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Research Article

The Impact of Online Media Big Data on Firm Performance: Based on Grey Relation Entropy Method

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The study uses the grey relation entropy method to explore the impact of online media big data on firm performance, based on 17 randomly selected Chinese A-share listed companies during the period from 2012 to 2017. It shows that the media big data, especially the negative media coverage, is highly associated with both short-term and long-term firm performance. Then, this study employs the system GMM method to testify how negative media coverage affects firm performance. It indicates that negative media coverage may be a damage crisis for the focal firm in the short term, but a favorable chance for change in the long run. These findings not only enrich the research on the influence of online media big data but also provide some references for enterprise managers.

1. Introduction

Past research has highlighted the "4V" features of big data [1], which garnered significant attention among scholars and managers. Online media coverage contains a huge amount of information and spreads quickly nowadays. There are more than 60 million pieces of original news and 8.3 million pieces of news of listed companies by the mid-2019 calculated by the Chinese Research Data Services Platform. Moreover, online media coverage also has characteristics such as relevance, scalability, and authenticity. Meanwhile, the value of online media coverage data resides in the fact that it contains multiple aspects of information [2, 3]. As such, we theorize that online media coverage with more massive volume, higher velocity, and more variety can be defined as online media big data.

With the development of China's media convergence process, media big data has become an essential factor influencing the development of enterprises. As a vital information infomediary [4], the media plays several major functions or roles as they report on firm issues [5]. It provides message about firm issues that curtails the information asymmetry and also frames issues through "persistent patterns of cognition, interpretation, and presentation, of selection, emphasis, and exclusion" [6, 7]. Thus, media coverage can affect firm's impression, reputation, and legitimacy [8]. Since the Internet drastically scales down the participation cost of information receivers, online media allows a huge number of users to communicate mutually [9], and public attention can be quickly focused [10]. Online media big data, especially online financial news, is a vital channel for stakeholders to obtain a focal firm's information [11]. The tones of financial news convey how journalists perceive the issue or the firm, which may form, enhance, or even alter the audience's impression of the focal firm.

A flood of positive media coverage of the film *Lost in Russia* released online for free watching during the 2020 Chinese New Year helped boost the share price of Huanxi Media Group Limited. Institutional experts regard this phenomenon as legitimation processes, in which firms can gain stakeholders preference. Pollock and Rindova (2003) provided substantial evidence by analyzing 225 IPOs and found that the positive tenor of media coverage has a positive relationship with underpricing [7]. In organizational literature, researchers emphasized the role of media in serving as an effective external governance mechanism. They hold that

the media can help ensure the interests of stakeholders, curtail information asymmetry, and offer overall strategic guidance [8]. Since July of 2018, the "fake doctor" scandal of Meinian Healthcare has pushed it to the focus of public attention, resulting in performance declining as well as market value shrinking. Meinian Healthcare survived the winter after having made many changes during the past two years. In this case, the media served as a social arbiter, which has increased the reputational cost of its misbehavior [12], but a firm change driver who helped executives realize the potential threat and take actively strategic change. However, these results are mainly driven by traditional media (e.g., newspaper) [13], and the conclusion is not yet consistent. Nevertheless, to date, research has not evaluated the different aspects of media coverage. The role of online media should be further explored, considering the immense volume of information and audiences' limited attention.

In this paper, by analyzing how online media big data affects firm performance, two methods are applied. To explore the complicated relationship between online media big data and firm performance, we first use the grey relation entropy method to measure what is the essential aspect and then conduct a dynamic panel-data model to further unfold whether it affects firm performance positively or not.

It is shown that the salience, the tones, and the overall tenor of media big data all matter in framing firm reputation. The impact is more pronounced when the media information spreads to a larger area. The positive tenor of media coverage may provide firms with chances to achieve sustained superior profit outcomes. What unexpected we found is that the negative media coverage has a long-lasting influence on firm performance. The negative media coverage may damage a focal firm's current financial performance. However, it can serve as an efficient external governance mechanism in the long run as well, which may provide executives with strategic guidance to focus on long-term firm performance.

2. Literature Review

Accordingly, there are two primary roles that the media plays [14]. Firstly, the media provides a platform to disseminate information, which can help reduce the information asymmetry between internal and external stakeholders of a focal firm [15]. Stakeholders can experience even distant events about a firm [16], especially in the case that the online media has broken the boundary of time and space [17]. In this espousing process, the firm can increase its familiarity with stakeholders, such as investors. Thus, the media has assisted firms in gaining public attention [7] which depends on the volume of media coverage. Signal theory holds that repeated signals increase the impression of the audience [18]. As demonstrated by Dyck et al., the impact of media is more pronounced when the media reach a larger number of relevant groups [12].

Secondly, the media can frame firm issues in positive or negative terms, which conveys the approval or disapproval judgements of firms and their actions [7, 19]. Therefore, the media can affect cognition and behavioural preferences of stakeholders, the reputation of firms [15], and the reputation of managers [12]. Past research proposes that positive media coverage is beneficial for firm reputation [15] and legitimacy [7]. These benefits above can improve the availability of resources the firm needs [20], which is conducive to the improvement of firm's profit outcomes [21]. Besides, it can also bring higher personal fame to managers and other internal stakeholders [22]. As an external incentive, it is beneficial to improve employees' work enthusiasm to a certain extent [23].

Online media coverage for adverse events, on the other hand, provides a field of public opinion, which may accelerate the fermentation of negative events, and therefore, damage the company reputation and legitimacy. The higher the volume of adverse online media coverage, the stronger the negative signals will be transmitted, which will cause deleterious online public opinions and lead to greater market punishment for enterprises [24]. For example, stock price crashes [20]. For enterprise managers and the internal staff, it can also cause negative emotions, resulting in a decline in confidence [12], and decrease work enthusiasm, which is not conducive to enterprise performance improvement.

However, the study believes that negative media reports have specific supervisory effects on enterprises. Dyck and Zingales first embark from the reputation mechanism and emphasize on the media as a social mediator of vital force to protect the interests of the investors [25]. Dyck et al. argue that the media plays a significant role in exposing corporate scandals and is able to stop unreasonable allocation of resources timely [26].

3. Data Sources and Variables

Data for corporate performance and corporate financial data are derived from the China Stock Market and Accounting Research (CSMAR) database. The data for online media big data comes from the database of China Services (CNRDS), which provides reliable support for various studies in the Chinese market [27]. The CNRDS platform gathered online financial media coverage articles posted by online media financial accounts, including 20 mainstream online financial media in China, such as Hexun.com, Sina Finance, and China Economic Net. All articles are coded by the sentiment of the title and content as positive, neutral, or negative by using artificial intelligence algorithms [28].

Moreover, we used a stratified random sampling method to obtain sample firms that cover almost every industry according to the two-digit industry codes of China Securities Regulatory Commission. Due to the particularity of the financial industry, it was not included in the sample. Finally, 17 Chinese A-share listed companies during the period from 2012 to 2017 were studied.

The variables for the grey relation entropy method include different aspects of online financial news. Salience, the boldness of the articles, was calculated based on the total number of articles with the firm named in the title. Volume was calculated by the total number of articles of a focal firm. Positive, which represents that there is a favorable tone of the

article, was measured by the total number of articles with a positive tone. Negative was measured by the total number of articles on an adverse tone. Besides, we also use the total number of original ones to see if there is any difference. Tenor, which means that the overall tenor of media coverage, was measured by the Janis–Fader coefficient of imbalance [7, 15, 29]. This measure was calculated using the formula:

$$\text{Tenor} = \frac{e^2 - ec}{t^2}, \quad \text{if } e > c; 0, \text{if } e = c, \qquad \frac{ec - c^2}{t^2}, \quad \text{if } c > e, \tag{1}$$

where e is the number of positive articles about a firm, c is the number of negative articles about it, and t is the total volume of articles about it, including articles that are neutral in tenor. The range of this variable is −1 to 1, where −1 equals "all negative presses" and 1 equals "all positive presses." Following the past literature, we use ROA (return on assets) and ROE (return on equity) to measure firm performance.

4. Mathematical Model and Data Analysis

4.1. Grey Relation Entropy Method. Grey relational analysis approach is a method to measure the degree of correlation among factors according to the degree of similarity or difference of the development trend among factors. However, because the average value of grey correlation coefficient conceals many sparse features of grey management, it is not possible to make full use of the rich information provided by the coefficient of point management. Based on the grey correlation analysis, the grey relation entropy method is introduced to ameliorate the lack of grey correlation analysis [30]. In this paper, we use the grey relation entropy method to decide which aspect or dimension of media big data is the most vital one and how the correlation may change from time to time. Some firms receive more media attention while others do not (see Table 1), which implies that media environment differs from firm to firm.

Firstly, we set the reference sequence and comparison sequence as below.

The reference sequence:

$$A_0 = \left[X_{01}, X_{02}, X_{0j}, \ldots, X_{0n}\right]. \tag{2}$$

The comparison sequence:

$$A_i = \left[X_{i1}, X_{i2}, X_{ij} \ldots, X_{in}\right], \quad i = 1, 2, 3, \ldots, m, \tag{3}$$

where X_{0j} refers to firm performance and X_i refers to different aspects of media big data.

First, we initialize the data:

$$X_i = \frac{\max X_i - X_i}{\max X_i - \min X_i}. \tag{4}$$

Calculate the grey correlation distance Δ_{0ij}, where Δ_{0ij} is the distance between each comparison sequence and the reference sequence. The formula is

$$\Delta_{0ij} = \left|X_{0j}^* - X_{ij}^*\right|. \tag{5}$$

Then, calculate the grey relation coefficient:

$$R_{oij} = \frac{\Delta_{\min} + \rho\Delta_{\max}}{\Delta_{0ij} + \rho\Delta_{\max}}, \tag{6}$$

where ρ is the discrimination coefficient [0, 1], usually $\rho = 0.5$. Results (part of them) are shown in Table 2.

The grey relation coefficient (R) distribution map value P:

$$P_h = \frac{R_h}{\sum_1^n R_h}, \; P_h \in P_i, \quad h = 1, 2, 3, \ldots, n. \tag{7}$$

The grey relation entropy value (see Table 3) is

$$H(R_i) = -\sum_1^n \left(P_h \ln\left(P_h\right)\right). \tag{8}$$

According to the law of entropy, when the grey correlation entropy of sequence X is the largest, it means that the influence of X points on the reference sequence is balanced. In other words, the grey correlation entropy reaches its maximum value when the distribution map values of each grey correlation coefficient are equal.

The maximum value is

$$\text{Hm}(X) = \ln n. \tag{9}$$

The grey relation entropy correlation degree is

$$E_j(X_i) = \frac{H(R_i)}{H_m}. \tag{10}$$

The GREM results (see Table 4) show that online media big data is highly associated with firm performance. Although there are subtle differences between several aspects of media big data, it can tell that the impact differs. Generally, the negative of online media coverage is highly associated with firm performance followed by the tenor of media coverage.

The positive (original) online media coverage is highly associated with both short-term and long-term firm performance, which indicates that audiences may prefer to believe credible sources when the news about a focal firm is framed in a positive tone.

Total online media coverage is highly associated with firm performance than the original ones when it comes to negative articles, which hints that the impact of negative media coverage may rely on the scope it spreads.

The correlation between the tenor of media coverage and firm performance has not changed much over time.

4.2. System GMM Method for Dynamic Panel Data. Following consideration of the negative media coverage is the highest correlated factor with firm performance, we conduct an econometric model to testify how it affects firm performance. Before the estimation, we use the Winsorize method to avoid the influence of extreme values on data analysis. Furthermore, there are some endogenous problems, for as much as firm performance and negative media coverage may have mutual causality and firm performance may be affected by previous firm performance. To reduce the aforementioned endogeneity, this study employs the system GMM method that fits a linear dynamic panel-data model

Table 1: The summary statistics of the variables for GREM.

Category	Variables	Mean	Std. dev.	Min	Max
A_{01}	ROA_t	0.033	0.069	−0.453	0.189
A_{02}	ROE_t	0.052	0.146	−1.067	0.243
A_{03}	ROA_{t+1}	0.023	0.121	−0.927	0.168
A_{04}	ROE_{t+1}	0.039	0.210	−1.433	0.248
A_1	Salience	161.029	137.830	1.000	656.000
A_2	Positive (total)	157.804	149.220	0.000	631.000
A_3	Positive (original)	47.029	46.525	0.000	216.000
A_4	Negative (total)	143.990	219.920	3.000	1588.000
A_5	Negative (original)	33.549	42.166	2.000	187.000
A_6	Tenor	0.057	0.154	−0.563	0.423

Table 2: The grey relation coefficient (e.g., A_{01} and A_1).

	A_{01}					
	[1]	[18]	[35]	[52]	[67]	[84]
	0.4722399	0.3956641	0.6797184	0.6525302	0.9256974	0.3996716
	0.5199922	0.4790806	0.4826101	0.4245426	0.8051225	0.3954566
	0.4540571	0.4029553	0.5769253	0.4296573	0.5136660	0.4099845
	0.4644591	0.4384371	0.7501023	0.4039934	0.4277149	0.3730879
	0.4388676	0.4658275	0.9753574	0.4119134	0.4921814	0.3956314
	0.4667398	0.4642610	0.5936379	0.4228632	0.4241844	0.3719485
	0.5463972	0.3794781	0.7400184	0.4766334	0.5625606	0.3896975
	0.7584622	0.4569635	0.5776415	0.7615225	0.5072221	0.4068271
A_1	0.4649920	0.4524507	0.3870351	0.3999047	0.4044883	0.4350132
	0.8396081	0.4531167	0.4089473	0.5365372	0.5481666	0.4579653
	0.5533175	0.5787409	0.4168465	0.4600016	0.4574930	0.3823617
	0.4453939	0.4358607	0.4730191	0.5835118	0.5072272	0.4256498
	0.4091393	0.4039758	0.4267023	0.6889290	0.5207435	0.4436271
	0.4476427	0.4698516	0.3714691	0.6078893	0.5436337	0.4825398
	0.4114355	0.4960617	0.5466753	0.4476838	0.4137933	0.5029635
	0.7126215	0.5398761	0.5837759	0.4117442	0.4247983	0.4509281
	0.4321090	0.6619091	0.9465222	0.6797493	0.4398294	0.4500233

Table 3: The grey relation entropy results.

Category	Variables	ROA_t	ROE_t	ROA_{t+1}	ROE_{t+1}
H_1	Salience	4.595743	4.59178	4.589593	4.586525
H_2	Positive (total)	4.589219	4.592326	4.591505	4.589894
H_3	Positive (original)	4.594324	4.597193	4.595985	4.593646
H_4	Negative (total)	4.615016	4.609228	4.608330	4.605134
H_5	Negative (original)	4.585639	4.582943	4.583577	4.581322
H_6	Tenor	4.610332	4.605310	4.607550	4.606146

Table 4: The entropy correlation degree.

Category	Variables	ROA_t	ROE_t	ROA_{t+1}	ROE_{t+1}
E_1	Salience	0.9936800	0.9928231	0.9923504	0.9916868
E_2	Positive (total)	0.9922695	0.9929412	0.9927636	0.9924154
E_3	Positive (original)	0.9933731	0.9939936	0.9937323	0.9932265
E_4	Negative (total)	0.9978472	0.9965957	0.9964016	0.9957105
E_5	Negative (original)	0.9914953	0.9909125	0.9910495	0.9905619
E_6	Tenor	0.9968345	0.9957486	0.9962329	0.9959293

Table 5: Results of system GMM for dynamic panel data.

Model	Model1 (FP = ROA)			Model2 (FP = ROE)		
Variables	Coef.	Std. Err.	z	Coef.	Std. Err.	z
Constant	−0.017	0.189	−0.09	−0.364	0.526	−0.69
FP L1.	0.050	0.139	0.36	−0.040	0.034	−1.18
FP L2.	0.119	0.148	0.80	−0.082***	0.030	−2.74
Firm age	0.018	0.016	1.11	0.023	0.035	0.64
Firm size	0.000	0.008	0.01	0.021	0.023	0.92
Slack	−0.001	0.006	−0.15	0.004	0.021	0.20
MSh	0.065*	0.034	1.90	0.251**	0.113	2.23
CEO tenure	−0.050**	0.023	−2.14	−0.186**	0.087	−2.14
CEO duality	0.008	0.011	0.75	−0.009	0.030	−0.31
Negative	−0.011*	0.006	−1.85	−0.038**	0.018	−2.06
Negative L1.	0.009*	0.005	1.68	0.023**	0.010	2.33
Negative L2.	0.007	0.005	1.38	0.004	0.014	0.30
Wald chi2	126.21***			111.39***		

Note. Obvious number = 68. Industry dummy variable is controlled but not presented. $^{*}P < 0.10$; $^{**}P < 0.050$; and $^{***}P < 0.010$.

where the unobserved panel-level effects are correlated with the lags of the dependent variable, to evaluate the relationship between media coverage and firm performance [31].

4.2.1. Dependent Variables. Firm performance (FP) was measured as the total return on assets (ROA) in a given year and the total return on equity (ROE) in a given year.

4.2.2. Explanatory Variables. Negative online media coverage was calculated as the natural logarithm of the total number of online media articles reporting about each listed firm in negative tones plus one in a given year.

4.2.3. Control Variables. Consistent with the previous literature of corporate performance, we employ control variables of organizational characteristics, corporate governance, and CEO characteristics [5]. We select *firm age* (calculated as the natural logarithm of its duration from the listed year to the sample year), *firm size* (measured as the natural logarithm of total assets), *firm slack* (current asset/current debt), *MSh* (management shareholding ratio), *CEO tenure* (measured as the entire year the CEO served in the focal firm), and *CEO duality* (dummy variable). We also control for *industry* as a dummy variable.

In this paper, the model used for the analysis of the impact of online media coverage on firm performance is

$$\begin{aligned} \mathrm{FP}_{\mathrm{it}} = {} & \alpha + \beta_1 \mathrm{FP}_{\mathrm{it}-1} + \beta_2 \mathrm{FP}_{\mathrm{it}-2} + \beta_3 \mathrm{Negative}_{\mathrm{it}} \\ & + \beta_4 \mathrm{Negative}_{\mathrm{it}-1} + \beta_5 \mathrm{Negative}_{\mathrm{it}-3} + \beta_6 \mathrm{Controls}_{\mathrm{it}} \\ & + \varepsilon, \quad n = 0, 1, 2. \end{aligned} \tag{11}$$

The Arellano–Bover/Blundell–Bond model estimation results (see Table 5) show that the negative online media coverage has different impacts on short-term firm performance and long-term firm performance. The coef. of Negative in Mode1 (−0.011, $P < 0.01$) implies that negative media coverage is adversely associated with short-term firm performance. However, the coef. of Negative L.1 (0.001, $P < 0.01$) indicates a positive relationship between negative media coverage and long-term firm performance. Moreover, the influence of negative media coverage on firm performance gradually converged in the third year and began to become insignificant (see coef. of Negative L2. of Model1). The consequences of Model2, where firm performance is measured by ROE, are consistent with Model1, which suggests the findings are robust.

5. Results and Discussion

Results show that online media big data plays a vital role in firm performance through a variety of aspects.

It is suggested in the results of grey relation entropy that the heterogeneity in different aspects of online media big data is not apparent. However, the subtle difference shows that the positive media coverage is highly associated with short-term firm performance and by the same token it is highly associated with long-term firm performance. And the original positive media coverage is more pertinent to corporate performance than total positive ones. This may be due to the dependence of information credibility when it comes to affirmative reporting. On the contrary, unlike the highlighted beneficial impact of the positive media coverage in the previous literature, the negative media coverage is of the highest correlation with firm performance. Furthermore, the total negative media coverage is highly associated with firm performance followed by the original negative ones, which indicates the scope of negative information may play a more essential role in affecting firm performance. Additionally, the tenor of media big data is highly associated with firm performance as well, followed by the salience.

The system GMM results indicate that the negative media coverage may have an opposite impact in the short and long run. Although the negative media coverage may cause considerable damage to the focal firm in a short-term, it can be positively associated with long-term firm performance due to the social arbiter role it plays. This is consistent with prior research that demonstrated that negative media

coverage may offer managers strategic guidance [5] and promote the efficiency of internal corporate governance (e.g., board quality) [32].

6. Conclusion

Based on the GRE method and the system GMM method, this paper explored which is the highest correlated factor of online media big data for firm performance and how it affects firm performance. The results have both theoretical and practical implications.

The results expanded the research on media coverage and firm performance by considering different aspects of online media big data. It is found that not only the volume and tenor of media coverage serve as vital roles in exposing and framing firm issues but also the salience of the news is of great importance especially in the big data era.

There are some practical implications given the high correlation between media big data and corporate performance. Firstly, managers can use media big data to predict corporate performance and keep abreast of stakeholders' evaluation of the company. In particular, the external supervisory role of media big data should be emphasized. Secondly, executives should incorporate online media coverage into decision-making reference. Specifically, managers should not indulge in a favorable media environment and be overconfident. On the contrary, they should reflect on and make corresponding adjustments in the face of negative public opinions given the vigorous impact of stakeholders' perception of the company. Timely and accurate response may help the company stop losses to a certain extent. Thirdly, managers can make full use of online media and timely disclose information through the network platform, such as the enterprise official accounts, to curtail information asymmetry with stakeholders. Audiences may take the initiative to disclose negative information as a manifestation of the company's responsibility and choose to trust the focal firm again. Thus, it would be better to learn firm information from official and credible sources rather than informal sources, especially negative information. Lastly and importantly, investors and consumers can also have a more comprehensive understanding of the company's information through online media coverage and avoid the potential loss caused by information asymmetry.

There are also several limitations to this study, which directs our suggestions for future research. An initial limitation is the rough category of the aspects of online media big data. Our analysis basically measures different aspects by the number of articles, but does not examine the content characteristics. It would be interesting to use the text analysis method to further explore the impact of specific words or phrases based on artificial intelligence algorithms. Furthermore, the current study mainly concentrated on the supervisory role of negative media coverage following the majority of previous studies. Nonetheless, it is supposed to delve into how negative media coverage serves as an external governance mechanism. It does highlight the lack of consideration of overall aspects of online media big data, while this in itself is not an apparent limitation. Future research may benefit from further unfolding the overall impacts of online media big data on firm performance through the use of various data mining methods.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare there are no conflicts of interest regarding the publication of this paper.

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