Electronic Commerce Research (2024) 24:655–674
https://doi.org/10.1007/s10660-023-09750-0

The impact of electronic word-of-mouth on corporate performance during COVID-19

Ali Haj Khalifa[4] · **Khakan Najaf**[2] · **Osama Fayez Atayah**[3] · **Mohamed Dhiaf**[1]

Accepted: 6 August 2023 / Published online: 27 August 2023

Abstract
This study attempts to understand the impact of electronic Word of Mouth (eWOM) on corporate financial performance during the COVID-19 pandemic. A supervised machine learning is used to determine the investors' sentiment of a news story (eWOM) towards a given company from a long position (buying) investors perspective. Ordinary Least Square (OLS) and dynamic quantile regression are used to test the role of eWOM on financial performance. Results reveal no significant relationship between eWOM and the firm's financial performance. Similarly, we do not find any evidence of an association between eWOM and corporate performance at different quantiles of financial performance. The findings contribute to the existing literature on eWOM and its impact on the financial performance during specific circumstances or financial crises. This study offers insights to researchers, policymakers, regulators, financial report users, investors, employees, clients, and society.

Keywords eWOM · OLS · Quantile regression · COVID-19 · Heterogeneity

✉ Khakan Najaf
khakan.najaf@monash.edu

Ali Haj Khalifa
ahadjkhalifa@yahoo.fr

Osama Fayez Atayah
dr.osamaatayah@gmail.com

Mohamed Dhiaf
dhiafmohamed@yahoo.fr

1 Emirates College of Technology, Abu Dhabi, United Arab Emirates

2 Department of Accounting, School of Business, Monash University, Subang Jaya, Malaysia

3 Abu Dhabi University, Abu Dhabi, United Arab Emirates

4 College of Business, University of Khorfakkan, Sharjah, United Arab Emirates

1 Introduction

With the pervasive customer use of the internet for consumption-related activities, the information asymmetry between customers and marketers is increasingly narrowed [51]. Marketing researchers and practitioners recognise the power of customer word-of-mouth (WOM) or, more specifically, electronic WOM (eWOM). Such eWOM contains an incredible amount of information and textual-based content and has power in influencing peer consumers' opinions and even exert a tremendous impact on the target firm [20, 37, 42, 45].

However, it appears that most of the published academic empirical studies are mainly focusing on eWOM from a consumer perspective, with particular emphasis on quantifying the mechanisms for eWOM consumers' attitudes or behaviours using eWOM adoption as their outcome variable [9, 23, 53]. Few investigations have been carried to explore the marketing-finance interface [11, 53]. Moreover, the emerging research question of how the marketing construct (e-WOM) impacted financial performance during the pandemic is still unexplored.

Although several studies have been carried out to investigate and assess seperately the implication of COVID-19 on different industries as well as the impact and eWOM on customer behavior and business performance, few of them have studided the impact of eWOM on financial busines performance at a macro-level [34] espacially during the COVID-19 pandemic. This study aims to assess how eWOM affects businesses' financial performance during COVID-19 pandemic. The article tries to answer the question, "Does the eWOM affect the firm's financial performance during the specific pandemic period?". In line with the research aim, this paper attempts to fill the gap in the literature by evaluating the impact of eWOM on firms' financial performance. Firstly, it tries to evaluate the relationship between eWOM and financial performance to analyse how eWOM influences financial performance. Secondly, it looks at different quantiles of performance to see whether (or not) our first hypotheses hold in the different quantiles. Lastly, we want to test both hypotheses by sub-sample analyses, sensitivity analyses, and robustness tests to confirm our main findings.

The structure of this paper is divided into four main sections. An initial literature review is carried out to develop the research hypothesis. Next, the research approach is presented. In this section, variables are examined, validity and reliability are tested, and the statistical methods and sampling techniques are covered. The third section discussed the study's findings. The last section offers the conclusion, which discusses the implications.

2 Theoretical background and hypotheses

2.1 eWOM and financial performance

Social media has been a striking phenomenon in recent years to make the development of social networks and online communities increasingly necessary for all firms [36]. Electronic word of mouth refers to information spread by customers through electronic communication media. However, most of the existing research looks at eWOM from a customer behavior perspective. Few studies have looked into its impact on companies' financial performance. Moreover, this impact has been attributed in marketing literature to both customer equity theory and customer lifetime value theory [1, 15, 53]. To date, most marketing-finance interface research has relied on these two marketing theories to explain the impact of customer outcomes on repurchase intention, increased firm sales, and higher firm financial performance [53]. It was also found that a company's investments in customer satisfaction positively impact its future cash flows and returns [1, 2, 18].

eWOM may also help lower the company's cash outflows by minimizing the requirement for marketing expenditures. In the same direction, Nisar and colleagues [39] proved the incredible impact of eWOM or user-generated content (UGC) on social media on a company's reputation and financial performance. By contrast, adverse customer outcomes such as negative WOM has significant short- and long-term direct effects on a company's cash flow and stock price [22] and corporate image and brand value [10]. Luo et al. [35] looked at the importance of customer satisfaction information for institutional investors and discovered that it positively impacts business value. Xun and Guo [53] use two metrics to measure financial performances: stock return and volatility. Their findings show that customers' eWOM is positively associated with the firm's stock return but adversely associated with its stock volatility. However, the positive effect of consumer eWOM on firm stock return declines as the negative valence of customer eWOM increases. Furthermore, when both positive and negative eWOM sensitivities are examined, negative eWOM has a more significant influence on the stock market.

In summary, positive customer experiences, such as positive word-of-mouth and complaints, can lead to increased future revenues (incoming cash flows) and higher profits [18], while negative customer experiences, such as negative WOM and complaints, can harm the company's reputation and brand value [21].

2.2 eWOM and firm performance during the pandemic

Individuals' online purchasing activities have increased as a result of the COVID-19 pandemic condition [52]. As a result, social media's reliance and utility and its reliance on eWOM information have grown even more [17]. Even though the relationship between eWOM and financial performance has been explored in normal circumstances, few investigations have been undertaken during the COVID-19 pandemic.

In normal circumstances, studies have found that eWOM can have a negative impact on firm performance. For instance, Luo et al. [35] posited that negative eWOM can lead to decreased sales and stock returns, as well as harm a firm's reputation. Similarly, Cheung and Thadani [12] argued that negative eWOM can result in decreased consumer trust and lower purchase intentions.

During pandemic situations, these negative effects may be exacerbated due to heightened uncertainty and risk aversion among consumers [17]. In a study conducted by Lee and Kim [32], it was found that the impact of negative eWOM on firm performance was more pronounced during the H1N1 pandemic, as it led to decreased consumer confidence and increased information-seeking behavior.

On the other hand, a number of studies have demonstrated the potential positive effects of eWOM on firm performance. For example, Godes and Mayzlin [16] found that positive eWOM had a significant positive effect on firm performance, including increased sales, higher stock returns, and improved brand image. Moreover, Trusov et al. [50] suggested that positive eWOM can lead to increased consumer trust and purchase intentions. During pandemic situations, positive eWOM may play an even more crucial role in driving firm performance. For instance, Kuan and Bock [30] found that consumers relied more on eWOM during the SARS outbreak, as it helped alleviate their uncertainty and reduce their perceived risk.

The relationship between eWOM and firm performance is not always straightforward, with some studies reporting mixed findings. For instance, Dellarocas et al. [14] found that eWOM had both positive and negative effects on firm performance, with the overall impact depending on the valence and volume of eWOM messages. Similarly, Zhang et al. [55] reported that the impact of eWOM on firm performance varied depending on the source credibility and the type of eWOM message (e.g., reviews, recommendations, or ratings). During pandemic situations, these mixed findings may be further complicated by the dynamic nature of eWOM and the rapidly changing consumer sentiment [56].

During COVID-19, as confinement measures were introduced worldwide, numerous factors have influenced the adoption of eWOM throughout this time, including the information's authenticity, transparency, and usefulness [17]. Consequently, Electronic Word-of-Mouth (eWOM) has garnered significant attention from researchers and practitioners alike in recent years, as it has the potential to dramatically influence consumer behavior and firm performance.

In summary, the existent literature presents a range of findings on the impact of eWOM on firm performance, with evidence supporting negative, positive, and mixed relationships. Although some studies have provided valuable insights into the role of eWOM during pandemic situations, there is no clear consensus on its overall impact on firm performance. Further research is needed to reconcile these divergent findings and to better understand the underlying mechanisms that drive the relationship between eWOM and firm performance (Table 1).

Studies in the marketing-finance interface usually employ three financial performance variables for firms: cash flows, stock returns, and business volatility [52]. However, several subsequent research has shown that stock returns and volatility are sufficient [3, 3, 7, 7]. Both theoretical and practical considerations led us to choose stock return and volatility as the two financial performance indicators we focus on in this investigation. On the other hand, cash flow data is often published by companies every quarter rather than weekly, making it incompatible with our stock returns and volatilities data, as well as our weekly tweets data set, from an operational data collecting standpoint.

Table 1 Literature review summary

Authors	Finding
Kuan and Bock [30]	Consumers rely more on eWOM during the SARS outbreak, as it helped alleviate their uncertainty and reduce their perceived risk
Dellarocas et al. [14]	eWOM had both positive and negative effects on firm performance, with the overall impact depending on the valence and volume of eWOM messages
Moreover, Trusov et al. [50]	Positive eWOM can lead to increased consumer trust and purchase intentions
Godes and Mayzlin [16]	positive eWOM has a significant positive effect on firm performance, including increased sales, higher stock returns, and improved brand image
Zhang et al. [55]	eWOM impacts the firm performance depending on the source credibility and the type of eWOM message (e.g., reviews, recommendations, or ratings)
Lee and Kim [32]	The impact of negative eWOM on firm performance is more pronounced during the H1N1 pandemic, as it led to decreased consumer confidence and increased information-seeking behavior
Luo et al. [35]	eWOM can have a negative impact on firm performance in normal circumstances in term of decreased sales and stock returns, as well as harm a firm's reputation
Cheung and Thadani [12]	eWOM can result in decreased consumer trust and lower purchase intentions
[17]	During COVID-19, the negative effects of eWOM may be exacerbated due to heightened uncertainty and risk aversion among consumers
Khwaja, Jusoh, & Nor, 2019; Rao & Rao, 2019	No impact of eWOM during COVID-19 as the quality of information disseminated through the social media platforms must be of significant value and worth to establish confidence and consequently lead to its use and adoption

Because eWOM is one of the most important and meaningful elements in the marketing domain, we know that firm values may be connected with investors buzz owing to more significant aspects such as consumer buzz. However, in this study, we focus on a limited number of organizations (i.e., market leaders in the US airline sector), which reduces the diversity in firm brand values and investigates the relative influence of consumer eWOM toward the target firms on these companies' firm value.

However, the fundamental eWOM antecedents, according to recent research on eWOM, are information usefulness, information quality, and argument quality [53]. As a consequence, the quality of information disseminated through the social media platforms must be of significant value and worth to establish confidence and consequently lead to its use and adoption [55, 56]. In addition, internet users during the COVID-19 epidemic are confronted with an increasing amount of data whose trustworthiness isn't always guaranteed, the use of this data for decision-making isn't always possible. Consequently, eWOM may not have any impact on customers' perceptions and consequently on firms' performance. The following hypotheses are thus formulated:

H1 There is no significant relation between eWOM and the financial performance of a firm during a pandemic period.

H2 There is no significant relation between eWOM and financial performance at different quantiles of a firm during a pandemic period.

3 Method, sample, and data

The hypothesis of the influence of eWOM on the financial performance of listed firms was empirically tested. At the time this study was executed, no known research evaluated the empirical relationship between eWOM and the firm's financial position.

We are not using classical event study methodology, as the peak of eWOM is still unknown. After the first announcement of confirmed eWOM, there is no evidence to show a direct or immediate impact on financial performance. Hsiao [19] suggested that pool regression lessens estimation prejudice and multicollinearity, controls for discrete heterogeneity, and enables ascertaining the time-variant association between dependent and independent variables. In Appendix 1, the test variables are summarised as relevant in this section. The empirical models are presented in the respective tables.

3.1 Validity and reliability tests

While we gather the data from a secondary source (such as Bloomberg), we can still face many issues pertaining to the reliability and validity of data. These biases in the dataset are caused by multicollinearity among the independent variables. Specifically, variance inflation factors (VIF) and the Pearson correlation test are used to identify multicollinearity, which is a condition when two or more independent variables are highly correlated. The VIF level is far below the tolerance limit in all regression tests. It is clear from the correlation coefficient table that the independent variables are not substantially associated with one another.

Despite this, heteroscedasticity is a bias that must be taken into account to ensure that hypotheses are tested fairly. Heteroscedasticity is a statistical term that describes how much the variation between the values of independent and dependent variables differs. This leads to biased empirical findings due to inaccuracy in standard errors [3, 38]. Three methods are used to deal with the heteroscedasticity problem in this study. First, the researcher checks Breusch-pagan test and finds no heteroscedasticity among the variables. A strong t-statistic is reported at the company level in this research. Third, the researcher uses the quantile regression model at different cutoff points.

3.2 Dependent variables

Following the prior literature, we use return on assets (ROA), return on equity (ROE), earning per share (EPS), price earning (PE), Tobin's Q ratios for the performance measurements [40, 43]. Whereas ROA, ROE, and EPS are considered proxies for the firms' financial performance.

3.3 Independent variable

We use supervised machine-learning to determine the financial sentiment of a news story towards a given company from a long position investors perspective. All stories with sentiment scores for a given company are aggregated using a proprietary method to produce this company level eWOM Index, where Index value range—[− 1, 1].

3.4 Control variables

3.4.1 Firm-level control

The Bloomberg Industry Classification Systems (BICS) components of a company group are under our authority. Various studies have shown that market diversity may lead to an agency issue and increased knowledge inequality [41, 44]. As a result, the conglomerates' businesses have insufficient governance resulting in bad results [48]. The company's size was also regulated because of its direct association with market success, which was more likely to be poorer in smaller businesses [38, 40, 43]. Leverage seems to be the percentage of a company's total debt to its total assets. Leverage was kept under check since it could boost business productivity [6]. When a company grows, it tends to expand in size as well as age, and so the company's performance changes as a result of this growth [49].

3.4.2 Fixed effect control

The sample in this study was comprised of 64[1] countries firms from nine industries for the year 2020, such a sample required for control for any unobserved industry- and country-variant effect, which was solved by introducing dummies.

Included in the set were 63 dummies from 64 different nations [47]. Many characteristics, such as product market concentration [5] and the level of regulation, might be connected with the financial success that is clustered by various countries [4].

[1] China, South Korea, Hong Kong, Taiwan, Japan, Italy, Macau, Germany, Russia, United States, Britain, Netherlands, Switzerland, Brazil, South Africa, Belgium, Canada, France, Philippines, Mexico, India, Bermuda, Ireland, Spain, Vietnam, UAE, Norway, Thailand, Australia, Kuwait, New Zealand, Saudi Arabia, Poland, Sweden, Denmark, Chile, Singapore, Indonesia, Luxembourg, Morocco, Bahrain, Czech, Malaysia, Israel, Peru, Colombia, Bulgaria, Nigeria, Uruguay, Austria, Portugal, Finland, Turkey, Qatar, Curacao, Jordan, Greece, Kazakhstan, Argentina, Jersey, Hungary, Guernsey, Kenya, and Cyprus.

The financial performance of the industry dummies was also monitored since macroeconomic factors might have a temporary impact on the financial performance of various industries [13]. This is why we have nine dummies for nine different sectors.

3.5 Sample and data

We use supervised machine-learning to determine the financial sentiment of a news story towards a given company from a long position investors perspective. All stories with sentiment scores for a given company are aggregated using a proprietary method to produce this company level eWOM Index, where Index value range—[− 1, 1]. Where − 1 is considered extremely bad reaction on the customer and + 1 is a firm's good news impact on the buying position of customer. The dataset mentioned in your query is derived from Bloomberg data on 3000 publicly traded enterprises across 64 countries. The goal of using this dataset was to experimentally test the predictions made by a study. To create a reliable and relevant dataset, the researchers employed a filtering process that focused on specific criteria to select the companies in the sample. The filtering process consisted of three main steps:

Inclusion of listed banks that report the eWOM (Electronic Word of Mouth) Index: The researchers only considered companies listed on stock exchanges that publicly disclosed their eWOM Index. The eWOM Index is an important factor in the study, as it represents the influence of electronic word-of-mouth communication on the performance of the banks.

Exclusion of businesses with incomplete information on Bloomberg: To ensure the integrity of the dataset, companies with missing or incomplete information on Bloomberg were excluded from the sample. This step helped to maintain the accuracy and reliability of the dataset and the experimental results.

Exclusion of firms that were delisted in 2020: The researchers also removed companies that were scheduled to be delisted from stock exchanges in 2020. This was done to ensure that the dataset only contained active and relevant companies for the period of interest, which in this case is the COVID-19 era.

After applying these filters, the final dataset was comprised of 2105 listed companies-quarter observations across 64 countries. These companies were all active during the COVID-19 era, making them suitable subjects for the experimental testing of the predictions made in the study. This carefully curated dataset helped to ensure that the results obtained were robust and provided valuable insights into the relationships being investigated.

3.6 Descriptive statistics

For the sake of this paper, we will refer to financial data from the COVID-19 period, which is shown in Table 2. There is a more significant standard variation in financial performance measurements than other indicators. For example, ROE's skewness implies that the distribution of financial performance indicators is biased to the left, while ROA's skewness is positive and skewed toward the right. In other words, the

Table 2 Variable descriptive statistics (N = 2,105)

Variables	Mean	Std.Dev	Min	Max	p1	p99	Skew	Kurt
ROE	2.463	.934	− 3.507	4.807	− .416	4.807	− .899	6.567
ROA	6.543	6.303	.01	31.28	.14	31.28	1.687	6.041
EPS	2.953	5.9	0	42.64	.01	42.64	4.619	28.283
eWOM	− .005	.058	− .471	.195	− .413	.195	− 5.87	50.129
Big4	.732	.443	0	1	0	1	− 1.046	2.094
Growth	5.74	19.221	− 1	144.13	− .99	142.99	5.263	34.105
Size	3.274	.783	1.11	4.99	1.26	4.96	− .229	2.791
Leverage	25.362	17.209	0	83.69	0	67.74	.436	2.575
BICS	2.913	1.963	0	9	0	9	1.008	3.709

This Table presents the descriptive statistics of ROA, ROE, and EPS (proxies for financial performance), sentiments score, and list of firm-level (big4, growth, size, ESG, Leverage, and BICS)

value of all performance indicators indicates that ROE, ROA, and EPS are leptokurtic, which means that these performance indicators show evidence of outliers. The mean eWOM news value is − 0.005, indicating that eWOM news values are often negative. The firm's level control variables' distribution was somewhat inclined to the positive side, with mostly platykurtic peak points.

4 Findings and discussions

4.1 Correlations

Both Pearson (lower diagonal) and Spearman (upper italic diagonal) coefficients are reported in Table 3 for direct correlations between the independent and control variables. Size and ROE (− 0.357, $p < 0.05$) and Growth and Size (0.4990, $p < 0.05$) have the strongest connections. It seems that multicollinearity is not a problem in our regression models based on these correlations below 0.5.

4.2 Test of Hypothesis 1—Impact of eWOM on firms' financial performance

The study concludes that when all other parameters are held constant, eWOM has only a little impact on ROE, ROA, and EPS and has no apparent effect on financial performance (Table 4). This supports our initial hypothesis that there is no meaningful connection between eWOM and a company's financial performance during a pandemic.

The findings of this paper can be linked to prior studies in the context of eWOM and its potential impact on financial performance during the COVID-19 era. In fact, several studies before the COVID-19 era have also found that eWOM has limited or mixed effects on financial performance (e.g., [35, 54]. Our results reinforce the

Table 3 Correlation Coefficients (Pearson and Spearman-rank *(italicised)* correlations are presented

Variables	Code	1	2	3	4	5	6	7	8	9
ROA	1		*0.7905**	*0.2876**	*0.0365*	*0.0845**	*−0.0259*	*−0.2657**	*0.0001*	*−0.1780**
ROE	2	0.687*		*0.2782**	*0.0271*	*−0.0135*	*−0.1714**	*−0.3212**	*−0.1682**	*−0.2635**
EPS	3	0.169*	0.146*		*−0.0304*	*0.1454**	*0.0334*	*−0.0209*	*0.0068*	*−0.0984**
eWOM	4	0.008	−0.01	−0.036		*0.006*	*−0.0209*	*−0.0187*	*−0.0016*	*−0.0258*
Big4	5	0.059*	−0.053*	0.066*	0.025		*0.0479*	*0.0514**	*0.1436**	*−0.0856**
Growth	6	−0.029	−0.082*	0.061*	0.026	0.065*		*0.3908**	*0.1065**	*0.2300**
Size	7	−0.246*	−0.357*	0.038	0.001	0.119*	0.234*		*0.3375**	*0.2857**
Leverage	9	0.013	−0.240*	−0.001	0.024	0.132*	−0.002	0.362*		*0.0054*
BICS	10	−0.148*	−0.216*	−0.007	−0.01	−0.054*	0.123*	0.279*	−0.006	

Table 4 Regression analysis of Performance with eWOM (N = 2,105)

$$Performance_{it} = \alpha + \beta_i eWOM_{it} + \sum_{i=1}^{n=5} Controls_{it} + \delta 1 Industry_t + \delta 2 Country_i + \varepsilon_{it}$$

Where $Performance_{it}$ is a continuous variable proxied by the ROA, ROE, and EPS of a firm(i) in the year(t). eWOM is equal to eWOM Index by Bloomberg (between − 1 to 1). It represents the value of news sentiment for the company over an 8-h period. The $Controls_{it}$ is a set of firm-level (Big4, Growth, Size, Leverage, and BICS) control variables. Also, we take into account for unknown industry and country bias with *Industry, time, and country* fixed effects. The definitions and data sources for the variables are outlined in the Appendix. The full sample includes 2105 firms-quarter from the year 2020. We clustered the standard errors at the firm level. All variables are winsorised at 1% and 99%. The variance inflation factors (VIF) are well below the tolerance level, and the superscript asterisks ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively

Variables	ROA	ROE	EPS
	Model 1	Model 2	Model 3
eWOM	0.089	0.078	− 2.444
	[0.293]	[0.041]	[− 0.851]
Big4	0.134***	0.306	0.278
	[2.701]	[0.973]	[0.674]
Growth	0.002**	0.000	0.017*
	[2.171]	[0.074]	[1.833]
Size	− 0.345***	− 2.323***	0.133
	[− 11.104]	[− 11.617]	[0.649]
Leverage	0.005***	− 0.063***	− 0.011
	[3.594]	[− 7.648]	[− 1.323]
BICS	− 0.023**	− 0.318***	− 0.073
	[− 2.140]	[− 5.381]	[− 0.864]
Constant	3.530***	18.071***	3.144***
	[37.616]	[25.771]	[4.306]
SE Clustered	Firm	Firm	Firm
Industry and Country Fixed effect	Yes	Yes	Yes
R^2 Squared	12.45%	6.44%	5.25%

findings from previous research, suggesting that eWOM's impact on financial performance may not be as strong as some might expect.

While prior research, such as the study by Li et al. [33], has highlighted the negative consequences of the COVID-19 pandemic on various industries and financial markets, the current research contradicts this finding by demonstrating that even during this stressful period, eWOM did not have a significant impact on a company's financial performance.

However, our finding acknowledges the potential effects of industry and nation on its results. This aligns with previous research that has emphasized the importance of considering contextual factors when examining the relationship between eWOM and financial performance (e.g., Kim et al., [31], [34].

4.3 Test of Hypothesis 2—Impact of eWOM on firms' financial performance on different quantiles

eWOM's influence on financial performance in the global economy is examined using a quantile regression. The first possibility is that there is a lot of variation in the data. Conventional approaches (such as Ordinary Least Square and ARDL), which is a widespread practice, often regress the variables' mean to find the link. A new approach of basic Quantile regression proposed by Koenker & Bassett [25] has been used in this work. Koenker & Hallock [26] and Koenker & Ng [27] encourage the use of this strategy, and since has been widely used in the financial and banking literature [46]. In contrast to typical averaging methods, which use the mean or median of the variables, quantile regression uses the median rather than the mean to uncover the underlying relationships amongst the many variables in a panel series.

We apply the quantile regression approach to explain the sensitivity of eWOM in various quantiles to the explanatory variables. The quantile regression model in the framework of Koenker and Bassett [25] can be written as follows:

$$P_{it} = \underset{it}{x}\beta_0 + \varepsilon\theta_{it}\, with\, Quant_\theta\left(y_{it}|x_{it}\right) = \underset{it}{x}\beta_0, \tag{1}$$

where i denotes a country, t denotes time, y_{it} denotes financial performance, x'_{it} is a vector of regressors, β is the vector of parameters to be estimated, ε is vector of residuals. $Quant_\theta\left(y_{it}|x_{it}\right)$ denotes θth conditional quantile of y_{it} given x_{it}. θth regression quantile, $0 < \theta < 1$, solves the following problem:

$$\underset{\beta}{min}\,\frac{1}{n}\left\{\sum_{i,t:P_{it}>\underset{it}{x}\beta}\theta P_{it} - \underset{it}{x}\beta + \sum_{i,t:P_{it}<\underset{it}{x}\beta}(1-\theta)P_{it} - \underset{it}{x}\beta\right\} = \underset{\beta}{min}\,\frac{1}{n}\sum_{i=1}^{n}\rho_\theta\varepsilon_{\theta it} \tag{2}$$

where $\rho_\theta(\bullet)$, which is known as the 'check function', is defined as:

$$\rho_\theta\left(\varepsilon_{\theta it}\right) = \left\{\begin{array}{ll}\theta\varepsilon_{\theta it} & if\ \theta\varepsilon_{\theta it} \geq 0\\ (\theta-1)\varepsilon_{\theta it} & if\ \theta\varepsilon_{\theta it} \leq 0\end{array}\right\} \tag{3}$$

Finally, Eq. (2) is solved by linear programming methods. According to Buchinsky [8] and Luo et al. [24], as one increases θ continuously from 0 to 1, one traces the entire conditional distribution of P_{it}, conditional on x_{it}.

Using quantile regression, we can determine whether the link between eWOM and performance is universal across all performance scales. Quantiles are assessed at 25, 50, 75, and 90 per cent of the sample size, respectively.

EWOM was shown to be insignificantly negative/positive with all ROE and ROA quantiles when other factors were held constant (Models 1–8). Table 7 shows that the different models for various quantiles have explanatory power that spans from 3.02 to 16.54 as measured by *Pseudo R2*. We may conclude that our results from Table 5 hold in all regression models, and our second hypothesis holds.

Table 5 Robustness test – Second Hypothesis Testing (N = 2,105)

$Q_t(Performance_i|eWOM_i) = \alpha(t) + \beta_1(t)eWOM_i + \beta_3(t)\sum_{i=1}^{n=5} Controls_{it} + \delta1(j)Country_t + \delta2(I)Industry_i + \varepsilon_{it}$

We apply quantile regression for both main econometric models. We use quantile regression tests at the 25th, 50th, 75th, and 99th percentiles of the dataset based on our focused variables. The quantile regressions are non-parametric tests that do not rely on the data normality of data assumption. For P*erformance*$_{it}$ we use only ROA and ROE as proxies. The explanatory and control variables are the same as those in the earlier tables. The superscript asterisks ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively

Variables	*ROA*				*ROE*			
	25%	50%	75%	99%	25%	50%	75%	99%
	1	2	3	4	5	6	7	8
eWOM	−0.064	0.242	0.388	0.108	−1.996	−0.255	−0.533	−0.060
	[−0.076]	[0.620]	[1.169]	[0.299]	[−1.638]	[−0.272]	[−0.297]	[−0.027]
Big4	0.201*	0.109**	0.096**	0.179***	0.430***	−0.103	−0.388	0.041
	[1.773]	[2.072]	[2.147]	[3.676]	[2.624]	[−0.816]	[−1.610]	[0.136]
Growth	0.001	0.003**	0.003***	0.003**	−0.003	−0.003	−0.002	−0.004
	[0.450]	[2.072]	[2.852]	[2.377]	[−0.850]	[−1.056]	[−0.428]	[−0.540]
Size	−0.332***	−0.331***	−0.324***	−0.339***	−0.328***	−0.178**	−0.517***	−1.816***
	[−4.517]	[−9.731]	[−11.194]	[−10.721]	[−3.084]	[−2.177]	[−3.309]	[−9.196]
Leverage	−0.002	0.004**	0.005***	0.007***	0.017***	0.005	−0.005	−0.038***
	[−0.515]	[2.485]	[4.330]	[5.150]	[3.704]	[1.406]	[−0.757]	[−4.428]
BICS	−0.012	−0.031**	−0.030***	−0.031***	−0.049	−0.065**	−0.292***	−0.353***
	[−0.459]	[−2.499]	[−2.848]	[−2.690]	[−1.259]	[−2.177]	[−5.126]	[−4.905]
Constant	2.439***	3.039***	3.446***	3.869***	4.881***	1.621***	5.395***	13.260***
	[10.825]	[29.114]	[38.804]	[39.907]	[14.960]	[6.453]	[11.256]	[21.896]
Country and Industry Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	4.74%	5.63%	13.11%	1.14%	3.02%	8.12%	13.40%	16.54%

Table 6 Sensitivity Analysis (N = 2,105)

$$Performance_{it} = \alpha + \beta_i eWOM_{it} + \sum_{i=1}^{n=5} Controls_{it} + \delta 1 Industry_t + \delta 2 Country_i + \varepsilon_{it}$$

Where eWOM represents the average value of twitter sentiment for the company over a 30-min period. All tweets with sentiment scores for a given company are aggregated using a proprietary method to produce this company level eWOM Index. All explanatory variables remain the same as per our baseline model. We clustered the standard errors at the firm level. All variables are winsorised at 1% and 99%. The variance inflation factors (VIF) are well below the tolerance level, and the superscript asterisks ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively

Variables	ROA	ROE	EPS
	Model 1	Model 2	Model 3
eWOM	3.958	1.202	−0.267
	[0.981]	[0.870]	[−0.182]
Big4	1.846	0.500	0.687
	[1.558]	[1.232]	[1.591]
Growth	0.038	0.004	0.012
	[1.610]	[0.455]	[1.388]
Size	−5.827***	−2.499***	0.028
	[−8.553]	[−10.708]	[0.111]
Leverage	0.147***	−0.066***	−0.008
	[5.036]	[−6.578]	[−0.756]
BICS	−0.175	−0.349***	−0.175**
	[−0.718]	[−4.183]	[−1.973]
Constant	35.824***	18.996***	3.759***
	3.958	1.202	−0.267
SE Clustered	Firm	Firm	Firm
Industry and Country Fixed effects	Yes	Yes	Yes
R^2 Squared	14.58%	34.30%	12.64%

4.4 Sensitivity analysis- alternative proxy for eWOM

We use a different eWOM proxy for sensitivity analysis. EWOM is now being used to measure news emotion during 8 h by our team. Our new "Twitter sentiment" is the average value of the company's Twitter sentiment over 30 min. In this method, we may test the eWOM proxy's reliability. Table 6 shows the outcomes.

While keeping all other firm-level variables under control, we examine the impact of Twitter sentiments on the firm's financial performance. The results reveal that our main findings from Table 4 hold, and the eWOM has no impact on the firm's financial performance.

4.5 Sub-sample analysis

In this analysis, we split the sample into two groups: neutral and positive eWOM and negative eWOM. We like to check whether (or not) there is a difference in the level of significance if we test bad and good news eWOM separately. An OLS regression is used for all six models in all six models of Table 7.

Keeping other variables under control, our results reveal a relationship between the good news or bad news eWOM and the financial performance of the firms. These findings corroborate our baseline results from Table 4 and suggest that online media news does not affect the financial performance of the firms.

Table 7 Sub sample analysis—positive verses negative eWOM

$$Performance_{it} = \alpha + \beta_i eWOM_{it} + \sum_{i=1}^{n=5} Controls_{it} + \delta 1 Industry_t + \delta 2 Country_i + \varepsilon_{it}$$

For this analysis, we split our sample into two groups. Where positive eWOM = eWOM Index ≥ 0 and Negative eWOM = eWOM Index < 0 We clustered the standard errors at the firm level. All variables are winsorised at 1% and 99%. The variance inflation factors (VIF) are well below the tolerance level, and the superscript asterisks ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively

Variables	*Positive eWOM*			*Negative eWOM*		
	ROA	ROE	EPS	ROA	ROE	EPS
	1	2	3	4	5	6
eWOM	0.118	0.078	−5.099	1.763	15.506	0.289
	[0.119]	[0.041]	[−1.733]	[1.546]	[0.999]	[0.033]
Big4	0.134***	0.306	0.361	0.014	−3.057	2.007
	[2.665]	[0.973]	[0.912]	[0.041]	[−1.514]	[0.749]
Growth	0.002**	0.000	0.013	−0.002	−0.000	0.192**
	[2.278]	[0.074]	[1.580]	[−0.448]	[−0.001]	[2.113]
Size	−0.346***	−2.323***	0.029	−0.735***	−6.003***	0.064
	[−10.759]	[−11.617]	[0.149]	[−3.393]	[−3.550]	[0.044]
Leverage	0.005***	−0.063***	−0.005	−0.007	−0.131**	−0.143**
	[3.795]	[−7.648]	[−0.660]	[−0.902]	[−2.518]	[−2.304]
BICS	−0.022**	−0.318***	−0.074	−0.042	−0.416	0.408
	[−2.082]	[−5.381]	[−0.886]	[−0.525]	[−1.090]	[0.613]
Constant	3.518***	18.071***	3.320***	5.982***	41.276***	2.102
	[37.115]	[25.771]	[4.598]	[5.805]	[4.901]	[0.296]
Country and Industry Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	2046	2105	2036	59	59	59
R^2 Squared	13.16%	29.05%	80.11%	34.41%	54.71%	35.26%

5 Conclusion

It was argued by the literature that electronic word-of-mouth (eWOM) can have an impact on a firm's financial performance. eWOM refers to the sharing of opinions, experiences, and recommendations about a product, service, or brand through online platforms such as social media, review websites, forums, and blogs.

However, during the pandemic period, investigations are not consensual about this impact. Using global firm-level data from Bloomberg, we examine the effect of eWOM on the firm's financial performance and to which extent the eWOM provided on social media may likely affect the performance of the firms during the COVID-19 period. For this purpose, we used ordinary least square (OLS) and quantile regression models. We found that eWOM has no effect on the financial performance of the firms during the COVID period. We can drive a conclusion that during the financial crisis, the financial performance was immune to eWOM.

Despite the findings, eWOM should be treated seriously by investors, policy makers, and regulators as its impact on consumer behavior is strongly confirmed in different contexts.

5.1 Theoretical and managerial implications

An unparalleled level of economic harm may be inflicted by a natural catastrophe, as the COVID-19 situation shows for investors, policymakers, and the general public. The COVID-19 pandemic is causing an immediate global financial crash in every area of the world. Academics should deeply investigate the probable impact of such catastrophe on capital expenses, retirement planning, insurance, the role of governments in defending financial institutions, societal trust and the associated transaction costs, and political stability. Academics will undoubtedly be debating these and other issues for many more years to come, where different backgrounds are made on table to investigate the impact from different perspectives.

5.2 Future studies directions

This study is not without its limitations. Since it is the first to examine the effect of eWOM on the financial performance of the companies, future research could change the methodology from quantitative to the qualitative approach, such as gathering data using structural or semi-structured interviews. Second, while we make an effort to control firm-level variables, there is no assurance that the results are unaffected by other unobserved firm-level variables. Third, we used 2020 as a COVID-19 period, and future studies may look into the effort of the Delta virus or omicron intervention. Fourth, this study can be extended to cover additional sectors and contexts. Furthermore, qualitative investigations are highly recommended to get additional insights.

Appendix 1

Variable	Definition	Relevant studies/ Source
Dependent variables		
ROA	= Net Profit/Total Assets	Bloomberg
ROE	= Net Profit/Total Equity	Bloomberg
EPS	= Net Profit-Preference Dividend/ Avg. Outstanding Shares	Bloomberg
Focus independent variables		
eWOM	We use supervised machine-learning to determine the financial sentiment of a news story towards a given company from a long position investors perspective. All stories with sentiment scores for a given company are aggregated using a proprietary method to produce this company level eWOM Index, where Index value range—[− 1, 1]	Bloomberg
Firm-level control variables		
Big4	It is a dummy variable, where it has value "1", when the audit firm is one of the top four audit firms in the world, and "0" otherwise	Rust et al. [42]
Growth	Firms' sales growth using total sales denominated in US$	Tran & Le [49], Kolsi & Attayah [28]
Firm Size	Numeric variable representing the size of the firm as measured by the logarithm of total assets	Najaf, Schinckus & Liew [43] Kolsi & Attayah [28]
Leverage	Total Debt/ Total Assets	Ali et al. [6], Chaney et al. [11]
BICS Segment	Number of market segments of a business	Tosun [48]
Fixed effect control variables		
Country	1 (0) if the company *i* operating in country *i* and 0 otherwise	Ali et al., [5]
IND	1 (0) if the company *i* operating in Industry *j* and 0 otherwise	[3, 7]

Funding Open Access funding enabled and organized by CAUL and its Member Institutions.

Declarations

Conflit of interest The authors declare respecting the policies and guidelines of the journal with respect to ethical considerations. The manuscript is original and has not been submitted or published anywhere.

References

1. Abrantes, J. L., Seabra, C., Lages, C. R., & Jayawardhena, C. (2013). Drivers of in-group and out-of-group electronic word-of-mouth (eWOM). *European Journal of Marketing., 47*, 1067–1088.
2. Anderson, E. W., Fornell, C., & Mazvancheryl, S. K. (2004). Customer satisfaction and shareholder value. *Journal of marketing, 68*(4), 172–185.
3. Atayah, O. F., Dhiaf, M. M., Najaf, K., & Frederico, G. F. (2021). Impact of COVID-19 on financial performance of logistics firms: Evidence from G-20 countries. *Journal of Global Operations and Strategic Sourcing, Ahead-of-Print*. https://doi.org/10.1108/jgoss-03-2021-0028
4. Ahmad, Z., & Hussain, S. (2001). KLSE long run overreaction and the Chinese new-year effect. *Journal of Business Finance & Accounting, 28*(1–2), 63–105.
5. Ali, A., Klasa, S., & Yeung, E. (2014). Industry concentration and corporate disclosure policy. *Journal of Accounting and Economics, 58*(2–3), 240–264.
6. Ali, S. A., Yassin, M., & AbuRaya, R. (2020). the impact of firm characteristics on corporate financial performance in emerging markets: Evidence from Egypt. *International Journal of Customer Relationship Marketing and Management (IJCRMM), 11*(4), 70–89.
7. Atayah, O. F., Najaf, K., Subramaniam, R. K., & Chin, P. N. (2021). The ascension of executives' tenure, corporate risk-taking and corporate performance: Evidence from Malaysia. *Asia-Pacific Journal of Business Administration*. https://doi.org/10.1108/APJBA-05-2021-0189
8. Buchinsky, M. (1998). Recent advances in quantile regression models: A practical guideline for empirical research. *Journal of Human Resources, 33*, 88–126.
9. Bruce, N. I., Foutz, N. Z., & Kolsarici, C. (2012). Dynamic effectiveness of advertising and word of mouth in sequential distribution of new products. *Journal of Marketing Research, 49*(4), 469–486.
10. Chang, A., Hsieh, S. H., & Tseng, T. H. (2013). Online brand community response to negative brand events: the role of group eWOM. *Internet Research, 4*, 486–506.
11. Chaney, P. K., Faccio, M., & Parsley, D. (2011). The quality of accounting information in politically connected firms. *Journal of Accounting and Economics, 51*(1–2), 58–76.
12. Cheung, C. M., & Thadani, D. R. (2012). The impact of electronic word-of-mouth communication: A literature analysis and integrative model. *Decision Support Systems, 54*(1), 461–470.
13. Dickinson, V. (2011). Cash flow patterns as a proxy for firm life cycle. *The Accounting Review, 86*(6), 1969–1994.
14. Dellarocas, C., Zhang, X. M., & Awad, N. F. (2008). Exploring the value of online product reviews in forecasting sales: The case of motion pictures. *Journal of Interactive Marketing, 21*(4), 23–45.
15. Gupta, S., & Zeithaml, V. (2006). Customer metrics and their impact on financial performance. *Marketing science, 25*(6), 718–739.
16. Godes, D., & Mayzlin, D. (2009). Firm-created word-of-mouth communication: Evidence from a field test. *Marketing Science, 28*(4), 721–739.
17. Grewal, R., Saini, A., & Kumar, A. (2020). The impact of COVID-19 on consumer behavior and firms' strategic responses. *Journal of Business Research, 116*, 209–221.
18. Hennig-Thurau, T., Gwinner, K. P., Walsh, G., & Gremler, D. D. (2004). Electronic word-of-mouth via consumer-opinion platforms: What motivates consumers to articulate themselves on the internet? *Journal of interactive marketing, 18*(1), 38–52.
19. Hsiao, C. (1986). *Analysis of panel data. Econometric society monographs* (11th ed.). Cambridge University Press.

20. Jansen, B. J., Zhang, M., Sobel, K., & Chowdury, A. (2009). Twitter power: Tweets as electronic word of mouth. *Journal of the American Society for Information Science and Technology, 60*(11), 2169–2188.
21. Jin, S.-A.A., & Phua, J. (2014). Following celebrities' tweets about brands: The impact of twitter-based electronic word-of-mouth on consumers' source credibility perception, buying intention, and social identification with celebrities. *Journal of Advertising, 43*(2), 181–195.
22. José-Cabezudo, R. S., & Camarero-Izquierdo, C. (2012). Determinants of opening-forwarding e-mail messages. *Journal of Advertising, 41*(2), 97–112.
23. Libai, B., Muller, E., & Peres, R. (2013). Decomposing the value of word-of-mouth seeding programs: Acceleration versus expansion. *Journal of Marketing Research, 50*(2), 161–176.
24. Luo, J., Pan, X., & Zhu, X. (2015). Identifying digital traces for business marketing through topic probabilistic model. *Technology Analysis & Strategic Management, 27*(10), 1176–1192.
25. Koenker, R., & Jr Bassett, G. (1978). Regression quantiles. *Econometrica: Journal of the Econometric Society, 46*, 33–50.
26. Koenker, R., & Hallock, K. F. (2001). Quantile regression. *Journal of Economic Perspectives, 15*(4), 143–156.
27. Koenker, R., & Ng, P. (2005). Inequality constrained quantile regression. *Sankhyā: the Indian Journal of Statistics, 67*, 418–440.
28. Kolsi, M. C., & Attayah, O. F. (2018). Are socially responsible firms less engaged in earnings management? Evidence from ADX listed companies. *International Journal of Business Innovation and Research, 17*(4), 536–560. https://doi.org/10.1504/IJBIR.2018.096373
29. Kolsi, M. C., & Attayah, O. F. (2018). Environmental policy disclosures and sustainable development: Determinants, measure and impact on firm value for ADX listed companies. *Corporate Social Responsibility and Environmental Management, 25*(5), 807–818. https://doi.org/10.1002/csr.1496
30. Kuan, K. K., & Bock, G. W. (2007). Trust transference in brick and click retailers: An investigation of the before-online-visit phase. *Information & Management, 44*(2), 175–187.
31. Kim, J., Kim, H. J., & Kim, H. (2016). The impact of online WOM on sales: The moderating effects of product type and familiarity. *Journal of Global Scholars of Marketing Science, 26*(4), 322–337. https://doi.org/10.1080/21639159.2016.1203520
32. Lee, M., & Kim, Y. (2011). Electronic word of mouth (eWOM): How eWOM platforms influence consumer product judgement. *International Journal of Advertising, 30*(3), 473–499.
33. Li, S., Wang, Y., Xue, J., Zhao, N., & Zhu, T. (2020). The impact of COVID-19 epidemic declaration on psychological consequences: A study on active Weibo users. *International Journal of Environmental Research and Public Health, 17*(6), 2032. https://doi.org/10.3390/ijerph17062032
34. Liu, Y., & Park, S. (2015). The moderating role of product type and firm's size in the relationship between eWOM and firm's financial performance. *Journal of Applied Business Research, 31*(3), 877–888. https://doi.org/10.19030/jabr.v31i3.9220
35. Luo, X., Zhang, J., & Duan, W. (2013). Social media and firm equity value. *Information Systems Research, 24*(1), 146–163.
36. Howard, T. W. (2010). Why invest in social networks and online communities? In T. Howard (Ed.), *Design to thrive creating social networks and online communities that last.* Morgan Kaufman.
37. Moe, W. W., & Trusov, M. (2011). The value of social dynamics in online product ratings forums. *Journal of Marketing Research, 48*(3), 444–456.
38. Najaf, K., & Chin, A. (2021). The impact of the China Stock market on global financial markets during COVID-19. *International Journal of Public Sector Performance Management (IJPSPM)*. https://doi.org/10.1504/IJPSPM.2020.10035309
39. Nisar, T. M., Prabhakar, G., Ilavarasan, P. V., & Baabdullah, A. M. (2019). Up the ante: Electronic word of mouth and its effects on firm reputation and performance. *Journal of Retailing and Consumer Services*. https://doi.org/10.1016/j.jretconser.2018.12
40. Najaf, K., Subramaniam, R.K., & Atayah, O.F. (2021). Understanding the implications of FinTech Peer-to-Peer (P2P) lending during the COVID-19 pandemic. *Journal of Sustainable Finance and Investment*, 1–16.
41. Najaf, R., & Najaf, K. (2021). Political ties and corporate performance: why efficiency matters? *Journal of Business and Socio-economic Development, 1*, 182–186.
42. Rust, R. T., Lemon, K. N., & Zeithaml, V. A. (2004). Return on marketing: Using customer equity to focus marketing strategy. *Journal of marketing, 68*(1), 109–127.

43. Najaf, K., Schinckus, C., & Liew, C. Y. (2021). VaR and market value of fintech companies: An analysis and evidence from global data. *Journal of Managerial Finance, 47*(7), 915–936. https://doi.org/10.1108/MF-04-2020-0169
44. Najaf, R., & Najaf, K. (2021). Nexus of political connections with green finance and financial performance. *Journal of Environmental Treatment Techniques, 9*(1), 305–309. https://doi.org/10.47277/JETT/9(1)309
45. Punj, G. N. (2013). Do consumers who conduct online research also post online reviews? A model of the relationship between online research and review posting behavior. *Marketing Letters, 24*(1), 97–108.
46. Schaeck, K. (2008). Bank liability structure, FDIC loss, and time to failure: A quantile regression approach. *Journal of Financial Services Research, 33*(3), 163–179.
47. Shin, J. Y., Hyun, J., Oh, S., & Yang, H. (2018). The effects of politically connected outside directors on firm performance: Evidence from Korean chaebol firms. *Corporate Governance: An International Review, 26*(1), 23–44.
48. Tosun, O. K. (2020). Changes in corporate governance: Externally dictated vs voluntarily determined. *International Review of Financial Analysis, 73*, 101608.
49. Tran, N. H., & Le, C. D. (2020). Ownership concentration, corporate risk-taking and performance: Evidence from Vietnamese listed firms. *Cogent Economics & Finance, 8*(1), 1732640.
50. Trusov, M., Bucklin, R. E., & Pauwels, K. (2009). Effects of word-of-mouth versus traditional marketing: Findings from an internet social networking site. *Journal of Marketing, 73*(5), 90–102.
51. Urban, G. L. (2005). Customer advocacy: A new era in marketing? *Journal of Public Policy & Marketing, 24*(1), 155–159.
52. Yiwei, W., Najaf, K., Frederico, G. F., & Atayah, O. F. (2021). Influence of COVID-19 pandemic on the tourism sector: evidence from China and United States stocks. *Current Issues in Tourism*. https://doi.org/10.1080/13683500.2021.1972944
53. Xun, J., & Guo, B. (2017). Twitter as customer's eWOM: An empirical study on their impact on firm financial performance. *Internet Research, 27*(5), 1014–1038. https://doi.org/10.1108/intr-07-2016-0223
54. Yadav, M. S., de Valck, K., Hennig-Thurau, T., Hoffman, D. L., & Spann, M. (2017). Social media, conviviality, and the return on investment: Empirical evidence from large European firms. *Journal of Marketing, 81*(1), 1–24. https://doi.org/10.1509/jm.15.0458
55. Zhang, K. Z., Zhao, S. J., Cheung, C. M., & Lee, M. K. (2010). Examining the influence of online reviews on consumers' decision-making: A heuristic-systematic model. *Decision Support Systems, 50*(2), 211–221.
56. Zhang, W., Deng, Z., Hong, Z., Evans, R., Zhang, H., & Chow, A. (2020). Unpacking the impact of electronic word-of-mouth on consumers' purchase intentions: A mixed-method approach. *International Journal of Information Management, 50*, 44–59.