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Social Media Strategies in Product Harm Crises

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When a focal firm undergoes a product-harm crisis, non-focal firms offering similar products or services can suffer from a negative spillover effect but can also benefit from customers switching from the troubled focal firm, which we call the competitive effect. In response, a non-focal firm can adapt its marketing strategy in consideration of these two opposing effects. Because social media is a flexible medium through which firms can quickly adjust marketing strategies in response to such unexpected events, we study how non-focal firms adjust their post-crisis social media efforts to induce purchases and to improve customer relationships—two strategies known in the literature as offensive and defensive marketing, respectively. In particular, we use the daily social media activities of 56 major airlines on Twitter around the time of the Germanwings Flight 9525 crash to study how non-focal airlines ran offensive and defensive marketing on social media before and after the crisis. We find that, on average, non-focal airlines increased their defensive marketing efforts but decreased their offensive marketing efforts after the crash, which we attribute to the negative spillover effect. However, the strategic adjustment of decreasing offensive marketing is attenuated by the competition between non-focal airlines and the focal one, which we attribute to the moderating role of the competitive effect. These results are shown to be robust in various tests and reveal how the interplay of the two effects of a product-harm crisis on non-focal firms shapes their post-crisis social media strategies.

Key words: Social Media; Offensive Marketing; Defensive Marketing; Product-Harm Crisis

1. Introduction

A product-harm crisis occurs when a product is defective, contaminated, or harmful to consumers and the information is widely publicized. Unfortunately, product-harm crises are common nowadays. For instance, in 2016, 339 new recalls were reported on the Consumer Product Safety Commission website[1] from various industries, such as food, toys, and vehicles. Product-harm crises are disasters for the focal firms, which suffer not only from the short-term financial cost of compensating affected consumers but also from damaged reputation that can lead to market share loss after a crisis. However, the effects of product-harm crises on non-focal firms in the same industry are more complex, depending on factors such as product or service similarities and competition. For example, if consumers deem similar products from non-focal firms to be of similar quality, then the perceived risk of consuming these products will also increase after the crises. Therefore, the misfortune of the focal firm extends to non-focal firms that offer similar products, resulting in a *negative spillover effect* of the product-harm crisis. On the other hand, firms that compete with the focal firm could benefit from the focal firm's catastrophe if there is a lack of close substitutes of the affected products (e.g., when the product is a necessity). For example, customers may decide to patronize a competitor in the future to avoid their perceived high risk of consuming the focal firm's products. We call this the *competitive effect* of the product-harm crisis. The potential existence of these opposite effects suggests that a non-focal firm in the aftermath of a product-harm crisis could face a complex situation. Consequently, it is unclear how a non-focal firm would or should respond to a product-harm crisis to minimize the impact of the negative spillover effect, as well as to exploit the competitive effect.

In the present study, we investigate how non-focal firms use social media to strategically respond to a product-harm crisis, searching for a balance between the opportunity to attract new customers and the need to retain existing customers. We believe social media is particularly suitable for this purpose because of its growing importance and startling immediacy. Over the past decade, social media has become an increasingly important arena in which firms spend their marketing budgets. A recent survey of 4,943 marketing decision makers shows that the expected spending on social media marketing will grow from 8.4% of firms' total marketing budgets in 2013 to about 22% in the next five years.[2] Today, many companies regularly post content on their Facebook and Twitter pages and constantly monitor their social media accounts, ready to interact with customers. This is particularly true for the airline industry. To this day, almost all U.S. commercial airlines and most major airlines in the world have official Twitter accounts. Each day, thousands of conversations between customers and airlines occur on Twitter. For example, American Airlines has posted about 1.6 million tweets since it joined Twitter in 2009. Unlike traditional marketing media such as TV and newspapers, where marketing is typically scheduled at least several months in advance, social media offer a more flexible alternative through which firms can quickly adjust their marketing strategies in response to unexpected events.

[1] See http://www.cpsc.gov/en/Recalls/

[2] See the 2013 Chief Marketing Officer Survey, http://www.cmosurvey.org.

To dissect a firm's social media strategy, we conceptualize two types of firms' social media activities: those that focus on **inducing purchases** from (1) competitors' customers through brand switching, (2) customers currently outside the market, or (3) existing customers through more purchases and those that focus on retaining current customers through **improved customer relationships** which can eventually translate into future purchases. In marketing, the former type is known as offensive marketing while the latter is often called defensive marketing (Fornell and Wernerfelt (1987)). Clearly, the goal of offensive marketing is to expand market share and the goal of defensive marketing is to retain it.

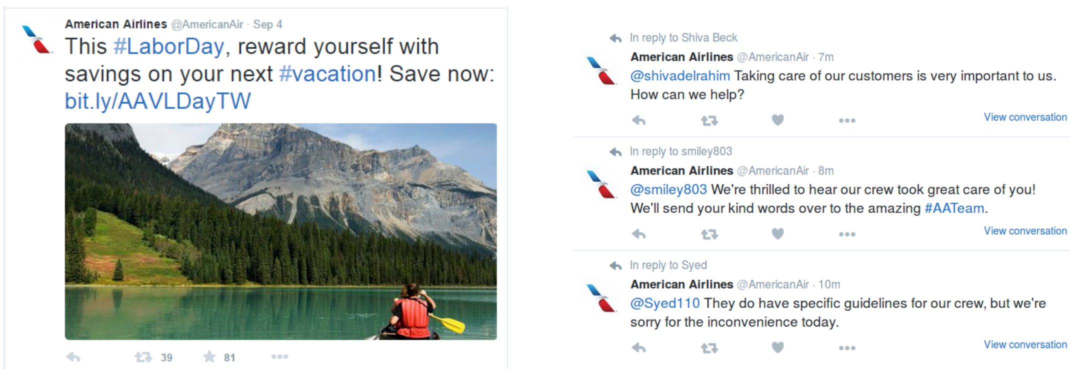

Figure 1 **Examples of offensive marketing (left) and defensive marketing (right) on Twitter by American Airlines**

In terms of content, offensive social media marketing typically involves promoting both the brand name and the products or services of a firm, which is probably the most important mission of the firm's social media strategy. The left panel of Figure 1 shows an example of an offensive marketing tweet posted by American Airlines. The tweet contains a scenery picture and a link, which is an apparent attempt to persuade its followers to book a vacation with American Airlines on Labor Day.

On the other hand, defensive social media marketing is often in the form of direct communication with *individual* customers to address their complaints, answer their questions, or simply socialize with them, as shown in the right panel of Figure 1 where American Airlines replied to customers on Twitter. This is expected because, unlike traditional mass media, social media allow for two-way communication between a brand and its customers and direct communication between an individual customer and the brand is the most natural way of building a relationship. Our operational strategy of distinguishing between offensive and defensive marketing messages largely relies on this intuition. In particular, we take advantage of the unique data structure of Twitter data and develop a classification scheme based on supervised learning algorithms.

To understand a non-focal firm's social media strategy amid a product-harm crisis, we first develop an analytical model to show how a firm should adjust its efforts in offensive and defensive social media marketing. Model analysis indicates that non-focal firms that do not directly compete with the focal firm will decrease their offensive social media marketing and increase their defensive social media marketing after a product-harm crisis, due to the negative spillover effect. For non-focal firms that compete with the focal firm, such a strategic reaction is attenuated by the competitive effect.

Equipped with these insights, we empirically investigate how airlines ran their offensive and defensive social media marketing on Twitter before and after the crash of Germanwings Flight 9525 on March 24, 2015, one of the worst aviation accidents in recent years. A severe aviation crash is an extreme form of product-harm crisis and can be a disaster for the whole airline industry. Previous empirical studies have shown that an aviation accident will result in a negative effect on sales and financial performance for all firms in the industry (Chance and Ferris (1987), Bosch et al. (1998), Wong and Yeh (2003), Ho et al. (2013)). According to a recent Wall Street Journal article titled "Terror Attacks, Air Crashes Weaken Appetite for European Travel,"[3] "tourism officials and airline executives typically brace for a sudden drop in flight and hotel bookings after a terror-related incident or headline-grabbing aircraft accident."

By using Twitter metadata and applying machine learning algorithms to tweets' content, we identify offensive and defensive marketing tweets from 56 major airlines around the world during a six-month period: three months before the accident and three months after. We then aggregate the tweets at the daily level and analyze the resulting count data using negative binomial models.

Comparing an airline's offensive and defensive marketing efforts on Twitter before and after the aviation accident, we find that, on average, non-focal airlines that did not directly compete with the focal one decreased their offensive marketing efforts and increased their defensive marketing efforts on Twitter after the crash. This finding supports our model prediction and clearly demonstrates the different strategic roles of these two components of social media strategy. We further find that the tendency for a non-focal airline to reduce its offensive marketing effort is attenuated by its competition with the focal airline. This result suggests that a non-focal airline's post-crisis social media strategy is moderated by the competitive effect.

Finally, to investigate whether non-focal airlines' strategic adjustments are well justified from an empirical perspective, we use the growth of Twitter followers as a social media performance measure to study the effectiveness of offensive and defensive social media marketing on Twitter. The estimation results suggest that the effectiveness of offensive social media marketing indeed decreased after the crisis, whereas the effectiveness of defensive social media marketing increased.

The rest of the paper is organized as follows: We first review the literature in Section 2. We develop an analytical model in Section 3 to motivate the main hypotheses. We then describe the

[3] `http://www.wsj.com/articles/terror-attacks-air-crashes-weaken-appetite-for-european-travel-1464133931`

data, measurements, and the empirical models in Section 4. In Section 5, we present our main empirical results as well as various robustness checks. Finally, we present the empirical justification of airlines' social media strategies in Section 6 before concluding our paper in Section 7.

2. Research Background

Our present paper is mainly related to three streams of the literature: product-harm crises, offensive and defensive marketing, and social media. We review each stream in this section.

2.1. Product-Harm Crisis

The literature on product-harm crises often examines the crises' effects on the focal firm and the whole industry, as well as firms' strategies in response to crises. In addition to the short-term financial cost of recalling defective products and compensating affected consumers, the focal firms suffer from lost sales, damaged reputation and quality perception, and market share loss after the crises. These effects could last for a prolonged period (Dawar (1998), Van Heerde et al. (2007), Chen et al. (2009)) and their dynamic impacts on both brand preference and advertising have also been studied (Liu and Shankar (2015)).

Beyond their negative effect on the focal firm, the literature suggests that product-harm crises—aviation crashes in our context—can induce significant negative spillover effect on a firm in the same category as the focal firm. For example, Freedman et al. (2012) found that, in 2007, after the Consumer Product Safety Commission (CPSC) issued a higher number of recalls than usual for toys and other children's products, Christmas sales for manufacturers producing non-recalled toys were about 25 % lower than in earlier years. This finding suggests industry-wide spillovers. The negative spillover from one product to similar products of other firms could arise from increased uncertainty about the products' mean quality and the precision of the signals perceived by consumers, as noted by Zhao et al. (2011). In addition, customers may regard similar products in the same category as being guilty by association. Roehm and Tybout (2006) used experiments to investigate the factors that influence the likelihood of spillover effects. The results show that accessibility and diagnosticity are the key factors. Considering the development of online social media, Borah and Tellis (2016) found evidence of online chatter's impact on the negative spillover effect following product recalls among related automobile name plates.

Aviation crashes, as the most severe product-harm crises for airlines, are disasters for the whole industry. Consumers may interpret a recent air crash as evidence that flying is more dangerous than they previously thought, thereby negatively affecting industry-wide demand and hurting all airlines. The literature focuses on the negative effects of an aviation crash on consumer demand and airline stock market performance. Wong and Yeh (2003) using data from Taiwan, showed that an aviation accident reduced the entire market's passenger traffic. Lirn and Sheu (2009) surveyed students at National Penghu University of Science and Technology about their transportation choices before and after the crash of China Airlines Flight 611 in the Taiwan Strait in 2002, and they found that "worry about flight safety" had a significant negative impact on the choice of airplane service. Using data from 1962 to 1985, Borenstein and Zimmerman (1988) found that consumer demand remained largely unaffected by fatal incidents prior to deregulation but fatal incidents did have a negative, although not statistically significant, effect on demand in the post-deregulation period. Using the fatality rate as the main explanatory variable and more recent data, Liu and Zeng (2007) found that the demand for air travel fell in years with relatively high fatality rates. Chance and Ferris (1987) examined the post-crash abnormal stock returns of the airline industry as a whole and found a run of five consecutive days of negative but statistically insignificant returns. More recent studies (e.g., Bosch et al. (1998),Ho et al. (2013)) have suggested that the stock prices of non-focal airlines also suffer from aviation crashes, especially when these are severe. It should be noted that, since the September 11 tragedy, there seems to have been a fundamental shift in consumers' perception of air travel safety that is responsible for more negative consumer reactions to aviation fatalities (Liu and Zeng (2007)).

Previous literature has also investigated firms' different strategies in product-harm crises. For example, Cleeren et al. (2013) compared the effectiveness of competitors' strategies in terms of advertising and price adjustments of the year before a product-harm crisis and the year after. Their findings suggest that the effectiveness of post-crisis price and advertising strategies may depend on the type of crisis. The present study differs from that of Cleeren et al. (2013) by distinguishing and jointly analyzing non-focal firms' offensive and defensive marketing strategies on social media within a shorter period and with much finer granularity before and after a product-harm crisis. We also distinguish non-focal firms in terms of their competition with the focal firm, whereas Cleeren et al. (2013) treated the affected category as a whole when they analyzed the strategies of the non-focal firms. Focusing on the focal firm, Gao et al. (2015) studied the effect of pre-recall advertising on a firm's stock market value, concluding that the effectiveness of the advertising is dependent on the product and the crisis characteristics. Bala et al. (2015) analyzed competitors' sales efforts in crises, considering effort allocation among a portfolio of products across categories.

2.2. Offensive and Defensive Marketing

From the perspective of strategic management, offensive and defensive strategies have distinct roles in shaping a firm's overall competitive strategy and most successful competitive strategies combine both offensive and defensive components (Porter (1985)). Given this perspective, firms' marketing strategies are categorized into offensive and defensive marketing strategies (Fornell and Wernerfelt (1987, 1988), Bridges and Freytag (2009)). Offensive marketing, usually initiated by firms, is mainly concerned with attracting new customers, including those from competing firms and outside the market, and increasing the purchase frequency of existing customers (Fornell and Wernerfelt (1987)). Examples of such strategies include the introduction of new products or services, brand marketing, and promotional sales. Defensive marketing, which can be both proactive and reactive, is primarily focused on keeping current customers (Fornell and Wernerfelt (1988)). Firms strive for this goal by reinforcing their relationships with current customers and discouraging dissatisfied customers from exiting and switching brand. Examples of such strategies include complaint management and loyalty programs. Since the 1990s, there has been a shift in marketing thought from an emphasis on the acquisition of new customers to relationships and the retention of valuable customers (Day and Montgomery (1999), Reichheld and Sasser (1990)).

It should be noted that the term defensive marketing was used differently by Hauser and Shugan (1983) who took a competitor-centered view and analyzed how a firm should adjust its marketing expenditures and prices to defend against an attack by a competitive new product. The authors defined such a competitive strategy as defensive marketing strategy. Our notion of defensive marketing is clearly different and has a customer-focused perspective, which is in line with most literature on defensive marketing (Fornell and Wernerfelt (1987, 1988), Fornell (1992), Zineldin (2006), Bridges and Freytag (2009), Martín-Herrán et al. (2012)).

Traditionally, the marketing literature emphasizes offensive strategies to "obtain additional customers, encourage brand switching, and increase purchase frequency" (Fornell and Wernerfelt (1987)). Therefore, the literature on defensive marketing is relatively sparse and very few studies have examined both offensive and defensive marketing within the same framework. Among those studying defensive marketing, most have focused on relationship marketing, whose objective is to build and maintain lasting relationships with existing customers, which can in turn foster customer loyalty and retention, reduce marketing costs, and improve firm profitability (Morgan and Hung (1994), Kumar et al. (2006)). Indeed, many papers have found evidence that improving customer satisfaction to retain existing customers could influence companies' sales and market shares (Anderson and Sullivan (1993), McGahan and Ghemawat (1994), Zeithaml et al. (1996), Homburg and Fürst (2005), Luo and Homburg (2007)).

From a practical point of view, defensive marketing is often justified, because the cost of winning a new customer is often much higher than the cost of retaining an existing one. For example, Volvo estimated that its cost to generate a new customer is three times the cost of retaining an existing one (Fornell and Wernerfelt (1988)).

From a theoretical point of view, two mechanisms can drive the return of defensive marketing. First, according to Hirschman's exit-voice theory (Hirschman (1970)), there are two feedback mechanisms through which a firm discovers its failure to achieve customer satisfaction: exit and voice. Exit implies customers desert the firm and voice implies customers make direct complaints to the firm. While exit is a powerful market mechanism, voice is more of a political phenomenon. Regardless of how excellent the service a company delivers, every company makes mistakes in meeting its customers' expectations. Previous studies have indicated that failures themselves do not necessarily lead to customers deserting the firm, since most accept that things can sometimes go wrong (del Río-Lanza et al. (2009)) and, by complaining, are attempting to change the practices or offerings of the firm and seek remedy. Rather, the service provider's response to the failure or lack of response is the most likely cause of dissatisfaction (Smith et al. (1999)). Therefore, defensive marketing can be viewed as the effort to reduce the proportion of customers who would otherwise exit to express their dissatisfaction with the firm. Second, defensive marketing can also promote the spread of positive word of mouth and prevent the spread of negative word of mouth, both of which can affect consumer behavior.[4] This function of defensive marketing has become even more important with the rise of social media, through which customers can easily broadcast their endorsements and criticisms of a brand to a large audience.

The few papers that have studied both offensive and defensive marketing are mostly theoretical. Fornell and Wernerfelt (1987) showed that defensive marketing strategies can reduce companies' expenditures on offensive marketing strategies and even total marketing costs. Erickson (1993) developed a modified Lanchester game to explore the balance between offensive and defensive marketing, indicating that defensive marketing is more critical for companies to maintain their market shares. Bridges and Freytag (2009) examined the relation between market condition and firm investment in offensive/defensive marketing through interviews with and a survey of 196 manufacturing companies and Martín-Herrán et al. (2012) investigated the optimal allocation between offensive and defensive marketing in a dynamic mature market with two firms.

The present paper is the first to measure and analyze offensive and defensive marketing strategies on social media.

2.3. Social Media Marketing

Although our paper is the first to study firms' social media strategies in product-harm crises, the literature on social media marketing is vast. Most papers have focused on either exploring the link between firms' social media activities and consumers' social media engagements or studying the link between consumers' engagements and their brand choices. For example, Lee et al. (2014) studied how persuasive content and informative content work differently in generating engagement on Facebook. Goh et al. (2013) combined consumer transactions data with user–marketer interaction

[4] For example, a recent 2013 Nielsen report showed that word of mouth is not only the most trusted source of information, but also the most likely to stimulate consumers to action. See `http://www.idiro.com/2013/09/nielsen-report-finds-that-word-of-mouth-is-the-most-trusted-source-again/` for details.

content data from a Facebook brand fan page to study the economic value of such engagement. Rishika et al. (2013) combined consumer transactions data with customers' social media participation data from a major social networking website to study the impact of such participation on the frequency of customer visits and customer profitability. Chung et al. (2016) estimated a system of simultaneous equations where the endogenous variables included both the consumer engagement measures, such as liking or commenting on a firm's post, and the firm's financial performance measures, such as abnormal stock returns. They found that the richness and responsiveness of a firm's social media efforts are significantly associated with its performance as measured by abnormal returns and Tobin's q. Generally, there is strong evidence of the business value of a firm's social media marketing efforts as Luo et al. (2013) and Hitt et al. (2014) have shown. Ma et al. (2015) found that intervening with customers' compliments and complaints on Twitter both improved customer relationships and motivated more complaints later. So far, this stream of literature has not distinguished firm social media strategy in terms of offensive and defensive marketing aspects.

3. Hypothesis Development

We draw upon the theoretical framework of offensive and defensive marketing to conceptualize and model firms' marketing activities on social media. To motivate testable hypotheses, we develop an analytical model to investigate how companies adjust their resource allocation between offensive and defensive marketing on social media in response to an exogenous product-harm crisis. This modeling exercise can inform the empirical analysis later, which is the focus of this paper.

According to Fornell and Wernerfelt (1987), the flows of customers into and out of a firm and the market consist of (1) additional customer entry into the market, (2) brand shifting or changes of patronage, (3) customer market exit, and (4) changes in purchase frequency. Following this conceptual framework, we consider the impact of a product-harm crisis on the flows of customers into and out of a non-focal firm. Denote the size of a firm's initial customer base by d_e and the retention rate of existing customers by r. We use d_n to represent the inflow of new customers who are currently outside the market. Alternatively, d_n also captures increased sales volume from existing customers due to increased purchase frequencies. We use d_s to represent the inflow of customers switching from competitors. Hence, without any marketing effort, in the next period, the firm will have $d_e r + d_n + d_s$ customers, and $d_e(1-r)$ of its current customers will deflect to its competitors or simply exit the market.

A firm seeks to influence the flows of customers through offensive and defensive marketing (Fornell and Wernerfelt (1987)). Consequently, we model a firm's social media marketing efforts in two dimensions: offensive marketing and defensive marketing, denoted by x and y, respectively. A firm's offensive marketing effort amplifies the inflow of new customers, whether from outside the market (d_n) or from competitors (d_s). We use $f(x)$ to model the effect of such an offensive marketing effort. On the other hand, a defensive marketing effort helps retain existing customers. We use $g(y)$ to model the effect of such defensive marketing. For the purpose of this study, we call the dual (x, y) a firm's social media marketing strategy. We model the customer volume in the next period corresponding to the strategy (x, y) as $D(x, y) \equiv (d_n + d_s)f(x) + d_e r + d_e(1-r)g(y)$. With our modeling approach, we expect $f(x)$ and $g(y)$ to be increasing in effort levels. Naturally, the marginal effectiveness of both offensive and defensive marketing efforts eventually diminishes as the effort level increases. A stylized way of modeling this is to assume concavity for both $f(x)$ and $g(y)$. For analytical tractability, we parameterize $f(x)$ and $g(y)$ using the exponential functions $f(x) = 1 + A - Ae^{-\alpha x}$ and $g(y) = 1 - e^{-\beta y}$ where A can be interpreted as the upper bound of the effectiveness of offensive marketing and α and β capture the decreasing marginal effectiveness of offensive marketing and defensive marketing, respectively.

To model the different rates at which offensive and defensive marketing consume resources, we first normalize the resource consumption intensity of offensive marketing to one and use θ to denote the resource consumption intensity of defensive marketing relative to that of offensive marketing. The total amount of resources available to the social media team is denoted by T which is assumed to be constant in the short run. The problem of optimal resource allocation between offensive and defensive marketing efforts can be formulated as one of maximizing $D(x, y)$ subject to the constraint $x + \theta y \leq T$, the solution to which is

$$\begin{cases} x^* = & \frac{\beta}{\alpha\theta+\beta}T - \frac{\theta}{\alpha\theta+\beta}\ln\frac{1-r}{d_n+d_s} - \frac{\theta}{\alpha\theta+\beta}\ln\frac{\beta d_e}{A\alpha\theta} \\ y^* = & \frac{\alpha}{\alpha\theta+\beta}T + \frac{1}{\alpha\theta+\beta}\ln\frac{1-r}{d_n+d_s} + \frac{1}{\alpha\theta+\beta}\ln\frac{\beta d_e}{A\alpha\theta} \end{cases}.$$

When an aviation accident happens, customers may question the safety standards of all airlines and will be less certain about the reliability of both the focal and other non-focal airlines. As noted previously, this phenomenon has been commonly referred to as the spillover effect (Roehm and Tybout (2006)). For non-focal airlines that do not compete with the focal airline, three model inputs are most likely to change after the crisis: d_n, d_s and r. We denote their corresponding values after the accident by $\tilde{d}_n$, $\tilde{d}_s$, and $\tilde{r}$. Hence, $\Delta x = -\frac{\theta}{\alpha\theta+\beta}\ln\delta$, and $\Delta y = \frac{1}{\alpha\theta+\beta}\ln\delta$ where $\delta \equiv \frac{1-\tilde{r}}{1-r}\cdot\frac{d_n+d_s}{\tilde{d}_n+\tilde{d}_s}$. The signs of Δx and Δy apparently depend on δ, which reflects the change in customer flows caused by the crisis. Due to the negative spillover effect, the retention rate of the firm's current customer, r, may decrease, and the inflow of new customers (d_n) may suffer too. Since there is no direct competition with the focal airline, the volume of new customers who switched from competitors (d_s) is likely to stay roughly the same, if not decrease. Therefore, for non-competing airlines, it is reasonable to assume that $\tilde{r} \leq r$ and $\tilde{d}_n + \tilde{d}_s < d_n + d_s$, which implies $\ln\delta > 0$. Hence, we expect $\Delta x < 0$ and $\Delta y > 0$, which leads to our first set of hypotheses.

Hypothesis 1. *A non-focal firm that does not directly compete with the focal firm will decrease its offensive marketing effort after the product-harm crisis.*

Hypothesis 2. *A non-focal firm that does not directly compete with the focal firm will increase its defensive marketing effort after the product-harm crisis.*

In addition to the negative spillover effect, firms that directly compete with the focal firm can also benefit from its product-harm crisis through the competitive effect. The misfortune of the focal firm can be an opportunity for non-focal firms to gain new customers who stop patronizing the focal firm (Chance and Ferris (1987), Bosch et al. (1998)).

Although one can still reasonably assume $\tilde{d}_n < d_n$ for a competing firm, whether $\tilde{d}_s < d_s$ and $\tilde{r} < r$ is not clear because of the co-existence of the negative spillover and the competitive effects. Then, the sign of $\ln\delta$ (and hence that of Δx and Δy) is ambiguous. A more interesting perspective is to examine the difference in differences between firms with different degrees of competition with the focal firm before and after the crisis. Continuing to use δ and θ for a firm with a low competition level with the focal one and denoting the corresponding values for a firm with a high competition level with the focal one by $\hat{\delta}$ and $\hat{\theta}$ respectively, we can write the difference between the change of offensive marketing of the two firms as $\Delta_2 x = \frac{\theta}{\alpha\theta+\beta}\ln\delta - \frac{\hat{\theta}}{\alpha\hat{\theta}+\beta}\ln\hat{\delta}$. Similarly, such a difference for defensive marketing would be $\Delta_2 y = \frac{1}{\alpha\hat{\theta}+\beta}\ln\hat{\delta} - \frac{1}{\alpha\theta+\beta}\ln\delta$. We argue that $\ln\delta > \ln\hat{\delta}$, a sufficient condition for which is $\left(\frac{1-\tilde{r}}{1-r}\right)_{high} < \left(\frac{1-\tilde{r}}{1-r}\right)_{low}$ and $\left(\frac{\tilde{d}_n+\tilde{d}_s}{d_n+d_s}\right)_{high} > \left(\frac{\tilde{d}_n+\tilde{d}_s}{d_n+d_s}\right)_{low}$ where we use the subscript *high* to denote a high competition level and *low* to denote a low competition level. The rational is that the percentage increase in the customer defection rate is **lower** for **high-competition firms** than that for low-competition firms and the percentage increase in customer inflow is **higher** for **high-competition firms** than for low-competition firms. Given the exogeneity of the crisis, ex ante, we expect there is no significant difference between θ and $\hat{\theta}$ for the two groups. Therefore, we expect $\Delta_2 x > 0$ and $\Delta_2 y < 0$, which leads to our second set of hypotheses.

Hypothesis 3. *The more competition between a non-focal firm and the focal firm, the less the non-focal firm will decrease its offensive marketing effort after the product-harm crisis.*

Hypothesis 4. *The more competition between a non-focal firm and the focal firm, the less the non-focal firm will increase its defensive marketing effort after the product-harm crisis.*

4. Data, Measurements, and Econometric Model

4.1. Data

We obtained a novel panel data set from a social media analytics company. The data include all the tweets posted by the official Twitter accounts of 56 major airlines[5] during the period between

[5] Each of these airlines had more than 10 million passengers annually in 2010. They were selected based on their sizes and whether they had verified Twitter accounts at the time when the social media analytics firm started monitoring their activities.

September 2014 and June 2015. There were two major aviation accidents during this period: the Indonesia AirAsia Flight 8501 crash on December 28, 2014, and the Germanwings Flight 9525 crash on March 24, 2015. Since the AirAsia accident occurred during the holiday season and near the year's end, there could be concerns of confounding factors. Therefore, we use the Germanwings data to test our hypotheses and the AirAsia data for a robustness check.

4.2. Measurements

Because the key variables of our empirical analysis are airlines' offensive and defensive marketing efforts on social media, our first empirical challenge is to properly measure these two theoretical constructs in our context.

To motivate our measurement scheme, it is helpful to review how these two concepts are defined in the literature, which is summarized in Table 1.

Table 1 Definitions of offensive/defensive marketing in the literature

Source	**Offensive Marketing**	**Defensive Marketing**
Fornell and Wernerfelt (1987)	"obtain additional customers, encourage brand switching, and increase purchase frequency"	"is concerned with reducing customer exit and brand switching," "the objective is to minimize customer turnover"
Fornell and Wernerfelt (1988)	"to generate new customers"	"to keep current customers"
Bridges and Freytag (2009)	"increase investment in the marketing mix with the intention of drawing new customers, frequently from competitors"	"focus on reinforcing relationships with the goal of retaining, and possibly growing the business of, current customers"
Martín-Herrán et al. (2012)	"marketing activities focused at attracting a rival firm's customers"	"marketing activities focused on retaining a firm's current customers"
Zineldin (2006)	"focuses on obtaining new customers and increasing customers' purchase frequency"	"focusing marketing strategy on the existing segments of customer base," "managing the dissatisfaction among a companys own customers"
Erickson (1993)	"to attract customers"	"to hold on to the firm's present customers"
Fornell (1992)	"capturing market share is an offensive strategy"	"creating customer satisfaction is defensive"
Cha (1993)	"the objective is to attract new customers," "by increasing market size or capturing market share"	"the objective is to retain the firm's current customers," "by increasing customer satisfaction or building switching cost"

The consensus from Table 1 is that marketing strategies with the objective of acquiring new customers from competitors or from outside the market pertain to offensive marketing, while marketing strategies with the objective of retaining current customers by developing better relationships pertain to defensive marketing. Although not without controversy, marketing strategies aiming at increasing purchase frequency or growing the business of current customers can also be categorized as offensive marketing strategies.[6]

To properly operationalize the measurements of the concepts of offensive and defensive marketing, we also examined the relevant empirical works, most of which focused on one of the two strategies. For defensive marketing, the focus was centered on customer satisfaction, complaint management, and loyalty marketing. For offensive marketing, traditional marketing mixes such as price and promotion seemed to dominate. The only empirical work we found that incorporated both offensive and defensive marketing was that of Cha (1993) where offensive marketing was measured using advertising expenditures and defensive marketing was measured indirectly using a combination of customer satisfaction and switching costs based on a partial least squares estimation.

Because we study offensive and defensive marketing on social media, we have the advantage of directly observing all marketing messages sent by firms. Following previous discussion and the resulting summary of the concepts of offensive and defensive marketing and given how they are measured in the literature (e.g., Cha (1993)), we propose the following criteria to categorize a social media message as either an offensive or a defensive marketing message:

- A social media message constitutes offensive marketing if the intention is to induce purchases through product or price promotion or brand marketing.
- A social media message constitutes defensive marketing if the intention is to improve relationships with existing customers.

We implemented the above criteria in two steps. First, we used Twitter metadata to identify all the tweets sent to **individual users**.[7] Each of these tweets is a reply to an individual user to answer questions and build a positive relationship with that particular user. Therefore, only that user will receive this tweet, in contrast with other tweets posted by the brand, which are broadcast to all its followers. From the brand's perspective, it is probably inefficient to use this "in reply to" format to communicate offensive marketing messages because there will typically only be one recipient of such a message. Based on our criteria for defensive marketing messages, we believe it is reasonable to categorize these tweets as defensive marketing messages. To see how this assumption

[6] The literature is not entirely consistent on this issue. Fornell and Wernerfelt (1987) and Zineldin (2006)) both suggested that strategies aiming at increasing purchase frequency (i.e., growing more business of current customers) should be classified as offensive marketing. However, Bridges and Freytag (2009) suggested otherwise. This is a subtle issue and we follow the view of Fornell and Wernerfelt (1987) and Zineldin (2006) because any defensive marketing strategy ultimately aims to do *more* business with its current customers, where *more* has both the first-order interpretation of new purchases in the future and the second-order interpretation of enhanced frequency of future purchases. Although these two interpretations are conceptually distinguishable, separating them operationally is at best ambiguous and messy.

[7] Twitter metadata contain a field called *in_reply_to_user_id*. It is set to the individual user ID if the tweet is a reply to a specific individual user and *Null* otherwise.

is supported by the data, we randomly selected 1,000 tweets in reply to individual users.[8] Manual checking suggested the tweets should all be classified as defensive marketing messages, based on our criteria. Hence, the precision of classifying all reply-to-user tweets as defensive marketing tweets is expected to be above 99.9%. Another perspective of understanding this practice is that the Twitter metadata field *in_reply_to_user_id* is such a strong predictor that it alone can classify defensive marketing messages with very high precision within a machine learning algorithm.

In the second step, we classified whether the textual content of broadcast tweets implied offensive marketing or not. To do so, we first randomly selected 5,000 of these tweets and had them each be manually and independently labeled by three persons. Each tweet was labeled as either an offensive marketing tweet or not. Using majority rule, we found roughly 86% of the 5,000 tweets implied offensive marketing. Those not classified as offensive marketing were typically tweets posted because of exogenous events–for example, a standard holiday greeting or an information update about the airport or flight disruption due to bad weather. We excluded these tweets because the timing of their posting was largely exogenous.

Once we labeled the data, we experimented with various supervised learning algorithms and eventually selected Support Vector Machine(SVM) due to its superior performance. Table 2 reports the 10-fold cross-validation results of the SVM classifier on the training data.

Table 2 Performance of the SVM on 5,000 tweets using 10-fold cross-validation

	Accuracy	Precision (+)	Recall (+)	F1 (+)	Precision (-)	Recall (-)	F1 (-)	AUC
fold 1	0.952	0.968	0.977	0.973	0.833	0.781	0.806	0.861
fold 2	0.950	0.971	0.975	0.973	0.784	0.755	0.769	0.837
fold 3	0.936	0.953	0.975	0.964	0.776	0.644	0.704	0.830
fold 4	0.932	0.951	0.972	0.961	0.782	0.662	0.717	0.826
fold 5	0.954	0.975	0.973	0.974	0.769	0.784	0.777	0.817
fold 6	0.926	0.950	0.966	0.958	0.732	0.651	0.689	0.827
fold 7	0.940	0.956	0.977	0.966	0.792	0.655	0.717	0.862
fold 8	0.920	0.950	0.959	0.955	0.684	0.639	0.661	0.850
fold 9	0.938	0.959	0.970	0.964	0.800	0.743	0.770	0.875
fold 10	0.966	0.971	0.991	0.981	0.915	0.768	0.835	0.851
Average	0.941	0.961	0.974	0.967	0.787	0.708	0.745	0.844

Note: This table reports the SVM's performance. The accuracy column measures the percentage of correctly predicted test observations. The symbol + indicates a positive class (i.e., offensive marketing tweets) and the symbol - indicates a negative class (i.e., non-offensive marketing tweets).

Based on the trained SVM classifier, we labeled all of the remaining tweets to extract the offensive marketing tweets. In addition, we categorized each offensive marketing tweet based on whether

[8] This random sample is available in the online supplementary material for this paper.

it contained multimedia content (e.g., image or video), a link, or a hashtag.[9] We use these as alternative measures of offensive social media marketing effort in our robustness check.

Finally, for each airline, we calculated the daily aggregated number of tweets classified as offensive/defensive marketing as a measure of the airline's offensive/defensive marketing effort on social media for that day.

In addition to the social media tweets, we collected each airline's route information,[10] which allows us to define the competition intensity.[11] In particular, we measured the competition intensity between an airline and the focal airline by using the variable *route_sim* which is defined as the percentage of routes that the airlines share. We also calculated a social media similarity measure, *follower_overlap*, using the normalized number of Twitter followers shared by two airlines:

$$follower\_overlap_{ij} = \frac{(\text{Number of shared followers between } i \text{ and } j)^2}{\text{Number of followers}_i \times \text{Number of followers}_j}$$

The definitions and summary statistics of the major variables used in our main empirical analysis are reported in Table 3. From the summary statistics, we see that the daily number of defensive marketing tweets is nearly 30 times the daily number of offensive marketing tweets. However, it should be noted that, unlike defensive marketing tweets, which are pushed only to individual customers, offensive marketing tweets are pushed to all the followers of an airline.

4.3. Econometric Models

4.3.1. Negative Binomial Model The key dependent variables–the number of offensive and defensive marketing tweets posted by an airline each day–are both positive integer variables, which are typically analyzed using count data models. From Table 3, we see that the variance of the daily number of offensive marketing tweets is about five times its mean and the variance of the daily number of defensive marketing tweets is hundreds of times its mean. An appropriate type of count data models that directly takes overdispersion into account is the negative binomial models. To control for unobserved confounding factors due to time-invariant airline heterogeneity, there are two common approaches: 1) estimating a conditional negative binomial model for panel data, as proposed by Hausman et al. (1984), and 2) estimating the unconditional negative binomial regression with the inclusion of airline dummies. According to Allison and Waterman (2002), the unconditional negative binomial estimator, although computationally more expensive, better

[9] Twitter hashtags, regarded as a powerful social media marketing tool for brand engagement, have been widely used by companies to promote customer participation and attract attention to their products and services. For example, the offensive marketing tweet in Figure 1 contains two hashtags: #vacation and #LaborDay.

[10] See http://ourairports.com/airlines/.

[11] The airline industry is naturally divided by routes. In the classic economic literature, researchers analyzed airline competition on each route-defined market (Ciliberto and Tamer (2009)).

controls for all stable predictors and also performs well in their simulation. Therefore, we follow Allison and Waterman (2002) and apply the unconditional negative binomial regression with airline dummies to control for airline fixed effects.[12]

More specifically, we model y_{it}, the number of offensive or defensive social media marketing tweets posted by airline i on day t, as follows:

$$\begin{aligned}
\Pr(y_{it}=k) &= \frac{\Gamma(k+1/\alpha)}{\Gamma(k+1)\Gamma(1/\alpha)}\left(\frac{1}{1+\alpha\mu_{it}}\right)^{1/\alpha}\left(\frac{\alpha\mu_{it}}{1+\alpha\mu_{it}}\right)^{k},\\
\ln\mu_{it} &= \beta_0+\beta_{11}D_{1t}+\beta_{12}D_{2t}+\beta_{13}D_{3t}+\beta_2X_{it}+Weekday_t+Airline_i,
\end{aligned}$$

where $\Gamma[\cdot]$ represents Gamma distribution; $\mu_{it}>0$ is the mean of y_{it} and α is an overdispersion parameter. Among the independent variables, D_{1t}, D_{2t}, and D_{3t} are dummy variables that indicate whether day t is within the first month, the second month, and the third month, respectively, after the aviation crash date. Their coefficients will be our main interest.

The categorical variable $Weekday_t$ stands for the day of week, which is included because airlines may have different posting strategies for different days of the week. The categorical variable $Airline_i$ is for airline fixed effects. Additionally, we include control variables such as the total number of tweets received by an airline from its customers each day, the average number of Twitter followers of an airline each day, and the average growth rate of an airline's number of followers in the past seven days. We use X_{it} to represent these additional control variables.

To test our hypotheses, we augment the baseline model by adding the interactions between monthly dummies and the route similarity measure. We summarize the specification of the augmented model as follows:

$$\begin{aligned}
\Pr(y_{it}=k) &= \frac{\Gamma(k+1/\alpha)}{\Gamma(k+1)\Gamma(1/\alpha)}\left(\frac{1}{1+\alpha\mu_{it}}\right)^{1/\alpha}\left(\frac{\alpha\mu_{it}}{1+\alpha\mu_{it}}\right)^{k},\\
\ln\mu_{it} &= \beta_0^{'}+\beta_{11}^{'}D_{1t}+\beta_{12}^{'}D_{2t}+\beta_{13}^{'}D_{3t}+\beta_2^{'}Z_i+\beta_{31}^{'}Z_iD_{1t}+\beta_{32}^{'}Z_iD_{2t}+\beta_{33}^{'}Z_iD_{3t}\\
&\quad+\ \beta_4^{'}X_{it}+Weekday_t+Airline_i,
\end{aligned}$$

where X_i includes the same set of additional control variables as in the baseline model and Z_i includes a variable that measures the degree of competition between airline i and the focal airline, which is our primary variable of interest, and a variable that measures the degree of similarity between airline i and the focal airline.[13]

[12] We also used the conditional approach for the estimation and found the results to be qualitatively the same as for the unconditional approach.

[13] According to Roehm and Tybout (2006), it is easier for customers to regard similar companies as being guilty in the crisis through association. Hence, the impact of the crash may be heterogeneous among airlines with different similarity measures.

4.3.2. Linear Models We supplement our negative binomial model specification with linear models with airline fixed effects. Although the negative binomial models best suits our data, there are certain advantages to fitting the data with linear models in our context.

First, despite its efficiency gain compared with a linear model for the count data, the negative binomial model is also prone to model misspecification, in which case the estimation will be biased. On the other hand, a linear model is more robust to distribution misspecification. Hence, supplementing the negative binomial models with linear models increases robustness against model misspecification.

Second, we see from Section 3 that an airline's offensive and defensive social media marketing efforts face the same resource constraint. Therefore, the error terms in the empirical models for these two decisions are likely correlated. Estimating the two models separately ignores this error correlation, which could lead to less efficient estimators (Zellner (1962)). Seemingly unrelated regression (SUR) allows us to exploit this error correlation to increase statistical power for our hypothesis testing. However, one drawback of the model of Zellner (1962) is its restrictive assumption on the error structure within equation. Hence, we mainly report the estimation results of linear models using the panel data fixed effects estimation and report the SUR estimates as a robustness check.

For the dependent variable representing the offensive marketing, we use the logarithmic-transformed number of daily tweets. To measure the defensive marketing effort, we use the reply ratio, which is the percentage of "@" tweets sent to airlines that they have replied.

5. Empirical Results

5.1. Main Results

The main estimation results are reported in Table 4. Columns (1) through (4) report the estimation results of the baseline model, with the results of the negative binomial models in columns (1) and (2) and the results for the linear models in columns (3) and (4). Columns (5) through (8) report the estimation results of the augmented model.

Column (1) shows that the estimated coefficients of the post-crash dummies are negative and significant, which suggests that, on average, companies decreased their offensive marketing efforts on social media after the accident of the focal airline. In terms of magnitude, on average, a non-focal airline reduced its offensive social media marketing by $13-19\%$ based on the incidence rate ratios of the negative binomial models. Column (2) shows that the estimated coefficients of the post-crash dummies are positive and mostly significant, which suggests that, on average, airlines increased their defensive marketing efforts on social media during the post-crash period. In terms of magnitude, on average, a non-focal airline's reply ratio increased by $3-9\%$ after the crash based on the incidence rate ratios of the negative binomial models. The results from the linear models (columns (3) and (4)) are consistent with the results from the negative binomial models, although less significant, possibly due to the reduced statistical efficiency. These results suggest that non-focal airlines' social media strategy in response to the negative spillover effect caused by a product-harm crisis is to increase defensive marketing and decrease offensive marketing. This finding echoes the literature findings that increasing advertising may not work for competitors of the focal firm (e.g., Cleeren et al. (2013)).

In columns (5) through (8) of Table 4, we again present the results of the negative binomial models (columns (5) and (6)) and the linear models (columns (7) and (8)) side by side, for ease of comparison.

First, we note in column (5) of Table 4 that the estimated coefficients of the post-crash dummies are negative and significant for offensive marketing, thereby supporting Hypothesis 1. On the other hand, in column (6), the estimated coefficients of the post-crash dummies are positive and mostly significant for defensive marketing, thus providing support for Hypothesis 2. The results from the linear models (columns (7) and (8)) echo these findings.

Second, columns (5) and (7) of Table 4 show that, for offensive marketing, the coefficients of the interaction terms between the post-crash dummies and the route similarity measure are all positive and significant in three of the cases.[14] This result suggests that the offensive social media marketing strategies of airlines that compete with the focal one are less affected by the negative spillover effect. This finding provides some support for Hypothesis 3 and can be interpreted through the competitive effect. Existing and potential customers will be less comfortable choosing the focal airline after the crash and are therefore more willing to switch to a competitor. Therefore, competitors will have incentives to seize the opportunity to acquire new customers and will thus be less affected by the negative spillover effect in forming their social media strategies.

Third, columns (6) and (8) of Table 4 show that, for defensive marketing, the coefficients of the interaction terms between the post-crash dummies and the route similarity measure are not significant. Hence, we find no empirical support for Hypothesis 4. There could be many reasons for the lack of empirical support for Hypothesis 4. For example, the heterogeneity of the parameter θ plays an important role in determining the sign of the difference in differences. Recall that the parameter θ is interpreted as the relative resource consumption intensity of defensive marketing, compared to offensive marketing. In our empirical setup, one factor that affects θ is the number of customer tweets received by an airline, because the more customer tweets an airline receives, the more effort it takes to increase the reply ratio. The number of customer tweets received by

[14] In Section 5.2, the estimated results with route-sharing dummy show greater statistical significance.

an airline varies greatly across airlines, which will certainly increase the variation of θ among the airlines and could consequently lead to the lack of empirical support for Hypothesis 4.

For the interaction terms between the post-crash dummies and the follower overlapping index, we find that most of the estimated coefficients are insignificant.

For the estimation results for the SUR in Table 5, we find that most of the coefficients are qualitatively similar to our main results in Table 4.

5.2. Robustness Test: Route Sharing Dummies

In our main analysis, we use the percentage of routes that an airline shares with the focal airline to represent the competition intensity between the two companies. The accuracy of such a measure of competition intensity is certainly limited and could affect our model estimation. To increase the robustness of our results, we re-estimate our models using an alternative measure of competition intensity: the route sharing dummy, which indicates whether one airline shares at least one route with the focal airline. Because airlines without shared routes do not directly compete with each other, this measure could alleviate concerns about the inaccuracy of a continuous measure. Table 6 reports the estimation results using the route sharing dummy, which are qualitatively the same as the results in Table 4. More importantly, the coefficients of the interaction terms between the month dummies and the route sharing dummy are more significant, which provides us greater empirical support for Hypothesis 3.

5.3. Robustness Test: Hashtags, Multimedia, and Links

Although our classifier for selecting offensive marketing tweets is highly accurate, one could still be concerned that the amount of offensive marketing content in each of these tweets is different. For example, some tweets may contain more offensive marketing content than others by including photos. To alleviate this concern, we construct alternative measures of offensive marketing by counting the number of offensive marketing tweets that contain hashtags, links to external sites, and multimedia content, respectively. We then use each of these three count variables as the dependent variable to measure the offensive marketing and re-estimate our models. The results are reported in Table 7. The main results are qualitatively the same and support Hypotheses 1, 2, and 3. The magnitudes of the estimated effects, however, are larger than those in Section 5.1, which indicates that such tweets could be more elastic to a shift in strategy.

5.4. Robustness Test: The AirAsia Flight 8501

On December 28, 2014, Indonesia's AirAsia Flight 8501 crashed into the Java Sea during bad weather. Because this tragedy happened both during the holiday season and at the end of year, many confounding factors could have affected airlines' social media strategies. Hence, we estimate our models using this data set only as a robustness check. Table 8 reports the estimation results.

The results related to the post-crash dummy of the first month are largely consistent with our main empirical results in Table 4. However, for the following months, the results regarding offensive social media marketing lack statistical significance. One possible explanation for this short-lived strategy shock is that the AirAsia Flight 8501 crash was widely believed at the time to have been caused mainly by extreme weather conditions rather than by human errors, as in the case of the Germanwings accident.

5.5. Robustness Test: A Placebo Test

Our data cover the three months from September 2014 to November 2014, during which there was no accident involving commercial aircraft.[15] This provides an ideal setup for a placebo test: If we estimate our models using data from this period with a hypothetical accident (e.g., on October 16, 2014, the date in the middle of the range), we should expect no significant difference before and after the hypothetical accident in terms of airlines' offensive and defensive marketing efforts on social media. The estimation results in Table 9 show that none of the crash dummy coefficients is significantly different from zero, which is expected, since there was no aviation accident during this period after all. Therefore, the results of the placebo test provide further evidence for our hypotheses from a different angle.

5.6. Robustness Test: Changes in Consumer Tweets

One alternative explanation to our empirical findings is that companies could be responding to the changing volume of consumers' tweeting to airlines. For example, customers could have been sending more tweets to airlines because they were more anxious or were paying more attention to the airlines after the crash event. Therefore, airlines' social media teams may have ended up putting more effort into defensive marketing and less into offensive marketing. Although we control the number of tweets received by an airline in our models either as an exposure variable in the count data models or by directly incorporating it into the linear models, a direct comparison of the number of tweets received by the airlines before and after the accident would still be interesting. To do so, we first fit a negative binomial model with airline fixed effects to the daily number of tweets sent to an airline, with the post-crash dummy and day-of-week dummies as explanatory variables. The results reported in columns (1) through (3) of Table 10 suggest no statistically significant difference before and after the crash in terms of the number of tweets received by an airline. Columns (4) through (6) report the results from the linear regression models, where we replace the count variable by its logarithmic-transformation. Again, none of the crash dummy coefficients is significantly different from zero. These results suggest that changes in customer tweets are unlikely to be the main driver of the change in airlines' social media strategies before and after the accident.

[15] See `https://en.wikipedia.org/wiki/List_of_accidents_and_incidents_involving_commercial_aircraft#2014`

6. Extension: Empirical Justification of an Airline's Social Media Strategy

Given that firms adjust their social media strategies in response to a product-harm crisis in the industry, it is natural to ask whether their strategic adjustment is well justified. Although our analytical model addresses this question from a theoretical perspective, it would be interesting to address this question from an empirical perspective as well.

Because we are studying a firm's marketing strategy on social media, it is natural to consider a performance measure on social media as well. On Twitter, a firm's number of followers can be viewed as a measure of customer interest in the company on social media and is highly valued by companies as both an indicator of their popularity and an instrument to quickly reach a large audience. According to Hoffman and Fodor (2010), returns from social media investments should also be measured in customer behaviors (consumer investments) tied to particular social media applications and the authors suggested that the number of followers is one of the most important metrics for brand awareness and brand engagement on microblogging platforms (e.g., Twitter). This sentiment is also echoed by Mintz and Currim (2013) who discussed marketing metrics for various marketing activities and used the number of followers as a major metric for social media marketing activities. In the industry, the number of followers of a business Twitter account is also an important Twitter Analytics metric and has been widely used as a key performance indicator of reach. Therefore, we choose the daily growth of the number of Twitter followers as the performance measure for a firm's social media strategy.

To measure the growth of a firm's followers, we use both the absolute value of daily change and the daily growth ratio of the number of followers. The explanatory variables of interest include the post-crash dummies and their interaction terms with the firm's social media efforts, which are again measured in two dimensions: offensive and defensive marketing. Our first dependent variable is a count variable measuring the daily increase in the number of followers of an airline which we use a fixed effects negative binomial model to analyze.[16] Our second dependent variable is the daily growth ratio of the number of followers. Hence, we fit it with the panel data fixed effects linear models.

Table 11 reports the estimation results. First, from the negative and significant coefficients of the crash dummy, we see that the growth in followers, in both absolute value and percentage change, suffered after the plane crash. This finding echoes the literature on the negative spillover effect and suggests that such an effect could extend to the social media sphere. This result can also

[16] In a few observations, airlines' number of followers actually decreased. To analyze the data using a negative binomial model, we truncated the variable at zero.

be interpreted as an alternative explanation for our key assumption in the analytical model, that non-focal firms will be exposed to a negative spillover effect after a product-harm crisis.

For the interaction term of the crash dummy and defensive marketing effort, we see the coefficients are positive and significant. This means that the average effect of defensive marketing efforts increased after the crash event. Given that airlines actually increased their defensive marketing after the crash, such an adjustment in social media strategy seems well justified.[17] For the interaction term of the crash dummy and offensive marketing efforts, the coefficients are generally insignificant, which suggests that the average effect of offensive marketing tweets, in terms of generating new followers, did not change much after the crash event. However, if we consider the fact that airlines reduced their offensive marketing efforts on Twitter after the crash event, the finding actually suggests that there was a decrease in the effectiveness of offensive marketing on Twitter after the crash event.[18]

Overall, the empirical evidence in this section seems to justify the adjustment of airlines' social media strategies.

7. Conclusions

We studied how non-focal airlines adjust their social media strategies after a major aviation disaster in the industry. Drawing upon the literature on offensive and defensive marketing, we conceptualized and then operationalized two distinct aspects of social media marketing currently utilized by the airline industry: offensive marketing and defensive marketing. Using both analytical modeling and the empirical analysis of a unique data set around the time of the crash of Germanwings Flight 9525, we analyzed and tested how the negative spillover effect and the competitive effect–two natural effects of a product-harm crisis on non-focal firms–jointly shaped a non-focal airline's social media strategy following the crisis. We find that non-focal airlines decreased their offensive social media marketing and increased their defensive social media marketing within three months after the crisis, a direct result of the negative spillover effect. However, due to the competitive effect, the decrease of offensive marketing is attenuated for non-focal airlines that compete with the focal airline. We also find empirical evidence justifying airlines' post-crash social media strategies.

Our paper makes several important contributions to the literature and practitioners. This is the first study in the literature to empirically identify non-focal firms' strategic adjustment on social media in response to a product-harm crisis. Our analytical model and performance analysis further

[17] One caveat is that we have assumed here a decreasing marginal effect of defensive marketing on social media in terms of generating new followers. If the effect of defensive marketing on social media is a convex function of effort, then we cannot distinguish whether the increased average effect is due to the crash event or the convexity.

[18] As in the previous footnote, the implicit assumption of this argument is that the effect of offensive marketing on social media is a concave function of effort.

suggest that the strategic responses on social media are well justified. Therefore, our findings provide direct guidance to firms in those industries where product-harm crises can occur. Unlike traditional marketing channels, the adjustment of social media strategies can be implemented almost in real time. Hence, for managers, social media offers an extremely flexible way to counter the negative spillover effect of a product-harm crisis to retain existing customers and attract potential new customers. For researchers studying product-harm crises, the availability of real-time social media data can potentially enable the exploration of research questions that are difficult to answer with quarterly or annual data.

Second, although the previous literature suggests the existence of a competitive effect during a product-harm crisis, we are among the first studies to empirically detect its effect in shaping a firm's social media strategy. Clearly, this has important implications to both the focal firm and those competing with it. For example, the focal firm should probably spend even more resources on defensive marketing, knowing that competitors would exploit its vulnerability and ramp up their offensive marketing efforts on social media. For non-focal firms, our findings suggest that they probably need to consider other competitors' strategic responses as well while forming their own strategies.

Finally, by examining firms' social media activities through the lens of offensive and defensive marketing, our research offers an example of analyzing and understanding firm social media strategy in different dimensions, both conceptually and operationally. Admittedly, our dichotomous approach is a simplification of the reality, future research can take a more refined perspective to further our understanding of firms' strategic interplay in the social media arena, which will help guide firms' strategies and investments in social media.

This paper has several limitations. First, we only used data from the airline industry. A natural extension is to study how other industries adjust their social media strategies after a product-harm crisis. For example, it would be interesting to study similar research questions in the automobile industry following the 2015 VW emissions scandal or the food industry following the 2015 *Escherichia coli* outbreak. Second, due to data limitations and model tractability, we did not consider dynamic pricing. It would be interesting to study how pricing decisions react to a product-harm crisis and interact with social media marketing decisions. Finally, we did not study how a non-focal firm's adjustment of social media strategy affects its sales following a product-harm crisis, which is a challenging but important future research question.

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Table 3 Definitions and summary statistics of key variables

Variable	Definition	Obs	Mean	Std. Dev.
num_offensive	Number of offensive marketing tweets posted by the company daily	9702	1.876	2.925
num_hashtag	Number of offensive marketing tweets with hashtag(s) posted by the company daily	9702	1.726	3.839
num_multi	Number of offensive marketing tweets with multi-media content posted by the company daily	9702	1.726	3.839
num_link	Number of offensive marketing tweets with links posted by the company daily	9702	1.726	3.839
num_defensive	Number of defensive marketing tweets posted by the company daily	9702	54.24	106.93
at_log	Log number of tweets sent to the company daily	9688	4.321	1.464
crash	Dummy variable indicating whether the day is before or after the airline crash	9702	.523	.499
route_sim	Percentage of routes that the airline shares with the focal airline	9702	.00255	.00900
route_share	Dummy variable indicates whether the airline shares at least one route with the focal airline	9702	0.111	0.314
follower_overlap	Normalized number of Twitter followers shared by two airlines	9702	0	1
follower_log	Log number of average Twitter followers	9702	11.889	1.442
lag_growth	Average growth rate of follower numbers for in the past seven days	9270	.00119	.00130
weekday	Categorical variable for weekdays	9702	2.975	1.992

Note: The data reported in this table are from December 29, 2014 to June 24, 2015.

Table 4 Airline social media strategies around the Germanwings accident

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Baseline				Interaction			
	NB		Linear		NB		Linear	
Variables	offensive	defensive	offensive	defensive	offensive	defensive	offensive	defensive
ind_1month	-0.155**	0.0315	-0.0912***	0.00293	-0.205**	0.0344	-0.0991***	0.000468
	(0.0705)	(0.0247)	(0.0309)	(0.00571)	(0.0816)	(0.0258)	(0.0334)	(0.00605)
ind_2month	-0.132*	0.0801**	-0.0588	0.00663	-0.174**	0.0877**	-0.0790*	0.00568
	(0.0706)	(0.0358)	(0.0423)	(0.00680)	(0.0761)	(0.0376)	(0.0444)	(0.00708)
ind_3month	-0.210***	0.0925**	-0.102**	0.0170*	-0.270***	0.105**	-0.123***	0.0178*
	(0.0726)	(0.0401)	(0.0403)	(0.00919)	(0.0833)	(0.0441)	(0.0433)	(0.0101)
int_1month					9.933	-0.222	2.773	0.991
					(6.738)	(1.879)	(2.606)	(0.971)
int_2month					17.08***	-1.243	7.391***	0.420
					(5.625)	(2.247)	(2.482)	(0.760)
int_3month					18.45	-3.078	7.474*	-0.250
					(11.41)	(5.301)	(4.433)	(1.033)
fol_1month					-0.205	0.0233	-0.0315	-0.00659
					(0.146)	(0.0209)	(0.0262)	(0.00824)
fol_2month					-0.0476	0.0637**	-0.0354*	-0.000178
					(0.0618)	(0.0266)	(0.0203)	(0.00741)
fol_3month					-0.153	0.0871*	-0.0461	0.00912
					(0.115)	(0.0456)	(0.0375)	(0.00951)
lag_growth	1.570	-8.155*	-4.833	-0.496	1.551	-7.636	-4.595	-0.442
	(10.40)	(4.868)	(7.266)	(1.254)	(10.38)	(4.898)	(7.258)	(1.268)
follower_log	0.272	-0.329	-0.0181	-0.0602	0.356	-0.356	0.00565	-0.0619
	(0.461)	(0.295)	(0.237)	(0.0699)	(0.442)	(0.285)	(0.233)	(0.0695)
log_at				-0.0435***				-0.0437***
				(0.00673)				(0.00670)
Observations	9,162	9,148	9,162	9,148	9,162	9,148	9,162	9,148
Number of airline	54	54	54	54	54	54	54	54

Note: This table reports the empirical results comparing companies' social media strategies before and after the Germanwings aviation crash. The three month dummy variables ind_1month, ind_2month, and ind_3month indicate whether the day is in the first, the second, and the third month after the crash, respectively. Similarly, int_1month, int_2month, and int_3month are the corresponding interaction terms between the month dummies and the route similarity measure. fol_1month, fol_2month, and fol_3month are the corresponding interaction terms between the month dummies and the follower overlapping measure. The observations include daily Twitter data from December 29, 2014 to June 24, 2015. For columns (1) − (2) and (5) − (6), we use negative binomial models with airline dummies to estimate the coefficients and the dependent variables are number of offensive and defensive tweets respectively. For columns (3) − (4) and (7) − (8), we use panel data fixed effects linear models to estimate the coefficients and the dependent variables are log number of offensive tweets and reply ratio respectively. We have controlled the number of "@" tweets sent to airlines as an exposure variable for columns (2) and (6). We have also included the day of week dummies. The standard errors are clustered by airline. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5 Airline social media strategies around the Germanwings accident, with seemingly unrelated regression

	(1)	(2)	(3)	(4)
	Baseline		Interaction	
Variables	offensive	defensive	offensive	defensive
ind_1month	-0.0913***	0.00294	-0.0991***	0.000476
	(0.0190)	(0.00382)	(0.0210)	(0.00422)
ind_2month	-0.0591***	0.00664	-0.0793***	0.00570
	(0.0202)	(0.00408)	(0.0223)	(0.00449)
ind_3month	-0.102***	0.0170***	-0.123***	0.0178***
	(0.0218)	(0.00440)	(0.0238)	(0.00480)
int_1month			2.770	0.990
			(3.395)	(0.684)
int_2month			7.398**	0.417
			(3.437)	(0.693)
int_3month			7.472**	-0.254
			(3.400)	(0.686)
fol_1month			-0.0315	-0.00658
			(0.0307)	(0.00618)
fol_2month			-0.0355	-0.000161
			(0.0310)	(0.00626)
fol_3month			-0.0461	0.00915
			(0.0307)	(0.00619)
Observations	9,148	9,148	9,148	9,148
Number of airline	54	54	54	54

Note: This table reports the empirical results comparing companies' social media strategies before and after the Germanwings aviation crash with seemingly unrelated regression. ind_1month, ind_2month, and ind_3month are the month dummies indicating whether the day is in the first, the second, and the third month after the crash, respectively. int_1month, int_2month, and int_3month are the corresponding interaction terms between the month dummies and the route similarity measure. fol_1month, fol_2month, and fol_3month are the corresponding interaction terms between the month dummies and the follower overlapping measure. The observations include daily Twitter data from December 29, 2014 to June 24, 2015. The dependent variables are log number of offensive tweets and reply ratio respectively. We have also included other control variables and the day of week dummies. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6 Airline social media strategies around the Germanwings accident, with route-sharing dummy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Baseline				Interaction			
	NB		Linear		NB		Linear	
Variables	offensive	defensive	offensive	defensive	offensive	defensive	offensive	defensive
ind_1month	-0.155**	0.0315	-0.0912***	0.00293	-0.195**	0.0290	-0.0919***	1.51e-05
	(0.0705)	(0.0247)	(0.0309)	(0.00571)	(0.0790)	(0.0260)	(0.0328)	(0.00587)
ind_2month	-0.132*	0.0801**	-0.0588	0.00663	-0.153**	0.0854**	-0.0717	0.00633
	(0.0706)	(0.0358)	(0.0423)	(0.00680)	(0.0752)	(0.0372)	(0.0453)	(0.00718)
ind_3month	-0.210***	0.0925**	-0.102**	0.0170*	-0.259***	0.102**	-0.121***	0.0179*
	(0.0726)	(0.0401)	(0.0403)	(0.00919)	(0.0766)	(0.0423)	(0.0423)	(0.0100)
int_1month					0.154	0.0439*	0.00216	0.0270**
					(0.138)	(0.0258)	(0.0624)	(0.0132)
int_2month					0.249***	-0.00833	0.109**	0.00415
					(0.0888)	(0.0795)	(0.0540)	(0.0253)
int_3month					0.360**	-0.0411	0.163**	-0.00613
					(0.171)	(0.0969)	(0.0725)	(0.0294)
fol_1month					-0.159	0.0139	-0.0101	-0.00333
					(0.146)	(0.0152)	(0.0189)	(0.00281)
fol_2month					0.0403	0.0556**	0.00442	0.00243
					(0.0549)	(0.0218)	(0.0118)	(0.00528)
fol_3month					-0.0802	0.0700***	-0.0146	0.00819
					(0.0645)	(0.0212)	(0.0126)	(0.00554)
lag_growth	1.570	-8.155*	-4.833	-0.496	1.816	-7.766	-4.313	-0.442
	(10.40)	(4.868)	(7.266)	(1.254)	(10.31)	(4.911)	(7.219)	(1.278)
Observations	9,162	9,148	9,162	9,148	9,162	9,148	9,162	9,148
Number of airline	54	54	54	54	54	54	54	54

Note: This table reports the empirical results comparing companies' social media strategies before and after the Germanwings aviation crash with route-sharing dummy. ind_1month, ind_2month, and ind_3month are the month dummies indicating whether the day is in the first, the second, and the third month after the crash, respectively. int_1month, int_2month, and int_3month are the corresponding interaction terms between the month dummies and the route-sharing dummy. fol_1month, fol_2month, and fol_3month are the corresponding interaction terms between the month dummies and the follower overlapping measure. The observations include daily Twitter data from December 29, 2014 to June 24, 2015. For columns $(1)-(2)$ and $(5)-(6)$, we use negative binomial models with airline dummies to estimate the coefficients and the dependent variables are number of offensive and defensive tweets respectively. For columns $(3)-(4)$ and $(7)-(8)$, we use panel data fixed effects linear models to estimate the coefficients and the dependent variables are log number of offensive tweets and reply ratio respectively. We have controlled the number of "@" tweets sent to airlines as an exposure variable for columns (2) and (6). We have also included other control variables and the day of week dummies. The standard errors are clustered by airline. $^{*}\ p<0.1$, $^{**}\ p<0.05$, $^{***}\ p<0.01$

Table 7 Airline social media strategies around the Germanwings accident, with alternative measures of offensive marketing

	(1)	(2)	(3)	(4)	(5)	(6)
	NB			Linear		
Variables	hashtag	link	multimedia	hashtag	link	multimedia
ind_1month	-0.336***	-0.273***	-0.209***	-0.149***	-0.107***	-0.0812***
	(0.129)	(0.0761)	(0.0711)	(0.0416)	(0.0329)	(0.0237)
ind_2month	-0.325**	-0.209***	-0.147**	-0.146***	-0.0789*	-0.0553*
	(0.130)	(0.0789)	(0.0722)	(0.0508)	(0.0438)	(0.0279)
ind_3month	-0.349**	-0.291***	-0.0912	-0.191***	-0.113**	-0.0402
	(0.149)	(0.0898)	(0.100)	(0.0536)	(0.0441)	(0.0325)
int_1month	0.548	12.49**	-0.549	3.242	3.459	0.472
	(13.45)	(5.928)	(6.552)	(3.219)	(2.193)	(2.275)
int_2month	35.45***	14.46***	24.53***	15.43***	4.799*	7.608**
	(9.400)	(4.637)	(9.304)	(3.263)	(2.419)	(3.389)
int_3month	11.61	15.49*	11.43	9.155	5.081	3.014
	(25.89)	(8.694)	(14.25)	(7.742)	(3.700)	(4.255)
fol_1month	-0.306	-0.237	-0.122	-0.0509*	-0.0346	-0.0130
	(0.224)	(0.167)	(0.136)	(0.0281)	(0.0219)	(0.0192)
fol_2month	-0.193**	-0.0522	-0.148	-0.110***	-0.0166	-0.0621**
	(0.0815)	(0.0575)	(0.0925)	(0.0259)	(0.0193)	(0.0287)
fol_3month	-0.0282	-0.103	-0.0449	-0.0505	-0.0212	-0.0282
	(0.243)	(0.0953)	(0.146)	(0.0655)	(0.0324)	(0.0354)
Observations	9,162	9,162	9,162	9,162	9,162	9,162
Number of airline	54	54	54	54	54	54

Note: This table reports the empirical results comparing companies' social media strategies before and after the Germanwings aviation crash. The observations include daily Twitter data from December 29, 2014 to June 24, 2015. ind_1month, ind_2month, and ind_3month are the month dummies indicating whether the day is in the first, the second, and the third month after the crash, respectively. int_1month, int_2month, and int_3month are the corresponding interaction terms between the month dummies and the route similarity measure. fol_1month, fol_2month, and fol_3month are the corresponding interaction terms between the month dummies and the follower overlapping measure. For columns (1) – (3), we use negative binomial models with airline dummies to estimate the coefficients and the dependent variables are number of offensive marketing tweets with hashtags, links, and multimedia content, respectively. For columns (4) – (6), we use panel data fixed effects linear models to estimate the coefficients and the dependent variables are log number of offensive marketing tweets with hashtags, links, and multimedia content, respectively. We have also included other control variables and the day of week dummies. The standard errors are clustered by airline. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8 Airline social media strategies around the AirAsia accident

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Baseline				Interaction			
	NB		Linear		NB		Linear	
Variables	offensive	defensive	offensive	defensive	offensive	defensive	offensive	defensive
ind_1month	-0.125	0.110***	-0.0780*	0.0213**	-0.355***	0.189***	-0.143***	0.0464***
	(0.106)	(0.0245)	(0.0432)	(0.00895)	(0.117)	(0.0626)	(0.0481)	(0.0114)
ind_2month	-0.0222	0.0832***	0.00239	0.0206**	-0.108	0.177**	-0.00999	0.0338**
	(0.0692)	(0.0307)	(0.0386)	(0.00931)	(0.116)	(0.0757)	(0.0545)	(0.0128)
ind_3month	-0.0191	0.0897*	-0.00754	0.0266***	0.0248	0.156**	0.0145	0.0394***
	(0.0761)	(0.0469)	(0.0426)	(0.00976)	(0.0835)	(0.0740)	(0.0487)	(0.0134)
int_1month					16.45*	-5.897	4.390	-1.668***
					(9.124)	(4.546)	(2.688)	(0.495)
int_2month					6.533	-7.012	0.788	-0.839
					(7.122)	(5.314)	(2.683)	(0.597)
int_3month					-3.710	-4.585	-1.569	-0.791
					(3.335)	(3.944)	(1.485)	(0.576)
fol_1month					-1.197*	0.431	-0.325	0.122***
					(0.674)	(0.332)	(0.199)	(0.0368)
fol_2month					-0.374	0.466	-0.0434	0.0578
					(0.517)	(0.385)	(0.196)	(0.0436)
fol_3month					0.295	0.349	0.113	0.0583
					(0.246)	(0.287)	(0.110)	(0.0419)
Observations	8,943	8,922	8,943	8,922	8,943	8,922	8,943	8,922
Number of airline	54	54	54	54	54	54	54	54

Note: This table reports the empirical results comparing companies' social media strategies before and after the AirAsia aviation crash. ind_1month, ind_2month, and ind_3month are the month dummies indicating whether the day is in the first, the second, and the third month after the crash, respectively. int_1month, int_2month, and int_3month are the corresponding interaction terms between the month dummies and the route similarity measure. fol_1month, fol_2month, and fol_3month are the corresponding interaction terms between the month dummies and the follower overlapping measure. The observations include daily Twitter data from September 28, 2014 to March 23, 2015. For columns $(1)-(2)$ and $(5)-(6)$, we use negative binomial models with airline dummies to estimate the coefficients and the dependent variables are number of offensive and defensive tweets respectively. For columns $(3)-(4)$ and $(7)-(8)$, we use panel data fixed effects linear models to estimate the coefficients and the dependent variables are log number of offensive tweets and reply ratio respectively. We have controlled the number of "@" tweets sent to airlines as an exposure variable for columns (2) and (6). We have also included other control variables and the day of week dummies. The standard errors are clustered by airline. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 9 Airline social media strategies around a hypothetical accident

	(1)	(2)	(3)	(4)
	NB		Linear	
Variables	offensive	defensive	offensive	defensive
crash	0.0524	-0.0104	0.0253	0.00425
	(0.0586)	(0.0330)	(0.0283)	(0.0117)
lag_growth	1.406	-2.811	-0.407	-1.265**
	(4.257)	(2.065)	(1.715)	(0.512)
follower_log	0.0867	-0.0472	-0.00927	0.118
	(0.873)	(0.650)	(0.460)	(0.173)
log_at				-0.139***
				(0.0200)
Observations	4,528	4,524	4,528	4,524
Number of airline	55	55	55	55

Note: This table reports the empirical results comparing companies' social media strategies before and after a hypothetical crash on October 16, 2014. The observations include daily Twitter data from September 1, 2014 to December 1, 2014. For columns $(1)-(2)$, we use negative binomial models with airline dummies to estimate the coefficients and the dependent variables are number of offensive and defensive tweets respectively. For columns $(3)-(4)$, we use panel data fixed effects linear models to estimate the coefficients and the dependent variables are log number of offensive tweets and reply ratio respectively. We have also included the day of week dummies. The standard errors are clustered by airline. $^{*}\ p<0.1$, $^{**}\ p<0.05$, $^{***}\ p<0.01$

Table 10 Comparing the number of tweets received by airlines before and after the Germanwings accident

	(1)	(2)	(3)	(4)	(5)	(6)
	NB			Linear		
Variables	1 month	2 month	3 month	1 month	2 month	3 month
indicator	0.0309	-0.000418	0.0291	0.0391	0.0219	0.0436
	(0.0466)	(0.0465)	(0.0419)	(0.0306)	(0.0320)	(0.0324)
Observations	6,245	7,864	9,536	6,245	7,864	9,536
Number of airline	54	54	54	54	54	54

Note: This table reports the empirical results comparing number of tweets sent to airlines using "@" before and after the Germanwings aviation crash. The observations include daily Twitter data from December 29, 2014 to June 24, 2015. For columns (1) − (3), we use negative binomial models to estimate the coefficients with airline dummies. For columns (4) − (6), we use log transferred daily number of "@" tweets as the dependent variable and panel data fixed effects linear models to estimate the coefficients. We have also included the day of week dummies. The standard deviations are clustered by airline. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11 Comparing the effectiveness of airlines' social media strategies before and after the Germanwing accident

	(1)	(2)	(3)	(4)	(5)	(6)
	follower_difference			follower_ratio		
Variables	1-month	2-month	3-month	1-month	2-month	3-month
crash	-0.276***	-0.352***	-0.375***	-0.000273	-0.000144	-0.000468***
	(0.103)	(0.0885)	(0.0876)	(0.000169)	(0.000148)	(0.000170)
num_offensive	0.113**	0.105*	0.0914*	0.000155	0.000162	0.000124
	(0.0545)	(0.0552)	(0.0517)	(0.000111)	(0.000109)	(0.000107)
num_defensive	0.143	0.130	0.148	-9.83e-05	-0.000152	-0.000177
	(0.149)	(0.156)	(0.167)	(0.000288)	(0.000292)	(0.000286)
offensive_int	0.0410	0.0160	0.0211	-0.000140	-0.000149	-0.000126
	(0.0532)	(0.0482)	(0.0406)	(0.000114)	(0.000100)	(8.89e-05)
defensive_int	0.252	0.386*	0.430**	0.000540	0.000683*	0.000748**
	(0.259)	(0.222)	(0.219)	(0.000420)	(0.000405)	(0.000376)
follower_lag	-2.55e-06*	-1.15e-06	3.00e-07	-0.00380***	-0.00498***	-0.00608***
	(1.50e-06)	(1.18e-06)	(7.64e-07)	(0.000901)	(0.000696)	(0.000511)
log_at	0.324***	0.327***	0.320***	0.000566***	0.000504***	0.000458***
	(0.0495)	(0.0452)	(0.0429)	(0.000145)	(0.000114)	(0.000101)
Observations	5,441	6,970	8,549	5,441	6,970	8,549
Number of airline	51	51	51	51	51	51

Note: This table represents the empirical results of social media strategies' effectiveness around Germanwings crash. Variables offensive_int and defensive_int are the interaction terms between the corresponding number of offensive or defensive marketing tweets and the crash dummy. The variable follower_lag represents the one day lagged number of Twitter followers for columns (1) – (3) and one day lagged log number of Twitter followers for columns (4) – (6). For columns (1) and (4), the observations include daily Twitter data from December 29, 2014 to April 24, 2015. For columns (2) and (5), the observations include daily Twitter data from December 29, 2014 to May 24, 2015. For columns (3) and (6), the observations include daily Twitter data from December 29, 2014 to June 24, 2015. For columns (1) – (3), we apply negative binomial models for the dependent variable of follower_difference using airline dummies. For columns (4) – (6), we apply fixed effect linear models for the dependent variable follower_ratio. The standard deviations are clustered by airline. We have also included day of the week dummies. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$