RESEARCH ARTICLE

The dynamic interdependencies among the negativity and the positivity in news and user-generated content about safety in a firm's products and the firm's product recalls

Vivek Astvansh[1,2,3,4]*, **Yen-Yao Wang**[5]

1 Associate Professor of Quantitative Marketing and Analytics, Desautels Faculty of Management, McGill University, Montreal, Canada, **2** Bensadoun School of Retail Management, McGill University, Montreal, Canada, **3** Adjunct Associate Professor of Data Science, Luddy School of Informatics, Computing and Engineering, Indiana University Bloomington, Bloomington, IN, United States of America, **4** Affiliate, Environmental Resilience Institute, Indiana University, MontrÂ©al, QC, Canada, **5** Department of Business Analytics and Information Systems, Harbert College of Business, Auburn University, Auburn, AL, United States of America

* vivek.astvansh@mcgill.ca

Abstract

This article examines the dynamic interdependencies among the negativity and the positivity in news and user-generated content about safety in a

highlighting the solution (recalls) [14]. Indeed, anecdotes support this coexistence of negativity and positivity in news and UGC about the safety of a firm's products [15, 16]. We thus consider the negativity and the positivity in news and UGC to empirically examine the interdependencies among the negativity/positivity in news and UGC about safety in a firm's products and the firm's number of recalls.

Our theoretical premise is as follows. We reason that managers may interpret the negativity discouraged to buy from, work for, and invest° in the firm ([46]: 223). For example, Blevins and Rogazzino e firm

firm's product recalls, mostly by analyzing secondary data. The dependent variable (DV) is usually a firm's number of recalls or the number

reputational costs nudge managers to lower the incidence of decisions that might further damage their reputations in the eyes of news organizations, and, by extension, the firm's stakeholders (i.e., business customers,

Now, consider the likely

sales volume of passenger cars in the United States. These manufacturers are Acura, Audi, BMW, Buick, Cadillac, Chevrolet, Chrysler, Dodge, FIAT, Ford, Honda, Hyundai, Infiniti, Jeep, KIA, Lexus, Mazda, Nissan, Porsche, Subaru, Toyota, and Volkswagen. Next, we gathered car recall data from June 2009 to June 2015 (a six-year period) from the NHTSA's recalls data file for each manufacturer. NHTSA is a federal agency within the U.S. Department of Transportation dedicated to enhancing transportation safety nationwide. It develops and enforces vehicle safety standards, investigates vehicle safety defects, and researches driver behavior and traffic. The NHTSA recall data is a part of its effort to improve transportation safety. This dataset is one of the primary sources for vehicle recalls and has been leveraged and validated in prior research (e.g., [3, 6, 35]). Our exercise on recall data collection yielded 207,489,321 recalled units. Third, we used a Python program to collect the text of user-generated tweets each month about safety in each manufacturer's vehicles. Following prior research (e.g., [11, 42]), we used the combination of the manufacturer name and defect keywordsÐsuch as safety, recall, defect, and faultyÐto obtain monthly user-generated tweets. This step yielded 164,944 tweets. In the fourth step, we applied identical search criteria on Factiva to compile the text of each distinct news articles on safety concerns in the products of each manufacturer. Factiva is a business information and research tool owned by Dow Jones & Company. It allows users to search, monitor, and analyze news and information to support research and decision-making processes. The reliability and validity of Factiva have been investigated extensively in prior studies (e.g., [3, 130, 131]). This step produced 19,812 news articles.

Fifth, we used the Linguistic Inquiry Word Count (LIWC) program [132] to measure the negativity and positivity in the news and UGC. LIWC was designed to evaluate text's psychological and structural components. The tool has been widely adopted in psychology and linguistics [133]. LIWC calculates the proportion of words that match predefined dictionaries using word counts for a given text. LIWC includes a psychometrically validated internal dictionary comprising approximately 6,549 labeled words and word stems, each classified into one or more categories [132]. Several management researchers have used LIWC to measure news sentiment [13, 79, 134]. The reliability and validity of LIWC variables have also been investigated extensively in settings such as news [e.g., 37], online review (e.g., [135]), and UGC (e.g., [136]).

We briefly discuss how LIWC processes the text in the following. Upon receipt of a text sample, the software processes each word in the sample, one at a time. While processing each word, LIWC scans its dictionary file to find a match, and if a match is found, the correspond-
ing categeach3foungj 0Td Td (word8 02d (word)Tj 2.0 Td (dic 2.7269 0 Td6519 0 Td 7d (the)Tj 1.4684

with the terms and conditions for the source of the data. Table 1 presents variables' definition, data sources, and summary statistics. Table A1 in the online S1 Appendix reports the Pearson pairwise correlation coefficients.

PVAR specification

A vector auto-regression (VAR) model can examine models that entail undefined or challenging-to-define constraints, such as causality [41]. Leveraging the benefits of the VAR model and the structure of the panel data set, the PVAR offers several benefits to examine the dynamic interdependencies compared to traditional statistical analyses. It has been applied in prior research in multichannel communication (e.g., [36±38]) to examine interdependencies between multiple channels and cumulative effects through impulse response functions [35]. Fourth, the panel structure of our data provides the ability to manage unobserved individual (i.e., manufacturer) heterogeneity and employ instruments within the model, such as lagged DVs in the GMM (generalized method of moments) to tackle issues related to reverse causality and endogeneity, thereby attaining consistent estimates [34, 142].

Our PVAR specification is the following:

$$\begin{pmatrix} Recalls_{i,t} \\ Neg\ news_{i,t} \\ Pos\ news_{i,t} \\ Neg\ UGC_{i,t} \\ Pos\ UGC_{i,t} \end{pmatrix} = \sum_{s=1} F_s \begin{pmatrix} Recalls_{i,t-s} \\ Neg\ news_{i,t-s} \\ Pos\ news_{i,t-s} \\ Neg\ UGC_{i,t-s} \\ Pos\ UGC_{i,t-s} \end{pmatrix} + \boldsymbol{\beta} \begin{pmatrix} Complaints_{i,t-1} \\ Public\ interest_{i,t-1} \\ Volume\ news_{i,t-1} \\ Volume\ UGC_{i,t-1} \\ Sales\ volume_{i,t-1} \\ Price_{i,t-1} \\ Ad\ spending_{i,t-1} \\ Crashes_{i,t-1} \\ Reliability_{i,t-1} \end{pmatrix} + \boldsymbol{f}_i + \xi_t + \boldsymbol{\varepsilon}_{it} \quad (1)$$

$y_{i,t} = (Recalls_{i,t};\ Neg\ news_{i,t};\ Pos\ news_{i,t};\ Neg\ UGC_{i,t};\ Pos\ UGC_{i,t})$ is a five-element column vector for firm *i i* at time t*t*, containing the natural logarithm transformation of the DVs; F_s are 5×5 matrix of coefficients for *s*-period lagged DVs; *p* is the number of lags. The log transformation means that we can interpret the coefficient estimates as elasticities, a unit of relationship that managers find most actionable and easier to understand. Following prior recall research, we include logarithm of each of the following control variables: complaints, public interest, the volume of UGC, the volume of news [88, 84], sales volume [43, 44, 49, 59], price [14], advertising spending [124], crashes, and product reliability [60]. Leveraging the panel data structure, we further incorporate $f_i = (f_{1,i}; f_{2,i}; f_{3,i}; f_{4,i}; f_{5,i})'$ as unobserved firm-specific fixed effects, characterizing firms' time-invariant attributes. To control for any industry-wide time trend and seasonality, we include $\xi_t = (\xi_{1,t}; \xi_{2,t}; \xi_{3,t}; \xi_{4,t}; \xi_{5,t})'$ as a column vector of month dummies. Finally, the five-element error vector $\varepsilon_{i,t} = (\varepsilon_{1,i,t}; \varepsilon_{2,i,t}; \varepsilon_{3,i,t}; \varepsilon_{4,i,t}; \varepsilon_{5,i,t})'(\varepsilon_{1,i,t}; \varepsilon_{2,i,t}; \varepsilon_{3,i,t})'$ satisfies the white noise assumption that $E(\varepsilon_{m,i,t}) = E(\varepsilon_{m,i,t}\varepsilon_{m,i,s}) = 0$ for any $m = 1, 2, 3, 4, 5$ and $t \neq s$.

PVAR estimation procedure

Prior to estimating the PVAR, we completed the following preparatory steps. First, we applied natural log-transformed to variables exhibiting non-normal distributions. Subsequently, the endogeneity issues inherent in dynamic panel data models (i.e., fixed-effects models with lagged DVs as regressors) have been extensively documented in previous studies [143]. To tackle the issues of endogeneity and serial correlation, we implemented the forward orthogonal deviation, also known the Helmert transformation [144]. During this step, the fixed effects are eliminated by concerting all variables in the model into deviations from the forward mean, which involves subtracting the mean of forthcoming observations available for each month. As a result, it maintains homoscedasticity and ensures orthogonality between the forward-differenced variables and lagged DVs [34]. Consequently, we can utilize the lagged regressors as instruments for the forward-differenced variables [40] and employ the coefficients by the system GMM to address the endogeneity issue [34, 144]. Furthermore, employing forward-orthogonal deviations does not induce autocorrelation in the error terms and alleviates us from concerns regarding serial correlation [145]. Following these prerequisites, we proceeded with the standard approaches to estimate our PVAR (see Table 2 for our procedure).

Results

Unit root tests and lag selection

Because our panel data are unbalanced, we conducted two unit root tests Ð Fisher-Type [90, 146] and Im-Pesaran-Shin [147] Ð to verify the absence of unit roots in our five main endogenous variables. The result suggests the absence of a unit root in our panel (see Table A2 in the online S1 Appendix for the results of the unit-root tests). Next, following Dewan and Ramaprasad [40], we calculated AIC for each cross-section and took the modal value of the optimal lag length among all cross-sections. The results indicate that first-order panel VAR (lag 1) is the preferred model. Subsequently, we followed Abrigo and Love [148] to apply the consistent moment and model selection criteria for GMM models to validate further lag 1 selected by AIC (see Table A3 in S1 Appendix for the result of the lag selection).

Granger causality tests

Given that the PVAR assumes all DV to be endogenous, researchers could conduct Granger causality test to ascertain whether the lagged DVs could predict future values of the same set of DVs within the PVAR system of equations [149]. The outcomes of our Granger causality test (Table 30 Td (Love)Tj 2.1430939l*eTj 2.75559 -Td (the)TTj 1.7802 0 Td (set)Tj 1.3833 0 Td (each)Tj 2.0

firm's product defects negatively correlates with its product recalls in the following period, supporting our theoretical argument (H_1). Stated differently, the result does not support our competing H_{1alt}, where we reasoned that the negativity in the news makes managers socially more responsible.

The negativity in UGC has an asymmetric association with recalls. Specifically, the negativity in UGC in a month about a firm's product defects positively correlates with the firm's number of units recalled in the following month, supporting our H_{2alt}. The data thus support our theoretical argument that the public criticism of safety of a firm's products helps the firm identify defects. We also reason that because regulators and product liability lawyers are known to use UGC in monitoring how proactive/reactive a firm has been in recalling its defective products, the firm has reason to use UGC as a signal of the defect recalling82 Td (Tty)Tj j 2.21918 0 Td (pro

ber of the nega defects1.4456 0 T5 (its)Tj ely

Table

Interaction association between news and UGC

We now answer whether news and UGC complement or substitute for each other (i.e., interaction associations) in determining a firm's recalls. The *Recalls* equation in Table 5 suggests heterogeneous interaction associations between news and UGC. The results show that the negativity in news and the negativity in UGC have a significantly negative interaction association on recalls at the 0.1% level, suggesting a substitution relationship between these two types of earned media. Therefore, our H_5 is supported. In contrast, the positivity in the news and that in UGC interact positively and significantly (3.648) at the 0.1% level to influence recalls, suggesting a synergistic association between the positivity in the news and that in UGC on the firm's recalls in the following month. This finding, thus, supports our H_6. Our results on interaction associations zero from month 1 to month 6. On the other hand, the change in recalls in response to a shock in the positivity in the news (Fig 1B) reaches a peak around month 1 and remains positive over time. We observe similarly asymmetric patterns in the associations of the negativity in UGC and the positivity in UGC. For example, the negativity in UGC positively correlates with recalls in month 1 (Fig 1C). However, this association is not significantly different from zero from month 2 to month 6, suggesting a transitory association of the negativity in UGC on recalls. This finding is also consistent with characterizing user-generated tweets as a fast-paced way to discover new content and see what trending is [42]. Finally, we find no evidence supporting short- and long-term associations of the positivity in UGC on recalls. Overall, IRFs show a graphical representation of how the system evolves and can provide important implications for managers who monitor the earned media. For example, because the negativity and the positivity in the news take

Table 6. PVAR estimation results for high-severity recalls.

	Dependent Variable				
Independent Variable	***High severity recalls$_{i,t}$***	***Neg news$_{i,t}$***	***Pos news$_{i,t}$***	***Neg UGC$_{i,t}$***	***Pos UGC$_{i,t}$***
High severity recalls$_{i,t-1}$	-0.029	0.015			

because managers need to involve high managerial discretion with more subjective judgment [49]. Thus, we expect to see different patterns for low-severity recalls. Following Astvansh and Eshghi [4] and Liu and Shankar [151], we classify a recall as a high-severity recall if keywords such as *injury*, *crash*, *death*, or *fire* appear in the consequence summary of the NHTSA recall data. A recall characterized by these conditions involves an immediate safety concern [151]. Otherwise, we treat the recall as low severity. Based on this classification, we differentiate two recall variables: high-severity recalls and low-severity recalls.

Tables 6 and 7 show the short-term dynamics for high-severity recalls and low-severity recalls, respectively. The results of high-severity recalls (Table 6) are consistent with the main results (Table 4). For example, the negativity in the news negatively correlates with the number of units recalled as part of high-severity recalls. In contrast, the positivity in news and the negativity in UGC positively correlate with the number of units recalled as part of high-severity recalls. In contrast, we observe very different patterns for low-severity recalls (see Table 7). For example, the positivity in the news is positively correlated with low-severity recalls, which has the opposite direction as the corresponding one for high-severity recalls.

Finally, we conduct interaction and IRF analyses for high and low-severity recalls. The result for high-severity recalls shows consistent patterns like the main results, while that for low-severity recalls demonstrates different patterns. Tables A4 and A5 in the online S1 Appendix present these results, and Figures A1 and A2 in S1 Appendix depict the IRF results for high- and low-severity recalls, respectively.

Discussion

This study examines the dynamic interdependencies of the negativity and the positivity in news and user-generated content on a firm's product recalls. We believe our findings have important theoretical implications for researchers and practical implications for managers.

find that the relationship among news, UGC, and recalls is not universal but is contingent could examine, for example, whether a firm's apology advertising and responses to tweets moderate the main associations of news and UGC.

Third, because we exclusively studied automobile failures and used data from Twitter only, researchers may want to extend the scope of this inquiry. Future studies may test the generalizability of our findings by studying failures in services and other product categories (e.g., medical devices), and sourcing UGC from Facebook, Instagram, and review websites and apps. Fifth, we incorporated organizational perception (media reputation and public reputation) as a theoretical mechanism. Further research could collect data on these mechanism variables and estimate mediation models. More broadly, researchers could develop a theory and test when, how, and why earned media affects recalls.

Moreover, although we have followed several prior recall research (e.g., [44, 49, 124] to control several firm- and recall-related characteristics in our models, our control sets may exclude some other possible control variables due to data limitations. Further research could consider these possible control variables when the data becomes available. Finally, our data covers the period from 2009 to 2015. Twitter (now X) has changed its data collection policy[nir7j 3.54aeivy

TS1Tj 1.4132 0 Td (hAe)pnd)ix

5. Cleeren K., Dekimpe M. G., & van Heerde H. J. (2017). Marketing research on product-harm crises: a review, managerial implications, and an agenda for future research. *Journal of the Academy of Marketing Science*, 45(4), 593±616.
6. Giannetti V., & Srinivasan R. (2021). The cloud and its silver lining: negative and positive spillovers from automotive recalls. *Marketing Letters*, 32(4), 397±409.
7. Giannetti V., & Srinivasan R. (2022). Corporate lobbying and product recalls: an investigation in the US medical device industry. *Journal of the Academy of Marketing Science*, 1±20
8. Mafael A., Raithel S., & Hock S. J. (2022). Managing customer satisfaction after a product recall: the joint role of remedy, brand equity, and severity. *Journal of the Academy of Marketing Science*, 50(1), 174±194.
9. Raithel S., & Hock S. J. (2021). The crisis-response match: An empirical investigation. *Strategic Management Journal*, 42(1), 170±184.
10. Raithel S., Mafael A., & Hock S. J. (2021). The effects of brand equity and failure severity on remedy choice after a product recall. *Journal of Product & Brand Management*, 30(8), 1247±1261.
11. Astvansh V., Wang Y-Y., & Shi W. (2022). The effects of the news media on a firm's voluntary product recalls. *Production and Operations Management*, 31(11), 4223±4244.
12. Beattie G., Durante R., Knight B., & Sen A. (2021). Advertising spending and media bias: Evidence from news coverage of car safety recalls. *Management Science*, 67(2), 698±719.
13. Zavyalova A., Pfarrer M. D., Reger R. K., & Shapiro D. L. (2012). Managing the message: The effects of firm actions and industry spillovers on media coverage following wrongdoing. *Academy of Management Journal*, 55(5), 1079±1101.
14. Hora M., Bapuji H., & Roth A. V. (2011). Safety hazard and time to recall: The role of recall strategy, product defect type, and supply chain player in the US toy industry. *Journal of Operations Management*, 29(7±8), 766±777.
15. Reports Consumer. (2015). The truth about car recalls: After a record year of problem cars, consumers are asking, What does that mean for me? https://www.consumerreports.org/cro/magazine/2015/04/the-truth-about-car-recalls/index.htm
16. Ducharme J. (2019), You're Not Imagining It: Food Recalls Are Getting More Common. Here's Why. TIME, (January 17), https://time.com/5504355/food-recalls-more-common/
17. Bednar M. K. (2012). Watchdog or lapdog? A behavioral view of the media as a corporate governance mechanism. *Academy of Management Journal*, 55(1), 131±150.
18. Farrell K. A., & Whidbee D. A. (2002). Monitoring by the financial press and forced CEO turnover. *Journal of Banking & Finance*, 26(12), 2249±2276.
19. Liu B., McConnell J. J., & Xu W. (2017). The power of the pen reconsidered: The media, CEO human capital, and corporate governance. *Journal of Banking & Finance*, 76, 175±188.
20. Shipilov A. V., Greve H. R., & Rowley T. J. (2019). Is all publicity good publicity? The impact of direct and indirect media pressure on the adoption of governance practices. *Strategic Management Journal*, 40(9), 1368±1393.
21. Duggirala H. J. (2018). FDA perspectives on social media for postmarket safety monitoring. Food and Drug Administration, (November 15), https://www.fda.gov/media/122897/download
22. Maher A. V. (2015). Adverse event reporting and social media, (June 24±25), https://www.fdanews.com/ext/resources/files/Conference2/SM15Presentations/Maher-Adverse-Event-Reporting-and-Social-Media.pdf.
23. Food and Drug Administration. 2020. Problems Reported with Essure, (December 7), https://www.fda.gov/medical-devices/essure-permanent-birth-control/problems-reported-essure
24. Taylor N. P. (2020). FDA posts Essure adverse events pulled from social media, (August 14), https://www.medtechdive.com/news/fda-posts-essure-adverse-events-pulled-from-social-media/583359/.
25. Astvansh V., Antia K. D., & Tellis G. J. (2024a). What Is (and Isn't) a Product Recall? *Journal of Public Policy & Marketing*, Forthcoming.
26. Iliff L. (2019). Honda uses social media to talk about car crashes. *Automotive News* (December 7), https://www.autonews.com/regulation-safety/honda-uses-social-media-talk-about-car-crashes
27. Abrahams A. S., Fan W., Wang G. A., Zhang Z., & Jiao J. (2015). An integrated text analytic framework for product defect discovery. *Production and Operations Management*, 24(6), 975±990.
28. AbbJapSdjeroh D., Abate M., & Zheng W. (2019). Don't Mention It? Analyzing User-Generated Content Signals for Early Adverse Event Warnings. *Information Systems Research*, 30(3), 1007±1028.

54. Lam H. K., Yeung A. C., & Cheng T. E. (2016). The impact of firms' social media initiatives on operational efficiency and innovativeness. *Journal of Operations Management*, 47, 28±43.

55. Nilsang S., Yuangyai C., Cheng C. Y., & Janjarassuk U. (2019). Locating an ambulance base by using

79. Pfarrer M. D., Pollock T. G., & Rindova V. P. (2010). A tale of two assets: The effects of firm reputation and celebrity on earnings surprises and investors' reactions. *Academy of Management Journal*, 53 (5), 1131±1152.

80. DeAngelo H., DeAngelo L., & Gilson S. C. (1994). The collapse of first executive corporation junk bonds, adverse publicity, and the `run on the bank' phenomenon. *Journal of Financial Economics*, 36 (3), 287±336.

81. Dyck A., Volchkova N., & Zingales L. (2008). The corporate governance role of the media: Evidence from Russia. *Journal of Finance*, 63(3), 1093±1135.

82. Liu B., & McConnell J. J. (2013). The role of the media in corporate governance: Do the media influence managers' capital allocation decisions? *Journal of Financial Economics*, 110(1), 1±17.

83. Core J. E., Guay W., & Larcker D. F. (2008). The power of the pen and executive compensation. *Journal of Financial Economics*, 88(1), 1±25.

84. Kang J., & Han Kim A. Y. (2017). The relationship between CEO media appearances and compensation. *Organization Science*, 28(3), 379±394.

85. Hersel M. C., Helmuth C. A., Zorn M. L., Shropshire C., & Ridge J. W. (2019). The corrective actions organizations pursue following misconduct: A review and research agenda. *Academy of Management Annals*, 13(2), 547±585.

86. Durand R., & Vergne J. P. (2015). Asset divestment as a response to media attacks in stigmatized industries. *Strategic Management Journal*, 36(8), 1205±1223.

87. Baumeister R. F., Bratslavsky E., Finkenauer C., & Vohs K. D. (2001). Bad is stronger than good. *Review of General Psychology*, 5(4), 323±370.

88. Gomulya D., & Boeker W. (2014). How firms respond to financial restatement: CEO successors and external reactions. *Academy of Management Journal*, 57(6), 1759±1785.

89. Gomulya D., Wong E. M., Ormiston M. E., & Boeker W. (2017). The role of facial appearance on CEO selection after firm misconduct. *Journal of Applied Psychology*, 102(4), 617±635. https://doi.org/10.1037/apl0000172 PMID: 27991800

90. Choi I. (2001). Unit root tests for panel data. *Journal of International Money and Finance*, 20(2), 249±272.

91. Gioia D. A., Schultz M., & Corley K. G. (2000). Organizational identity, image, and adaptive instability. *Academy of Management Review*, 25(1), 63±81.

92. Dellarocas C. (2003).

104. Korn C., & Einwiller S. (2013). Media coverage about organisations in critical situations: Analysing the impact on employees. *Corporate Communications*: *An International Journal*.

105. Dai L., Parwada J. T., & Zhang B. (2015). The governance effect of the media's news dissemination role: Evidence from insider trading. *Journal of Accounting Research*, 53(2), 331±366.

106. Tang Z., & Tang J. (2016). Can the media discipline Chinese firms' pollution behaviors? The mediating effects of the public and government. *Journal of Management*, 42(6), 1700±1722.

107. Gan A. (2006). The impact of public scrutiny on corporate philanthropy. *Journal of Business Ethics*, 69 (3), 217±236.

108. Bernheim B. D., Shleifer A., & Summers L. H. (1986). The strategic bequest motive. *Journal of Labor Economics*, 4(3, Part 2), S151±S182.

109. Nikolaeva R., & Bicho M. (2011). The role of institutional and reputational factors in the voluntary adoption of corporate social responsibility reporting standards. *Journal of the Academy of Marketing Science*, 39(1), 136±157.

110. Jia M., Tong L., Viswanath P. V., & Zhang Z. (2016). Word power: The impact of negative media coverage on disciplining corporate pollution. *Journal of Business Ethics*, 138, 437±458.

111. Zhao X., Lee Y., Flynn B. B., & Ng S. (2009). Impact of product recall announcements on shareholder wealth in China. *Global Supply Chain Quality Management*: *Product Recalls and their Impact*, 142(1), 197±217.

112. Wanta W., Golan G., & Lee C. (2004). Agenda setting and international news: Media influence on public perceptions of foreign nations. *Journalism & Mass Communication Quarterly*, 81(2), 364±377.

113. Hayward M. L., & Hambrick D. C. (1997). Explaining the premiums paid for large acquisitions: Evidence of CEO hubris. *Administrative Science Quarterly*, 42(1), 103±127.

114. Reuters Institute. (2020). Digital News Report 2020. https://reutersinstitute.politics.ox.ac.uk/sites/default/files/2020-06/DNR_2020_FINAL.pdf.

115. Watson A. (2020). Social media as a news source worldwide 2020, (June 23), https://www.statista.com/statistics/718019/social-media-news-source/.

116. Shearer E. (2018). Social media outpaces print newspapers in the U.S. as a news source. https://www.pewresearch.org/short-reads/2018/12/10/social-media-outpaces-print-newspapers-in-the-u-s-as-a-news-source/

117. Sismeiro C., & Mahmood A. (2018). Competitive vs. complementary effects in online social networks and news consumption: A natural experiment. *Management Science*, 64(11), 5014±5037.

118. BBC. (2020). Instagram will take overtake Twitter as a news source, (June 15), https://www.bbc.com/news/technology-53050959.

119. Maloney D. (2016). Everyone on Twitter is talking about it' is not the same as everyone talking about it, (January 12), https://www.theguardian.com/technology/2016/jan/12/twitter-talking-journalists-social-media.

120. Chatterjee A., & Hambrick D. C. (2011). Executive personality, capability cues, and risk taking: How narcissistic CEOs react to their successes and stumbles. *Administrative Science Quarterly*, 56(2), 202±237.

121. Wagner I. (2019). Number of vehicles recalled in the United States from 2000 to 2017. Statista, (March 14), https://www.statista.com/statistics/541703/united-states-vehicle-recalls/.

122. Hill K., Menk D., Cregger J., & Schultz M. (2017). Contribution of the automotive industry to the economies of all fifty states and the United States. Center for Automotive Research, (January), https://www.cargroup.org/wp-content/uploads/2017/02/Contribution-of-the-Automotive-Industry-to-the-Economies-of-All-Fifty-States-and-the-United-States2015.pdf.

123. Williams R. (2019). Toyota and other auto brands favor Facebook, Instagram for social media ads. *Marketing Drive*, (May 8), https://www.marketingdive.com/news/toyota-and-other-auto-brands-favor-facebook-instagram-for-social-media-ads/554309/.

124. Liu Y., Shankar V., & Yun W. (2017). Crisis management strategies and the long-term effects of product recalls on firm value. *Journal of Marketing*, 81(5), 30±48.

125. Berger J., Sorensen A. T., & Rasmussen S. J. (2010). Positive effects of negative publicity: When negative reviews increase sales. *Marketing Science*, 29(5), 815±827.

126. Horverak Ø. (2009). Research NoteÐ Wine JournalismÐ Marketing or Consumers' Guide? *Marketing science*, 28(3), 573±579.

127. **127.** Kaniel R., & Parham R. (2017). WSJ Category Kingswood (pod.) R. Infumen inst 3.111 Tf (,)Tj 4.0418 0 Td ((20

129.

155. Wang Y.-Y., Wang T., & Calantone R. (2021). The effect of competitive actions and social media perceptions on offline car sales after automobile recalls. *International Journal of Information Management*, 56, 1±12.

156. Pauwels K., Demirci C., Yildirim G., & Srinivasan S. (2016). The impact of brand familiarity on online and offline media synergy. *International Journal of Research in Marketing*, 33(4), 739±753.