The Effects of the News Media on a Firm's Voluntary Product Recalls[1]

Forthcoming in *Production and Operations Management*
Departmental Editor: Fred Feinberg (POM-Marketing Interface department)

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[1] This article is inspired by Vivek's doctoral dissertation. If you find errors, have questions on the article, or have ideas on how to extend this research, please consider emailing Vivek. Thank you!

Abstract

Does the news media's reporting of the safety (or the lack thereof) in a firm's products impact managers' voluntary recalls of the products? The current article empirically answers this question in the context of safety defects in vehicles of 22 manufacturers from June 2009 to December 2020 in the United States. Results show that the volume of news reports about safety in a manufacturer's products increases voluntary recalls by managers. Further, the negativity in these news reports strengthens the main effect of news volume, whereas news positivity does not moderate the main effect. Lastly, the media's rating of the manufacturer's products weakens the news volume effect, thus acting as a buffer. The supplementary analysis demonstrates that none of the main or moderation effects exist for involuntary recalls, confirming the theory that news affects managers' voluntary behavior. Lastly, the effects exist for high (and not low) severity voluntary recalls only. The findings unearth the news media's role in enhancing public safety by affecting managerial decisions about recalls.

Key words: News, product recalls, negativity, positivity, quality, safety

1. Introduction

Empirical research in marketing, operations management (OM), and strategic management has identified factors that determine the number of product safety failures a firm acknowledges in a period—as manifest in voluntary product recalls[2] (e.g., Bendig et al. 2018; Haunschild and Rhee 2004; Kalaignanam, Kushwaha, and Eilert 2013). Although this evidence offers insights for academics and practitioners, it overlooks whether and how news organizations can impact the managerial decision of recalls. More broadly, this question helps business disciplines understand the influence of news organizations—a nonproduct market stakeholder—on managerial decisions in the product market. This influence is consequential because as the fourth pillar of democracy, news media are expected to protect and promote the rights of the public and ward it against businesses. Thus, our research question is: *How does the volume of news reports about the safety of a manufacturer's products impact the manufacturer's voluntary recalls?* We focus on voluntary recalls because, unlike their involuntary counterparts, voluntary recalls involve managerial discretion.

Researchers have theorized that the news media may discipline managers, leading them to make socially responsible decisions (Dai, Parwada, and Zhang 2015; Dyck, Volchkova, and Zingales 2008; Farrell and Whidbee 2002). This theory, therefore, predicts that the volume of news about the safety of a firm's products would increase the number of product units the firm's managers recall voluntarily.

Next, we consider how the valence of the news reports and the news media's prior overall rating of the firm's products (based on critics' rating, performance, interior, safety, quality, and reliability) moderate the main effect of news volume on recalls. In the context of safety, news organizations can frame their reports negatively, emphasizing the problem (defects) (Beattie et al. 2021; Zavyalova et al. 2012), and/or positively, highlighting the solution (recalls) (Hora, Bapuji, and Roth 2011). Indeed, anecdotes support this coexistence of negativity and positivity in the news about product safety (*Consumer Reports* 2015; Ducharme 2019). We reason that the negativity in the news causes managers to perceive greater reputational costs (Bednar 2012; Farrell and Whidbee 2002; Liu, McConnell, and Xu 2017; Shipilov, Greve, and Rowley 2019), strengthening the main effect of news volume on voluntary recalls. Conversely, the positivity in the news about product safety makes managers less concerned about news about product defects, weakening the main effect of news volume on voluntary recalls. Similarly,

[2] A voluntary product recall is one that a firm initiates without *any* intervention of the safety regulatory agency. For example, in the case of an automobile recall in the United States, a recall is voluntary if the U.S. National Highway Traffic Safety Administration (NHTSA)—the automobile safety regulator—does not open any safety investigation into the recalled automobiles prior to the manufacturer's initiation of the recall. Should the NHTSA open such an investigation, the mere opening makes the manufacturer's initiation of recall involuntary (Astvansh, Ball, and Josefy 2022; Kalaignanam, Kushwaha, and Eilert 2013; Liu, Shankar, and Yun 2017). As we will discuss later, in the example of air bag recalls by Honda, the harm is highly severe, but Honda indeed voluntarily initiated the recall because the NHTSA did not open an investigation before Honda's initiation of the recall. Thus, voluntariness of a recall and severity of the harm caused are two unrelated dimensions of a recall.

the news media's prior overall rating of the firm's products acts as a reputational buffer, weakening the effect of news volume.

We test our expectations in the context of automobile recalls initiated by 22 firms in the United States. We looked at each month between June 2009 and December 2020 for a total of 2,921 firm-month observations. Results from instrumental variables regressions (control function method) suggest that news volume about product safety increases a firm's voluntary recalls. In addition, news negativity strengthens this effect, whereas news positivity does not moderate the effect. Collectively, these results suggest the public-safety enhancing role of the volume and the negativity of news organizations' coverage of product safety. Next, we find that the media's rating of the firm's products weakens the effect, suggesting a buffering role of the media's prior rating. Supplementary analysis documents that none of the main or moderation effects exists for involuntary recalls, further supporting our theory that news coverage affects recalls that managers can control. Further, all the effects exist for voluntary recalls that involve high severity, life-threatening defects that have serious consequences for firms and managers. In contrast, none of the effects exists for low-severity voluntary recalls. These findings suggest that the news media are more effective in motivating managers to pursue high-severity voluntary recalls than low-severity voluntary recalls. Lastly, we topic modeled textual content of news reports to explore the heterogeneity by the topics contained in news. We find that the volume of news that emphasize safety and recall (as opposed to other topics, such as emissions and legal) drives our observed main effect of news volume.

Our findings contribute to two multidisciplinary bodies of research: product recalls and the role of media in business decisions. First, by studying how news coverage of safety in a firm's products affects its voluntary product recalls, we take multidisciplinary product recall research into new but consequential territory (Hora, Bapuji, and Roth 2011; Wowak et al. 2021). Specifically, we demonstrate that recalls are as much a response to external pressure as they are to internal characteristics (Chakravarty, Saboo, and Xiong 2021; Haunschild and Rhee 2004; Shah, Ball, and Netessine 2017) or managerial values (Mayo, Ball, and Mills 2021; Wowak et al. 2021).

Second, our findings contribute to the literature at the intersection of news organizations and businesses (i.e., media's effects on business). This rich literature has demonstrated that media coverage of a firm affects its managers' discretionary choices in the social and environmental responsibility domains (Chiu and Sharfman 2011). We add to this literature by documenting a public safety-enhancing effect of news coverage—that is, recalls of unsafe products. Relatedly, in documenting the mitigating effect of news organizations' rating of a firm's products, we inform managers that they should seek such validation of their products and strive for higher ratings.

2. News Media and Voluntary Recalls

News "is an attempt to reconstruct the essential framework of an event" or an issue (Schramm 1949: 288). The news media refer to professional news *organizations* that produce and deliver news to the public. They include print media (newspapers and magazines), broadcast or tape media (television and radio), and the Internet (online newspapers, news blogs, and news videos) (Jonsson and Buhr 2011).

The news media's coverage of firms provides "institutional and cultural accounts within which the appropriateness and desirability of [a firm's] actions can be evaluated" and thus "affects impression formation and legitimation of firms" (Pollock and Rindova 2003, p. 632). By acting as conduits of institutional pressure, news organizations "prompt firms to conform to prevailing institutional logics" (Bednar 2012: 137). Importantly, news organizations do not just disseminate factual information about a firm (i.e., the volume of coverage), but also tend to use an evaluative tone (i.e., negative/positive valence in the presentation of the information) that shapes stakeholders' perceptions of firm actions and inactions (Bansal and Clelland 2004). This evaluative tone becomes particularly consequential when the focal issue is of public interest, such as a safety defect in a product (Desai 2014; Hoffman and Ocasio 2001). Further, the media's need to tell a "story" (Nilsson and Enander 2020) and tendency to sensationalize information (Hideg et al. 2020) mean that the stories they tell often portray a firm's managers as characters. In doing so, the media elevate managers to celebrity status (Pfarrer et al. 2010), particularly in the event of positive news. Conversely, negative news spills over—perhaps, more easily and more often than its positive counterpart—to a firm's managers, raising doubts about their credibility and integrity (DeAngelo et al. 1994).

Institutional theory suggests that firm actions are often driven by institutional pressures to build and maintain legitimacy in the eyes of the firm's stakeholders (DiMaggio and Powell 1983; Meyer and Rowan 1977). Therefore, firm actions are often in response to how the news media report about the firm and its decisions (Graf-Vlachy et al. 2020). The positivity in the media's coverage of the firm builds legitimacy for the firm and grants it the license to operate. In contrast, negative media coverage may damage a firm's reputation among customers and, thus, negatively impact the firm's sales and earnings (e.g., Kölbel et al. 2017). In addition, negative media coverage may influence investors' beliefs about a firm's value and, thus, lead to stock price drops and stock turnover (e.g., Griffin, Hirschey, and Kelly 2011). Lastly, negative media coverage for labor and employment issues may hurt a firm's employer brand, challenging the firm's ability to attract and retain talented employees for long-term competitive advantages (Dineen et al. 2019). Building on such research, we next investigate how three aspects of the news media—volume, valence, and product rating—shape firms' product recall decisions.

2.1. News Volume

When news organizations choose to report about the safety (or the lack thereof) of a firm's products, they lower information asymmetry between the firm's stakeholders and the managers (Core, Guay, and Larcker 2008; Dai, Parwada, and Zhang 2015). A decrease in information asymmetry gives stakeholders a clearer picture of managers' voluntary actions and inactions, increasing the future scrutiny on managerial behaviors on the safety issue (Sutton and Gallunic 1996). This scrutiny may discipline managers to act in socially responsible ways (Core, Guay, and Larcker 2008; Dai, Parwadam and Zhang 2015; Dyck, Volchkova, and Zingales 2008; Farrell and Whidbee 2002; Tang and Tang 2013) by increasing the number of unsafe product units voluntarily recalled. Moreover, the voluntary aspect of these recalls can help the managers generate moral capital (Gan 2006), which they can appropriate on the labor market (Dyck, Volchkova, and Zingales 2008; Liu and McConnell 2013).

The main effect of news volume on voluntary recalls could be moderated by the valence of the news reports. Although intuition suggests that in the context of product safety, media coverage would be predominantly negative, researchers have discovered that coverage of this issue may be positive as well (e.g., Zavyalova et al. 2012). Following research in the management discipline (Baumeister et al. 2001; Gomulya and Boeker 2014; Gomulya et al. 2017; Shipilov, Greve, and Rowley 2019), we consider both dimensions—news negativity and news positivity—and the reason why they might differentially influence managers' voluntary recalls.

2.2. News Valence

The negativity in the news about the safety of a firm's products can discipline managers by making salient three types of perceived reputational costs: economic, social, and psychological (Bednar 2012; Farrell and Whidbee 2002; Liu et al. 2017; Shipilov et al. 2019). First, the negativity signals managers' inability to shape public perceptions of their firm, damaging their reputations in the eyes of future employers (Dyck, Volchoka, and Zingales 2008; Farrell and Whidbee 2002). Second, the negativity may also damage the managers' reputations within their communities; in extreme cases, leading to embarrassment, shame (Skeel 2001), and stigmatization (Bednar et al. 2013; Pozner 2008). Third, criticism from news organizations can reduce managers' self-confidence and evoke in them negative emotions (such as anger, annoyance, and fear) (Gamache and McNamara 2019; Sutton and Gallunic 1996). We thus have reason to expect that news negativity strengthens the positive main effect of news volume on voluntary recalls.

While commenting on a *Time* magazine report on why recalls have become more common, an expert opined, "Most recalls could even be a good thing" (Ducharme 2019: 1). Similarly, a *Consumer*

Reports' assessment of "the truth about car recalls" found that contemporary "cars are actually safer" (*Consumer Reports* 2015: 1). As these anecdotes illustrate, while reporting on the safety of a firm's products, news organizations "may portray the [recalling] firm in a positive light" (Hora, Bapuji, and Roth 2011: 768). Specifically, they may frame a recall in terms of a firm's diligence about quality issues (Zhao et al. 2009), and as a corrective (Hersel et al. 2019) and a socially responsible (Hora, Bapuji, and Roth 2011) response to the unsafe product. This positivity in the news deflects attention away from a firm's wrongdoing (e.g., safety defects) and instead emphasizes the firm's positive response (e.g., recall) (Zavyalova et al. 2012). Such positivity reflects the media's belief that a firm is acting appropriately by accepting responsibility for its unsafe products and effectively executing corrective actions (e.g., Deephouse 2000; Pollock and Rindova 2003). Such positivity may make managers accrue reputational benefits (Chatterjee and Hambrick 2011; Hayward and Hambrick 1997), lowering their voluntary recalls.

2.3. Media's Rating of the Products

Several news organizations rate a firm and its offerings. For example, *U.S. News & World Report* rates a car manufacturer's models on multiple dimensions (performance, interior, safety, quality, and reliability), publishing an overall rating of the products. Because firms rely on the approval of relevant others (e.g., news organizations) to obtain needed resources and survive (McDonnell and King 2013), managers view these ratings as an external confirmation of their product's reputation (Chen, Ganesan, and Liu 2009; Liu, Liu, and Luo 2016). The reputation of a firm's products is the outcome of a more deliberate process based on the firm's ability to deliver value as defined by the expectations of the evaluators such as news organizations (McDonnell and King 2013). Noticeably, the reputation-as-asset logic (Shipilov et al. 2019) suggests that managers may conclude that the positive reputation can help the firm withstand the pressure exerted by the volume of news about the safety of its products (Pfarrer et al. 2010; Zavyalova et al. 2012). Consequently, we expect the media's rating of the firm's products to weaken the number of voluntary recalls (Hayward and Hambrick 1997).

3. Data and Methodology

3.1. Research Context

We chose the U.S. automobile industry as the context for three reasons. First, recalls are pervasive in the automobile industry, increasing the relevance of our research question to the industry (Wagner 2019). Second, the economic significance and public relevance of the U.S. automobile industry (Hill et al. 2017) increase the industry's coverage in the news (Beattie et al. 2021). High coverage makes relevant the measurement of the effectiveness of news (e.g., Wang et al. 2021). Third, focusing on a single industry rather than multiple industries also helps obviate the need to include a wide array of cross-industry factors to control for potential heterogeneity in multi-industry studies. Because industry factors are common for all the manufacturers within the industry, the results have higher internal validity (Liu, Shankar, and Yun 2017).

3.2. Data

We collected the data in six steps. First, we consulted Ward's Intelligence database to obtain the list of 22 passenger car manufacturers that account for 95% of the annual sales volume of passenger cars in the United States (Astvansh 2018). 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. Second, for each manufacturer, we collected car recall data from June 2009 to December 2020 from the NHTSA's recalls data file (FLAT_RCL.txt archived in https://www-odi.nhtsa.dot.gov/downloads/folders/Recalls/FLAT_RCL.zip). Third, following Wang, Wang, and Calantone (2021), we searched Factiva by the manufacturer name and the presence of any safety-related keywords—such as safety, defect, and faulty—to collect the text of each unique news report about the safety of each manufacturer's vehicles. Fourth, to measure the negativity and the positivity in each news report, we created a support vector machine (SVM) built on Bidirectional Encoder Representations from Transformers (BERT) and trained on news reports about corporations (see appendix B in the e-companion for details). Fifth, for each manufacturer-month, we computed a mean score for *news negativity* and *news positivity*. Sixth, we collected from various sources data on an exhaustive set of control variables that can affect safety news and managers' recall decision (i.e., "third" variables). Our final sample is an unbalanced panel of 2,921 manufacturer-month observations, covering 2,501 recalls initiated by 22 manufacturers for up to 139 months, ranging from June 2009 to December 2020. Table 1 names the key variables in our model and lists for each the measures, data sources, measurement, and role in regression (Table A1 in the e-companion lists all the variables). Table 2 reports the descriptive statistics for the variables used in the study. Table A2 in the e-companion reports the Pearson pairwise correlation coefficients.

Table 1: Measures and Data Sources for the Variables

Variable name	Variable measure	Data source	Measurement	Role in Regression, Logic (for Control Variables), and Reference Articles
Voluntary recalls	The number of vehicles the focal manufacturer recalled *voluntarily* in the focal month divided by the sum of the number of vehicles the	NHTSA's FLAT_RCL.txt and Wards Intelligence	Monthly measure at $t+1$ Multiplied by 1,000 to	DV (Kalaignanam, Kushwaha, and Eilert 2013; Liu and Shankar 2015)

	manufacturer sold in the previous 12 months		facilitate interpretation	
Involuntary recalls	The number of vehicles the focal manufacturer recalled *involuntarily* in the focal month divided by the sum of vehicles sold by the make in the previous 12 months	NHTSA's FLAT_RCL.txt and Wards Intelligence	Monthly measure at $t+1$ Multiplied by 1,000 to facilitate interpretation	DV for supplementary analysis (Haunschild and Rhee 2004)
Media coverage of incidents that create environmental, social, and governance (ESG) risk for the peers	The average of the number of news reports about the focal manufacturer's peers in the prior quarter about events that create ESG risk. We weighted each report by the reach/influence of the publication.	RepRisk's News Data file	Quarterly measure at t	Instrument (Deephouse and Carter 2005; Kang and Kim 2017)
News volume	The number of unique news reports in the focal month about the safety of the focal manufacturer's vehicles	Factiva	Monthly measure at t	IV (Chakravarty, Saboo, and Xiong 2021; Kang and Kim 2017)
News negativity	The average of the negativity in the news reports in the focal month about the safety of the focal manufacturer's vehicles	BERT-based Support Vector Machine trained on https://www.kaggle.com/ankurzing/sentiment-analysis-for-financial-news	Monthly measure at t	Moderator (Kuhnen and Niessen 2012)
News positivity	The average of the positivity in the news reports in the focal month about the safety of the focal manufacturer's vehicles	BERT-based Support Vector Machine trained on https://www.kaggle.com/ankurzing/sentiment-analysis-for-financial-news	Monthly measure at t	Moderator (Kuhnen and Niessen 2012)
News media's product rating	U.S. News & World Report' overall rating of models of the focal manufacturer in the focal year. The rating is based on critics' rating, performance, interior, safety, quality, and reliability.	*U.S. News & World Report*	Annual measure at t	Moderator (Chen, Ganesan, and Liu 2009; Liu, Liu, and Luo 2016)

Table 2: Descriptive Statistics

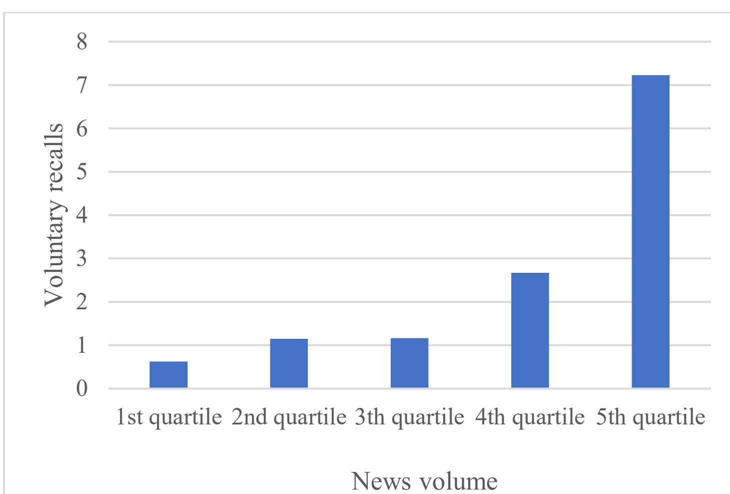
Variables	N	Mean	SD	p25	p50	p75
Voluntary recalls	2,921	2.45	13.79	0.00	0.00	0.32

Involuntary recalls	2,921	1.92	16.13	0.00	0.00	0.00
Peers' ESG risk media coverage	2,921	6.17	7.58	1.00	3.78	8.11
News volume	2,921	9.70	31.37	1.00	3.00	9.00
News negativity	2,117	0.31	0.27	0.00	0.34	0.52
News positivity	2,117	0.10	0.12	0.00	0.07	0.14
News media's product rating	2,921	7.95	0.40	7.74	8.00	8.24
UGC volume	2,921	68.45	235.93	6.00	16.00	42.00
Advertising spending	2,921	23973.44	20545.48	9948.70	19060.60	31278.90
Recall experience	2,921	11.48	10.64	4.00	8.00	15.00
Safely complaints	2,921	71.90	34.51	40.00	100.00	100.00
Deaths	2,921	0.57	3.87	0.00	0.00	0.00
Reputational risk	2,921	21.34	11.11	13.38	20.43	29.80
Debt ratio	2,921	0.65	0.17	0.59	0.64	0.75
Cash flow ratio	2,921	0.11	0.06	0.08	0.11	0.13
R&D intensity	2,921	0.01	0.02	0.00	0.00	0.00
Price	2,921	40252.92	19670.38	28463.55	34440.87	48653.10
Road test score	2,921	74.07	8.50	71.55	75.00	79.50
Product portfolio	2,921	12.80	9.11	6.00	10.00	17.00

3.3 Model-Free Evidence

Before imposing a functional form on the relationship between news volume and voluntary recalls, we offer model-free evidence on the relationship between these two variables. The Pearson correlation coefficient between these two variables is 0.16 ($p < .01$), indicating that these two variables have a positive relation. In addition, we created a bar chart to pictorially depict the relationship. To do so, we first divide news volume into five quartiles and then calculate the average of voluntary recalls for each quantile. Figure 1 demonstrates that the average of voluntary recalls increases with the quartile of news volume, further indicating a positive relationship between news volume and voluntary recalls.

Figure 1. Bar Chart of News Volume and Voluntary Recalls



3.4 Model Specification and Estimation

We test our arguments using ordinary linear squares (OLS) panel data regressions, where the manufacturer identifier serves as the cross-sectional variable and the calendar month acts as the time variable. To mitigate the concern associated with reverse causality (i.e., voluntary recalls attract news about product safety), we measure our dependent variable in $t+1$, whereas predictors and control variables are measured in t. The inclusion of manufacturer-level fixed effects controls the effect of unobservable time-invariant manufacturer-level heterogeneity that may affect recalls. Similarly, the inclusion of month-specific fixed-effects allows us to control for time heterogeneity that may impact recalls.

Despite the inclusion of fixed effects for manufacturers and calendar months, our specification likely omits time-varying variables that impact news volume and directly affect a manufacturer's number of recalls. For example, a manufacturer may appoint managers who manage simultaneously relations with news organizations and supervise the quality of the manufacturer's product. Omitting such variables makes news volume endogenous to our specification, leading to biased estimates.

The two common methods to correct for endogeneity are matching followed by difference-in-differences regression, and the two-stage least squares (2SLS) regression. Because our independent variable—news volume—is a continuous (as opposed to a binary) variable, matching is not an ideal fit. Further, because we aim to test the moderating effect of news valence and product rating on the relationship between news volume and recalls, 2SLS would require us to correct separately for the endogeneity of the interaction terms as well, suggesting that we need a more general approach. Unlike 2SLS, the control function method represents a more general form of the instrumental variable (IV) approach (Rossi 2014). It also does not require such separate correction for the endogeneity of interaction terms. In addition, the control function method is more general than maximum likelihood as the first stage function can be semiparametric or nonparametric (Wooldridge 2015). We, therefore, use the control function method to correct endogeneity of news volume.

The instrument that we choose for news volume is the news media's coverage of peers' environmental, social, and governance (ESG) risk (Deephouse and Carter 2005; Kang and Kim 2017). To measure this instrument, we first need to identify a manufacturer's peers. We consider other manufacturers from the same geographic region (Asia, Europe, and North America) and pursuing the same market position (luxury versus nonluxury) as peer manufacturers. Next, for each peer, we collected from RepRisk the number of news reports of incidents that create ESG risk for the peer. For each news report, RepRisk also provides the level of influence of the publication. For example, international publications such as the *Wall Street Journal* or the *Financial Times* are more influential than local publications. RepRisk classifies each publication into one of the three levels of influence: high (assigned an integer value of 3), medium (2), and low (1). Our instrument thus is the average of weighted news reports about incidents that create ESG risk for the focal manufacturer's peers. We consider reports published in the prior quarter.

We believe that this instrument is both relevant and exogenous. News coverage tends to cluster at the regional level (Kaustia and Knüpfer 2012) and the product group level (Liu and Shankar 2015). Consequently, media coverage of a manufacturer's peers' ESG risk can impact the news volume about the safety and recalls of the manufacturer's products. However, peers' ESG risk should not directly influence the focal manufacturer's voluntary recall decisions.

We use the following two-step procedure. We estimate the following first-stage regression where we regress our endogenous variable (i.e., news volume) on the instrumental variable and all control variables.

$$News\ volume_{i,t} = \beta_1 Media\ Coverage\ of Peers'ESG\ risk_{i,t} + Manufacturer_i + Controls_{i,t} + Year - month\ FE + \varepsilon_{i,t}\ (1)$$

where subscript *i* indexes the manufacturer, and *t* indexes the month.

We collected the residuals from the above regression and included them as "control function" in the following second stage model.

$$Voluntary\ recalls_{i,t+1} = \beta_1 News\ volume_{i,t} + Manufacturer_i + Controls_{i,t} + Year - month\ FE + Residuals + \varepsilon_{i,t+1}\ (2)$$

To test the interaction effect between news volume and news negativity/positivity, we sample manufacturer year-month observations that have at least one report about the safety of the manufacturer's vehicles. This selection may bias our sample. In other words, there can be unobservable heterogeneity that drives both whether a firm has product safety news in a year-month and its voluntary recalls in the following month. To address this potential bias, we estimate a Heckman selection model (Pfarrer, Pollock, and Rindova 2010). Specifically, we estimate a first-stage probit regression, using as a dependent variable whether a manufacturer receives product safety news in a year-month. The predictors in the first-stage regression are sales (measured as the total sales volume), product portfolio (the number of car models from the manufacturer), luxury (receiving a value of 1 if an automaker manufactures luxury cars and 0 otherwise), Asia (receiving a value of 1 if an automaker is from Asia and 0 otherwise), Europe (receiving a value of 1 if an automaker is from Europe and 0 otherwise), North America (receiving a value of 1 if an automaker is from North America and 0 otherwise), price, advertising spending, recall experience, complaints, deaths, and time fixed effects. We used estimates from the first-stage probit regression to calculate the inverse Mills ratio (IMR) and include it as a control variable in specifications that include the interaction term between news volume and news negativity/positivity.

4. Results

Table 3 reports estimates from the first-stage regression of the control function method (Model 1) and results for our second-stage regression (Models 2-6). As expected, we find that media coverage of peers' ESG risk increases the number of news reports about the safety of the focal manufacturer's products (Model 1: $b = .998$, $p < .01$).

We next report estimates from four nested models for our second-stage regression. Model 2 includes only the control variables. Model 3 adds the key independent variable—news volume—to model 2. Model 4 adds to model 3 the two two-way interaction terms, interacting news volume with news negativity and news positivity. Model 5 is model 3 plus the two-way interaction term between news volume and the news media's overall rating of the manufacturer's products. Model 6 reports a full model with all the interaction terms. We next discuss the estimates from models 3, 4, 5, and 6.

Table 3: Regression Estimates

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
	First-stage	Second-stage				
Variables	DV = News volume	DV = Voluntary recalls				
Instrument: Media coverage of peer ESG risk	0.998***					
	(0.099)					
News volume			0.229***	-0.048	0.925***	0.283
			(0.051)	(0.153)	(0.264)	(0.331)
News negativity				-1.090		-1.032
				(1.645)		(1.646)
News volume × News negativity				0.692***		0.652***
				(0.197)		(0.200)
News positivity				-0.391		-0.632
				(3.281)		(3.288)
News volume × News positivity				-0.603		-0.529
				(0.462)		(0.467)
News volume × News media's product rating					-0.086***	-0.039
					(0.032)	(0.035)
News media's product rating	10.850***	2.851**	0.542	-0.343	1.225	0.070
	(2.330)	(1.216)	(1.317)	(1.584)	(1.340)	(1.625)
UGC volume	0.033***	0.000	-0.008***	-0.008***	-0.007***	-0.007***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Price	18.010***	3.387	0.744	1.997	1.271	2.191
	(6.667)	(3.462)	(3.501)	(4.829)	(3.502)	(4.832)

Advertising spending	-0.852	-0.305	-0.073	-0.048	-0.116	-0.064
	(0.623)	(0.328)	(0.331)	(0.424)	(0.331)	(0.424)
Recall experience	0.351***	-0.049	-0.142***	-0.157***	-0.138***	-0.156**
	(0.089)	(0.046)	(0.051)	(0.061)	(0.051)	(0.061)
Safely complaints	0.273***	0.046**	-0.015	-0.008	-0.007	-0.005
	(0.038)	(0.020)	(0.024)	(0.029)	(0.024)	(0.029)
Deaths	1.018***	0.057	-0.183**	-0.129	-0.152*	-0.117
	(0.128)	(0.067)	(0.086)	(0.107)	(0.086)	(0.107)
Reputational risk	0.737***	0.138**	-0.111	-0.082	-0.122	-0.086
	(0.122)	(0.061)	(0.083)	(0.097)	(0.083)	(0.097)
Debt ratio	35.339***	2.227	-5.917	-7.721	-5.850	-7.790
	(8.714)	(4.542)	(4.881)	(6.090)	(4.875)	(6.090)
Cash flow ratio	27.969	-8.261	-13.382	-18.868	-13.256	-19.212*
	(17.405)	(9.081)	(9.122)	(11.472)	(9.112)	(11.475)
R&D intensity	139.425***	-34.053	-53.166**	-69.607**	-53.373**	-69.216**
	(49.441)	(25.670)	(25.939)	(30.145)	(25.910)	(30.145)
Road test score	0.244*	0.071	0.014	-0.130	0.027	-0.113
	(0.142)	(0.074)	(0.075)	(0.108)	(0.075)	(0.109)
Product portfolio	-0.166	-0.022	0.017	0.089	0.011	0.082
	(0.129)	(0.067)	(0.068)	(0.074)	(0.068)	(0.074)
Inverse Mills ratio				4.044		4.078
				(3.045)		(3.045)
Residuals (from the first-stage regression)		0.033***	-0.196***	-0.170***	-0.170***	-0.160***
		(0.010)	(0.052)	(0.058)	(0.053)	(0.059)
Constant	-341.958***	-66.057*	-3.456	-5.876	-15.670	-12.552
	(72.192)	(37.494)	(39.916)	(53.530)	(40.128)	(53.852)
Manufacturer fixed effects	YES	YES	YES	YES	YES	YES
Year-month fixed effects	YES	YES	YES	YES	YES	YES
Overall-R-squared	0.227	0.107	0.103	0.192	0.103	0.192

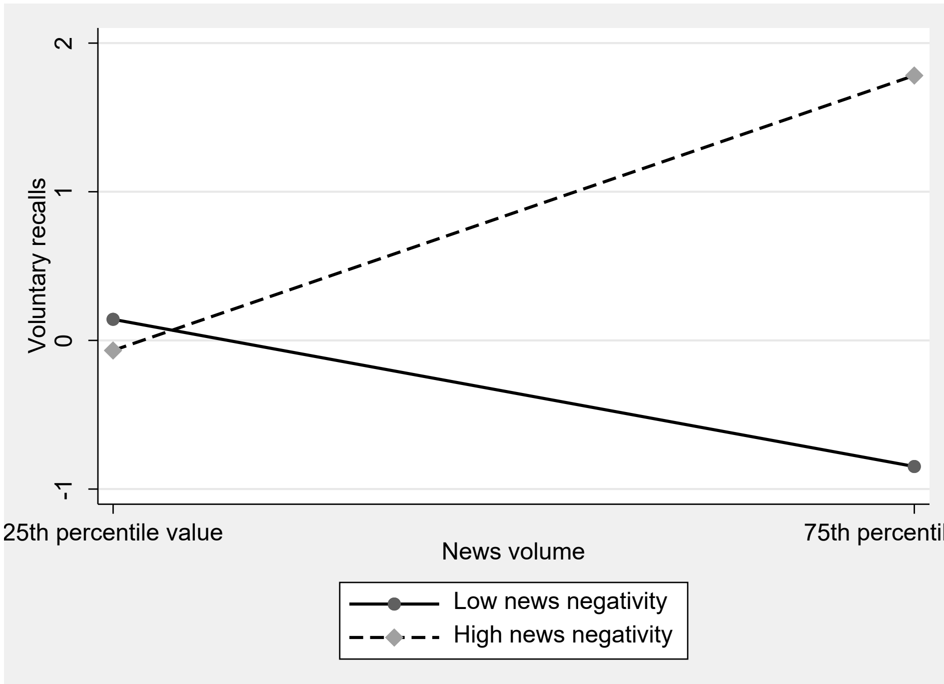
Notes: The number of observations is 2,921 except for Models 4 and 6 (2,117). The number of observations for Models 4 and 6 is smaller because it excluded manufacturer-month observations that had zero news reports about product safety. The number of manufacturers is 22. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Two-tailed tests.

Consistent with our expectation, the main effect model (i.e., Model 3) shows that the number of news reports in a month about the safety of a manufacturer's products is positively associated with the scaled number of units the managers recall voluntarily in the following month (Model 3: $b = .229$, $p < .01$). We interpret the effect as follows. When news volume increases from its 25th percentile value (= 1) to its 75th percentile value (= 9), the number of vehicles voluntarily recalled (scaled by the number of vehicles sold in the previous 12 months) increases by 75% of its mean value.

Model 3 reports significant correlations between our DV (voluntary recalls) and four control variables: UGC volume, recall experience, R&D intensity, and deaths. UGC volume about the safety of a manufacturer's products is negatively associated with voluntary recalls—a relationship that is opposite of that of news volume. This finding is consistent with prior research (e.g., Wang et al. 2021) that shows that social media and news have different characteristics (e.g., the former is generated by the public whereas the latter by journalists), and they thus affect managerial behaviors and firm outcomes differently. Next, consistent with prior research (e.g., Thirumalai and Sinha 2011), we find that prior recall experience is negatively related to future recalls, indicating the effect of learning. R&D intensity is also negatively associated with recalls, suggesting that it helps mitigate product defects (e.g., Wowak et al. 2021). The most surprising result is that the deaths are negatively associated with recalls. We urge caution in interpreting this association because the number of deaths is correlated with other control variables. Indeed, when we later test robustness of our findings with alternative identification methods—specifically, the instrument-free method of Gaussian copula and entropy balancing—we find that the number of deaths is insignificantly associated with voluntary recalls.

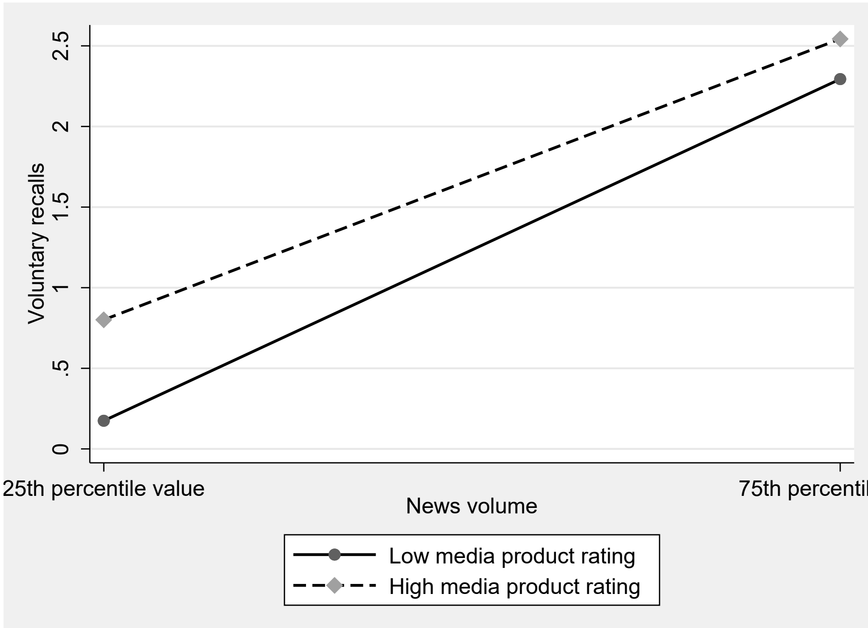
When we include the interaction of news volume with news negativity and news positivity (Model 4), the effect of news volume on voluntary recalls becomes insignificant (Model 4: $b = -.048$, $p > .1$). Further, the negativity in the news strengthens the main effect of news on voluntary recalls (Model 4: $b = .692$, $p < .01$). Specifically, when news negativity takes its 25th (75th) percentile value, and as news volume increases from its 25th percentile value to its 75th percentile value, the number of vehicles recalled decreases by 41% (increases by 76%) of its mean value. These findings suggest that the influence of news volume hinges on the degree of news negativity. Figure 2 helps interpret the interaction effect. It demonstrates a positive predicted relationship between news volume and voluntary recalls in the presence of high negativity tone (the dotted line). However, the relationship between news volume and voluntary recalls is negative in the presence of a low negativity tone (the solid line). The positivity in the news, on the other hand, does not significantly moderate the main effect of news volume on voluntary recalls (Model 4: $b = -.603$, $p > .1$).

Figure 2. The Moderating Effect of News Negativity on the Relationship between News Volume and Voluntary Recalls



We now turn our attention to how the news media's rating of the manufacturer's products may moderate the relationship between news volume and voluntary recalls. Model 5—which includes the interaction term between news volume and the news media's rating of the manufacturer's products—shows that the effect of news volume on voluntary recalls is positive and significant (Model 5: $b = .925$, $p < .01$). Moreover, the news media's rating of the manufacturer's products weakens this main effect of the news on voluntary recalls (Model 5: $b = -.086$, $p < .01$). We interpret the moderation effect as follows. When the news media's rating of the manufacturer's products takes its 25th (75th) percentile value, and as news volume increases from its 25th percentile value to its 75th percentile value, the number of vehicles recalled increases by 87% (71%) of its mean value. Figure 3 graphically shows a stronger positive relationship between news volume and voluntary recalls in the presence of low media product rating (the solid line) than in the presence of high media product rating (the dotted line). The figure suggests that when a firm's products are rated highly by the news media, the rating shields the firm from the pressure exerted by the volume of news about the safety of the firm's products. This shield weakens the effect of news volume on voluntary recalls—a mechanism that academics call "buffering" (e.g., McDonnell and King 2013).

Figure 3. The Moderating Effect of Media Product Rating on the Relationship between News Volume and Voluntary Recalls



Model 6 includes all three interaction terms and thus is the full model. It reports that the moderating effect of news negativity is positive and significant (Model 6: b = .652, $p < .01$). The moderating effect of news positivity continues to be negative but insignificant (Model 6: b = −.529, $p > .10$). In addition, the moderating effect of the news media's rating of the manufacturer's products is also negative but insignificant (Model 6: b = −.039, $p > .10$). The drop in the significance level of the moderating effect of news media's rating in Model 6 as opposed to Model 5 is probably due to a smaller number of observations (2,921 observations in Model 5 versus 2,117 observations in Model 6). Relatedly, the inclusion of three interaction terms may create multicollinearity issues, leading to an insignificant finding for the interaction between news volume and new media's product rating.

5. Supplementary Analyses

5.1. Do the Effects Exist for Involuntary Recalls?

Our theory is that news influences managerial recall decisions. Should the theory be true, we should see the effects for voluntary recalls and not for involuntary recalls. Therefore, we next estimate our regressions for involuntary (instead of voluntary) recalls. The 22 manufacturers in our sample initiated 2,501 recalls from June 2009 to December 2020. Of the 2,501 recalls, 2,122 (84.85%) are voluntary and the remaining 379 (15.15%) involuntary. Because our main analyses focused on voluntary recalls, we used the 2,122 voluntary recalls for estimation.

Our supplementary analysis used the 379 involuntary recalls for estimation. Table 4 reports the estimates. Model 1 is our main effect model. Model 2 includes the two two-way interaction terms between news volume and news negativity and between news volume and news positivity. Model 3 includes the interaction term between news volume and the news media's rating of the manufacturer's products.

Table 4: Regression Estimates for Involuntary Recalls

	Model 1	**Model 2**	**Model 3**
Variables	DV = Involuntary recalls		
News volume	0.055	0.093	0.177
	(0.060)	(0.211)	(0.306)
News negativity		-2.686	
		(2.267)	
News volume × News negativity		0.090	
		(0.272)	
News positivity		-3.368	
		(4.522)	
News volume × News positivity		-0.466	
		(0.637)	
News volume × News media's product rating			-0.015
			(0.037)
News media's product rating	-2.277	-2.781	-2.158
	(1.528)	(2.182)	(1.556)
UGC volume	-0.001	-0.002	-0.001
	(0.002)	(0.003)	(0.002)
Price	-5.228	-0.252	-5.136
	(4.060)	(6.655)	(4.067)
Advertising spending	0.007	-0.032	-0.000
	(0.383)	(0.585)	(0.384)
Recall experience	-0.023	-0.059	-0.022
	(0.059)	(0.084)	(0.059)
Safely complaints	-0.018	-0.016	-0.016
	(0.028)	(0.040)	(0.028)
Deaths	-0.084	-0.117	-0.078
	(0.099)	(0.147)	(0.100)
Reputational risk	-0.125	-0.199	-0.127
	(0.096)	(0.134)	(0.096)
Debt ratio	1.734	4.557	1.745
	(5.661)	(8.392)	(5.662)
Cash flow ratio	-5.490	-2.180	-5.468
	(10.580)	(15.809)	(10.582)
R&D intensity	94.678***	114.188***	94.641***
	(30.085)	(41.540)	(30.089)

Road test score	0.063	-0.045	0.065
	(0.087)	(0.149)	(0.087)
Product portfolio	-0.081	-0.076	-0.082
	(0.079)	(0.102)	(0.079)
Inverse Mills ratio		-5.737	
		(4.866)	
Residuals	-0.052	-0.067	-0.047
	(0.061)	(0.080)	(0.062)
Constant	69.892	36.860	67.762
	(46.295)	(73.765)	(46.601)
Manufacturer fixed effects	YES	YES	YES
Year-month fixed effects	YES	YES	YES
Overall-R-squared	0.112	0.153	0.112

Notes: The number of observations is 2,921 except for Model 2 (2,117). The number of observations for Model 2 is smaller because it excluded manufacturer-month observations that had zero news reports about product safety. The number of manufacturers is 22. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Two-tailed tests.

None of the main effects or the three interaction effects is statistically significant. Specifically, news volume does not affect involuntary recalls (Model 1: $b = .055$, $p > .1$). Further, neither news negativity (Model 2: $b = .090$, $p > .1$) nor news positivity (Model 2: $b = -.466$, $p > .1$) moderates the effect of news volume on involuntary recalls. Lastly, media's rating of the manufacturer's products does not moderate the effect of news volume on involuntary recalls (Model 3: $b = -.015$, $p > .1$).

5.2. Do the Effects Vary by Recall Severity?

Academics (e.g., Ball, Shah, and Wowak 2018; Eilert et al. 2017; Liu, Liu, and Luo 2016) and safety regulators consider recall severity[3] an essential characteristic of recalls that has the largest impact on public health and safety. Some products have life-threatening defects (e.g., defects that may lead to death, fire, or crash) and their recalls are thus labeled as high severity recalls. For example, in 2019 and 2020, Honda recalled its cars that had defective airbags manufactured by Takata Corporation (Honda 2022). A malfunctioning airbag could deploy improperly, causing significant injuries in head and chest. Alternatively, it may fail to deploy in a crash, leading to fatalities. Such recalls are highly severe.

Alternatively, the product may have nonlife-threatening defects (e.g., labeling errors), and their recalls are low severity. For example, in 2019, Honda recalled its cars because "the owner's guide incorrectly describes when the Passenger Airbag Off Indicator should illuminate and therefore is noncompliant with FMVSS 208, Occupant Crash Protection, S4.5.1 Labeling and Owner's Manual Information" (NHTSA 2019). Such recalls are low in severity.

[3] Recall severity refers to the severity of the harm that the underlying defect may cause to consumers.

Wowak et al. (2021) have reported that the effects of female board representation—which determines corporate governance—on the recall count and the time-to-recall vary by the recall severity. Primed by Wowak et al.'s (2021) findings, we next assess whether the effect of news also varies by the recall severity. Were the effects to exist for high- (and not for low) severity voluntary recalls, the inference would be that news affects recalls of products that have a life-threatening defect. Such an effect suggests a more powerful role of the news media as opposed to what our main findings suggest. Conversely, if news impacts only low severity voluntary recalls, the effect is less consequential in terms of consumer safety.

We subsample our voluntary recalls by high and low levels of severity, and test whether the main and moderation effects exist for both levels. Our main analyses used a sample of 2,122 voluntary recalls initiated by 22 manufacturers from June 2009 to December 2022. Of these 2,122 recalls, 1,946 (91.71%) are highly severe and the remaining 176 (8.29%) are less severe. Table 5 reports the estimates for the two subsamples of high-severity voluntary recalls and low-severity voluntary recalls. In short, the results indicate that our effects exist for only high-severity recalls and not for their low-severity counterparts. The insight is that in influencing the number of high severity voluntary recalls, the news media's role is more profound than what our main findings suggest.

Table 5: Regression Estimates: Heterogeneity by Recall Severity

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Variables	High-severity voluntary recall scale			Low-severity voluntary recall scale		
News volume	0.290***	0.056	1.103***	-0.006	-0.010	-0.001
	(0.078)	(0.256)	(0.399)	(0.005)	(0.017)	(0.025)
News negativity		-3.665			-0.111	
		(2.748)			(0.187)	
News volume × News negativity		0.763**			0.019	
		(0.329)			(0.022)	
News positivity		-3.726			-0.033	
		(5.483)			(0.374)	
News volume × News positivity		-0.993			-0.076	
		(0.772)			(0.053)	
News volume × News media's product rating			-0.100**			-0.001
			(0.048)			(0.003)
News media's product rating	-1.821	-3.276	-1.024	0.086	0.152	0.091
	(1.993)	(2.646)	(2.029)	(0.127)	(0.180)	(0.130)
UGC volume	-0.009***	-0.010**	-0.008**	0.000	0.000	0.000
	(0.003)	(0.004)	(0.003)	(0.000)	(0.000)	(0.000)
Price	-4.249	1.792	-3.633	-0.235	-0.046	-0.232
	(5.296)	(8.070)	(5.301)	(0.338)	(0.550)	(0.339)
Advertising spending	-0.047	-0.054	-0.096	-0.019	-0.026	-0.020
	(0.500)	(0.709)	(0.500)	(0.032)	(0.048)	(0.032)
Recall experience	-0.171**	-0.224**	-0.166**	0.006	0.009	0.006

	(0.077)	(0.101)	(0.077)	(0.005)	(0.007)	(0.005)
Safely complaints	-0.035	-0.030	-0.025	0.002	0.005	0.002
	(0.037)	(0.048)	(0.037)	(0.002)	(0.003)	(0.002)
Deaths	-0.273**	-0.259	-0.237*	0.006	0.013	0.007
	(0.129)	(0.179)	(0.131)	(0.008)	(0.012)	(0.008)
Reputational risk	-0.246**	-0.291*	-0.258**	0.009	0.010	0.009
	(0.125)	(0.162)	(0.125)	(0.008)	(0.011)	(0.008)
Debt ratio	-4.263	-3.388	-4.184	0.079	0.223	0.080
	(7.384)	(10.176)	(7.380)	(0.471)	(0.694)	(0.471)
Cash flow ratio	-18.735	-20.577	-18.588	-0.137	-0.471	-0.136
	(13.801)	(19.169)	(13.793)	(0.881)	(1.307)	(0.881)
R&D intensity	37.253	41.018	37.011	4.259*	3.564	4.257*
	(39.244)	(50.371)	(39.221)	(2.504)	(3.435)	(2.504)
Road test score	0.061	-0.185	0.076	0.016**	0.010	0.016**
	(0.113)	(0.181)	(0.113)	(0.007)	(0.012)	(0.007)
Product portfolio	-0.069	0.009	-0.076	0.005	0.005	0.005
	(0.103)	(0.123)	(0.103)	(0.007)	(0.008)	(0.007)
Inverse Mills ratio		-1.099			-0.108	
		(5.088)			(0.347)	
Residuals	-0.255***	-0.253***	-0.225***	0.007	0.012*	0.007
	(0.079)	(0.097)	(0.080)	(0.005)	(0.007)	(0.005)
Constant	66.224	32.802	51.964	0.212	-1.818	0.128
	(60.390)	(89.446)	(60.743)	(3.853)	(6.100)	(3.879)
Manufacturer fixed effects	YES	YES	YES	YES	YES	YES
Year-month fixed effects	YES	YES	YES	YES	YES	YES
Overall-R-squared	0.126	0.184	0.126	0.0876	0.112	0.0875

Notes: The number of observations is 2,921 except in Models 2 and 5 (2,117). The number of observations in Models 2 and 5 is smaller because it excluded manufacturer-month observations that had zero news reports about product safety. The number of manufacturers is 22. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Two-tailed tests.

5.3. Does the Content of Recall News Matter?

We measured our independent variable—news volume—by searching Factiva for unique news articles that Factiva classified as (1) mentioning the focal car manufacturer, (2) discussing product safety and recall of the focal manufacturer's vehicles—Factiva calls this content the "product recall subject." That is, we follow Factiva's identification of safety- and recall-related news articles and consider all articles to be equal. We next explore whether the heterogeneity in the textual content of these news articles about a manufacturer differentially affects the manufacturer's voluntary recalls.

We ran a topic model—specifically, Bidirectional Encoder Representations from Transformers (BERT) topic model, BERTopic—at the level of bigrams and trigrams in the corpus of news articles (see appendix C in e-companion). We found five topics that we labeled as recall, recall communications, emissions, profit and sales, and legal. The first topic—recall—includes terms for manufacturing defect, design flaw, and of course, recall. The second topic—recall communications—focuses on the manufacturer, its dealers, and the regulator communicating with the affected customers about the recall. Topic #3—emissions—relates to recalls due to violations of emissions standards (as opposed to motor vehicle safety standards). Topic #4—profit and sales—includes terms on the implications of product safety and recall on the manufacturer's profit and sales. The last topic is about product liability that underlies product recalls.

For each manufacturer-month, we computed the number of unique recall-related news articles that focused primarily on topic #1—that is, among the five topics, the "recall" topic must have the highest proportion of terms. Similarly, we computed the number of articles that focused the most on recall communications, the number of topics that emphasized the most emissions, and so on. In summary, we replaced our one independent variable—news volume—with five independent variables.

The results (Table 6) suggest that the number of news articles that focus on recall of a manufacturer's vehicles in a month increases the manufacturer's voluntary recalls in the following month (b = .171, $p < .01$). The counts of news articles on recall communications, or emissions, or legal topics do not matter. However, the number of articles that emphasize profit and sales decreases voluntary recalls (b = −2.98, $p < .10$). We conjecture that when news emphasizes business outcomes associated with recalls, it primes managers to consider the performance consequences of recalls and thus may suppress recalls.

Table 6: Regression Estimates: Heterogeneity by Topics of Recall News Articles

	Model 1
Variables	Voluntary recall scale
News volume: recall as primary topic	0.171***
	(0.061)
News volume: recall communications as primary topic	0.193
	(1.060)
News volume: emissions as primary topic	-0.008
	(0.290)
News volume: profit and sales as primary topic	-2.980*
	(1.583)
News volume: legal as primary topic	-0.155
	(0.302)
Constant	-59.609
	(37.714)
Other control variables	YES
Manufacturer fixed effects	YES
Year-month fixed effects	YES
Overall-R-squared	0.103
Notes: The number of observations is 2,921. The number of manufacturers is 22. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Two-tailed tests.	

6. Robustness Checks

6.1. Robustness to Instrument-Free Identification (Gaussian Copula)

Our estimates from the control function method would be unbiased provided our instrument meets the exclusion restriction—that is, it does not directly affect the dependent variable. Despite our theoretical arguments for why our instrument (media coverage of peers' ESG risk) meets the exclusion restriction, we cannot rule out the plausibility that the instrument may correlate with omitted variables. Unfortunately, this plausibility is a challenge with all instrument-based methods (Wooldridge 2010).

To alleviate concerns about whether our instrument truly meets the exclusion restriction, we next conduct analyses using Gaussian copula. The copula is an instrument-free method introduced in the marketing discipline (Park and Gupta 2012) and has been adopted by academics in finance, economics, and management (read excellent reviews by Eckert and Hohberger 2022; Becker, Proksch, and Ringle 2021). Among all the instrument-free methods, Gaussian copula has received the greatest adoption (Becker, Proksch, and Ringle 2021) and we thus prefer this method over others.

The copula method is similar to the control function method because each relies on estimating two regressions separately (the "two-stage" or "two-step" method). The first-stage regression of the control function method involves regressing the endogenous independent variable (e.g., news volume in our case) on the instrument and other covariates. One estimates the residuals from this regression. These residuals serve as a "control function" in the second-stage regression. The mere inclusion of these residuals in the second-stage regression allows the independent variable to be exogenous and, thus its effect on the dependent variable to be causal (Rutz and Watson 2019). The control function method trumps the default instrument-based method of two-stage least squares (2SLS) in three situations: (1) when the endogenous variable is nonlinear, (2) the specification includes nonlinear (e.g., quadratic) terms of the endogenous regressor, or (3) it includes interaction terms (Papies, Ebbes, and Van Heerde 2017). The last situation applies in our case.

The copula method is similar in principle yet slightly different in approach. The key identification criterion in the copula method is that the endogenous variable must *not* be normally distributed (Eckert and Hohberger 2022; Becker, Proksch, and Ringle 2021). Like the control function method, the copula method includes two stages. The first stage involves computing the inverse normal of the cumulative distribution of the endogenous variable (Becker, Proksch, and Ringle 2021). The resulting variable is the Gaussian copula for the endogenous variable. Next, the copula is included as a control function for the second-stage regression. Thus, the second-stage regression in the control function method and the copula method are the same. The difference lies in how one estimates the control function.

A Shapiro-Wilk test confirmed that our endogenous independent variable—news volume—is *not* normally distributed ($z = 18.36$; $p < .00$), meeting the key identification criterion for using Gaussian copula. Table 7 reports the results from the copula method. These results are consistent with our main results (Table 3). Specifically, news volume increases voluntary recalls, and this effect is strengthened by news negativity but weakened by news media's product rating.

Table 7: Regression Estimates from the Gaussian Copula Method

	Model 1	**Model 2**	**Model 3**
Variables	Voluntary recalls		
News volume	0.044***	-0.226	1.166***
	(0.011)	(0.140)	(0.286)
News negativity		-0.777	
		(1.667)	
News volume × News negativity		0.746***	
		(0.197)	
News positivity		0.226	
		(3.285)	
News volume × News positivity		-0.667	
		(0.464)	
News volume × News media's product rating			-0.133***
			(0.034)
News media's product rating	2.563**	1.462	3.445***
	(1.226)	(1.485)	(1.243)
UGC volume	-0.001	-0.002	-0.001
	(0.001)	(0.001)	(0.001)
Price	2.819	3.088	3.003
	(3.462)	(4.824)	(3.454)
Advertising spending	-0.252	-0.167	-0.258
	(0.328)	(0.423)	(0.327)
Recall experience	-0.063	-0.085	-0.066
	(0.046)	(0.056)	(0.046)
Safely complaints	0.036*	0.039	0.039*
	(0.020)	(0.024)	(0.020)
Deaths	0.013	0.042	0.017
	(0.067)	(0.089)	(0.067)
Reputational risk	0.106*	0.111	0.070
	(0.063)	(0.077)	(0.064)
Debt ratio	0.853	-1.875	-0.298
	(4.551)	(5.788)	(4.548)
Cash flow ratio	-8.949	-12.999	-9.228
	(9.077)	(11.378)	(9.054)
R&D intensity	-36.677	-55.767*	-38.858
	(25.671)	(29.944)	(25.610)
Road test score	0.073	-0.097	0.105
	(0.075)	(0.108)	(0.075)
Product portfolio	-0.019	0.060	-0.028
	(0.068)	(0.073)	(0.067)
Inverse Mills ratio		4.482	
		(3.048)	

Gaussian copula correction term	-0.476	-0.629	-1.348**
	(0.555)	(0.776)	(0.596)
Constant	-56.175	-44.240	-66.615*
	(37.572)	(52.062)	(37.568)
Manufacturer fixed effects	YES	YES	YES
Year-month fixed effects	YES	YES	YES
Overall-R-squared	0.107	0.193	0.106
Notes: The number of observations is 2,921 except for Model 2 (2,117). The number of observations for Model 2 is smaller because it excluded manufacturer-month observations that had zero news reports about product safety. The number of manufacturers is 22. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Two-tailed tests.			

6.2. Robustness to Entropy Balancing

To check the robustness of our findings, we implemented entropy balancing that reweights control observations so that the post-weighting means of treatment firms and control firms are nearly identical. A key advantage of entropy balancing as opposed to propensity score matching and coarsened exact matching is that it ensures covariate balance without sacrificing observations (Hainmueller 2012). To implement entropy balancing, we first need to identify treatment and control groups. However, news volume is a continuous treatment variable, and entropy balancing requires a binary treatment variable. Therefore, following Shi, Zhang, and Hoskisson (2019), we used the median value of media coverage as the cutoff to identify treatment firms (i.e., high news volume) and control firms (i.e., low news volume). The dependent variable in the entropy balancing matching is a dummy variable that equals 1 for treatment firms (i.e., those that received greater than the median value of news volume) and 0 for control firms (i.e., those that received equal to or lower than the median value of news volume). Our results are similar if we use the 75th percentile value of news volume as the cutoff to identify treatment firms and control firms. The predictors used in the matching include all the control variables. We next implemented reweighting regressions with the weight calculated from entropy balancing. Although our findings are robust to using a different cutoff to identify treatment and control firms, we would like to highlight that a key limitation of entropy balancing in our setting is that we are faced with a continuous treatment variable instead of a binary treatment variable.

As Table 8 reports, we continue to find that news volume is positively associated with voluntary recalls. This relationship is strengthened by news negativity but weakened by news media's product rating.

Table 8: Estimates from Reweighting Regressions with Weights from Entropy Balancing

	Model 1	**Model 2**	**Model 3**
Variables	DV = Voluntary recalls		
News volume	0.039***	-0.217	1.017***

	(0.011)	(0.145)	(0.292)
News negativity		-1.179	
		(1.828)	
News volume × News negativity		0.764***	
		(0.204)	
News positivity		-1.885	
		(3.311)	
News volume × News positivity		-0.861*	
		(0.479)	
News volume × News media's product rating			-0.116***
			(0.035)
News media's product rating	4.117***	1.686	4.905***
	(1.548)	(1.631)	(1.563)
UGC volume	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Price	3.027	2.670	3.015
	(4.097)	(5.087)	(4.089)
Advertising spending	-0.628	-0.396	-0.624
	(0.490)	(0.522)	(0.489)
Recall experience	-0.056	-0.092*	-0.062
	(0.048)	(0.053)	(0.048)
Safely complaints	0.049**	0.043*	0.052**
	(0.024)	(0.025)	(0.024)
Deaths	0.023	0.067	0.028
	(0.058)	(0.091)	(0.058)
Reputational risk	0.075	0.120	0.024
	(0.073)	(0.079)	(0.075)
Debt ratio	0.563	-8.503	-0.750
	(5.651)	(6.381)	(5.654)
Cash flow ratio	-2.069	-15.799	-4.976
	(11.793)	(12.913)	(11.803)
R&D intensity	-55.162*	-75.112**	-57.780*
	(31.379)	(32.990)	(31.330)
Road test score	0.090	-0.122	0.112
	(0.092)	(0.111)	(0.092)
Product portfolio	-0.005	0.079	-0.017
	(0.072)	(0.071)	(0.072)
Inverse Mills ratio		7.766**	
		(3.061)	
Constant	-73.293	-36.884	-79.145
	(68.652)	(101.099)	(68.547)
Manufacturer fixed effects	YES	YES	YES
Year-month fixed effects	YES	YES	YES
Overall-R-squared	0.0912	0.133	0.0945

Notes: The number of observations is 2,921 except Model 2 (2,117). The number of observations for Model 2 is smaller because it excluded manufacturer-month observations that had zero news reports about product safety. The number of manufacturers is 22. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Two-tailed tests.

6.3. Robustness to an Alternate Measure of Voluntary Recalls?

Following Kalaignanam, Kushwaha, and Eilert (2013) and Liu and Shankar (2015), our main analysis measures voluntary recalls as the number of vehicles the focal manufacturer recalled in the focal month divided by the number of vehicles the manufacturer sold in the previous 12 months. Researchers have used an alternative measure of recalls—the number of voluntary recalls the focal manufacturer initiated in the focal month. We test the robustness of our findings to this alternative DV, including sales volume as an additional covariate to our specification. Table 9 reports results that are consistent with those from our main analysis (Table 3).

Table 9: Robustness to Alternate Measure of the DV

	Model 1	**Model 2**	**Model 3**
Variables		Voluntary recalls	
News volume	4.260***	0.728	23.065***
	(1.343)	(3.986)	(6.910)
News negativity		-58.431	
		(42.811)	
News volume × News negativity		18.482***	
		(5.133)	
News positivity		89.717	
		(85.437)	
News volume × News positivity		-49.701***	
		(12.031)	
News volume × News media's product rating			-2.317***
			(0.835)
Sales	-14.470	5.666	-18.650
	(17.580)	(21.369)	(17.623)
Inverse Mills ratio		180.292**	
		(85.043)	
Residuals	-3.101**	-1.744	-2.405*
	(1.368)	(1.517)	(1.389)
Constant	-51.636	-210.653	-317.739
	(1,077.500)	(1,420.585)	(1,080.455)
Other control variables	YES	YES	YES
Manufacturer fixed effects	YES	YES	YES
Year-month fixed effects	YES	YES	YES
Overall-R-squared	0.122	0.250	0.118
Notes: The number of observations is 2,921 except Model 2 (2,117). The number of observations for Model 2 is smaller because it excluded manufacturer-month observations that had zero news reports about product safety. The number of manufacturers is 22. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Two-tailed tests.			

6.4. Robustness to Alternate Measures of News Valence?

Following management research (e.g., Bednar, Boivie, and Prince 2013), we measured news negativity (positivity) as the mean negativity (positivity) across all news reports reported in the focal month about the safety of the products of the focal manufacturer. The negativity and positivity scores were produced by our SVM. Management research has used an alternative measurement method (Bermiss, Zajac, and King 2014; Pfarrer, Pollock, and Rindova 2010; Pollock and Rindova 2003; Zavyalova et al. 2012). This method involves classifying each news report as negative, if its negativity score exceeds its positivity score, or as positive, if its positivity score exceeds its negativity score. We created these measures and re-estimated our regressions.

Model 1 of Table 10 provides the results. We find that the volume of negative news about the safety of a manufacturer's products increases voluntary recalls (b = .511, $p < .01$), whereas the volume of positive news does not matter (b = -0.004, $p > .1$), which are consistent with what our main analysis (Table 3) reported.

6.5. Is UGC Valence Driving the Results?

Our main analysis controlled for the volume of UGC but not for the valence of UGC because including the UGC valence will require us to sample observations with the nonzero UGC volume, and such selection could bias our sample. However, one could argue that UGC valence is an omitted "third" variable, which influences news valence and directly impacts managerial decisions about voluntary recalls. We test this possibility by controlling in our specification UGC negativity and positivity.

The inclusion of UGC valence variables means that we select manufacturer-month observations for which UGC is nonzero. This selection potentially biases our sample. We correct for this sample selection bias by estimating a Heckman selection model and obtaining an IMR (like the method we followed when we included news valence). Therefore, Model 3 of Table 10 includes the IMR for news (from our main specification) and the IMR for UGC (from the current Heckman model). Next, we created a BERT-based SVM—trained on U.S. Airline Sentiment data set (https://www.kaggle.com/crowdflower/twitter-airline-sentiment) and Amazon data set (http://jmcauley.ucsd.edu/data/amazon/)—and used it to score UGC on the negativity and positivity (the process is similar to the BERT-based SVM for news, which we have detailed in the appendix B in the e-companion).

Results in Models 2-4 (Table 10) are consistent with what our main analysis reported in Table 3. Specifically, news volume continues to increase voluntary recalls (Model 2: b = .235, $p < .01$). News negativity (Model 3: b = .730, $p < .01$) strengthens this main effect, whereas news positivity does not matter (Model 3: b = -.605, p > .10). The news media's rating of the manufacturer's products weakens the main effect (Model 4: *b* = -.088, *p* < .01). Lastly, neither UGC negativity nor UGC positivity impact voluntary recalls any of the three models (Models 2 through 4).

Table 10. Robustness to Alternate Measures of News Valence and Controlling for UGC Valence

Variables	Model 1	Model 2	Model 3	Model 4
Negative news volume	0.511***			
	(0.076)			
Positive news volume	-0.004			
	(0.223)			
News volume		0.235***	-0.064	0.953***
		(0.053)	(0.155)	(0.266)
News negativity			-1.905	
			(1.689)	
News volume × News negativity			0.730***	
			(0.199)	
News positivity			-0.485	
			(3.329)	
News volume × News positivity			-0.605	
			(0.464)	
News volume × News media's product rating				-0.088***
				(0.032)
UGC negativity		0.986	1.957	1.222
		(3.189)	(3.730)	(3.186)
UGC positivity		3.592	4.206	3.746
		(3.330)	(3.937)	(3.326)
UGC volume	-0.007***	-0.008***	-0.008***	-0.007***
	(0.002)	(0.002)	(0.002)	(0.002)
News media's product rating	0.400	0.726	-0.290	1.448
	(1.279)	(1.350)	(1.616)	(1.374)
Price	1.048	0.896	1.610	1.386
	(3.474)	(3.605)	(4.929)	(3.605)
Advertising spending	-0.117	-0.084	-0.086	-0.133
	(0.328)	(0.350)	(0.439)	(0.350)
Recall experience	-0.131***	-0.135***	-0.147**	-0.131**
	(0.050)	(0.051)	(0.061)	(0.051)
Safely complaints	-0.009	-0.021	-0.016	-0.014
	(0.023)	(0.030)	(0.034)	(0.030)
Deaths	-0.156**	-0.193**	-0.137	-0.163*
	(0.079)	(0.087)	(0.108)	(0.087)
Reputational risk	-0.137*	-0.093	-0.078	-0.106
	(0.077)	(0.084)	(0.098)	(0.084)
Debt ratio	-5.089	-6.345	-5.411	-6.304
	(4.801)	(5.065)	(6.210)	(5.058)
Cash flow ratio	-12.485	-12.500	-15.329	-12.865

	(9.096)	(10.300)	(12.389)	(10.288)
R&D intensity	-57.224**	-57.427**	-82.219***	-57.767**
	(25.812)	(27.741)	(31.760)	(27.707)
Road test score	0.031	-0.017	-0.172	-0.001
	(0.074)	(0.077)	(0.111)	(0.077)
Product portfolio	0.016	0.009	0.103	0.007
	(0.067)	(0.079)	(0.087)	(0.078)
Residuals	-0.178***	-0.201***	-0.172***	-0.176***
	(0.043)	(0.054)	(0.059)	(0.054)
Inverse Mills ratio for news			4.941	
			(3.136)	
Inverse Mills ratio for UGC		1.041	-0.940	0.259
		(7.522)	(9.073)	(7.518)
Constant	-7.629	-6.410	-3.874	-18.472
	(39.089)	(41.312)	(54.766)	(41.491)
Observations	2,921	2,783	2,033	2,783
Manufacturer FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Overall-R-squared	0.111	0.109	0.196	0.109

Notes: In Model 1, we include all the observations. In Models 2 and 4, we use observations associated with non-zero UGC volume. In Model 3, we use observations associated with both non-zero news volume and non-zero UGC volume. The number of manufacturers is 22. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Two-tailed tests.

7. Discussion

This study answers how the news media in the context of a product defect affect firm decisions about a product recall. We believe our findings have important theoretical implications for researchers and practical implications for managers.

7.1. Theoretical Implications

What factors determine a firm's recalls? Accounting, economics, finance, marketing, OM, and strategic management disciplines have answered this question, documenting a broad range of factors. These factors include the *firm's decisions* in the domains of production (Shah, Ball, and Netessine 2017; Thirumalai and Sinha 2011), supply chain (Kalaignanam, Kushwaha, and Nair 2017; Kini, Shenoy, and Subramaniam 2017), corporate management and governance (Byun and Shammari 2021; Wowak et al. 2021), labor (Kini, Shen, Shenoy, and Subramaniam 2021), financing (Kini, Shenoy, and Subramaniam 2017), the stock market (Bendig et al. 2018), and prior experience (Haunschild and Rhee 2004; Kalaignanam, Kushwaha, and Eilert 2013; Thirumalai and Sinha 2011). Decisions by firm stakeholders—specifically, safety regulators (Ball, Siemsen, and Shah 2017), rivals (Ball, Shah, and Wowak 2018), investors (Chakravarty, Saboo, and Xiong 2021), and consumers (Çolak and Bray 2016; Mukherjee and Sinha 2018)—also impact a firm's recalls). A notable omission in this exhaustive list is news media—specifically, news organizations' coverage of the safety of the firm's products. Because the topic of product safety is consequential for the public and thus relevant to the news media, this omission is surprising. The omission may make academics ignore the role of news media in influencing this important operational and marketing decision, or worse case, assume that the media do not matter. We address this omission by documenting that news about the safety of a firm's products—on average—increases the firm's voluntary (but not involuntary) recalls. Besides, the negativity in the news strengthens this effect, the positivity in the news does not moderate, and the media's rating of the firm's products weakens the effect.

In examining the media's role in influencing a product-market decision by the firm, we extend the literature at the intersection of the news media and businesses. Like the literature on product recall, the literature on the news media's effect on business is extensive. Research has documented that the news media's coverage of a firm affects the firm's decisions in financial markets (McMillan and Joshi 1997; Roberts and Dowling 2002) and consumer markets (Van Heerde, Gijsbrechts, and Pauwels 2015), and in domains of social responsibility (e.g., Chiu and Sharfman 2011), corporate governance (e.g., Farrell and Whidbee 2002), and strategic decisions (Gamache and McNamara 2019; Liu and McConnell 2013; Shi, Connelly, and Cirik 2018). However, academics have paid relatively little attention to how news affects a firm's marketing decisions (Bednar, Boivie, and Prince 2013; Berger, Sorensen, and Rasmussen 2010; Stephen and Galak 2012). Research on the effect of the news on a firm's operational decisions is even more scarce (see Bednar, Boivie, and Prince 2013 for an exception). We add to this extensive literature by documenting that the news media's coverage of the safety of a firm's products affects the firm's voluntary recalls. In addition, we consider how news valence and the news media's rating of a firm's products moderate the main effect of news volume. The findings that news negativity strengthens the impact of the news media, whereas news positivity does not moderate, supports the theory of the negativity bias/effect—that is, the negativity has a stronger effect than the positivity. Further, we document that the media's product rating serves as a reputation buffer, mitigating the effects of media coverage. This finding adds to the literature on organizational commensuration and the reputational benefits thereof (Rindova et al. 2005).

7.2. Managerial Implications

Our findings are of value to three nonacademic stakeholders: product managers, firm rating managers in media houses, and journalists. We discuss the implication for each stakeholder next.

Foremost, our findings alert product managers about how their voluntary recall decisions might be influenced by the volume of and the negativity in the news about the safety of their firm's products. Further, because the positivity in such news does not moderate the effect of news volume, it serves as a hygiene factor. In documenting that the news media's rating of a firm's products buffers the firm from the effect of news volume, we inform product managers about the value of such ratings. Relatedly, this finding allows people who manage media houses' (e.g., *U.S. News & World Report*, *Fortune*, *Forbes*) ratings of firms and their offerings to strengthen the business case for these ratings (Bermiss, Zajac, and King 2014). These media managers can use our findings to inform their business clients how such ratings can potentially help them subvert media pressure.

As representatives of the fourth pillar of democracy, journalists assume the responsibility of serving society, independent of business influences and preferences. Our findings speak directly to the impact that journalist accounts of product safety have on a firm's voluntary recalls. The safety topic is particularly interesting because journalists can report about the product safety using negative and positive tones. Consistent with this, we document that whereas the positivity in journalists' accounts of product safety does not moderate the main effect of news volume, the negativity in their reports strengthens this effect. The asymmetric moderation effect supports the "negativity bias"—that is, managers pay greater attention to the negativity in the news than to its positivity.

7.3. Limitations and Future Research

We note three limitations of our study, each of which merits future research. First, a common theme in business communications research is the interdependency among earned media (e.g., news, customers' reviews of a firm's offerings), paid media (i.e., advertising on social media platforms, Internet search keywords, Internet displays, and email), and owned media (e.g., press releases, firm-generated content on social media platforms, executives' blogs on a firm's website) (Hewett et al. 2016; Stephen and Galak 2012). Our focus has been on the news. Future research can extend our focus by examining the interdependencies between different types of media (Hewett et al. 2016) and a firm's voluntary recalls and other decisions.

Second, to maintain our research's focus, we did not explore how the actions of the focal firm and its rivals (e.g., advertising spending and content, firm response to user-generated content on product defects) can moderate the effects of news on recalls (Borah and Tellis 2016; Hsu and Lawrence 2016). Future research could take this contingency perspective and identify short- to medium-term actions that managers can take to suppress the news' effect.

Third, we aggregate news across all outlets—that is, we do not differentiate between publications. Recent research by Beattie et al. (2021) documents that a firm's advertising spending in a particular media outlet can bias the outlet's coverage of the firm's product recalls. Future studies can extend Beattie et al.'s (2020) research to test whether managers take less seriously news coverage from publishers who receive advertising revenue from the focal firm. Because recalls involve government regulators, they involve political undertones. Therefore, another avenue is to weigh news reports by the political ideology of the publication. For example, commentators view the *New York Times* as liberal and *Fox News* as conservative (Blake 2014).

In sum, we believe that our research offers novel findings on how news about the safety of a firm's products affects the firm's voluntary recalls. These findings extend theory and offer actionable value to managers, while providing avenues for future research.

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The Effects of News Media on a Firm's Voluntary Product Recalls
E-Companion
Appendix A
Table A1: Measures and Data Sources for the Variables

Variable name	Variable measure	Data source	Measurement	Role in Regression, Logic (for Control Variables), and Reference Articles
Voluntary recalls	The number of vehicles the focal manufacturer recalled *voluntarily* in the focal month divided by the sum of the number of vehicles the manufacturer sold in the previous 12 months	NHTSA's FLAT_RCL.txt and Wards Intelligence	Monthly measure at $t+1$ Multiplied by 1,000 to facilitate interpretation	DV (Kalaignanam, Kushwaha, and Eilert 2013; Liu and Shankar 2015)
Involuntary recalls	The number of vehicles the focal manufacturer recalled *involuntarily* in the focal month divided by the sum of vehicles sold by the make in the previous 12 months	NHTSA's FLAT_RCL.txt and Wards Intelligence	Monthly measure at $t+1$ Multiplied by 1,000 to facilitate interpretation	DV for supplementary analysis (Haunschild and Rhee 2004)
Media coverage of incidents that create environmental, social, and governance (ESG) risk for the peers	The average of the number of news reports about the focal manufacturer's peers in the prior quarter about events that create ESG risk. We weighted each report by the reach/influence of the publication.	RepRisk's News Data file	Quarterly measure at t	Instrument (Deephouse and Carter 2005; Kang and Kim 2017)
News volume	The number of unique news reports in the focal month about the safety of the focal manufacturer's vehicles	Factiva	Monthly measure at t	IV (Chakravarty, Saboo, and Xiong 2021; Kang and Kim 2017)
News negativity	The average of the negativity in the news reports in the focal month about the safety of the focal manufacturer's vehicles	BERT-based Support Vector Machine trained on https://www.kaggle.com/ankurzing/sentiment-analysis-for-financial-news	Monthly measure at t	Moderator (Kuhnen and Niessen 2012)
News positivity	The average of the positivity in the news reports in the focal month about the safety of the focal manufacturer's vehicles	BERT-based Support Vector Machine trained on https://www.kaggle.com/ankurzing/sentiment-analysis-for-financial-news	Monthly measure at t	Moderator (Kuhnen and Niessen 2012)

News media's product rating	U.S. News & World Report' overall rating of models of the focal manufacturer in the focal year. The rating is based on critics' rating, performance, interior, safety, quality, and reliability.	*U.S. News & World Report*	Annual measure at *t*	Moderator (Chen, Ganesan, and Liu 2009; Liu, Liu, and Luo 2016)
User-generated content (UGC) volume	The number of tweets in the focal month about the safety of the focal manufacturer's vehicles	Twitter	Monthly measure at *t*	Control News organizations and firms (Borah and Tellis 2016; Iliff 2019) may pick on UGC to decide the volume of news and recalls, respectively (Hsu and Lawrence 2016; Liu, Shankar, and Yun 2017)
Price	The average price of vehicles sold by the focal manufacturer in the focal year	*Consumer Reports*	Annual measure at *t*	Control Price signals product quality. The media may scrutinize the sellers of premium products more than sellers of budget products. Further, Shah, Ball, and Netessine (2017) have reported that manufacturers of luxury (vs. middle and regular) class vehicles are less likely to initiate recalls.
Advertising spending	The dollars (in thousands) that the focal manufacturer spent on advertising in the focal month	Kantar Media's Stradegy database	Monthly measure at *t*	Control A firm's advertising makes the firm visible to all stakeholders, and consequently, the firm may lower or raise the intensity of its social responsibility actions, such as voluntary recalls (Liu, Shankar, and Yun 2017)
Recall experience	The number of (voluntary and involuntary) recalls initiated by the focal manufacturer in the 12 months prior to the focal month	NHTSA's FLAT_RCL.txt	Monthly measure at *t*	Control Prior recalls may prime the news organizations to look out for similar news from the focal manufacturer and may thus increase news volume. Recall experience helps the managers better estimate the direct and indirect costs of recalls and thus allows them to strategically determine the number of recalls in a period (Gao et al. 2015; Haunschild and Rhee 2004; Liu, Liu, and Luo 2016; Liu, Shankar, and Yun 2017).

Safety complaints	The number of complaints received by the NHTSA in the focal month about safety incidents attributed to defects in vehicles of the focal manufacturer	NHTSA's FLAT_CMPL.txt	Monthly measure at *t*	Control The more the safety complaints, the more likely the media to report the safety defect, and the more negative the report. Further, safety complaints and the extent of harm caused by the defective product—deaths—have been found to affect a firm's recalls (Chakravarty, Saboo, and Xiong 2021; Çolak and Bray 2016; Eilert et al. 2017; Kalaignanam, Kushwaha, and Eilert 2013).
Deaths	The number of deaths reported to the NHTSA in the focal month and attributed to safety incidents caused by defects in vehicles of the focal manufacturer	NHTSA's FLAT_CMPL.txt	Monthly measure at *t*	
Reputational risk	The risk to the focal manufacturer's reputation (based on news reports of corporate social irresponsibility events attributed to the focal manufacturer) in the focal month	RepRisk's RRI (Reputational Risk Index) Data file	Monthly measure at *t*	Control The higher the risk to the firm's ESG reputation, the more negatively the media may report about the safety of the firm's products and the higher the incentive for the firm to initiate more recalls voluntarily (Gao et al. 2015).
Debt ratio	Total liabilities in a quarter divided by total assets in the focal quarter, for the focal manufacturer	Thomson Reuters' Worldscope	Quarterly measure at *t*	Control A higher debt ratio may pressure managers not to make decisions (e.g., recalls) that may hurt cash flow (Chen, Ganesan, and Liu 2009; Gao et al. 2015; Hsu and Lawrence 2016; Liu, Shankar, and Yun 2017).
Cash flow ratio	Sum of cash and cash equivalents in a quarter divided by total assets in the focal quarter, for the focal manufacturer	Thomson Reuters' Worldscope	Quarterly measure at *t*	Control Higher cash flow grants managers a higher level of decision autonomy (Deb, David, and O'Brien 2017).
R&D intensity	The ratio of R&D expenditure to total sales in the focal quarter, for the focal manufacturer	Thomson Reuters' Worldscope	Quarterly measure at *t*	Control R&D intensity has been found to affect a firm's recalls (Wowak, et al. 2021).
Road test score	The average of road-test scores in a year for models of the focal manufacturer	*Consumer Reports*	Annual measure at *t*	Control A higher road test score may indicate that the harm caused by a firm's products may be an occasional blip rather than symptomatic of a defect (Liu Shankar, and Yun 2017). Thus, the news media may report leniently, and managers may be less motivated to recall

				voluntarily (Kalaignanam, Kushwaha, and Eilert 2013).
Product portfolio	The number of models sold by the focal manufacturer in the focal year	Wards Intelligence	Annual measure at *t*	Control The higher the number of product lines, the more dispersed the media attention to any one product line. Consequently, the media may report less about any particular product line. Further, Shah, Ball, and Netessine (2017) have reported that greater variety among products increases the number of recalls.

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Table A2: Correlation Coefficients

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	Voluntary recalls	1.00																		
2	Involuntary recalls	-0.01	1.00																	
3	Peers' ESG risk media coverage	0.09	0.03	1.00																
4	News volume	0.17	0.04	0.20	1.00															
5	News negativity	0.10	0.07	0.14	0.21	1.00														
6	News positivity	0.02	0.02	0.10	0.08	0.07	1.00													
7	News media's product rating	0.01	-0.05	-0.18	0.12	0.07	0.04	1.00												
8	UGC volume	0.01	0.02	-0.04	0.30	0.13	0.05	0.10	1.00											
9	Price	0.02	0.01	0.18	-0.02	-0.07	-0.02	0.18	-0.10	1.00										
10	Advertising spending	-0.03	-0.03	-0.08	0.12	0.20	0.08	0.18	0.19	-0.28	1.00									
11	Recall experience	-0.03	-0.01	0.20	0.09	0.13	0.08	0.05	0.08	-0.02	0.44	1.00								
12	Complaints	0.00	-0.01	0.07	0.07	0.07	0.06	-0.10	0.15	-0.41	0.45	0.50	1.00							
13	Injuries	0.01	0.00	0.10	0.40	0.17	0.08	0.07	0.31	-0.17	0.48	0.56	0.46	1.00						
14	Deaths	0.00	0.01	0.02	0.18	0.03	0.02	0.04	0.10	-0.04	0.12	0.16	0.11	0.36	1.00					
15	Reputational risk	0.09	0.02	0.50	0.15	0.17	0.11	-0.24	-0.02	0.07	0.12	0.39	0.25	0.32	0.07	1.00				
16	Debt ratio	0.02	0.01	0.05	-0.02	-0.02	0.04	0.49	-0.06	0.50	-0.22	-0.09	-0.24	-0.15	-0.03	-0.13	1.00			
17	Cash flow	0.03	0.00	0.04	0.10	0.18	0.13	-0.19	-0.02	-0.43	0.25	0.29	0.26	0.13	0.04	0.12	-0.22	1.00		
18	Road test score	-0.04	-0.02	-0.17	-0.05	-0.08	-0.08	0.03	0.01	-0.41	0.06	0.04	0.18	0.00	0.01	-0.12	-0.02	-0.06	1.00	
19	Product portfolio	-0.05	-0.04	0.08	0.00	0.06	0.06	0.12	0.03	0.12	0.44	0.61	0.37	0.41	0.10	0.29	0.11	0.28	-0.13	1.00

Appendix B
BERT-Based Support Vector Machine (SVM) Classifier for News Negativity and News Positivity

Training Data Set

We searched for relevant data sets involving the news text and their related sentiment to train the SVM. We considered data sets that met the following criteria:

1. The text should come from some form of the news source.
2. The substantial number of observations, say, at least 2,500.
3. Each observation should label the news text on sentiment (negative, neutral, and positive).

We found the following four data sets that met our criteria (in order of preference):

1. Kaggle: https://www.kaggle.com/ankurzing/sentiment-analysis-for-financial-news
2. PerSenT: https://github.com/StonyBrookNLP/PerSenT
3. MPQA Opinion Corpus: https://mpqa.cs.pitt.edu/
4. AG's Corpus: http://groups.di.unipi.it/~gulli/AG_corpus_of_news_articles.html

We chose the Kaggle data set because its text is more related to corporate news rather than world news. The data set has 4,845 unique rows, distributed as: 604 labeled as negative, 2,878 as neutral, and 1,363 as positive.

Cleaning and preprocessing the data set

1. Since we were using Bidirectional Encoder Representations from Transformers (BERT) to vectorize our model, we did not need to perform most of the text cleaning tasks as BERT looks at the sentence as a whole, i.e., the context in which the text is written rather than just at a word individually.
2. We removed punctuation words, Latin and special characters, numbers, blank spaces, and stop words (*NLTK* Python library).
3. To obtain the equal number of news reports for each sentiment, we used the *SMOTE* functions in the Python library *imblearn* (*SMOTE* creates 'similar' samples instead of replicated samples thus helping the model learn better). This step increased our sample to 8,634 with 2,878 observations for each sentiment.

Training the SVM Classifier

1. We used 80% observations (6,907) of the combined data set for training and 20% for validation (1,727)
2. We used different permutations of the SVM parameters for hypertuning. tuned_parameters = [{'kernel': ['rbf', 'linear'], 'C': [1, 10, 100]}]. *GridSearchCV* from Python library *sklearn* was used

for doing so and for cross validation. The following parameters were finalized to give the best results: Kernel = 'rbf, C=10.

3. We used *Svm.SVC* function from the Python library *sklearn*. We set the parameter *probability* to *True* to give probabilities of the text belonging to each sentiment rather than classification. Had we not set *probability* to True, SVM would have used the highest of the three probabilities (the probability of the SVM classifying the tweet as neutral, as negative, and as positive) to classify the tweet as negative, neutral, or positive. That is, setting *probability* to True produces more nuanced values.
4. The trained model gave an accuracy of .91.

Results

We view the confusion matrix from the perspective of the SVM classifier. That is, a news text is *positive* if the classifier classified it as 1, *negative* if it classified it as −1 and *neutral* if it is classified as 0. By extension

1. True Positive = an article that the training data set classified as **positive** and the classifier classified as **positive**
2. True Negative = an article that the training data set classified as **negative** and the classifier classified as **negative**
3. True Neutral = an article that the training data set classified as **neutral** and the classifier classified as **neutral**
4. False Negative1 = an article that the training data set classified as **neutral** and the classifier classified as **negative**
5. False Negative2 = an article that the training data set classified as **positive** and the classifier classified as **negative**
6. False Positive1= an article that the training data set classified as **negative** and the classifier classified as **positive**
7. False Positive2= an article that the training data set classified as **neutral** and the classifier classified as **positive**
8. False Neutral1= an article that the training data set classified as **negative** and the classifier classified as **neutral**
9. False Neutral2= an article that the training data set classified as **positive** and the classifier classified as **neutral**

Table B1: SVM Confusion Matrix

Classification in the Training Data Set	**Classification by the SVM**			
−1		−1	0	1
0	553	540 (True Negatives) 97.64%	6 (False Neutral1) 1.08%	7 (False Positive1) 1.12%
1	563	15	486	62

		(False Negative1) 2.66%	(True Neutral) 86.32%	(False Positive2) 11.01%%
	611	11 (False Negative2) 1.80%	53 (False Neutral2) 8.67%	547 (True Positive) 89.52%
Total	1,727	566	545	616

Table B2: SVM Confusion Matrix

	Precision	***Recall***	***F1 score***
−1	0.95	0.97	0.97
0	0.89	0.86	0.88
1	0.89	0.90	0.89
Accuracy			0.91

Testing the Classifier

We cleaned, preprocessed, and applied BERT on the safety news text data set in the same way as the training data set along with a few additions. We separated some falsely connected words (e.g., recallManufacturer, SummaryToyota). Lastly, we applied our trained SVM model to the 14,994 data points in our testing automobile data set. Because we aimed at predicting probabilities instead of classifying, we used ‘predict_proba’ to calculate sentiment probabilities on the test data set. We used the highest value among the three probabilities to classify the text as negative, neutral, or positive.

Appendix C

BERT-Based Topic Modeling

BERTopic[4] uses the power of word embeddings to understand the semantic similarity between words. Unlike TF-IDF, a word embedding accounts for semantic closeness between words. For example, it keeps a short distance between the words "man" and "woman" along with "king" and "queen." It is also able to map the relation "king" – "man" + "woman" ≈ "queen" as these words have a semantic relation.

BERTopic generates topic representations through three steps:

1. It converts each document to its embedding representation using a pre-trained language model.
2. Before clustering these embeddings, BERTopic reduces the dimensionality of the resulting embeddings to optimize the clustering process.
3. Lastly, from the clusters of documents, it extracts topic representations using a custom class-based variation of TF-IDF.

The pre-trained model used by BERTopic is Sentence-BERT (Nils et al. 2019) which is a modified BERT network. It works by using two networks or twin networks. These twin networks allow the model to process two sentences at the same time. Pairs of sentences are passed through the twin networks to identify a similarity score. The similarity score of each sentence (say, sentence 1) with another sentence (say, sentence 2) is compared with sentence 1's similarity score with each of the remaining sentences (say, with the eight similarity scores, measuring the similarity of sentence 1 with sentences 3 through 10). This lower-level breakdown of documents into sentences and the calculation of similarity enables BERTopic to address latent Dirichlet allocation's (LDA) limitation of producing topics that may not make intuitive sense.

A word embedding model can create thousands or even millions of features, which makes training almost impossible. BERTopic solves this problem of exploding dimensions or vectors by using Uniform Manifold Approximation and Projection (UMAP) to reduce the number of dimensions. UMAP preserves more of the local and global features of high-dimensional data in lower projected dimensions. While the mathematics UMAP uses to construct the high-dimensional graph is advanced, in simple terms UMAP constructs a high dimensional graph representation of the data and optimizes a low-dimensional graph to be as structurally similar as possible.

Data Characteristics and Transformation

1. We collected 14,985 unique news reports from Factiva. Factiva had classified these reports as mentioning at least one of the 22 car manufacturers in our sample and had text on the subject of "product recall." For each report, the textual columns include the news report's *Headline* and *Body*.

[4] BERT refers to Bidirectional Encoder Representations from Transformers.

2. We wanted to consider both headline and body for topic modeling and thus, for each news report, we merged the values of these two columns and created a new column named *Text*.

3. Converted *Text* to lowercase

4. Removed stop words and names of car manufacturers and component/part names

5. Removed all punctuations

6. Removed all one-character words, such as “a.”

7. Lemmatized all words (e.g., *cars* is converted to *car*)

8. Applied BERTopic on bigrams and trigrams

References

Nils Reimers, Iryna Gurevych, 2019, “Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks”, *Conference on Empirical Methods in Natural Language Processing (2019).*