered more independent and potentially less biased (Embong & Hosseini, 2018). Analysts are incentivized to provide accurate forecasts (Hong & Kubik, 2003), and thus, they expend efforts throughout the period to gather and process precise information from various sources.

The existing literature presents the effects of the corporate information environment on analysts' forecasting errors. For example, Rogers and Grant (1997) report that analysts use non-financial information both within and outside of annual reports. Vanstraelen et al. (2003) show that a higher level of non-financial disclosure is associated with greater accuracy in analysts' earnings forecasts. Dhaliwal et al. (2012) demonstrated that the issuance of independent corporate social responsibility reports is associated with lower analysts' forecasting errors. Tsao et al. (2016) indicate that more organizational disclosures lead to more accurate and less dispersed analysts' forecasts. They also highlight the importance of voluntary disclosure in generating idiosyncratic information by analysts.

Amin et al. (2020) mention that, in light of technological advancements, analysts can collect information from sources beyond financial statements and traditional media. In this regard, technological tools, particularly social media, have an interactive characteristic that highlights information considered important by users through sharing, likes, and comments (Parveen et al., 2016). Thus, they contribute to the dissemination of information and capture the market's reaction and response to publications more rapidly.

The dissemination of corporate information on social media encompasses a wide range of activities, from marketing efforts to the publication of financial information, including both voluntary and mandatory disclosures aimed at increasing the visibility of organizational results. The use of new technologies, such as social media, in the corporate environment enables researchers to analyze the effects of these tools on the capital markets. Social media offers a new data source on transactions, opinions, and social interactions to the users of these channels, particularly investors (Teoh, 2018). Additionally, these platforms reach a broader audience, which can influence more investors and provide benefits to other stakeholders in the organization (Tumasjan et al., 2021; Zhang, 2015).

Regarding the use of social media and the capital market, studies have shown that these tools encompass financial, operational, and corporate social performance aspects (Paniagua & Sapena, 2014). They can improve organizational performance (Arnaboldi et al., 2017; Giordani et al., 2020; Giordani et al., 2023), provide companies control over the image they wish to establish (Yang & Liu, 2017), are positively associated with corporate liquidity (Blankespoor et al., 2014), mitigate negative price reactions (Lee et al., 2015), and maximize the relevance of accounting information (Giordani & Klann, 2022). Mota and Pinto (2017) analyzed companies that adhered to different levels of Corporate Governance at BM&FBovespa and found that large companies are more likely to disclose voluntary information on Twitter. However, there is limited evidence regarding how the corporate use of social media reflects or affects sophisticated information intermediaries, such as analysts (Amin et al., 2020).

Social media has gradually become a popular communication channel for companies (Tumasjan et al., 2021; Kaplan & Haenlein, 2010). In a high-flow trading environment where the instantaneous dissemination of information is crucial, companies are increasingly using social media to interact with investors (Amin et al., 2020), aiming to disclose organizational results and maintain two-way communication. The disclosure of financial information on these channels can highlight organizational results.

Analysts, as sophisticated intermediaries of corporate information, can interpret the managers' intent when disclosing and emphasizing specific information, publishing the same information in different ways, and using this data in their forecasting formulation. Amin et al. (2020) report that corporate information disclosed on social media helps improve the accuracy of analysts' forecasts.

This study specifically addresses the disclosure of financial information on X, as it is suggested that the disclosure of this information reflects the organization's desire to give greater visibility to its results. Thus, the financial information disclosed by companies on this social media platform can enrich the information environment for analysts and help minimize forecasting errors. Given this, this study explores the tweets related to financial information disclosed on the corporate X page of the analyzed companies, through the following research hypothesis:

H_1 – The publication of corporate tweets about financial information is negatively related to analysts' forecasting errors.

In addition to publishing tweets, companies can enhance the impact of the information disclosed on social media by increasing the frequency of messages. Bilinski (2019) argues that a greater number of posts on X leads to more positive price reactions, as well as greater user engagement with a tweet through retweets, comments, and likes. This behavior can have a similarly positive effect on organizational value.

In this sense, users, particularly investors, can enrich the companies' messages through comments and can share these messages within their own networks, increasing the impact of the news (Amin et al., 2020). This broadens the scope of action as the information is accessed simultaneously by all investors and is easier to process for less sophisticated investors (Bilinski, 2019).

The market/investor reaction reflects their expectations regarding the published news, which can also be useful for sophisticated investors, such as analysts, as it may reduce the dispersion of their forecasts (Amin et al., 2020). Overall, communication on social media can help align investors' expectations regarding the company's prospects (Bilinski, 2019).

Thus, in addition to providing greater visibility to results, the published tweets also allow for stakeholder reactions, manifested through likes, shares, and comments, which can be useful for analysts in improving the accuracy of their forecasts. Based on this, the second research hypothesis is presented:

H_2 – Retweets, likes, and comments related to corporate tweets published about financial information are negatively related to analysts' forecasting errors.

3 METHODOLOGICAL PROCEDURES

The population of this study consists of publicly traded companies listed on B3 (Brasil, Bolsa e Balcão). For the sample, companies with available data in the Refinitiv database regarding analysts' forecasts were selected. Thus, the following criteria were followed: i) publicly traded companies listed on B3; ii) with data in the Refinitiv database; iii) with data on analysts' forecasts.

Subsequently, it was observed whether the sample companies had a social media presence on X. Next, it was verified whether the sample companies with a presence on social media X published tweets about financial information. X was chosen because it corresponds to one of the most utilized platforms by organizations (Dlamini & Johnston, 2018; Jung et al., 2018; Tumasjan et al., 2021).

For collecting information on social media X, the methodology discussed by Jung et al. (2018) was used. According to this methodology, the corporate website of each company covered by analysts was first consulted to check if there was a link directing to the social media page. According to the authors, this process is essential as it ensures that the verified social media account is indeed the official one for the company. After this process, the company's X page was accessed to confirm the existence of the page and to collect the information.

The next step involved identifying tweets related to financial information. To do this, tweets from the social media of each company were loaded from the year 2013, the start of the analyzed period. Then, based on the study by Jung et al. (2018), filters were applied using the keywords: revenue, results, earnings, profits, quarter, earnings per share, and growth. It is noteworthy that in this study, the disclosure of financial information on X corresponds to the disclosure of information containing the aforementioned keywords. Thus, tweets containing financial information and the number of likes, comments, and retweets were collected from the social media of each company.

The sample consisted of 91 companies listed on B3. The analysis period covered the years 2013 to 2019. The data were analyzed quarterly, totaling 2,548 observations. Table 1 shows the number of companies with analysts' coverage (research sample), the number of tweets with financial information, as well as the number of retweets, likes, and comments related to these publications, grouped by year of analysis.

Table 1
Research Sample

Items	2013	2014	2015	2016	2017	2018	2019
Research Sample	91	91	91	91	91	91	91
Companies with Publications on X	2	4	6	9	14	13	16
Number of Publications on X *(tweets)*	15	22	42	81	124	88	101
Retweets	20	22	42	475	778	253	2.201
Likes	2	23	84	1.227	4.065	1.339	14.711
Comments	0	1	4	77	271	93	426

Source: Research Data.

It can be seen in Table 1 that the number of publications of financial information on social media X intensified in the last four years of the analysis period. Consequently, there was also an increase in the number of retweets, likes, and comments. When these variables are analyzed together, the year 2019 shows the highest volume of data. From the sample, the number of companies that published information on X during the analyzed period corresponds to a total of 17 companies.

In this study, the variable analysts' forecasting error (EPA) was used as the dependent variable, while tweets (TW), likes (CUR), comments (COM), and retweets (RT) related to financial information were used as independent variables. Market-to-book (MTB), leverage (ALAV), company size (TAM), return on equity (ROE), and analysts' coverage (CA) were included in the model as control variables. These variables were extracted from the Refinitiv® database and social media X. The analyzed variables in the study are detailed in Table 2.

Table 2
Variables Used in the Study

Variables / Definition		Formula	Collection	Authors
Dependent Variable				
EPA	Analysts' Forecasting Error	$\frac{LPA_{it} - PLPA_{it}}{LPA_{it}}$	*Refinitiv* ®	Schipper (1991); Brown (1993); Chi & Ziebart (2014); Tsao et al. (2016); Amin et al. (2020).
Independent Variables				
TW	*Tweets*	Log of the Number of Publications Related to Financial Information	X	Giordani e Klann (2022); Manetti e Belluci (2016); Manetti et al. (2017); Jung et al. (2018).
CUR	Likes	Log of the Number of Likes Related to Financial Information	X	Jung et al. (2018); Manetti e Belluci (2016); Zhang (2015).
COM	Comments	Log of the Number of Comments Related to Financial Information	X	Manetti e Belluci (2016); Manetti et al. (2017); Jung et al. (2018).
RT	*Retweets*	Log of the Number of Retweets Related to Financial Information	X	Zhang (2015); Manetti e Belluci (2016); Manetti et al. (2017); Jung et al. (2018).
Control Variables				
MTB	Market-to-book	$\frac{\text{Market Value}}{\text{Book Value}}$	*Refinitiv* ®	Tsao et al. (2016); Smith et al. (2018); Amin et al. (2020).
ALAV	Leverage	$\frac{\text{Total Liabilities}}{\text{Total Assets}}$	*Refinitiv* ®	Zhang (2015); Jung et al. (2018); Smith et al. (2018).
TAM	Size	Log of Total Assets	*Refinitiv* ®	Chi & Ziebart (2014); Lee et al. (2015); Zhang (2015); Parveen et al. (2016); Jung et al. (2018);
ROE	Return on Equity	$\frac{\text{Net Income}}{\text{Shareholders' Equity}}$	*Refinitiv* ®	Amin et al. (2020).

CA	Analysts' Coverage	Number of Analysts Making Forecasts	Chi & Ziebart (2014); Tsao et al. (2016); Smith et al. (2018); Amin et al. (2020).

Legend: LPA = Earnings per share reported by the company; PLPA = Average of analysts' earnings per share forecasts
Source: Research Data.

Regarding data analysis, the variables (EPA, MTB, ALAV, TAM, and ROE) were first winsorized at the 1% level. Additionally, with respect to the analysts' forecasting error variable, the negative sign was disregarded, as it is understood that the further from zero, the greater the analysts' forecasting error (which can be positive or negative). Subsequently, the Shapiro-Wilk test was conducted to verify normality, which showed that the data do not follow a normal distribution (Z = 11.894; p<0.000). Next, Pearson and Spearman correlations were performed. Finally, to meet the study's objective, OLS regressions with robust standard errors (using White's correction) and fixed effects control for sector and quarter were conducted using STATA software. The empirical model is presented in Equation 1:

$$EPA_{it} = \beta_0 + \beta_1 VI_{it} + \beta_2 VC_{it} + \text{Fixed effects\_sector} + \text{Fixed effects\_quarter} + \varepsilon \qquad \text{Equation 1}$$

Equation 1 was operationalized with and without the control variables (CV), to highlight the direct relationship between the independent variables (IV) (tweets (TW) and the reaction to tweets (retweets (RT)), likes (CUR), and comments (COM)) on analysts' forecasting errors (EPA), as well as when the control variables were included. Regarding the independent variables, it is noted that separate regressions were performed for each variable.

The justification for conducting robust regression lies in the presence of heteroscedasticity, as indicated by the significant White test (P = 449.39; p<0.000). Concerning the non-normality of the data, the Central Limit Theorem was considered, and this assumption was relaxed due to the number of observations. Additionally, multicollinearity between variables was tested using the Variance Inflation Factor (VIF) test, and residual autocorrelation was tested using the Durbin-Watson test, with the results provided in the results analysis section.

To provide robustness to the results, an additional analysis was conducted. A profitability variable was included in the model, as well as its interaction with the other independent variables. This test aimed to verify the effect that profitable or unprofitable companies, which publish information on X, have on analysts' forecasting errors.

4 RESULTS ANALYSIS

First, the descriptive statistics of the variables used in this research are presented. Subsequently, the Pearson and Spearman correlation matrices are shown, followed by the regression results that aim to meet the proposed objective.

The variables analysts' forecasting error (EPA), market-to-book (MTB), leverage (ALAV), size (TAM), and return on equity (ROE) were operationalized using their winsorized values at 1%. The analysts' coverage variable was not winsorized, as it corresponds to the number of analysts covering the company. Additionally, for the social media variables, logarithms were used for standardization.

Table 3 presents the descriptive statistics of the variables, which include the mean, standard deviation, 25th percentile, median, and 75th percentile. Panel A corresponds to the total sample, Panel B refers to companies that publish financial information, and Panel C represents the group of companies that do not publish such information.

Table 3
Descriptive Statistics

Variable	Mean	Standard Deviation	25th Percentile	Median	75th Percentile
Panel A – Total Sample					
EPA	0.119	0.182	0.014	0.045	0.129
MTB	2.550	2.727	0.976	1.629	3.098
ALAV	0.589	0.212	0.450	0.582	0.745
TAM	23.257	1.505	22.269	23.085	24.041
ROE	0.027	0.061	0.009	0.026	0.048
CA	2.942	1.526	2	3	4
Panel B – Companies with Publications					
TW	0.754	0.874	0	0.693	1.098
CUR	2.447	1.863	1.098	1.397	3.401
COM	0.522	1.089	0	0	0.693
RET	1.460	1.429	0	1.386	2.197
EPA	0.128*	0.177	0.018	0.064	0.134
MTB	2.093	1.757	0.957	1.480	2.261
ALAV	0.601	0.197	0.496	0.576	0.750
TAM	24.718***	1.665	23.527	24.664	25371
ROE	0.028	0.052	0.010	0.028	0.045
CA	3.828***	1.647	2	4	6
Panel C – Companies without Publications					
EPA	0.118	0.183	0.014	0.044	0.129
MTB	2.576	2.769	0.977	1.637	3.106
ALAV	0.588	0.213	0.448	0.583	0.745
TAM	23.176	1.453	22.242	23.036	23.982
ROE	0.027	0.062	0.009	0.026	0.048
CA	2.893	1.504	2	3	4

Legend: EPA = Analysts' Forecasting Error; TW = Tweets; CUR = Likes; COM = Comments; RT = Retweets; MTB = Market-to-book; ALAV = Leverage; TAM = Size; ROE = Return on Equity; CA = Analysts' Coverage. Significance levels of the Mann-Whitney Test: * p<0.1. ** p<0.05. *** p<0.01.

Table 3 shows that, on average, the analysts' forecasting error for companies that publish financial information on X is higher compared to companies that do not publish. This difference is significant at the 10% level according to the Mann-Whitney Test. Additionally, the variables size and analysts' coverage also showed significant differences between the groups. On average, companies that publish information are larger in size and have more analysts covering them.

Furthermore, the companies in the sample, on average, have a market value (MTB) 2.5 times greater compared to their book value. For every R$ 1.00 of assets, they have R$ 0.58 in third-party capital, and the company's equity generates an average profit of about 2%. Regarding analysts' coverage, it is observed that, on average, the companies in the sample are followed by approximately 3 analysts, with the 25th and 75th percentiles showing a variation from 2 to 4. According to non-tabulated data, the minimum and maximum values for this variable are 1 and 6, respectively. Next, Table 4 presents the correlation matrices, with Pearson's correlation in the lower triangle and Spearman's correlation in the upper triangle.

Table 4
Spearman and Pearson Correlation

Variável	EPA	TW	CUR	COM	RT	MTB	ALAV	TAM	ROE	CA
EPA	1	-0.009	0.011	0.039	0.002	-0.073**	0.053**	0.056**	0.004	-0.067**
TW	0.016	1	0.719**	0.476**	0.711**	-0.039*	-0.035	0.171**	-0.012	0.127**
CUR	0.002	0.770**	1	0.581**	0.844**	-0.051**	0.021	0.228**	-0.027	0.133**
COM	0.029	0.418**	0.727**	1	0.568**	-0.072**	0.021	0.158**	-0.038	0.086**
RT	-0.002	0.724**	0.917**	0.763**	1	-0.042*	0.006	0.213**	-0.005	0.128**
MTB	-0.009	-0.061**	-0.070**	-0.053**	-0.061**	1	0.007	-0.224**	0.445**	0.200**
ALAV	0.039*	-0.035	0.014	0.024	0.006	0.082**	1	0.368**	-0.015	0.112**
TAM	0.057**	0.165**	0.251**	0.202**	0.238**	-0.213**	0.383**	1	-0.035	0.451**
ROE	0.041*	-0.031	-0.024	-0.026	-0.021	0.322**	-0.051**	-0.044*	1	0.186**
CA	-0.057**	0.169**	0.156**	0.072**	0.144**	0.144**	0.135**	0.485**	0.115**	1

Legend: EPA = Analysts' Forecasting Error; TW = Tweets; CUR = Likes; COM = Comments; RT = Retweets; MTB = Market-to-book; ALAV = Leverage; TAM = Size; ROE = Return on Equity; CA = Analysts' Coverage. Significance Levels: * p<0.1. ** p<0.05. *** p<0.01. Source: Research Data.

Table 4 shows that the social media variables, companies that publish financial information on X (TW), and reactions to these publications, evidenced by Likes (CUR), Comments (COM), and retweets (RT), did not show a significant correlation with the dependent variable (EPA). In a preliminary analysis, these results differ from expectations.

Regarding the other variables used as controls in this study, the Pearson correlation results indicate that leverage, size, and return on equity were positively correlated with analysts' forecasting errors. This suggests that analysts may have greater difficulty forecasting for larger, more leveraged, and more profitable companies. The analysts' coverage variable showed a negative correlation, suggesting that the more analysts cover a company, the smaller the forecasting error. In terms of Spearman correlation, similar results were observed. However, it is noteworthy that market-to-book had a negative correlation with EPA, while return on equity did not show a significant correlation.

Table 5 presents the results of the relationship between the corporate use of social media X to disclose financial information and the reaction of other users on the platform with analysts' forecasting errors, which is the focus of this research. It is important to highlight that the analysis data is quarterly. Specifically, data referring to analysts' forecasting errors in quarter t+1 and data related to X in quarter t1 were used to verify whether tweets from the current quarter influence analysts' forecasts for the following quarter.

It is worth noting that the assumptions of residual autocorrelation (Durbin-Watson) and multicollinearity (Variance Inflation Factor) of the variables were verified and did not present any issues, as shown in Table 5 by the Durbin-Watson and VIF tests, respectively.

Table 5
Analysts' Forecasting Error and Corporate Use of Social Media

Variables	Dependent Variable: Analysts' Forecasting Error (EPA)							
	Mod 1 Coef. (Est. *t*)	Mod 2 Coef. (Est. *t*)	Mod 3 Coef. (Est. *t*)	Mod 4 Coef. (Est. *t*)	Mod 5 Coef. (Est.*t*)	Mod 6 Coef. (Est.*t*)	Mod 7 Coef. (Est.*t*)	Mod 8 Coef. (Est. *t*)
Constant	0.123*** (4.68)	0.424*** (5.37)	0.117*** (4.58)	0.437*** (5.52)	0.112*** (4.37)	0.433*** (5.44)	0.113*** (4.46)	0.446*** (5.65)
TW	0.011 (0.71)	0.022 (1.39)	-	-	-	-	-	-
CUR	-	-	0.010* (1.71)	0.012** (2.13)	-	-	-	-
COM	-	-	-	-	0.028* (1.84)	0.027* (1.74)	-	-
RT	-	-	-	-	-	-	0.021**	0.025***

							(2.24)	(2.85)
MTB	-	-0.010***	-	-0.010***	-	-0.010***	-	-0.010***
		(-6.29)		(-6.29)		(-6.33)		(-6.30)
ALAV	-	0.191***	-	0.191***	-	0.189***	-	0.193***
		(8.24)		(8.27)		(8.17)		(8.33)
TAM	-	-0.014***	-	-0.014***	-	-0.015***	-	-0.015***
		(-3.81)		(-4.04)		(-4.00)		(-4.22)
ROE	-	-0.527***	-	-0.527***	-	-0.528***	-	-0.528***
		(-5.28)		(-5.59)		(-5.59)		(-5.60)
CA	-	-0.003	-	-0.003	-	-0.002	-	-0.003
		(-1.22)		(-1.14)		(-0.96)		(-1.17)
EF Sector/Tri	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Est. F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R^2	6.47	16.04	6.58	16.13	6.61	16.09	6.70	16.31
R^2 aj.	5.06	14.59	5.16	14.69	5.20	14.65	5.29	14.88
VIF	1.11	1.15-2.89	1.13	1.17-2.93	1.11	1.15-2.94	1.11	1.19-2.94
DW	2.038	2.048	2.035	2.043	2.038	2.037	2.034	2.042
N	2.548	2.548	2.548	2.548	2.548	2.548	2.548	2.548

Legend: EPA = Analysts' Forecasting Error; TW = Tweets; CUR = Likes; COM = Comments; RT = Retweets; MTB = Market-to-book; ALAV = Leverage; TAM = Size; ROE = Return on Equity; CA = Analysts' Coverage; Mod. = Model; Coef. = Coefficient; Est. t = t-Statistic; Ef. Fixo = Fixed effect for sector and quarter; VIF = Variance Inflation Factor; DW = Durbin-Watson; N = number of observations. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Source: Prepared by the authors.

In Table 5, it can be observed through the F-statistic that all regression models were significant. When examining the direct relationship between the publication of financial tweets, likes, comments, and retweets with analysts' forecasting errors, the explanatory power of the models ranges from 6.47% to 6.70%, respectively. When control variables are included, there is an increase in the explanatory power of approximately 10% in the models.

The association between the publication of financial information and analysts' forecast errors was not confirmed. Despite the technological environment being characterized by direct, real-time communication and driving organizations to adopt social media for the dissemination of important information, such as financial disclosures, this type of publication does not appear to affect analysts' forecasts. Another reason that may be related to this finding is that the financial information disclosed by companies on the X social media platform may not be new, meaning it may be information already obtained by analysts and, therefore, does not impact their profit forecasts.

Furthermore, contrary to theoretical expectations, a positive relationship is noted between market reaction, measured by likes, comments, and retweets, and analysts' forecasting errors. This result may reveal that the market's reaction to the financial information published by companies seems to create some noise in analysts' forecasts. This suggests that the feedback companies receive regarding the information published on X generally reflects the market's evaluation of the company and leads to less accurate forecasts from analysts.

In economic terms, an increase of one standard deviation in the variable Likes is associated with a 5.82% increase in the analysts' forecasting error relative to the average ((0.692*0.010)/0.119)[1]. Regarding the variable Comments, it is observed that an increase of one standard deviation is associated with a 6.47% increase in the analysts' forecasting error relative to the average ((0.275*0.028)/0.119) [1]. Finally, looking at retweets, an increase of one standard deviation in this variable is associated with an 8.14% increase in the analysts' forecasting error relative to the average ((0.461*0.021)/0.119) [1].

[1] Non-tabulated data related to the overall sample: the standard deviation for the likes variable (CUR) is 0.692; the standard deviation for the comments variable (COM) is 0.275; the standard deviation for the retweets variable (RT) is 0.461.

Regarding the control variables, the models in Table 5 showed the same results in terms of direction and significance. Market-to-book (MTB) exhibited a negative relationship with analysts' forecasting error, indicating that the higher the market value of the companies, the more accurate the analysts' forecasts. This finding differs from Amin et al. (2020), who did not find a significant relationship. In line with the market value of the companies, the variable size (TAM) also showed a negative relationship with EPA. This result suggests that the larger the company, the smaller the analysts' forecasting error. This evidence may be tied to the fact that larger companies are more structured, which can facilitate analysts' forecasting accuracy. This result contrasts with the findings of Amin et al. (2020) and Chi and Ziebart (2014), who found a positive relationship, as also observed in the correlation analysis (Table 4).

Leverage showed a positive relationship at the 1% level, suggesting that the more indebted a company is, the higher the analysts' forecasting error, a result also observed by Amin et al. (2020). Return on equity (ROE) exhibited a negative relationship with analysts' forecasting error. This finding suggests that analysts achieve greater accuracy in their forecasts for more profitable companies. This result differs from Amin et al. (2020), who did not find a significant relationship, as well as from the correlation result (Table 4).

Conforme os resultados evidenciados, se rejeita a hipótese H_1 da pesquisa, pois verificou-se que The corporate tweets published about financial information showed no relationship with the forecasting error. This result aligns with the findings of Amin et al. (2020), who did not find a relationship between corporate posts on Facebook and analysts' forecasts. Thus, this study does not provide evidence that corporate posts offer analysts any information that influences the accuracy of their forecasts.

Hypothesis H2 of the study was also rejected, as retweets, likes, and comments related to the corporate tweets published about financial information showed a positive relationship with forecasting errors. It was expected that the market's reaction to financial information published by companies would decrease analysts' forecasting errors. However, the opposite effect was found—the results showed that the reaction of stakeholders to the published tweets increases analysts' forecasting errors.

A possible explanation for this phenomenon could be that when companies publish information on their social media, specifically financial information, it may engage other users, especially those interested in corporate decisions. These stakeholders may react and subsequently generate new information and data. The reaction to these posts seems to influence the informational environment of financial analysts. One explanation for the result could be that companies publish overly optimistic information, leading to an optimistic reaction from stakeholders, which may, in turn, induce analysts to make errors.

These findings contradict Amin et al. (2020), who reported that the more reactions on social media, the richer the content, which can help financial analysts reduce forecasting errors. However, this difference could be tied to the fact that those authors analyzed companies from the S&P 500 index and did not assess specific information, as this study did with financial information.

The evidence supports the research by Mota and Pinto (2017), who examined the use of social media by Brazilian companies to disclose financial information. To strengthen the results, an additional test was conducted. A dummy variable was included in the models, representing 1 if the company made a profit during the period and 0 otherwise (loss during the period). Additionally, the interaction between this variable and the social media variables was tested. Table 6 presents the results of the dummy variable as well as the interactions. This test aims to verify whether profitable companies that disclose financial information on X increase analysts' forecasting errors, in order to corroborate the main analysis.

Table 6
Profitable Companies, Negative Analysts' Forecasting Error, and Corporate Use of Social Media

Variables	Dependent Variable: Analysts' Forecasting Error (EPA)							
	Mod 9 Coef. (Est. *t*)	Mod 10 Coef. (Est. *t*)	Mod 11 Coef. (Est. *t*)	Mod 12 Coef. (Est. *t*)	Mod 13 Coef. (Est.*t*)	Mod 14 Coef. (Est.*t*)	Mod 15 Coef. (Est.*t*)	Mod 16 Coef. (Est. *t*)
Constant	0.297***	0.531***	0.295***	0.543***	0.286***	0.534***	0.289***	0.552***
	(10.69)	(6.94)	(10.84)	(7.10)	(10.64)	(6.89)	(10.73)	(7.21)
TW	-0.036	-0.021	-	-	-	-	-	-
	(-1.14)	(-0.69)						
CUR	-	-	-0.019	-0.011	-	-	-	-
			(-1.60)	(-1.06)				
COM	-	-	-	-	-0.036	-0.025	-	-
					(-1.30)	(-0.99)		
RT	-	-	-	-	-	-	-0.015	-0.005
							(-0.89)	(-0.35)
D_L	-0.187***	-0.152***	-0.189***	-0.154***	-0.186***	-0.151***	-0.188***	-0.153***
	(-13.76)	(-10.48)	(-13.83)	(-10.51)	(-13.69)	(-10.41)	(-13.80)	(-10.49)
D_L*TW	0.078**	0.066*	-	-	-	-	-	-
	(2.17)	(1.87)						
D_L*CUR	-	-	0.040***	0.033***	-	-	-	-
			(3.04)	(2.61)				
D_L*COM	-	-	-	-	0.085***	0.071**	-	-
					(2.60)	(2.33)		
D_L*RT	-	-	-	-	-	-	0.051**	0.043**
							(2.51)	(2.20)
MTB	-	-0.008***	-	-0.008***	-	-0.008***	-	-0.008***
		(-5.57)		(-5.57)		(-5.61)		(-5.60)
ALAV	-	0.123***	-	0.122***	-	0.120***	-	0.124***
		(5.52)		(5.47)		(5.36)		(5.57)
TAM	-	-0.011***	-	-0.012***	-	-0.012***	-	-0.013***
		(-3.33)		(-3.54)		(-3.47)		(-3.73)
ROE	-	-0.313***	-	-0.310***	-	-0.316***	-	-0.314***
		(-3.42)		(-3.38)		(-3.44)		(-3.42)
CA	-	-0.002	-	-0.002	-	-0.001	-	-0.002
		(-0.86)		(-0.73)		(-0.52)		(-0.74)
EFSector/Tri	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Model Sig.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R^2	19.99	23.82	20.26	24.02	20.11	23.87	20.28	24.14
R^2 aj.	18.71	22.45	18.99	22.65	18.84	22.50	19.01	22.77
VIF	1.12–4.83	1.26-4.87	1.12-5.26	1.26-5.32	1.10-3.98	1.26-4.01	1.12-4.97	1.26-5.03
DW	2.083	2.069	2.078	2.063	2.083	2.069	2.075	2.060
N	2.548	2.548	2.548	2.548	2.548	2.548	2.548	2.548

Legend: EPA = Analysts' Forecasting Error; TW = Tweets; CUR = Likes; COM = Comments; RT = Retweets; D_L = Profit Dummy; MTB = Market-to-book; ALAV = Leverage; TAM = Size; ROE = Return on Equity; CA = Analysts' Coverage; Mod. = Model; Coef. = Coefficient; Est. *t* = Statistic *t*; Ef. Fixo = Fixed effect for sector and quarter; Sig. Modelo = Model Significance; VIF = Variance Inflation Factor; DW = Durbin-Watson; N = number of observations. Significance levels: * p<0.1, ** p<0.05, *** p<0.01. Source: Prepared by the authors.

In Table 6, it is noted that the regression models were significant, and analysts' forecasting errors were explained by an average of 21% through social media variables, profit dummy, and other control variables. Additionally, all regression assumptions were met. The results show a significant and negative relationship between the profit dummy variable and analysts' forecasting errors. This indicates that analysts provide more accurate forecasts for companies with profits during the period. When observing the moderation between companies with profit/loss during the period and social media variables, it is found that the relationship remains significant with analysts' forecasting errors, but with a positive sign. By adding the coefficients of the D_L and D_L*TW variables (-0.187 + 0.078 = -0.109), it is noted that the relationship is still negative, meaning that publishing information on social media has a marginal effect on the negative relationship between company profitability and analysts' forecasting errors. This result is evident both for the publication of information (tweets) by companies on X and for the reaction to these publications (likes, comments, and retweets).

These findings suggest that profitable companies that disclose information on X tend to have higher forecasting errors from analysts compared to profitable companies that do not disclose information on social media. This indicates that analysts may have more difficulty making predictions for profitable companies that publish financial information tweets. Such publications may contribute to lower accuracy in analysts' forecasts, leading to higher forecasting errors. However, the forecasting error for profitable companies that publish information on X is smaller than the forecasting error for companies that report losses during the period.

Additionally, the variation in company profitability was analyzed using a dummy variable (positive variation = 1, negative = 0), and the most profitable companies were measured with a dummy variable for the 75th percentile (1 for companies with profits above the 75th percentile, 0 otherwise). The results (not tabulated) showed a reduction in analysts' forecasting errors related to both variables. These findings are consistent with what is presented in Table 6. However, when observing the interaction between the dummy variables (profit variation and 75th percentile) and social media variables, there was no moderating effect on analysts' forecasting errors. These findings suggest that when observing companies with an increase in results during the period, especially those with higher profitability, the fact of disclosing information on X does not appear to influence analysts' forecasting errors.

Companies are increasingly adopting social media as a means of corporate communication due to the constant expansion of these tools (Bartov et al., 2018; Hales et al., 2018; Giordani & Klann, 2022). Furthermore, the interactive aspect enables bidirectional communication, which can be beneficial for the organization and influence investors (Xiang & Birt, 2021). Additionally, companies that post on these platforms may present a better image to the market, thereby maximizing their value. This combination of factors can form part of the company's strategies and provide insights into future intentions, which are crucial for analysts' forecasts. However, excessive importance given to certain information can successively lead to an optimistic market reflection, potentially distorting analysts' forecasts.

In summary, the importance of generating and disseminating information is highlighted. Specifically, this study provides evidence suggesting that corporate pages on X can affect analysts' forecasts but with the opposite effect of what was expected. Posts about financial information on corporate pages of X, and the reactions to these posts, were associated with a reduction in the accuracy of analysts' forecasts.

Although the financial information published on X had already been disclosed by the companies and was available to analysts, the fact that companies share it on social media may reveal their intent to give more emphasis and visibility to the information. Therefore, even though the information itself is not new, the company's intention behind the post and the reactions it generates may add value to the set of information already available to analysts, negatively influencing the accuracy of their forecasts.

5 CONCLUSION

The research aimed to investigate whether the corporate use of the social media platform X, for disseminating financial information, as well as the Comments, Likes, and retweets related to this information, can improve analysts' forecasting accuracy. The main findings of this research demonstrate a positive relationship between reactions to the corporate use of X and analysts' forecasting errors, considering the Brazilian companies in the sample, observed from 2013 to 2019. The corporate use of X was measured by the number of financial information posts, while the reactions to these posts considered the number of retweets, Comments, and Likes.

The primary analysis indicated that analysts' forecasting errors are maximized according to reactions to the company's financial information posts, specifically the Likes, Comments, and retweets from the previous quarter. Additionally, additional tests support the primary analysis, providing evidence that profitable companies that disclose information on X show a higher analysts' forecasting error compared to profitable companies that do not post tweets.

Given these findings, hypothesis H1 of the research was rejected, as it was found that corporate tweets about financial information had no relationship with analysts' forecasting errors in the main analysis. Hypothesis H2 of the research was also rejected, as the retweets, Likes, and Comments related to corporate tweets were positively related to forecasting errors, contrary to theoretical predictions. This result suggests that stakeholders' reactions to the company's tweets increase analysts' forecasting errors, thus being uninformative to the market and generating noise in analysts' predictions.

The corporate use of social media and the publication of financial information are part of the organization's strategies, and thus require attention from organizations. Although the information disclosed may not correspond to new financial information from the analysts' perspective, the company's goal in disseminating it through these channels may signal additional evidence to analysts. However, reactions to corporate posts on social media X are new data in the market, which, if analyzed, can generate timely information that could be considered in forecasting the company's performance.

The practical implications consist of demonstrating the corporate use of social media platform X for disseminating financial information, as well as the interaction with other users, verified through Likes, Comments, and retweets, and subsequently the effect on the accuracy of analysts' forecasts. From a theoretical perspective, the research advances by identifying the corporate use of social media in the Brazilian context and recognizing the effect of information from these channels on the financial market.

This research presents limitations, such as the inability to generalize the results, as only companies listed on the B3 with available information on analysts' forecasts in the Refinitiv® database were analyzed, which considerably limited the sample size. The social media platform studied and the terms used for searching financial information may also represent limitations, as they do not cover all types of media/financial information used by analysts. However, investigating other social media platforms and using different search terms may represent opportunities for future research. Additionally, future research could analyze the sentiment positive, neutral, and negative of Comments on corporate posts and their relationship with analysts' forecasts.

REFERENCES

Amin, A., Hasan, R., & Malik, M. (2019). Social media information and analyst forecasts. *Managerial Finance*. *46*(2), 197-216. https://doi.org/10.1108/MF-07-2018-0323

Arnaboldi, M., Busco, C., & Cuganesan, S. (2017). Accounting, accountability, social media and big data: revolution or hype?. *Accounting, Auditing & Accountability Journal*, *30*(4), 762-776. https://doi.org/10.1108/AAAJ-03-2017-2880

Bartov, E., Faurel, L., & Mohanram, P.S. (2018). Can twitter help predict firm-level earnings and stock returns?. *The Accounting Review, 93*(3), 25-57. https://doi.org/10.2308/accr-51865

Bilinski, P. (2019). Bilinski, Pawel, Living in the Digital Age: The Usefulness of Twitter, YouTube and Instagram in Corporate Communication (January 3, 2019). http://dx.doi.org/10.2139/ssrn.3311183

Blankespoor, E., Miller, G. S., & White, H. D. (2014). The role of dissemination in market liquidity: Evidence from firms' use of Twitter™. *The Accounting Review, 89*(1), 79-112. https://doi.org/10.2308/accr-50576

Brown, L. D. (1993). Earnings forecasting research: its implications for capital markets research. *International journal of forecasting*, *9*(3), 295-320. https://doi.org/10.1016/0169-2070(93)90023-G

Cade, N. L. (2018). Corporate social media: How two-way disclosure channels influence investors. *Accounting, Organizations and Society, 68,* 63-79. https://doi.org/10.1016/j.aos.2018.03.004

Chi, Y. H., & Ziebart, D. A. (2014). Benefits of management disclosure precision on analysts' forecasts. *Review of Accounting and Finance, 13,* 371-399. https://doi.org/10.1108/RAF-06-2012-0061

Dhaliwal, D. S., Radhakrishnan, S., Tsang, A., & Yang, Y. G. (2012). Nonfinancial disclosure and analyst forecast accuracy: International evidence on corporate social responsibility disclosure. *The Accounting Review*, *87*(3), 723-759. https://doi.org/10.2308/accr-10218

Dlamini, N. N., & Johnston, K. (2018). The use of social media by South African organisations. *Journal of Advances in Management Research*, *15*(2), 198-210. https://doi.org/10.1108/JAMR-05-2017-0063

Giordani, M. S.; Ferreira, L. B.; Ames, A. C.; Silva, T. P. (2023) Governança Corporativa E Desempenho De Mercado: O Efeito Moderador do Uso do Twitter. *Contabilidade Vista & Revista*,*34*(1), 74-97.

Giordani, M., & Klann, R. C. (2022). Uso Corporativo de Mídias Sociais e a Relevância da Informação Contábil. *Advances in Scientific and Applied Accounting, 15*(1). https://doi.org/10.14392/asaa.2022150102

Giordani, M., Lunardi, M. A., & Klann, R. C. (2020). Uso corporativo de mídias sociais e o desempenho de mercado. *Revista de Contabilidade e Organizações, 14,* e169560. https://doi.org/10.11606/issn.1982-6486.rco.2020.169560

Hales, J., Moon Jr, J. R., & Swenson, L. A. (2018). A new era of voluntary disclosure? Empirical evidence on how employee postings on social media relate to future corporate disclosures. *Accounting, Organizations and Society*, *68,* 88-108. https://doi.org/10.1016/j.aos.2018.04.004

Embong, Z., & Hosseini, L. (2018). Analyst Forecast Accuracy and Earnings Management. *Asian Journal of Accounting & Governance*, *10,* 97-108. http://dx.doi.org/10.17576/AJAG-2018-10-09

Hong, H., & Kubik, J. D. (2003). Analyzing the analysts: Career concerns and biased earnings forecasts. *The Journal of Finance*, *58*(1), 313-351. https://doi.org/10.1111/1540-6261.00526

Jung, M. J., Naughton, J. P., Tahoun, A., & Wang, C. (2018). Do firms strategically disseminate? Evidence from corporate use of social media. *The Accounting Review*, *93*(4), 225-252.

Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of Social Media. *Business horizons*, *53*(1), 59-68. https://doi.org/10.1016/j.bushor.2009.09.003

Lee, L. F., Hutton, A. P., & Shu, S. (2015). The role of social media in the capital market: Evidence from consumer product recalls. *Journal of Accounting Research*, *53*(2), 367-404. https://doi.org/10.1111/1475-679X.12074

Manetti, G., & Bellucci, M. (2016). The use of social media for engaging stakeholders in sustainability reporting. *Accounting, auditing & accountability journal*, *29*(6), 985-1011. https://doi.org/10.1108/AAAJ-08-2014-1797

Manetti, G., Bellucci, M., & Bagnoli, L. (2017). Stakeholder engagement and public information through social media: a study of Canadian and American public transportation agencies. *The American Review of Public Administration*, *47*(8), 991-1009. https://doi.org/10.1177/0275074016649260

Mota, S. L., & de Pinto, S. K. (2017). A utilização do *Twitter* na análise do disclosure voluntário das empresas brasileiras com níveis diferenciados de governança corporativa. *Revista Evidenciação Contábil & Finanças*, *5(*1), 22-38. https://doi.org/10.18405/recfin20170102

Nerantzidis, M., Tampakoudis, I., & She, C. (2024). Social media in accounting research: A review and future research agenda. *Journal of International Accounting, Auditing and Taxation*, 100595. https://doi.org/10.1016/j.intaccaudtax.2024.100595

Paniagua, J., & Sapena, J. (2014). Business performance and social media: Love or hate?. *Business horizons*, *57*(6), 719-728. https://doi.org/10.1016/j.bushor.2014.07.005

Parveen, F., Jaafar, N. I., & Ainin, S. (2016). Social media's impact on organizational performance and entrepreneurial orientation in organizations. *Management Decision*, *54*(9), 2208-2234.

Rogers, R. & Grant, J. (1997). Content analysis of information cited in reports of sell-side financial analysts. *Journal of Financial Statement Analysis*, *3*(1), 17-30.

Schipper, K. (1991). Analysts' forecasts. *Accounting horizons*, *5*(4), 105-121.

Smith, A. L., Alfonso, E., & Hogan, R. (2018). The impact of an SEC investigation on conference call participation and analysts' forecast quality. *Research in Accounting Regulation*, *30*(2), 148-158. https://doi.org/10.1016/j.racreg.2018.09.006

Statista, (2022). *Number of monthly active Twitter users worldwide from 1st quarter 2010 to 1st quarter 2022*. https://www.statista.com/statistics/282087/number-ofmonthly-active-twitter-users/

Teoh, S. H. (2018). The promise and challenges of new datasets for accounting research. *Accounting, Organizations and Society*, *68*, 109-117. https://doi.org/10.1016/j.aos.2018.03.008

Tsao, S. M., Lu, H. T., & Keung, E. C. (2016). Voluntary monthly earnings disclosures and analyst behavior. *Journal of Banking & Finance*, *71*, 37-49. https://doi.org/10.1016/j.jbankfin.2016.04.010

Tumasjan, A., Braun, R., & Stolz, B. (2021). Twitter sentiment as a weak signal in venture capital financing. *Journal of Business Venturing*, *36* (2), 106062. https://doi.org/10.1016/j.jbusvent.2020.106062

Vanstraelen, A., Zarzeski, M. T., & Robb, S. W. (2003). Corporate nonfinancial disclosure practices and financial analyst forecast ability across three European countries. *Journal of International Financial Management & Accounting*, *14*(3), 249-278. https://doi.org/10.1111/1467-646X.00098

Xiang, Y., & Birt, J. L. (2021). Internet reporting, social media strategy and firm characteristics–an Australian study. *Accounting Research Journal*, *34*(1), 43-75. https://doi.org/10.1108/ARJ-09-2018-0154

Yang, J. H., & Liu, S. (2017). Accounting narratives and impression management on social media. *Accounting and Business Research*, *47*(6), 673-694. https://doi.org/10.1080/00014788.2017.1322936

Zhang, J. (2015). Voluntary information disclosure on social media. *Decision Support Systems*, *73*, 28-36. https://doi.org/10.1016/j.dss.2015.02.018

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding this submitted work.

AUTHOR CONTRIBUTIONS

Roles	1ª author	2º author
Conceptualization	♦	♦
Data Curation	♦	
Formal Analysis	♦	♦
Funding Acquisition		♦
Investigation	♦	
Methodology	♦	
Project Administration	♦	♦
Resources		♦
Software	♦	
Supervision		♦
Validation	♦	
Visualization	♦	
Writing – Original Draft	♦	
Writing – Review and Editing	♦	♦