

# **Trains and Twitter: Firm-generated Content, Consumer Relationship Management and Message Framing**

**Abstract.** In this paper, we examine the impact of Twitter content on users' train journeys and how train providers' message framing moderates these relationships. Framing regards the way in which messages are worded concerning a particular object. In many consumer markets such as train journeys, firms frame messages in both positive and negative lights to persuade individuals to make purchase decisions (take intended journeys). We thus go beyond the literature's current focus on consumer-generated content (CGC), and bring into contention the important role that marketer-generated content (MGC) plays in shaping the social media-based consumer relationship management (CRM) strategies. Specifically, we analyze commuter tweets about 14 train operators, along with the companies' Twitter feeds. The findings, obtained using sentiment analysis tools, suggest that consumer sentiments only moderately impact travel performance, as measured by operator ratings, CPM (consumer performance measure; a measure based on travel incidents) and firm financial performance. On the other hand, it appears that train operators use tweets in relation to their services particularly well, while keeping customers engaged by listening to and learning from criticism, thus confirming the moderating role of their Twitter-based message framing strategies. Train operators should look to maintain their social media use practices, ensuring they are consistently applied within an overarching CRM framework, particularly in key 'pain' areas such as delay and cancellation.

**Keywords:** Trains; Twitter; Sentiment; Consumer Relationship Management; Framing Effect; Source Credibility; Performance Measure; Financial Performance

## **Introduction**

Commuters are often hit with travel misery when a series of rush-hour problems strike their transport network. For example, signaling failures may see a part suspension on line 1 of the network, while line 2 may be held up at a station due to a safety alarm. Another signaling problem may lead to delays on line 3, and a faulty train at a different station may add to the problems, causing severe delays on line 4. In a situation like this, crowds of commuters could be seen queuing for buses, with scores of others choosing to join the long wait for taxis. Rail staff could be seen busily directing travellers as the queues often snake along the pavements and into the road. Commuters may also endure these miserable journeys to and from work when a dispute between rail workers and managers disrupts the whole or part of the network. Overcrowding is also a common occurrence on commuter trains, which can be a source of

great inconvenience for passengers, and, in some situations, it can be potentially highly dangerous.

The rail industry is no stranger to criticism, from repeated questions around the quality and frequency of services to the regular outrage at fare increases. All providers of rail services have the responsibility to ensure that consumers have a safe and enjoyable journey: yet commuter journeys frequently attract negative sentiment, whether the issue is a train delay, overcrowding or crime. The severity of network-related incidents can be such that operators are frequently subject to complaints from commuters. In the past, the preferred method to deal with such complaints was to write letters and through running annual surveys, meaning that concerns could be addressed in a system away from public view. However, commuters now have an open forum to provide feedback, voice dissatisfaction with service and make complaints. They can now use Twitter to alert rail providers to the challenges and problems experienced on running services. The high variance of the information that propagates through large user communities in Twitter makes this network a significant player in service-oriented markets. Social media offers commuters a free, interactive and real-time platform for the publication of grievances, which can be viewed by millions of other users (Schroeder and Pennington-Gray, 2014; Bernoff and Li, 2008; Pan and Zhang, 2011). For instance, consumer-generated content (CGC) on social media has heightened the significance of consumer relationship management (CRM) as criticisms of companies posted online can reach a large and geographically diverse audience (Mkono and Tribe, 2016; Kietzmann and Canhoto, 2013; Hudson et al., 2016), achieve viral status and pose reputational risks to those companies (Mkono and Tribe, 2016). The platform can also be used by the providers to reduce the number of customer complaints, besides its use for other purposes such as setting targets for adding extra carriages or sharing information through Twitter about the alternative route options that may be available (Berger and Iyengar, 2013; Tirunillai and Tellis, 2012).

In this research, we examine how online buzz and attention is created for different rail operators and how that affects their relationships with customers. Specifically, we focus on how positive and negative opinions propagate via Twitter and the degree to which train providers' message frames influence consumers' travel experiences. Although a few studies have already examined the scope of marketer-generated content (MGC) along with the CGC (Godes and Mayzlin 2009; Trusov et al. 2009; Goh et al., 2013; Christodoulides and Jevons, 2011), they, nonetheless, focus on limited textual aspects of MGC content. In this study, we

address this gap and investigate the MGC by asking a number of questions: for instance, do negative consumer sentiments affect their travel experience? How do positive reviews and opinions affect their travel plans and journeys taken? What is the specific role of MGC in mediating such relationships? By understanding the interaction of user-generated and marketer-generated contents, we can show that consumer sentiment on social media tangibly influences a company's product offering. More specifically, we aim to understand the way in which train operators use Twitter to word a particular message, in order to persuade the commuters to complete their intended journeys. Our main source of data is chatter from Twitter, as previous studies have found that the chatter of a community can be used to make more informed and stable predictions (Asur and Huberman, 2010; Das and Chen, 2007; Tirunillai and Tellis, 2012). We analyze commuter tweets about the services provided by the 14 main rail providers that serve London. We gather our data by mainly looking at Twitter handles that contain references to and complaints around cancellation and delays. For example, we have explored in detail Twitter data on negative sentiments - there were, in total, 457,853 tweets using negative language in 2014. Commuters express positive sentiments as well, which we have also used in the research.

Using sentiment analysis from data obtained for 2014 and 2015, we find that a potent mix of delays, crowding and cancellations creates deeply uncomfortable situations for passengers. This results in often strong reactions on services as reflected through Twitter. We further examine the impact of user sentiments on an operator's performance rating (RATINGS), CPM (consumer travel performance measure) and financial performance. We use rail operators' star rating as our first measure of train operators' performance. CPM is a Twitterbased performance measure, incorporating incidents of delays, cancellations and overcrowding. We also measure the impact of consumer sentiments on rail operators' financial performance, and obtain relevant data from each operator's annual reports. We show a modest impact of negative sentiments on both RATINGS and CPM but there is no such effect for positive sentiments. However, we find support for the moderating role of companies' message frames on consumers' travel experiences as reflected in the stronger impact of a company's positive message frames on both RATINGS and CPM. This suggests that companies' own engagement with passengers via Twitter can be a vital component in the commuter-train provider relationship. These findings also highlight the importance of a company's Twitter-based CRM strategy. We thus see the potential of using social media as a

CRM tool, and applies it in a local public transportation setting, which is an industry in which daily complaints from commuters are common. It appears that both the instantaneity of social media communications and the directionality of Twitter tweets (from marketers to consumers) make Twitter an ideal candidate for managing commuter relationships.

The arguments developed within this paper are organized as follows. The first section presents a literature review, which argues that CRM practices can be used to support a company's social media strategy. The following section introduces our data and provides information about the paper's methodology. We then examine the specific research questions and present our findings. The final section reflects on key results and suggests pathways for future research within this largely unexplored field.

## **Literature Survey**

### **Customer relationship management**

Since its emergence in the mid-1990s' (van Doorn et al., 2010; Payne and Frow, 2005), CRM has attracted vast amounts of managerial and academic interest (Palmatier, 2008) and, as such, is widely recognized as an important business concept. Nevertheless, whilst numerous definitions have been offered by various academics, Ngai (2005) highlights that a universal definition continues to remain elusive. Goldenberg (2002) suggests a reason for this is that CRM carries different implications for each organization; thus an organization must define CRM contextually in order to fully understand and apply the concept. Consequently, CRM is often defined as a combination of people, processes and specific technological solutions within an organization that allows for the managing of customer relationships (Payne and Frow, 2005; van Doorn et al., 2010; Harrigan, Evers, Miles and Daly, 2017). Grunewalder (2008) proposes that CRM is not just the managing of relationships, but also involves an understanding of one's customer base. In understanding customers, it is suggested businesses have the means to engage in communications that facilitate continuous relationship development (Grunewalder, 2008). It is in this context that Harrigan, Evers, Miles and Daly (2017) emphasize the strategic role of CRM in social media environments. Regardless of the

existence of numerous definitions, Parvatiyar and Sheth (2001) note that cooperation and collaboration between the firm and its customers is a core theme amongst all definitions.

It can be noted that just as CRM definitions differ amongst authors, so do the motivations behind its implementation. The majority of literature recognizes the core purpose of CRM to improve customer retention and loyalty in order to reduce customer acquisition costs and maximize profitability (Bose, 2002; Payne and Frow, 2005; Faase et al., 2011). Parvatiyar and Sheth (2001), however, suggested that the reason for employing CRM is to “create superior value for the company and customer” (p.5). Others (e.g., Hobby, 1999; Storbacka, 2000; Buttle, 2001) also suggested that, as not all customers hold equal profitability, an alternative motive for implementing CRM is to strategically improve the company’s value, through the attraction and retention of specific, profitable customers. Prior research has argued that there are three main factors that led to the rapid evolution of CRM, including the fast development of sophisticated computer technologies. As technology advanced, producers began to sell directly to consumers and the need for salesmen began to dissolve; emotional bonds between consumer and producer began to flourish, and literature began to recognize the need for relationship management. Technological development, combined with increased competition and “the growing availability of advanced product features and services” also led to an increase in customer expectations (Parvatiyar and Sheth, 2001). Literature subsequently began to recognize the need to build strong, co-operative customer relationships in order to monitor expectations, plan marketing responses accordingly, and compete successfully (Sheth and Sisodia, 1995). Whilst its presence within previous literature is minimal, this notion begins to intimate a customer intelligence use for CRM.

### **Twitter effect**

An individual can broadcast a brief statement in real time to some or all members of the sender’s social network through Twitter. Twitter, which has large audience potential, currently attracts an estimated average of 271 million users every month (McGee, 2012; Beevolve, 2012; Jansen, et al., 2009). It has quickly become the preferred channel for the airing of commuter complaints, further supported by high-quality phone cameras that can quickly capture, record and share railway delays and incidents online at the touch of a button (Which? 2015). In 2014, commuters sent a staggering 290,000 tweets about delayed trains in

the UK. They also directed 81,367 tweets to the 14 operators running services into London complaining over cancellations; and there were 66,700 tweets about overcrowding (Evening Standard, 2015a). Recent research has explored whether the ‘Twitter effect’ is economically substantial (Hennig-Thurau, Wiertz and Feldhaus, 2015). Twitter effect has been shown to be particularly relevant to experiential media products (e.g., movies, music, and electronic games). These are generally the products for which ‘instant’ success is essential (Corliss, 2009; Singh, 2009; Funt, 2012). While looking at prior literature, it becomes apparent that whilst social-consumer relationship management has attracted a degree of academic interest, the field has remained largely unexplored (Wahlberg et al., 2009; Beevolve, 2012; Mkono and Tribe, 2016).

Twitter-based models can be built to aggregate the opinions of the collective population. They can also be used to predict future trends while gaining useful insights into individual behavior (Asur and Huberman, 2010). Twitter is characterized by the real-time transmission of product quality information and reviews, and thus it enables feedback. The receiver of such information can potentially be a very large group, and not just an individual or a small group (McGee, 2012). Microblogging is also recognized to hold huge potential for the successful implementation of many other related organization and management practices (Coyle et al., 2012). Microblogs are a form of social communication whereby users can express their interests and attitudes in short posts, which are instantly distributed to other users via mobile phones, instant message, and the web (Chen and Xie, 2008). Coyle et al. (2012) argue that it is microblogging’s instant, real-time access to consumers that makes it ideal for managing wider market relationships. However, regardless of its simple exterior, with its numerous features this straightforward platform has proved itself to be incredibly valuable to businesses (Chen and Xie, 2008; Comm, 2010). Not only do ‘@mentions’ allow consumers to tag companies in posts, thereby enabling businesses to stay up to date with market opinions and monitor their product performance, but the employment of ‘hashtags’ aids communication further, as it allows businesses to search for key words within tweets, thus identifying potential new customers and markets (Comm, 2010). Nevertheless, some argue that the real communication advantage of using Twitter is not a result of its tools, but of its core feature - tweets. Tweets enable businesses to directly communicate with customers and other market participants, building trust and consequently developing stakeholder relationships (Comm, 2010). The informal nature of tweeting facilitates the deepening of

these user relationships through humanizing the business relationships and demonstrating empathy (Chen and Xie, 2008).

### **Framing effect**

Framing effects were first introduced by Tversky and Kahneman (1981) who conducted an experiment known as the Asian Disease framing problem. In their study, participants were presented with two options for fighting an outbreak of an Asian disease: one was certain and the other was probabilistic. Participants generally chose the certain option when the situation was framed positively, while they chose the alternative when framed negatively. The results found that people were more risk-averse when exposed to positively framed messages that emphasized benefits or gains and more risk-seeking when exposed to negatively framed messages that emphasized risks or losses. Prospect theory has been predominantly used to explain this preference reversal, which suggests that people are prone to minimize risks when contemplating benefits and prone to taking risks when contemplating risks or losses (Tversky and Kahneman, 1979). Subsequently, a typology was provided that allowed categorization of framing effects, based on '(1) what is framed (2) what is affected and (3) how the framing effect is measured' (Levin et al, 1998, pp.181). This resulted in three types of framing effect - risky choice framing, attribute framing and goal framing. In risky choice framing the outcomes of a choice vary according to the level of risk involved. Attribute framing focuses on framing a particular characteristic of an object or event. Finally, goal framing is concerned with framing a desired action or behavior (a "goal"). A number of studies have been carried out to verify framing effects in a number of applications, particularly in health (e.g., Banks et al., 1995; Krishnamurthy et al., 2001; Apanovitch et al., 2003) and consumer research (e.g., Jain et al., 2006; Graus and Folse, 2007).

Within consumer research, message framing has been tested in terms of its influence on perceptions of product attractiveness; findings show it has a significant influence on consumer decisions (Jain et al., 2006). Message framing was also applied to a Cause-Related Marketing (CRM) context, testing involvement levels of participants with differing messages in terms of a CRM campaign (Graus and Folse, 2007). This research contributed to the framing literature, as it is suggested that positive framing affects the perceived value of a campaign to less involved customers; however, this does not necessarily reflect actual behavior. While in some cases framing has demonstrated preference shift, there have been a

number of studies which have found “no effect”. This has been particularly evident in testing goal framing effects (Lalor and Hailey, 1987; Lauver and Rubin, 1990; Lerman et al., 1992; Siminoff and Fetting, 1989; Steffen et al., 1994). A number of other cases have drawn contrasting conclusions regarding framing effects. Exploration of the reasons behind this has revealed a number of potential explanations. Varying degrees of issue involvement was one reason suggested by Maheswaran and Meyers-Levy (1990) for this variation in results. This paper contends however that there are a number of possible reasons regarding individual differences that allow for inconclusive results. Previous research has been looking into these differences; one study tested framing effects on two different types of individuals, namely “promotion-focused” and “prevention-focused” individuals (Jain et al, 2006). They found that promotion-focused individuals were more persuaded by maximal comparisons (i.e. Brand A is superior to Brand B) and prevention-focused individuals were either equally persuaded by the frames or more persuaded by the minimal frame (i.e. the two brands are similar or equal) (Jain et al, 2006). Overall, it is suggested that reliable framing effects were not evident for goal framing (Levin et al, 2002); thus there is a greater need to clarify the potential reasons behind this. In particular it was recommended that “even more can be learned by going beyond aggregate level results and examining individual differences” (Levin et al., 2002, p. 427). It is also proposed that examining other variables may further our understanding of general framing effects (Jain et al., 2006).

## **Hypotheses**

### **Commuting and Twitter sentiments**

Commuters have generally been able to use Twitter to post information about their daily commute. For instance, London has one of the biggest and most complex commuter networks in Europe. However, commuters often find that their services are cancelled, severely delayed or diverted when they arrive at a station (Evening Standard, 2015a). They are then advised to try and find alternative ways to reach their destinations. A pan-European survey of commuters found that some rate the worry and strain of the journey as on a par with the breakdown of a relationship - and often worse than their job itself (Evening Standard, 2015b).



More than 5,500 commuters in London, Rome, Barcelona, Berlin, Madrid, and Paris participated in the survey and London performed worst in terms of delays and unpredictability. London commuters are more likely to leave for work early and arrive late: of those participating, four out of five said they are delayed on their daily journey at least once a month, while 47% admit to being late two or three times a month. They also suffer the most stress: 41% commented that the commute is getting ‘increasingly stressful’, while 37% found the journeys ‘increasingly unpredictable’. Because of frequent hold-ups, a massive 93% now allow extra time for their commute and some add 30 minutes or more to original journey times. More worryingly, nearly half (48%) have been prevented at some time or other from reaching their work place altogether because of travel problems.

A satisfaction survey by Which? (a consumer advocacy group) revealed that London commuter services were the ones train passengers were least happy with (Which? 2015). Another rail customer survey showed that overall passenger satisfaction had dipped from 83% in 2013 to 81% in 2014 (Transport Focus, 2015). In 2014, there were a total of 1.7m tweets directed at the 14 rail providers<sup>1</sup>. Consistent with previous insight into user behavior on social media, there were more negative than positive tweets about commuter journeys (the negative-to-positive ratio is 7.3). As discussed, commuter sentiments are likely to affect a train operator’s performance, not least because train franchises are granted for a limited period of time by the regulatory authority, which is likely to be sensitive to the opinions expressed by the passengers. When people buy a product or service, or access product-related company information, they may then express opinion or raise concerns about their experience on a social media platform (Godes and Mayzlin, 2009; Xiang, Du, Ma and Fan, 2017). They may exhibit favorable attitudes and sentiments if their experience of the product or attachment to the company’s policies has been satisfying. The converse may be true if they had found something troubling or felt unpleasant when consuming the product. These general evaluations of a company or its products and services can be referred to as valence embedded in CGC (Trusov et al., 2009). One may argue that positive valence of CGC should drive consumer purchases. Indeed, a great deal of marketing research shows that positive valence results in increases in consumer purchases (Godes and Mayzlin, 2009; Hudson et al., 2016). However, valence also refers to negative product or company reviews.

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<sup>1</sup> In 2014, First Great Western’s @fgw Twitter handle received 266,832 tweets from commuters, closely followed by Greater Anglia @greateranglia at 256,762 and Virgin Train’s @virgintrains on 254,618.

Classic prospect theory suggests that people may weigh negative reviews more than they do positive reviews (Tversky and Kahneman, 1981). Ren, Harper and Drenner (2012) find valence is not the sole influencer of consumer decision-making; negative reviews that are of a higher quality have a greater impact than lower-quality negative reviews. As a result, people may weigh negative online reviews more than they do positive reviews (or negative reviews online are more likely to be read as they stand out to users) (Ren, Harper and Drenner, 2012). Further research shows that negative information affects consumer decisions more than positive information because negativity stays in people's minds more than positivity does (Trusov et al., 2009). As the environment is generally more positive, consumers notice when negative details arise, and these may have a significant effect on decision-making. In the context of train journeys, this means that customers' journeys may be affected by both positive eWOM and negative eWOM. These factors may make the distance between reputation claims and their realization particularly noticeable. Hence, in line with our general discussion on Twitter's likely impact on company behavior and performance, we propose the following two hypotheses.

*Hypothesis 1. Positive Twitter sentiments have a significant positive effect on travel performance.*

*Hypothesis 2. Negative Twitter sentiments have a significant negative effect on travel performance.*

## **Message framing**

Advertising is an important aspect of all businesses' marketing activities. It involves getting the right message across to the target audience, in order to acquire – and retain - customers. Thus, it is important to understand the way in which to word a particular message, in order to persuade the customer to purchase your product. Previously, CRM on social media often lacked marketers' input, which severely limited the scope of social media as a tool for brand building and marketing communication. In recent developments, many companies have set up their own social media accounts that open the way for direct engagement with consumers. Consequently, the concept of framing has begun to contribute to this understanding by

looking into the framing of products, either positively or negatively, against others in order to affect choice. Framing involves creating ‘frames’ (in other words, messages about a certain object) that emphasize gains or losses depending on whether the message is framed positively or negatively, respectively. For example, a cheaper product may be framed positively to emphasize that an individual would benefit (in monetary terms) from buying the cheaper product over the more expensive one.

In contrast, the more expensive product could be framed negatively in terms of the money lost by an individual by buying the more expensive product over the cheaper one. In both cases the frames are intended to persuade the customer toward purchasing the cheaper product. Framing effects have been of significant importance since Tversky and Kahneman (1989) put forward their contribution of preference reversal, based on the framing of messages in both positive and negative forms. Since then the theory has been tested in a number of disciplines, mainly in health issues (Banks et al., 1995; Krishnamurthy et al., 2001; Apanovitch et al., 2003), but most recently the trend toward its use in marketing has expanded (Jain et al, 2006; Graus and Folse, 2007). While many have tested whether framing effects are evident in the decision-making associated with the purchase of consumer goods, little research has been done in relation to the effects of consumer searches on the relevant decision-making process. The investigation of these effects is important in today’s communication environment because search engines such as Google as well as social networking sites such as Facebook and Twitter allow the consumers to undertake extensive searches before making a purchase decision.

As prospect theory argues, consumers are likely to be more risk-averse in order to secure potential gains when a message is framed positively than when a message is framed negatively (Levin et al., 2002). Consequently, consumers will conduct more thorough searches to refine their product or market knowledge as when they encounter a positive message from a marketer. Garner (1986) has earlier shown that consumers who are more risk-averse conduct more thorough analysis of the available information prior to decisionmaking. Given the current social media environment, it is also likely that consumers will make every effort to obtain the latest information about the nature and scope of a particular market offering, such as a train operator’s service. We can therefore predict that the effect of tangible cues such as train breakdowns on performance risk will be less (greater) for consumers who are exposed to a positively (negatively) framed message. This is expected because, under

conditions of risk-aversion, these consumers would already have done extensive searches before embarking on a train journey; the expectation is that they would already have taken all necessary travel precautions. In this way, consumers can not only minimize risk in the face of potential obstacles, they can also increase their chances of completing their journeys as intended.

The idea is to get the consumers to do in-depth searching about their planned course of action; as we argue, this can be achieved by giving consumers positive information about the operations of a train operator. This can also be seen from the fact that when negativity is rife in the external environment, any positive information from the service provider will be leapt on by commuters who are considering making a purchase decision. The positive frame is thus a key factor in how consumers are likely to acquire more information or perform extensive searches before boarding a train. MGC will thus be more effective in influencing consumers' travel experiences if they are exposed to a positively framed message than a negatively framed message. Furthermore, as people have developed a general tendency to disbelieve or be sceptical toward advertising (Ren, Harper and Drenner, 2012), MGC may exert a weaker persuasive effect than CGC if messages are not carefully worded in the manner desired. This means positive frames (or MGC) will be intended to persuade the commuters to take the intended journeys by emphasizing the positive elements of a train journey event.

### **Source credibility**

It is well understood that whenever consumers attribute reporting or knowledge bias to the source, the persuasive impact of the message is typically lessened. It is thus important to determine a spokesperson's credibility, which is generally seen as the source's expertise, trustworthiness and reputation (Garner, 1986). When source credibility is low, it is likely that consumers will discount the arguments in a message. The moderating effect of source credibility have been widely studied in previous research on consumer risk behavior (Garner, 1986). Reputation is an organizational characteristic that can be examined in relation to a firm's source credibility (Mahon and Mitnick, 2010). In the current media environment, social media content may be particularly relevant to facilitate the exchange of information, which can be critical to enhancing the productive potential of a firm's operations and its

reputation. For example, to provide the exceptional service usually associated with high-rated (or more reputable) operators, their managers and employees need “customer-specific knowledge regarding the demand characteristics of particular individuals or segments and need to know how to use that knowledge to negotiate customized offerings” (Batt, 2002, p. 508). Since higher-rated operators differentiate themselves from lower-rated operators on the basis of exceptional service, the productivity-enhancing implications of the social media content that service-oriented operations facilitate will be more relevant for higher-rated operators than lower-rated operators. This is because, in an operational environment such as a train journey, the sharing of social media user content and the resulting productivity improvements are critical to the successful implementation of a service-quality strategy and the ability to charge higher prices.

Although the sharing of social media user content will also lead to productivity improvements in lower-rated operators, it will have little or no impact on the ability of operators pursuing this strategy to charge higher prices and successfully implement a low cost strategy. Customers patronize these train operators not because of their service quality but rather because of their affordability or low prices. This discussion shows that source credibility is important in how a firm uses social media to enhance the productivity of its operations (i.e. better use of social media outlets). More credible firms are more likely to be successful in getting across their messages than less credible firms. It is likely that these interventions will impact in some important way the expected level of customers’ travel experience. We measure these relationships in terms of Public Performance Measure (PPM) that assesses the arrival punctuality of individual trains at their final destination against their planned timetable. The PPM measure essentially allows the public to compare the performance of train operating companies against one another; as a result, operators can be held to account on rail performance. We now present our next sets of hypotheses.

*Hypothesis 3a. A positively framed message and PPM moderate the Twitter positive sentiments – travel performance relationship.*

*Hypothesis 3b. A positively framed message and PPM moderate the Twitter negative sentiments – travel performance relationship.*

*Hypothesis 4a (Competing). A negatively framed message and PPM moderate the Twitter positive sentiments – travel performance relationship.*

*Hypothesis 4b (Competing). A negatively framed message and PPM moderate the Twitter negative sentiments – travel performance relationship.*

## **Methodology**

We specifically examine the volume of tweets directed at the 14 rail providers that bring people into London, during the period of 2014 and 2015. We extracted the data using an algorithm that captures tweets using a list of key words as search arguments (Das and Chen, 2007). For example, we looked at Twitter handles that contain references to and complaints around cancellations and delays. Companies particularly use Twitter handles to measure and respond to the severity of incidents that trigger the negative sentiment. We also sourced tweets using the Twitter Search API, which included information about the author, timestamp and tweet text. We extracted 2.47 million tweets referring to 14 train operators over a period of 24 months. To harness the data into a form that allows for specific predictions about particular outcomes, we employ sentiment methodology that enables us to probe key points relevant to the research (Pang and Lee, 2008; Hall et al., 2009; Hennig-Thurau, Wiertz and Feldhaus, 2015). We rely on keyword-based text classification and sentiment analysis to identify relevant tweets and categorize the valence of the tweets. Sentiment analysis, in particular, is notoriously difficult to do well, particularly on microblogs such as Twitter which have few words per text item and tend to use highly context-dependent language. We created a list of keywords and then used the Twitter Search API to search for Tweets that contain these keywords. We retrieved 24 months' worth of tweets from the Web Science Institute's laboratory, as the Search API will only release tweets up to two weeks old.

We included three variables to capture the effect of Twitter tweets: (1) the share of commuter Tweets who traveled on a weekday and sent a positive tweet about it within 24 hours (hereafter, PTWEET share); (2) the share of commuter Tweets who traveled on a weekday and sent a negative tweet about it within 24 hours (hereafter, NTWEET share); and (3) the ratio of positive to negative TWEETS (TWEETRATIO). We also included the total number of tweets sent within 24 hours of a weekday train journey as a measure of TWEETVOL. To eliminate confounding effects and to rule out any alternative explanations, we included a number of control variables in our analysis, and we drew on the extant risk and organizational behavior research to select our controls. Since we identify Twitter CGC and separate positive CGC from the negative one, we carried out a multistage sentiment analysis

to determine the valence of the individual tweets. We eliminated all tweets with identical content by the same author. We also excluded non-English tweets, spam, tweets not related to the weekday journeys in question, and tweets that contained no post-journey quality assessment (tweets expressing buzz, e.g., “I look forward to my journey today”). Using the open-source data mining software WEKA (Hall et al., 2009), we divided the remaining tweets into positive and negative CGC using sentiment analysis. The analysis was executed simultaneously for all tweets in our data. As discussed, various specialist software products are now available to mine documents, identifying words or phrases that denote sentiments (He et al., 2013). The software can also generate a sentiment score reflecting the percentage of posts that express a ‘positive’, ‘negative’ or ‘neutral’ sentiment (Pang and Lee, 2008).

We give a few examples of this data collection process below. We particularly discuss key ‘pain’ points in the rail commuter experience, drawing on Twitter sentiment around cancellations, overcrowding and delays. The highest volume of tweets captured in our study is about complaints related to train delays, followed by cancellations. Based on references and complaints around cancellation such as ‘cancel’, ‘replacement’ and ‘bus replacement,’ we found that there were 84,639 tweets directed at the 14 companies in 2014. Overcrowding is frequently cited as a cause of commuter dissatisfaction and delayed services. To obtain these data, our algorithm focused on key words including ‘crowd,’ ‘no seat’ and ‘sardine.’ From the data obtained, we established that Southern Rail received the most online criticism for overcrowding on its services with 13,956 tweets referencing crowding language in 2014. In 2014, there were a significant number of complaints regarding train delays impacting commuter journeys. We tracked 312,654 tweets that are about rail delays using sentiments such as ‘delay’, ‘stuck’ and ‘late’. Figure 1 presents percentage tweet data (including tweets about cancellations, delay and overcrowding) on 14 train operators for 2013 and 2014<sup>2</sup>.

### **Travel performance measures**

Services offered by train operators are akin to making online purchases. Online product descriptions usually only provide details of objective measures of performance such as model design, length or weight, without giving much detail or a customer opportunity to experience these or other related product features. In contrast, customers can obtain more intangible

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<sup>2</sup> The 14 train companies are as follows: 1. C2C\_Rail; 2. Chilternrailway; 3. Eastcoastuk; 4. Emtrains; 5. Fgw; 6. Firstcc; 7. Gnrailuk; 8. Greateranglia; 9. Londonmidland; 10. Se\_railway; 11. Southernrailuk; 12. SW\_Trains; 13. Tlrailuk; 14. Virgintrains.

information about a product or service from an off-line retail store or shop. Similarly, train operators can provide only objective measures of performance such as arrival time, or the frequency of a service, when they announce a planned service. There is thus an inherent risk involved in not getting a service (i.e. regular service) that is on time, comfortable and delivers full amenities as advertised. Our measures of performance are designed to capture these risks; hence, we define new measures of train journey performance.

In the rail industry, the number of stars a rail provider receives denotes its reputation in how it provides quality service and hospitality observed by a panel of experts. “higher starrated” train operators have the reputation of offering exceptional service, and “lower starrated” train operators are patronized not for their quality of service but for their low cost (Hoque, 2000). We use rail operator star rating (RATINGS) as our first measure of train operators’ performance. It is assumed that higher star-rated train operators are perceived better performers in how they provide quality service compared with their peers. Which? allocates star RATINGS based on expert opinions; therefore, it indicates the reputation of a rail operator and ranges from 1 to 5 (Which? 2015)<sup>2</sup>. The train operators in the study were all star-rated. Secondly, we employ Customer Performance Measure (CPM), which is constructed based on how a particular train operator is performing in real time; to obtain this information we draw on live information from Twitter (Which? 2015; CommuteLondon, 2014). This combines the Twitter-based feedback on the number of incidents commuters experienced such as cancellations, delays and overcrowding (Which? 2015; CommuteLondon, 2014). We only count their numbers and not their consequences or effects. Finally, we use financial performance (a train operator’s annual revenues in US\$) as another measure of train operator’s performance. This information is available from operators’ annual reports.

[Insert Figure 1 about here]

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<sup>2</sup> Which? is the trading and brand name for the Which? Group, wholly owned by the Consumers’ Association. Which? identifies and works to alleviate the problems consumers face.



## **Moderator variables**

As discussed, commuters may suffer disruption to their journey due to problems including signal failures and faulty trains. Such engineering and fleet issues are a reminder of just how challenging the environment is for train providers. Those challenges are ratcheted up by the ever growing number of commuters on the network. Social media has also given commuters an opportunity to voice their dissatisfaction with such delays in services. Against this background, train providers have created their own Twitter accounts to benefit from the feedback from instant social media response. The feeds are used to share information and interact with commuters. The levels of activity between Twitter handles and commuters may be influenced by a number of factors, including capacity, frequency of journeys available and the general level of public awareness of the company. For instance, train cancellations can be a major source of concern for commuters. These concerns can be dealt with by using a Twitter feed to share alternative route information whenever possible. As we argue, the decision of rail providers to engage with commuters instantly with service information via their Twitter feeds is derived from their consumer relationship management approach. This is to ensure that commuters feel they are being listened to and their concerns are addressed. We thus use positive Twitter feeds (PFEED) as a moderator variable that influences the relationship between commuters' use of Twitter and rail providers' performance. PFEED includes all those tweets that provide constructive and useful information with regard to the services provided. For instance, in the following example, those manning the Twitter feeds for individual tube lines seem to be doing a decent job of answering commuter queries about which parts of the line are open. The update presented in Figure 2 is, however, a little baffling as information given is not as clear cut as it could be. These and other negatively framed messages are denoted as NFEED. More specifically, PFEED are tweets that include positive words or statements like on-time, punctuality, and customer service, among others, whereas NFEED includes words or statements like breakdown, delay and damage, to name a few.

[Insert Figure 2 about here]

The varied nature of rail operations means that different countries have adopted a variety of performance management systems. A performance management system used when services are predominantly for short commuter trips will be different from when there is a

mix of longer distance and commuter journeys. In the UK, the Public Performance Measure (PPM) measures the arrival punctuality of individual trains at their final destination against their planned timetable. The driving principle behind this approach is that, by allowing the public to compare the performance of train operating companies against one another, operators can be held to account on rail performance. More specifically, the performance of individual trains advertised as passenger services is measured against their planned timetable as agreed between the operator and Network Rail at 22:00 the night before<sup>3</sup>. In other words, PPM is the percentage of trains ‘on time’ compared to the total number of trains planned<sup>4</sup>. It combines figures for punctuality and reliability into a single performance record. This also means that services that are cancelled or fail to operate their entire route, calling at every station, count as a PPM failure<sup>5</sup>. We take these figures to represent commuters’ trust in the regular operations of a train operator: in other words, we use PPM as a proxy for source credibility (CRED). There are many different ways to measure source credibility, and firm reputation is one of them (Mahon and Mitnick, 2010). As PPM measures the credibility of train operators with regard to the percentage of time they were on time, it is likely that these operators will care about their reputation in terms of the trust that commuters place in their operations. As it happens, there are many factors that cause PPM to fluctuate widely periodby-period. These factors are not always within the control of the train providers such as other train operators’ performance or Network Rail contributing to poor PPM performance<sup>7</sup>. Figure 3 provides an example of PPM measures for 3 May to 30 May 2015; as it shows, the national PPM is 91.8%, which compares to 91.8% for the same period last year. The moving annual average (MAA) is 89.6%.

[Insert Figure 3 about here]

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<sup>3</sup> The plans are called ‘plan of the day’, which are usually the same as the published timetable with amendments reflecting pre-published engineering amendments. However, they may differ from their originally published timetable.

<sup>4</sup> A train is defined as on time if it arrives at the destination within five minutes (i.e. 4 minutes 59 seconds or less) of the scheduled destination arrival time for London and South East or regional services, or within ten minutes (i.e. 9 minutes 59 seconds or less) for long distance services. Where a train fails to run its entire planned route calling at all timetabled stations it will count as a PPM failure.

<sup>5</sup> Network Rail (the Government regulatory body) had set targets for the rail industry to achieve a PPM of 93% for the London and South East sector and 92% for the long-distance and regional sectors by 2013/14. <sup>7</sup> It is understandable that adding this breakdown would necessarily make the data and their interpretation considerably more complex.

## Controls

Several firm characteristics served as control variables in the study. Train operator size is included as a control variable because larger organizations are likely to operate more frequent services. They may also have better physical and human resources at their disposal (Jackson and Schuler, 1995) and, as a result, may experience reduced level of cancellations and delays.

It is also generally assumed that size has a direct effect on financial performance because of economies of scale and market power (Shepherd, 1975). Train operator size is measured as the number of full-time employees. Train operator age is our second control variable, which is operationalized as the years from the founding date of the train company in the UK.

Learning curve advantages in productivity are generally associated with an organization's age (Guthrie, 2001); besides the opportunity that an organization can avail itself of to adopt best organizational practices over time. NETEXP is the railway network's annual spending on rail network in US\$. We log-transformed those variables that are heavily skewed (i.e., the network rail spending) to approximate a normal distribution.

Our regression models are described below.

$$\begin{aligned} \text{RATINGS}_{i,t} = & \beta_0 + \beta_1 \text{NETEXP}_{i,t} + \beta_2 \text{TFEED}_{i,t} + \beta_3 \text{CRED}_{i,t} + \beta_4 \text{AGE} + \beta_5 \text{SIZE} + \\ & \beta_6 \text{TWEETRATIO}_{i,t} + \beta_7 \text{TWEETVOL}_{i,t} + \beta_8 \text{PTWEET}_{i,t} + \beta_9 \text{NTWEET}_{i,t} + \beta_{10} \text{PTWEET}_{i,t} \times \\ & \text{PFEED}_{i,t} \times \text{CRED}_{i,t} + \beta_{11} \text{PTWEET}_{i,t} \times \text{NFEED}_{i,t} \times \text{CRED}_{i,t} + \beta_{12} \text{NTWEET}_{i,t} \times \text{PFEED}_{i,t} \times \\ & \text{CRED}_{i,t} + \beta_{13} \text{NTWEET}_{i,t} \times \text{NFEED}_{i,t} \times \text{CRED}_{i,t} + \varepsilon_{i,t}, \end{aligned} \quad (1)$$

where RATINGS is the dependent variable and independent variables include both Twitterbased and train operator-based variables.

$$\begin{aligned} \text{CPM}_{i,t} = & \beta_0 + \beta_1 \text{NETEXP}_{i,t} + \beta_2 \text{TFEED}_{i,t} + \beta_3 \text{CRED}_{i,t} + \beta_4 \text{AGE} + \beta_5 \text{SIZE} + \\ & \beta_6 \text{TWEETRATIO}_{i,t} + \beta_7 \text{TWEETVOL}_{i,t} + \beta_8 \text{PTWEET}_{i,t} + \beta_9 \text{NTWEET}_{i,t} + \beta_{10} \text{PTWEET}_{i,t} \times \\ & \text{PFEED}_{i,t} \times \text{CRED}_{i,t} + \beta_{11} \text{PTWEET}_{i,t} \times \text{NFEED}_{i,t} \times \text{CRED}_{i,t} + \beta_{12} \text{NTWEET}_{i,t} \times \text{PFEED}_{i,t} \times \\ & \text{CRED}_{i,t} + \beta_{13} \text{NTWEET}_{i,t} \times \text{NFEED}_{i,t} \times \text{CRED}_{i,t} + \varepsilon_{i,t}, \end{aligned} \quad (1)$$

where CPM is the dependent variable and independent variables include both Twitter-based and train operator-based variables.

$$LN(FPER)_{i,t} = \beta_0 + \beta_1 NETEXP_{i,t} + \beta_2 TFEED_{i,t} + \beta_3 CRED_{i,t} + \beta_4 AGE + \beta_5 SIZE + \beta_6 TWEETRATIO_{i,t} + \beta_7 TWEETVOL_{i,t} + \beta_8 PTWEET_{i,t} + \beta_9 NTWEET_{i,t} + \beta_{10} PTWEET_{i,t} \times PFEED_{i,t} \times CRED_{i,t} + \beta_{11} PTWEET_{i,t} \times NFEED_{i,t} \times CRED_{i,t} + \beta_{12} NTWEET_{i,t} \times PFEED_{i,t} \times CRED_{i,t} + \beta_{13} NTWEET_{i,t} \times NFEED_{i,t} \times CRED_{i,t} + \varepsilon_{i,t}, \quad (3).$$

where  $LN(FPER)$  is the dependent variable and independent variables include both Twitterbased and train operator-based variables. Table 1 summarizes all the latent variables examined in the study and their corresponding proxies and/or observed variables. [Insert Table 1 about here]

## Results

In Table 2, we present the descriptive statistics and correlations among variables in the study. As shown, Twitter content (both negative and positive sentiments) is related to both RATINGS and CPM. Positive and negative sentiments are also related to Twitter feed (TFEED), our proxy for a firm's CRM system. We first use logit regression and then pooled ordinary least squares regression (OLS) to estimate the models. As we have a wide variety of data, we use a blockwise approach for entering variables to see whether adding variables increased the model fit significantly. The control variables and moderators NETEXP, TFEED, CRED, AGE, SIZE, TWEETRATIO, and TWEETVOL comprise the first block. The second block consists of the Twitter CGC variables; namely, PTWEET and NTWEET. The third and final block consists of the interaction terms PTWEET x TFEED, PTWEET x SRATINGS, NTWEET x TFEED, and NTWEET x SRATINGS. As can be seen, the overall model fit when estimating our model with RATINGS as the dependent variable is good. We find a similar model fit when estimating our model with financial performance. In the first instance, the R-square (adjusted R-square) is .514 (.493) after the first block. The addition of the Twitter CGC variables as the second block leads to an additional increase in explained variance of 4.0 percentage points (significant at  $p < .05$ ), so that the R-square (adjusted Rsquare) is .557 (.538). We do not report our results here regarding multicollinearity but it

was below critical thresholds; the variance inflation factors (VIFs) for PTWEET and NTWEET were below 4, and no other VIF was above 2.4.

[Insert Tables 2 and 3 about here]

Table 3 presents the findings of our empirical analysis when the dependent variable is RATINGS. The baseline model, Model 1 in Table 3, shows the effects of the controls and the moderators on RATINGS. Notably, size of train operators is positively related to RATINGS in such a way that smaller operators are less able to meet the RATINGS standard than bigger operators are. The parameters for the other controls mostly behave as expected. For instance, improvements in performance are affected by network expenditures, suggesting that a rail network's performance is inextricably linked to investment in physical infrastructure. Twitter feeds is positively related to RATINGS in that the higher the volume of Twitter feeds, the higher its influence on meeting the RATINGS parameters. Furthermore, Age and TWEETVOL are insignificant, explaining no variance above and beyond the CGC-related measures. Although the correlation between positive sentiments and RATINGS was highly significant ( $r = .357, p < .01$ , from Table 2), the regression coefficient for positive sentiments in Model 2 of Table 3 is only marginally significant ( $\beta = .761, p < .10$ ). In contrast, negative sentiments NTWEET is moderately related to the rail industry's PRAT standard ( $\beta = -36.539, p < .05$ ), providing some support for Hypothesis 2. Model 3 examines the moderating influence of Twitter feed (message frames and source credibility) on RATINGS. As shown in the table, the effects of the interaction terms of positive Twitter feed (PFEED), positive (and negative) sentiments and source credibility (Model 3) are significant, but the effects of the interaction terms of negative Twitter feed (NFEED), negative (and positive) sentiments and source credibility are not. These results suggest that the effect of a positive message frame (PFEED) on RATINGS is stronger for both positive and negative sentiments than a negative Twitter frame (NFEED). This implies an important role for message frames in how a train operator can improve a consumer's travel experience by delivering positive messages on Twitter. We thus find confirmation for Hypothesis 3a/b. Model 4 presents the fixed effect regression results as there may be a concern that factors other than the "Twitter Effect" are at play. However, we do not find any significant difference from the results reported in earlier models.

Table 4 investigates the impacts of consumer sentiments and message frames on consumer performance measure (CPM). The findings mirror the RATINGS results (Models 5-8). Model 8 examines the moderating influence of Twitter feeds on CPM. As shown in the table, the effect of the interaction term of Twitter negative feeds, negative sentiments and source credibility was not significant (Model 8), but the effect of the interaction term of Twitter positive feed, positive sentiments and source credibility is significant. This significant, positive interaction suggests that the effect of Twitter positive feeds is an important consideration in how a train operator frames its messages. This also implies an important role for consumer relationship management in that a train operator can enhance the commuter experience by focusing on their positive experiences (e.g. giving more novel and accurate information). We thus again find confirmation for Hypothesis 3a/b. Table 5 shows the effects of Twitter sentiments, Twitter feeds, and source credibility on the financial performance of train operators. Models 9 to 12 show results of a set of parallel tests with financial performance of the train operators as the dependent variable. Similar to the results in Tables 2 and 3, the direction of PTWEET on financial performance is positive as proposed, and the parameter is not significant. Taken together, Models 11 and 12 depict procedures for testing moderation. To test Hypotheses 3a/b and 4a/b, we examine the moderating influences of Twitter feeds (both positive and negative – PFEED and NFEED), positive and negative sentiments, and the source credibility-financial performance relationship. As shown in Model 11 in Table 5, Twitter positive feeds moderates the positive sentiments by enhancing their impact on an operator's financial performance. In contrast, the effect of the interaction of Twitter negative feeds and negative sentiment on a firm's financial performance is not significant. Our fixed effect results, as shown in Model 12, do not differ significantly from the OLS regression results.

We conducted a Wald test to determine the relative strength of the effects of positive and negative Twitter CGC by comparing the absolute size of the regression parameters of NTWEET and PTWEET. The test constrains the parameters to equality and uses a nested Ftest to ascertain the resulting change in the model's R-square (Judge et al., 1985). We find that the F value for the comparison is 5.67, which is significant at  $p < .05$ . This suggests that the effect of negative Twitter CGC dominates that of positive Twitter CGC. These findings confirm our earlier argument that the focus on variance, rather than absolute measures, is particularly relevant for the social media context, as characterized by a wealth of information

and a poverty of attention (Kietzmann and Canhoto, 2013). The temporal perspective may enable managers to detect dramatic changes resulting from a risk situation.

[Insert Table 4 and 5 about here]

Figure 4 depicts the interaction between Twitter feed and total marketer-generated content (MGC). The first thing to notice is that CPM (Consumer Performance Measure) decreases at MGC. For the negatively framed tweets (NFEED), this difference is significant at 5% level (difference = 0.06;  $p = 0.059$ ). For the positively framed tweets (PFEED), the difference is significant at 10% (difference=0.01;  $p < 0.01$ ). The next important result is that the negatively framed tweets perform better than the positively framed tweets in generating higher CPM at low MGC levels (lower volumes of marketer generated content), but the relationship reverses at higher MGC levels (higher volumes of marketer-generated content). The differences between the positive feed and negative feed are -0.015 ( $p < 0.01$ ) at the top and 0.035 ( $p < 0.01$ ) at the bottom. This suggests that the effect of Twitter feed on CPM varies at different levels of MGC. Therefore, more use of MGC will boost train operators' relationships with their customers. The magnitude of decrease in CPM as we move from the low levels to the higher levels is much larger for positively framed messages in comparison to negatively framed messages. This also suggests that the performance of positive messages vis-à-vis negative messages improves as we move up the MGC levels. We further use quality and price (tweets that refer to 'price' and 'quality') as other measures of MGC to evaluate the robustness of our findings. The results are presented in Figure 5a, and 5b, respectively. Our findings are consistent with the analysis provided in Figure 4, as quality (-0.01;  $p < 0.01$  at the higher and 0.03;  $p < 0.01$  at the lower levels) and price (-0.01;  $p < 0.01$  at the higher and 0.05;  $p < 0.01$  at the lower levels) as two other components of MGC have very similar relationships with CPM.

[Insert Figures 4, 5a and 5b about here]

## **Discussion and Managerial Implications**

In this study, we empirically tested the ‘Twitter effect’ of user sentiments on consumers’ travel experiences (Trusov et al. 2009; Goh et al., 2013; Hennig-Thurau, Wiertz and Feldhaus, 2015). Findings have alluded to numerous insights concerning the use of Twitter to manage commuter relationships. Amongst the most significant of our findings is the role that a train operator’s consumer relationship management system plays in mitigating the unfavorable impact of delays and cancellations. Train operators use their Twitter feeds to engage with commuters in real time and provide up-to-date information, the impact of which can be seen in the message frames- PPM/CPM/Financial Performance relationships. We also find an effect for negative sentiments on train operators’ performance. The parameter for negative sentiments dominates that of positive sentiments, indicating a negativity bias for Twitter based eWOM. We further investigate the processes underlying the Twitter effect and the role of message framing and source credibility in moderating the effects of both positive and negative sentiments. We discovered that the higher the level of consumer positivity, the more likely it was that the positive frame was chosen. This means that the positive frame is a key factor in how consumers are able to perform extensive searches before embarking on a train journey. Knowing that the positive frames intended to persuade the participant toward taking the intended journeys, consumers acquired more information about the train operators’ services and were thus able to minimize their risks in the event of a delay or cancellation. In other words, these consumers were largely unaffected when they faced a service breakdown or delay. This research therefore rejects the idea that negative frames are more persuasive than positive frames (Levin et al., 2002; Tversky and Kahneman, 1989). In this sense, we make an important theoretical contribution to the literature on message framing and information transformation processes in the new social media environment.

Overall, our findings should serve as a platform for social media strategists and company managers to acknowledge the fact that there is room for improvement around Twitter engagement policies, regardless of their organization’s position in the league table. Our results shed light on how the discriminating characteristics of consumer-generated content influence decision-making as highlighted in the importance of a company’s CRM practice (Payne and Frow, 2005). Consequently, this research offers substantial implications for company managers, particularly those who are responsible for the success of their CRM strategies. Twitter engagement reduces the information asymmetry between rail providers



and travelers, disseminating evaluative post-purchase quality opinions about the services so widely that they influence other travelers' decisions with regard to their traveling plans. This information can be used to identify potential hazards, from narrow and slippery platforms to out-of-date first-aid boxes on trains, thereby enriching the company's risk management system. The data can also be used to understand the conditions that cause the greatest stress for the customer base. Twitter handles may be used to address criticisms, share advice, and improve the handling of potential disruption. In many instances, the impacts are felt by customers long after the official sources declare services have been restored. In these cases, continuous engagement can be a source of encouragement and open communication, building trust and confidence. Our findings should motivate train companies to increase their focus on developing further their social media-based consumer relationship management systems and thus ensure the delivery of high-quality services that meet commuter needs. The need for high-quality rail services is increased by the negativity bias that we have identified empirically, because negative Twitter posts become particularly noticeable during the crucial weekday period.

The present analysis of Twitter data also substantiates the need for implementing consumer relationship management methods and techniques that differ from PR activities in the broadcast media world (Hennig-Thurau and Walsh, 2004; Jenkins et al., 2013; Bernoff and Li, 2008). Our findings suggest that the implementation of CRM strategies in response to the rise of social media that is presently favored by train operators (i.e. focusing on sending positive messages through Twitter feeds) are largely effective. This insight can be used to tailor a company's messages and further improve the effectiveness of its risk management system. By communicating positively with the passengers on a regular basis, organizations can turn a negative relationship into a positive one. Both our regressions and model-free observations identify opportunities for rail providers to utilize Twitter data for the formation of future market strategies, ranging from directly asking commuters for their opinions (Comm, 2010), to monitoring campaign reactions. As a general indicator, our findings reveal that nearly half a million tweets last year expressed negative sentiment about commuter experiences. More importantly, they also provided insight into the specific reasons for this. Social media sites like Twitter can assist in this process of winning over travelers by providing an instant, real-time service (Chen and Xie, 2008). As we establish, Twitter is a data-rich pool from which companies can capture and analyze market trends and intelligence. They can build their CRM models that are attuned to making better use of CGC by listening

and learning from criticism. As Twitter is being used by commuters to report incidents such as a fire safety alarm and health alert, it is important that users' tweets become an essential component of a train operator's CRM system. This will in turn enable commuters to make greater use of social media for engagement with their rail providers. Twitter will be seen as a medium for legitimate service feedback and not simply a forum for frustration and criticism. Clear, factual engagement around commuter concerns will also enable rail companies to take the necessary steps for improvement, an essential component of a consumer relationship management strategy.

## **Conclusion**

In this paper, we suggest that the firm's social media content, specifically the framing of their messages, moderate the impact of consumer generated content on key performance indicators: train operators' ratings, CPM, and the firm's financial performance. Our research adds to the growing literature on potential managerial intervention on the impact of user content and social media participation on firm performance (Trusov et al. 2009; Goh et al., 2013; Godes and Mayzlin 2009; Christodoulides and Jevons, 2011). More specifically, the paper investigates how effectively train companies utilize social media to support their CRM - a phenomenon which is relatively unexplored in the rail industry (Payne and Frow, 2005). Social media is a tool for providing people with a platform to make their voices heard. Social media channels such as Twitter can be an effective medium for dealing with customer complaints around delays and issues with services (Chen and Xie, 2008). To implement this research, we analyze Twitter-based user content or tweets about 14 train operators. We particularly highlight the extent to which rail commuters express their negative opinions of rail services on Twitter. There can be many reasons for commuters choosing social media as a platform to criticize services, including the fact that it is convenient and instant. For instance, commuters are rapidly becoming experts at flagging incidents and capturing evidence for the rail authorities. The paper examines key commuter concerns around disruption and poor services on the rail network and how train providers are using Twitter to respond to these concerns within their general framework of risk management. We study how sentiments are created, and how problems on the network give way to greater demonstration

of people's sentiments. Companies can use such information in their risk identification and assessment processes so as to identify times and train services of most concern.

We empirically tested the 'Twitter effect' of user sentiments on their travel experience (Hennig-Thurau, Wiertz and Feldhaus, 2015). Embedding sentiment analysis in a regression framework, we report that (1) Twitter sentiments of a sample of UK train commuters affect their travel experience, and (2) train operators' tweets moderate this effect. Findings have alluded to numerous insights concerning the use of Twitter to manage commuter relationships. Amongst the most significant of findings is the role that a train operator's message frames play in mitigating the unfavorable impact of delays and cancellations. Train operators use their Twitter feeds to engage with commuters in real time and provide up-to-date information, the impact of which can be seen in how positive messages enhance consumers' train journey purchase risk performance by allowing them to do more searches, thereby minimizing their risks. We thus find strong support for the moderating role of message frames and source credibility. Contrary to our predictions, positive sentiments do not have much of an impact on an operator's performance. As we have seen, rail providers currently use their Twitter feeds to reduce negative sentiment by responding to commuter complaints. Evidence that action is being taken - and a few goodwill gestures - can go a long way to restoring consumer confidence (Weick and Sutcliffe, 2001; Hennig-Thurau and Walsh, 2004). Our results thus have important implications for social media strategists and company managers; that there is room for improvement around Twitter engagement policies, regardless of an organization's position in the league table. Moreover, the discriminating characteristics of consumer-generated content influence decision-making as highlighted in the importance of a company's CRM practice. Although this research takes a first step toward understanding the strategies that consumers use to communicate on social media, our focus on rail providers leaves room for studies regarding the role of Twitter-type social media in other contexts. The majority of measures used in our regression analysis are proxies for certain control variables as is usually the case with secondary data. Therefore, there is a need to replicate our research to further investigate the robustness of our analyses using different or additional proxies.

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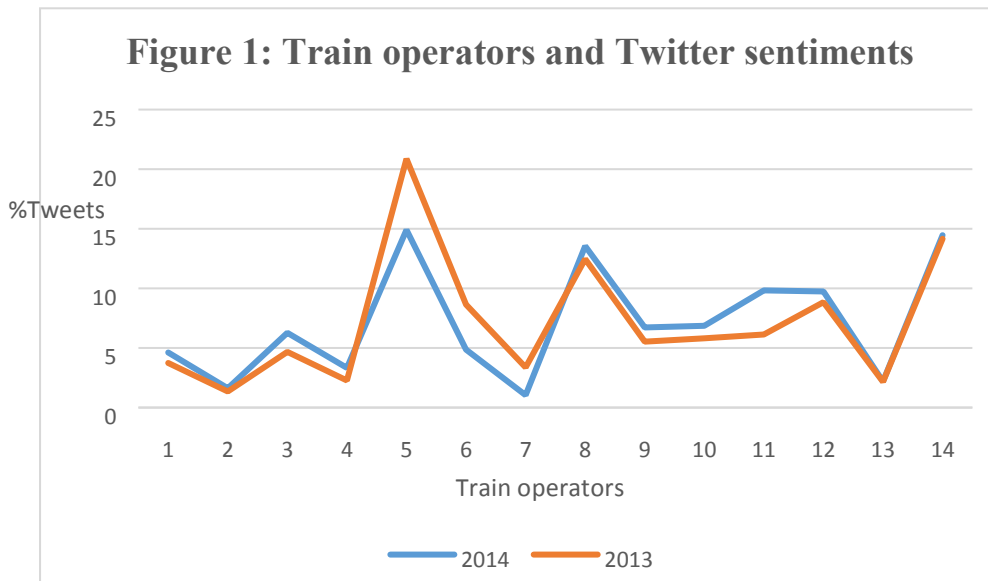


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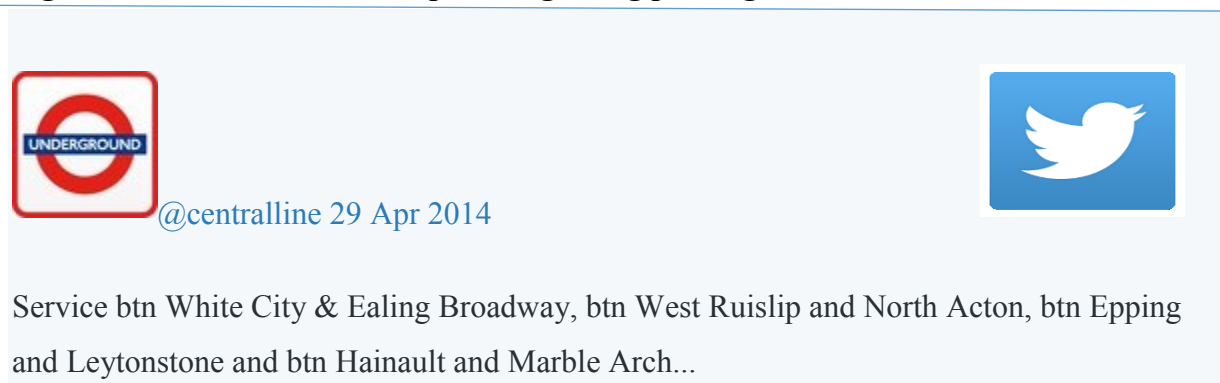
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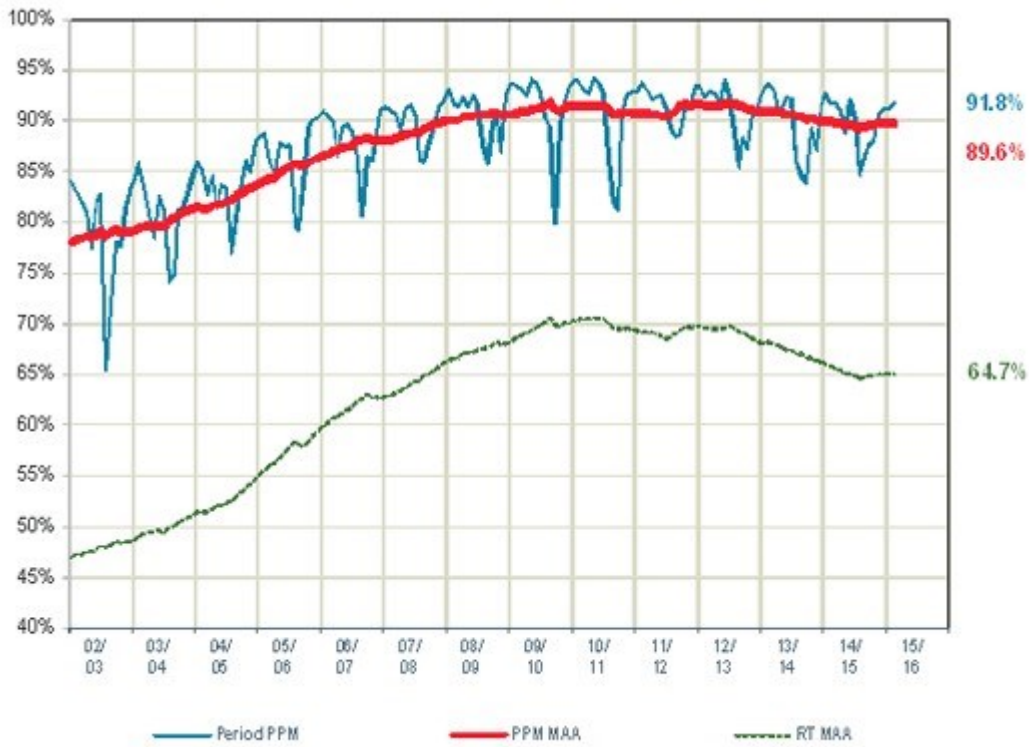
**Figure 2: A tweet from a rail operator guiding passengers about its services**



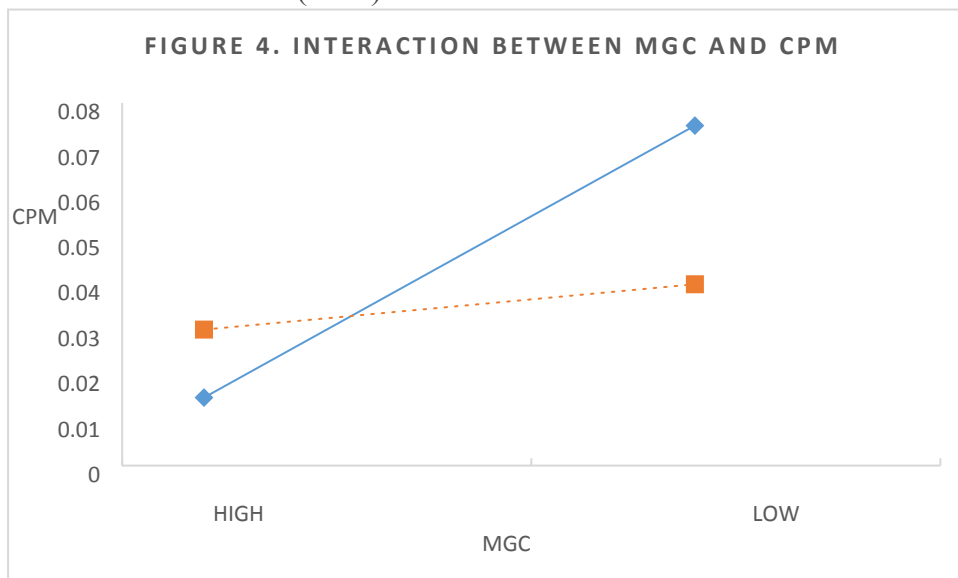
- Retweets 6
- Favourite 1



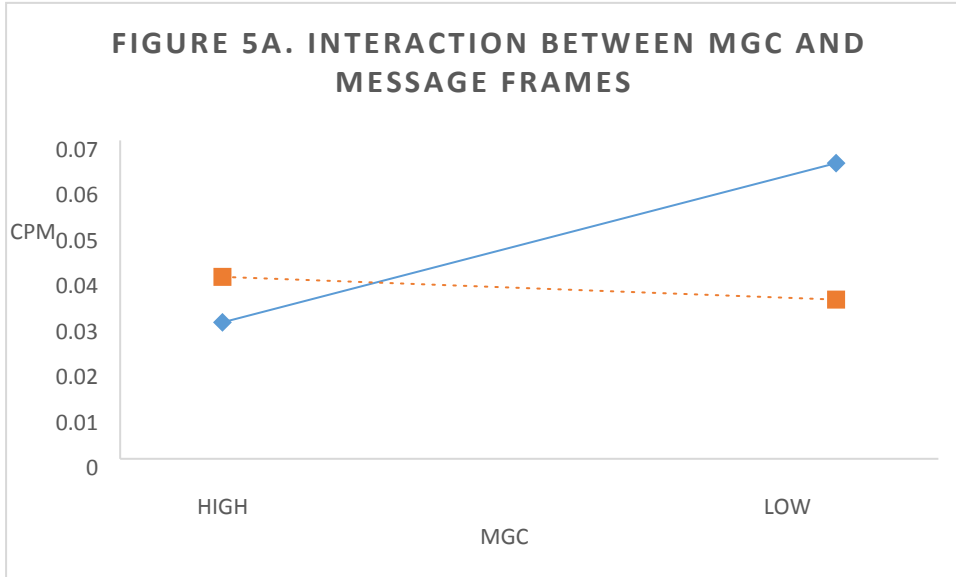
Figure 3. PPM Performance for 3 May to 30 May 2015



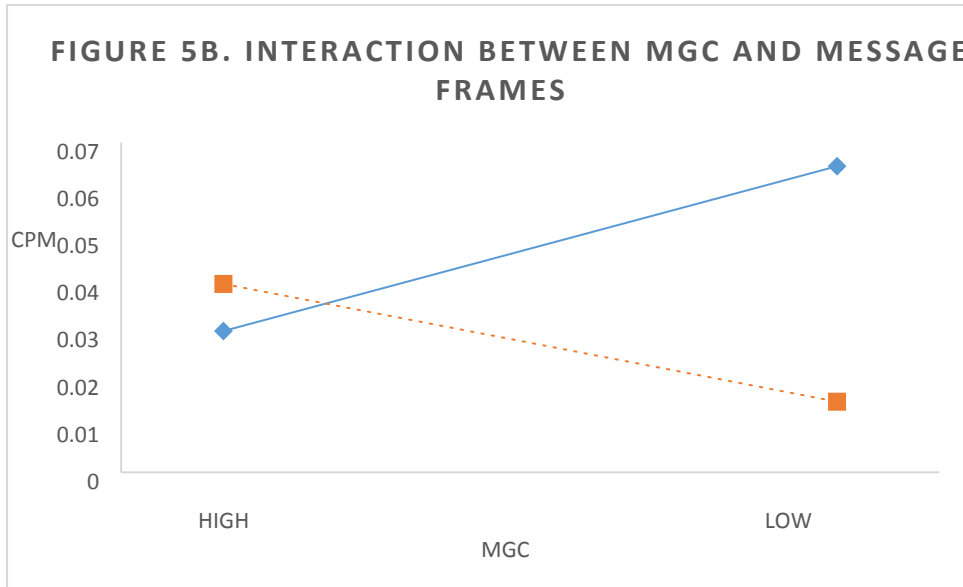
Source: Networkrail (2015).



Note: Positive message (———) Negative message (-----)



Note: Positive message (———) Negative message (-----)



Note: Positive message (———) Negative message (-----)

**Table 1. Latent variables**

| Variable              | Proxy / Observed variable | Full description  |
|-----------------------|---------------------------|---|
| Twitter Feed          | TFEED                     | Company Twitter account   |
| Positive Twitter Feed | PFEED                     | Positively framed messages  |
| Negative Twitter Feed | NFEED                     | Negatively framed messages  |
| Rail Operator Rating  | RATINGS                   | Rail operator star ratings indicating the reputation of a rail operator   |
| Positive Tweet        | PTWEET                    | Positive consumer-generated content   |
| Negative Tweet        | NTWEET                    | Negative consumer-generated content   |
| Source Credibility    | CRED                      | Public performance measure (PPM): PPM is the percentage of trains ‘on time’ compared to the total number of trains planned. |

**Table 2. Descriptive statistics and correlations**

|               | Mean      | SD        | 1      | 2       | 3       | 4    | 5      |
|---------------|-----------|-----------|--------|---------|---------|------|--------|
| 1. LN(NETEXP) | 9.784     | 8.362     |        |         |         |      |        |
| 2. TFEED      | .0261     | .0252     | -.312  |         |         |      |        |
| 3 RATINGS     | 3.372     | 0.736     | .301** | .192**  |         |      |        |
| 4. AGE        | 17.563    | 15.924    | .082   | .013    | .065    |      |        |
| 5. SIZE       | 5,727.830 | 3,873.242 | .253   | .392*** | .332*** | .124 |        |
| 6. TWEETRATIO | 8.064     | 7.382     | -.078  | .382    | .276    | .093 | .083   |
| 7. TWEETVOL   | .000      | 3,583.473 | .432   | .416**  | .074    | .088 | .256** |
| 8. PTWEET     | .051      | .0453     | .103   | .325*** | .282**  | .123 | .152** |
| 9. NTWEET     | .357      | .326      | .186   | .123**  | .133    | .255 | .237*  |
| 10. CRED      | 0.932     | 0.917     | .132** | .112    | .197    | .176 | .236** |

|               |          |          |          |          |           |      |       |
|---------------|----------|----------|----------|----------|-----------|------|-------|
| 11. LN(FPER)  | 3.456    | 3.382    | .157**   | .282     | .119      | .143 | .247* |
|               | <b>6</b> | <b>7</b> | <b>8</b> | <b>9</b> | <b>10</b> |      |       |
| 1. LN(NETEXP) |          |          |          |          |           |      |       |
| 2. TFEED      |          |          |          |          |           |      |       |
| 3. RATINGS    |          |          |          |          |           |      |       |
| 4. AGE5. SIZE |          |          |          |          |           |      |       |
| 6.            |          |          |          |          |           |      |       |
| TWEETRATIO    |          |          |          |          |           |      |       |
| 7. TWEETVOL   |          |          |          |          |           |      |       |
|               | .094     |          |          |          |           |      |       |
| 8. PTWEET     | .173**   | .175**   |          |          |           |      |       |
| 9. NTWEET     | .143*    | .248***  | .215***  |          |           |      |       |
| 10. CRED      | .124*    | .226*    | .357***  | .364***  |           |      |       |
| 11. LN(FPER)  | .187*    | .135*    | .184**   | .254**   | .334*     |      |       |

Notes. \*\*\*  $p < .01$ , \*\*  $p < .05$ , \*  $p < .10$ .

**Table 3. Estimation results for RATINGS**

|                   | <b>Model 1</b>       | <b>Model 2</b>       | <b>Model 3</b>       | <b>Model 4</b>       |
|-------------------|----------------------|----------------------|----------------------|----------------------|
|                   | Coef. (Std. Err)     | Coef. (Std. Err)     | Coef. (Std. Err)     | Coef. (Std. Err)     |
| Constant          | 51.598***<br>(5.863) | 51.683***<br>(5.468) | 52.274***<br>(5.681) | 51.389***<br>(5.372) |
| <i>LN(NETEXP)</i> | 3.648**<br>(1.757)   | 6.896**<br>(1.608)   | 4.517*<br>(1.723)    | 3.331**<br>(1.613)   |

|              |                    |                        |                        |                       |
|--------------|--------------------|------------------------|------------------------|-----------------------|
| TFEED        | 4.473***<br>(.546) | 4.389***<br>(.384)     | 3.298***<br>(.542)     | 3.273***<br>(.550)    |
| CRED         | .132<br>(.392)     | -1.914***<br>(.362)    | .027<br>(.022)         | .063<br>(.051)        |
| AGE          | -.253<br>(.737)    | -.218<br>(.552)        | -.172<br>(.532)        | -.012<br>(.357)       |
| SIZE         | 2.463**<br>(.783)  | 2.158**<br>(.682)      | 3.105**<br>(.502)      | 2.319**<br>(.423)     |
| TWEETRATIO   | 1.894***<br>(.039) | 1.843**<br>(.192)      | 1.193<br>(.233)        | 1.593*<br>(.174)      |
| TWEETVOL     | 2.783*<br>(1.648)  | -1.843<br>(1.273)      | -1.284<br>(1.054)      | 1.432<br>(1.252)      |
| PTWEET       |                    | .761*<br>(.337)        | .490*<br>(.609)        | .052*<br>(.142)       |
| NTWEET       |                    | -36.539***<br>(11.372) | -28.161***<br>(12.009) | -27.256**<br>(11.492) |
| PTWEET x     |                    |                        | 4.331***<br>(.889)     | 8.491***<br>(.711)    |
| PFEED x CRED |                    |                        | .112<br>(.015)         | .134<br>(.017)        |
| PTWEET x     |                    |                        | 3.886**<br>(.576)      | 3.810**<br>(.434)     |
| NFEED x CRED |                    |                        |                        |                       |
| NTWEET x     |                    |                        |                        |                       |
| PFEED x CRED |                    |                        |                        |                       |

|                           |      |      |        |        |
|---------------------------|------|------|--------|--------|
| NTWEET x                  |      |      | .167   | .047   |
| NFEED x CRED              |      |      | (.075) | (.010) |
| R <sup>2</sup> =          | .514 | .557 | .593   | .548   |
| Adjusted R <sup>2</sup> = | .493 | .538 | .542   | .537   |

Notes: \*\*\*  $p < .01$ , \*\*  $p < .05$ , \*  $p < .10$ .

**Table 4. Estimation results for CPM**

|            | <b>Model 5</b>       | <b>Model 6</b>       | <b>Model 7</b>       | <b>Model 8</b>       |
|------------|----------------------|----------------------|----------------------|----------------------|
|            | Coef. (Std. Err)     | Coef. (Std. Err)     | Coef. (Std. Err)     | Coef. (Std. Err)     |
| Constant   | 52.752***<br>(5.268) | 52.893***<br>(5.745) | 51.696***<br>(5.463) | 51.947***<br>(5.564) |
| LN(NETEXP) | 4.728**<br>(1.154)   | 5.393**<br>(1.958)   | 6.737*<br>(1.325)    | 3.642**<br>(1.528)   |
| TFEED      | 5.738***<br>(.846)   | 3.583***<br>(.659)   | 4.549***<br>(.736)   | 4.693***<br>(.683)   |
| CRED       | .056<br>(.067)       | .078<br>(.051)       | .045<br>(.017)       | .072<br>(.032)       |
| AGE        | -.084<br>(.356)      | -.043<br>(.487)      | -.026<br>(.397)      | -.059<br>(.268)      |
| SIZE       | 0.284*<br>(.593)     | 1.356**<br>(.368)    | 2.574***<br>(.649)   | 1.639**<br>(.472)    |



|                           |                  |                        |                       |                       |
|---------------------------|------------------|------------------------|-----------------------|-----------------------|
| TWEETRATIO                | 0.256<br>(.047)  | 0.431<br>(.068)        | 1.255**<br>(.035)     | 0.362<br>(.026)       |
| TWEETVOL                  | -1.326<br>(.258) | -1.564<br>(.186)       | -1.788<br>(.065)      | 1.643<br>(.072)       |
| PTWEET                    |                  | .598*<br>(.752)        | .729*<br>(.963)       | .836*<br>(.583)       |
| NTWEET                    |                  | -28.763***<br>(17.638) | -34.854***<br>(9.563) | -25.747**<br>(15.869) |
| PTWEET x<br>PFEED x CRED  |                  |                        | 6.674***<br>(.953)    | 7.879***<br>(.642)    |
| PTWEET x<br>NFEED x CRED  |                  |                        | .268<br>(.137)        | .272<br>(.159)        |
| NTWEET x<br>PFEED x CRED  |                  |                        | 4.386**<br>(.764)     | 4.752**<br>(.683)     |
| NTWEET x<br>NFEED x CRED  |                  |                        | .298<br>(.126)        | .075<br>(.068)        |
| R <sup>2</sup> =          | .482             | .579                   | .493                  | .464                  |
| Adjusted R <sup>2</sup> = | .412             | .467                   | .395                  | .386                  |

Notes: \*\*\*  $p < .01$ , \*\*  $p < .05$ , \*  $p < .10$ .

**Table 5. Estimation results for financial performance**

|                    | <b>Model 9</b>      | <b>Model 10</b>        | <b>Model 11</b>       | <b>Model 12</b>      |
|--------------------|---------------------|------------------------|-----------------------|----------------------|
|                    | Coef. (Std. Err)    | Coef. (Std. Err)       | Coef. (Std. Err)      | Coef. (Std. Err)     |
| Constant           | 53.628**<br>(5.638) | 52.287**<br>(5.481)    | 53.172**<br>(5.278)   | 53.484**<br>(5.852)  |
| <i>LN</i> (NETEXP) | 7.056**<br>(1.495)  | 6.298<br>(1.632)       | 7.389**<br>(1.563)    | 7.517**<br>(1.754)   |
| TFEED              | 4.812**<br>(.839)   | 5.427**<br>(.691)      | 4.562**<br>(.854)     | 4.331**<br>(.713)    |
| CRED               | -2.147**<br>(.795)  | -.172**<br>(.432)      | -1.914*<br>(.482)     | -1.273**<br>(.752)   |
| AGE                | -.551<br>(.488)     | -.105<br>(.332)        | -.256<br>(.192)       | -.124<br>(.347)      |
| SIZE               | 2.110**<br>(.383)   | 3.077**<br>(.261)      | 2.158**<br>(.382)     | 3.063**<br>(.382)    |
| TWEETRATIO         | 2.805**<br>(.801)   | 1.193**<br>(.626)      | 1.178**<br>(.615)     | 1.193**<br>(.534)    |
| TWEETVOL           | .143<br>(.376)      | .284<br>(.128)         | .387<br>(.324)        | .184<br>(.151)       |
| PTWEET             |                     | .386<br>(.235)         | .061<br>(.003)        | .294<br>(.127)       |
| NTWEET             |                     | -31.161***<br>(11.793) | -26.132**<br>(11.473) | 27.389**<br>(13.827) |
| PTWEET x           |                     |                        | 2.455**               | 2.826**              |
| PFEED x CRED       |                     |                        | (.575)                | (.553)               |
| PTWEET x           |                     |                        | .810                  | .792                 |
| NFEED x CRED       |                     |                        | (.772)                | (.784)               |

|                           |      |      |        |        |
|---------------------------|------|------|--------|--------|
| NTWEET x                  |      |      | .898   | .712   |
| PFEED x CRED              |      |      | (.631) | (.546) |
| NTWEET x                  |      |      | .452   | .436   |
| NFEED x CRED              |      |      | (.269) | (.027) |
| R <sup>2</sup> =          | .504 | .549 | .582   | .558   |
| Adjusted R <sup>2</sup> = | .496 | .522 | .536   | .543   |

Notes: \*\*\*  $p < .01$ , \*\*  $p < .05$ , \*  $p < .10$ .