MIS Quarterly

RESEARCH ARTICLE

COMMUNITY INTELLIGENCE AND SOCIAL MEDIA SERVICES: A RUMOR THEORETIC ANALYSIS OF TWEETS DURING SOCIAL CRISES[1]

Onook Oh
Warwick Business School, University of Warwick,
Coventry, CV4 7AL UNITED KINGDOM {onookoh@gmail.com}

Manish Agrawal
Department of Information Systems and Decision Sciences, College of Business Administration, University of South Florida,
4202 E. Fowler Avenue, CIS 1040, Tampa, FL 33620 U.S.A. {magrawal@usf.edu}

H. Raghav Rao
Department of Management Science and Systems, School of Management, Jacobs Management Center,
SUNY at Buffalo, Buffalo, NY 14269-4000 U.S.A. and Global Service Management,
Sogang University, Seoul, SOUTH KOREA {mgmtrao@gmail.com}

Recent extreme events show that Twitter, a micro-blogging service, is emerging as the dominant social reporting tool to spread information on social crises. It is elevating the online public community to the status of first responders who can collectively cope with social crises. However, at the same time, many warnings have been raised about the reliability of community intelligence obtained through social reporting by the amateur online community. Using rumor theory, this paper studies citizen-driven information processing through Twitter services using data from three social crises: the Mumbai terrorist attacks in 2008, the Toyota recall in 2010, and the Seattle café shooting incident in 2012. We approach social crises as communal efforts for community intelligence gathering and collective information processing to cope with and adapt to uncertain external situations. We explore two issues: (1) collective social reporting as an information processing mechanism to address crisis problems and gather community intelligence, and (2) the degeneration of social reporting into collective rumor mills. Our analysis reveals that information with no clear source provided was the most important, personal involvement next in importance, and anxiety the least yet still important rumor causing factor on Twitter under social crisis situations.

Keywords: Twitter, social reporting, social information processing, rumor theory, social crisis, extreme events, community intelligence

[1]Hsinchun Chen was the accepting senior editor for this paper. Michael Chau served as the associate editor.

Introduction

Social media services and consumer computing devices are rapidly changing the way we are creating, distributing, and sharing emergency information during social crises (Palen et al. 2010; Palen et al. 2009; Shklovski et al. 2010; Shklovski et al. 2008; Starbird and Palen 2010). During large-scale crises (e.g., natural disasters and terrorist attacks), it has become the norm that the incident is initially reported by a local eyewitness with a mobile communication device, the report is rapidly distributed through social media services, and mainstream media involvement follows (Oh et al. 2011; Oh et al. 2010). Indeed, online citizens have shown the potential of being first responders who can improvise an effective emergency response by leveraging their local knowledge, typically not available to professional emergency responders who are not familiar with the local community (Li and Rao 2010). Despite these advantages, many warnings have been raised about the information quality of crisis reports contributed by voluntary online citizens. A recent examination of some of Google's real-time search results for Tweeter and blogs reveals that real-time information was mostly "fabricated content, unverified events, lies and misinterpretation" (Metaxas and Mustafaraj 2010, p. 1). For this reason, and despite the potential of social media services and voluntary reports, they are often despised as collective rumor mills that propagate misinformation, gossip, and, in extreme cases, propaganda (Leberecht 2010).

Acknowledging the duality of social media as a potential tool for social reporting and a collective rumor mill, this study explores the information quality issue in the context of social crises and media crises. We conceptualize the participatory social reporting phenomenon as collective intelligence and information processing to make sense of, cope with, and adapt to situational and informational uncertainties under crises (DiFonzo and Bordia 2007). This study attempts to answer two questions:

(1) Under what conditions does collective social reporting function as a community intelligence mechanism to address crisis problems?

(2) Under what conditions does social reporting degenerate into a rumor-mill?

To develop a theoretical framework for these questions, we rely on the literatures on rumor and social crises. To empirically test the framework, we analyze Twitter data from three different crisis incidents: the Mumbai terrorist attack in 2008, the Toyota recalls in 2010, and the Seattle café shooting incident in 2012.

This paper proceeds as follows. In the next section, we introduce the literatures on rumors and social crises. We then synthesize these two literatures to develop our research model and hypotheses. After that, the research methodology is introduced, hypothesis tests are performed, and results are discussed. In closing, limitations and future research possibilities are suggested.

Social Crisis and Information Issues

Social crises are characterized by the severe consequences of the incident, low probability of incident occurrence, informational and situational uncertainty, and decision-making pressure under time constraints (Runyan 2006). Unfamiliar, unplanned, and unpredictable crisis situations quickly render inoperative day-to-day routine practices which sustain some level of social behavior, communication norms, and normalized interaction (Stallings and Quarantelli 1985). Inevitably, this out-of-the-ordinary crisis situation accompanies collective anxiety, improvised group behaviors, and adaptive collaboration among the public (Bharosa et al. 2010; Janssen et al. 2010; Kendra and Wachtendorg. 2003; Majchrzak et al. 2007).

One of the main problems that have caused obstruction of improvised collaboration within and between the public and emergency responders has been the complexity in information processing and sharing (Bharosa et al. 2010; Jenvald et al. 2001; Singh et al. 2009; Yang et al. 2009). Scanlon (2007) relates the unusual and improvised communication behavior under large-scale social crisis to the *information convergence* phenomenon that suddenly overloads major communication systems. This out-of-the-ordinary communication behavior during a crisis is associated with the twin problems of *information overload* and *information dearth* (Shklovski et al. 2008).

Information overload and information dearth signify the two enduring and interlocking problems that prevent sense-making of urgent situations and emergency response operations. First, from the emergency responders' perspective, too many inquiries and reports, many of which are not accurate or reliable, hamper emergency response teams in efficiently delivering relevant and trustworthy information to the right responders at the right time (Bharosa et al. 2008; Bharosa et al. 2010). For example, during the Mumbai terrorist attacks, the police control room was flooded with incorrect reports of explosions at leading hotels such as the J. W. Marriott (Chakraborty et al. 2010). Second, from the perspective of a citizen, the information dearth problem indicates a lack of local information, desperately needed by citizens of affected areas to make localized decisions. As the main cause of the information dearth problem, the disaster literature identifies mainstream media. The literature maintains that institutional mainstream media have a tendency to repeatedly zoom in on the sensational aspects of a disaster from a single onlooker's perspective (Wenger and Friedman 1986), and they are highly dominated by cultural influences or institutional policies. As a result, rather than trusting mainstream media, citizens often turn to their own local social networks or resources at hand to obtain local information that is relevant and needed for their understanding of the local situation and decision making (Mileti and Darlington 1997; Shibutani 1966; Wenger and Friedman 1986). Therefore, it is not surprising that unexpected social crises in recent years almost always involve high traffic in social media websites through various forms of information exchange, including online posting, linking, texting, tweeting, retweeting, etc.

To root the study in a robust theoretical framework, the next section introduces rumor theory in the context of crisis communication, and suggests testable hypotheses along with key variables.

Theoretical Foundation: Rumor Theory and Social Crises

From a social psychological perspective, Shibutani (1966) relates rumor phenomena to information convergence, which typically occurs in the early stages of a social crisis. He considers rumoring as a collective and improvised information seeking and exchanging behavior among citizens to control social tension and solve crisis problems. Rumoring is defined as a collective and collaborative transaction in which community members offer, evaluate, and interpret information to reach a common understanding of uncertain situations, to alleviate social tension, and to solve collective crisis problems (Bordia 1996; Bordia and DiFonzo 1999, 2004; Shibutani 1966). Rumor, as an instance of crisis communications in a community, is born and makes its way through social support (Festinger 1962). From its birth, as rumor involves communication dynamics surrounding shared issues in a community, the generation and transmission of rumor are inseparable in practice. Therefore, to highlight the connective and dynamic nature of rumor, this paper uses the terms like *rumor*, *rumoring*, and *rumormongering* interchangeably.

When people encounter unexpected crisis events, emotional tension in the affected community increases. To release the social tension, people initially turn to reliable institutional channels such as the mainstream media and attempt to make sense of uncertain situations with the information collected. At this initial stage, if people in the affected community fail to obtain relevant and timely information, they begin to mobilize informal social networks such as friends, neighbors, local news, and other possible sources. Then, using the information collected through these backchannels, people improvise news to fill the information gap of mainstream media. Shibutani (1966) calls this informally improvised news as rumor, which functions as a collective effort to reach a common understanding of the situational uncertainty and to relieve emotional tension. In this view, rumoring helps the community to cope with and adapt to ambiguous crisis situations until the level of social tension is brought under check.

Shibutani's description of the rumoring procedure as a kind of emergency communication endeavor concurs with many findings of crisis research, which report that victims avoid mainstream media and actively adopt informal communication channels during social crisis events (Quarantelli and Wenger 1989). According to a survey of citizens affected by the Southern California wildfires in 2007, many respondents felt that the institutional mainstream media were not providing local information, desperately needed by residents of the affected areas, in a timely manner (Mills et al. 2009; Sutton et al. 2008). In response, many people turned to social media services to fill the information gap left by mainstream media (Shklovski et al. 2008), and others intentionally learned how to use texting devices and online message boards to exchange crisis information and to stay connected with their acquaintances (Shklovski et al. 2010).

Although originating from different domains, the rumor research and crisis research camps have close affinity in that both camps view improvised and emergent crisis communication as a typical nonroutine group behavior. One major difference is that, while the former camp approaches the improvised crisis communication as a rumor phenomenon, the latter takes the perspective of information convergence, which overloads the communication infrastructure. However, a close reading of both literatures reveals that rumor phenomena and information convergence are interlocking problems born out of unpredictable, unfamiliar, and unplanned social crisis situations. This is easy to see when rumor researchers argue that "disasters and other crises are characterized by high importance, high ambiguity, low critical sensibility, and many rumors" (Rosnow and Fine 1976, p. 52), or "in wartime…the conditions for rumor are optimal" (Allport and Postman 1947, p. 34).

Close kinship between studies of rumor and social crises is also found in the seminal rumor model of Allport and Postman (1947). The rumor model was the product of a study of unusual group communication during social crises. After investigating the characteristics of rumors prevalent during World War II, they suggested that rumor spread is a function of *importance* and informational *ambiguity*. This implies that, for the birth and dissemination of a rumor, the theme of the story must be important to both message sender and recipient, and the truthfulness of the story must be masked with some level of ambiguity. If the story is not important, there is no psychological incentive for people to pass along the story to other persons. Also, if the story does not contain some level of ambiguity, then it is already a fact that does not need subjective elaboration and interpretation. This seminal rumor model is expanded, refined, and tested in this paper. The next sections introduce key rumor variables to build empirically testable hypotheses.

Anxiety

Although Allport and Postman's rumor model offered key variables for rumormongering conditions, measurement of the *importance* variable was a thorny problem until Anthony (1973) introduced *anxiety* as its proxy variable. Her rationale for employing the anxiety measurement scale (i.e., Taylor Manifest Anxiety Scale) was that it may be difficult for a person to articulate the importance of a particular rumor. However if one feels *anxious* about the rumor, it signals that the content in the rumor message is *important* to her/him. Otherwise, it is not.

The inclusion of the anxiety concept contributes in differentiating two conceptually distinct dimensions of rumormongering motives: the affective dimension (anxiety) and the cognitive dimension (ambiguity). Allport and Postman expressed a similar notion that rumor is motivated by "intellectual pressure along with the emotional" (p. 37). Emotional pressure indicates the affective dimension (anxiety), and intellectual pressure points to the cognitive dimension (ambiguity) of rumoring. To develop the first hypothesis, in this section, we focus on the affective dimension of anxiety, and the cognitive dimension will be revisited when we introduce the second hypothesis in the next section.

According to Allport and Postman, seen from the affective dimension, rumoring is a justification process to relieve one's emotional tension by elaborating a story to gain acceptance from listeners. Therefore, the more anxious an individual, the more likely he/she is to spread rumors. The consistent conclusion of rumor research on social crisis is that rumor endures until the perceived external uncertainty disappears and its attendant anxiety subsides (Knapp 1944; Prasad 1935, 1950; Rosnow and Fine 1976). Following these findings, and given the uncertain and apprehensive nature of social crises, the first hypothesis is presented:

> *H1: The level of anxiety during social crises is positively associated with rumors (rumormongering).*

Information Ambiguity: Source Ambiguity and Content Ambiguity

In addition to anxiety, ambiguous information is another important factor of rumor spread. Ambiguous information is mainly caused either by the destructive impact of disasters, which suddenly incapacitate communication infrastructures (Kendra and Wachtendorg 2003), or by the deliberate holding back of critical information by organizations in the interests of security (Rosnow 1991). Under extreme and ambiguous situations, people frequently experience a shortage of reliable information to understand uncertain situations and, consequently, tend to improvise news to fill the gap of information ambiguity with subjective elaboration, fanning the rumor mill (Shibutani1966).

Rumor researchers implicitly present two different dimensions of information ambiguity: source ambiguity and content ambiguity. Source ambiguity concerns the trustfulness of the information source, which guarantees the veracity of the circulating information. Content ambiguity attends to the interpretative clarity of meaning contained in the information. Shibutani's notion of improvised news as rumor implies both dimensions of source ambiguity and content ambiguity. Facing social crises, people initially turn to institutional news channels to obtain reliable information, and then mobilize unofficial social networks to fill the information gap of the institutional news channels. In a similar vein, many rumor researchers have also argued that, when information is void of trustful sources, people tend to make predictions with their own subjective wishes or bounded knowledge to reduce cognitive ambiguity (Knopf 1975; Rosnow 1991; Rosnow and Fine 1976). It can be inferred from this logic that, if information is attached with verifiable sources, then it may suppress the incentive to devise rumors.

Content ambiguity refers to the level of interpretive ambiguity contained in the information. Fundamentally, it stands on the underlying assumption that "our minds protest against chaos" (Allport and Postman 1947, p. 37). From a cognitive perspective, the intellectual effort to extract clear meaning out of a chaotic state is an endeavor to remove ambiguity from the information (DiFonzo and Bordia 2007; Festinger 1962; Kapferer 1990; Knopf 1975; Rosnow and Fine 1976). Therefore, the more ambiguous the information content, the more frequent communications of information seeking, sharing, and elaboration among community members.

Festinger's (1957) description of *cognitive dissonance* exemplifies the relationship between ambiguous information and rumoring. He explains cognitive dissonance with the example of an earthquake in India in 1934. Subsequent to the severe earthquake, fearsome rumors began to circulate *outside*, but not *inside*, the affected community. These rumors were mostly about the aftermath of the earthquake: "The water of the River Ganges disappeared at the time of the earthquake, and people bathing were embedded in sand" (p. 238). To explain why these rumors were prevalent only *outside,* but not *inside* the destruction area, Festinger argues that the neighboring people outside the destruction area were experiencing cognitive dissonance. That is, although they had the feeling of fear from hearing about the earthquake, because they had not witnessed the disaster, they only had uncertain and equivocal information about the earthquake. What Festinger's cognitive dissonance work suggests is that rumor sets in motion "in situations of relative collective ignorance and ambiguity about an event" (Tierney and Aguirre 2001, p. 5). Given that social crises create uncertain information, which is void of trustful source and contains interpretive ambiguity, the second hypothesis is presented as follows:

> *H2a: The level of source ambiguity in the circulating information during social crises is positively associated with rumors (mongering).*

> *H2b: The level of content ambiguity in the circulating information during social crises is positively associated with rumors (mongering).*

Personal Involvement

Although Anthony employs anxiety as a proxy to measure the *importance* variable of Allport and Postman's original rumor model*,* Rosnow (1991) suggests including the perceived *importance* as a separate variable. He refines it as "outcome-relevant involvement" to indicate that "the amount of rumor-mongering will vary according to an incident's thematic importance" to the people involved (Rosnow 1991, p. 486). This is consistent with Allport and Postman's postulate that "the amount of rumor circulation will vary with the importance of the subject to the individuals concerned" (p. 34). This means that for a rumor to spread, the incident's subject matter must be important for both the information sender and recipient. Otherwise, there is no incentive for the recipient to pass along the story to other persons. In this sense, importance is represented as a subjective feeling of *personal involvement*[2] in the rumor related incident, which is conceptually different from Anthony's *anxiety*.

Rosnow believes that the personal "affective state—acute or chronic" is an important rumor spreading factor, because it is not necessarily evoked by external events, but somehow is already imbued with personal disposition even before experiencing the rumor related incidents (p. 487). The external incident's importance to the individual concerned is based on "a synthesis of the relevance of a situation and whether it evoked caring or involvement" (p. 487). Rosnow et al.'s (1988) rumor research on a murder incident at a local college supports the argument. It revealed that the student group of the college, which experienced the murder incident, transmitted almost twice the number of rumors compared to the control group of the neighboring college. While this research did not include *importance* or *personal involvement* as an independent variable, we can surmise that the college student group who experienced the shocking murder incident in their campus dorm may have had higher levels of personal involvement perception with the incident than the control group. From this, we submit a third hypothesis on the role of personal involvement feeling in rumor transmission:

> *H3: Feelings of personal involvement with regard to social crises is positively associated with rumors (mongering).*

Social Ties: Direct Message

Rumoring involves collective talking, interactive information sharing, and social support (Festinger 1962) among like-minded groups of people. By nature, people tend to share information with acquaintances within their communal boundary, and "people are biased toward believing rumors from those they know" (Garrett 2011, p. 259). Therefore, social ties, personal contacts, and relations in close proximity are factors that influence people to share information with other community members (Collins 2001), and they form repeatable communication routines through which information flows (Tsai and Ghoshal 1998).

Although the social tie concept has not been extensively tested as a distinct variable in previous rumor studies, its importance has been sporadically mentioned with different expressions. For example, Allport and Postman maintain that

[2]We thank an anonymous reviewer who suggested adding the personal involvement variable to our original rumor model.

rumors "avoid crossing social barriers and therefore have a restricted circulation" (p. 35). In a similar vein, Festinger suggests that social support is mandatory for rumor dissemination. These concepts imply that a rumor is more likely to spread within a community that is sustained by affective trust and strong social ties. That means, in a tightly woven community, affective social ties are likely to impose "social pressure against fact-checking," reducing "the probability that recipients will verify the information for themselves" (Garett 2011, pp. 259-260).

Garett's (2011) political rumor research shows the effect of existing social ties on rumor transmission. His survey provides evidence that, compared to rumors learned from the public web, rumors received through e-mails from acquaintances (e.g., friends, colleagues, or family members) are more likely to be believed and biased in the pattern of dissemination and credulity. As a reason for the strong bias effect of e-mail communication on rumor, Garret maintains that, different from the public web, e-mail is a closed and more informal communication channel, capitalizing on existing social networks such as friends, colleagues, and family members.

As an extension of this rumor study, Garret suggests that social networking services (i.e., Facebook and Twitter) may replicate rumor dynamics similar to those shown in e-mail communication. The main reason is that, similar to informal e-mail communication and different from the public web, social networking sites are mainly built around existing social relations. Acknowledging the effect of social relations on rumor transmission, we propose that directed messages (DM) in Twitter,[3] which are addressed to specific individuals in the Tweeter's social network, may be more likely to result in rumors. Therefore, a fourth hypothesis is proposed:

> *H4: Directed messages in Twitter are positively associated with rumor (mongering).*

In aggregate, our research model on rumormongering is represented as Figure 1.

Research Methodology

To test our hypotheses, we used three different Twitter data sets: (1) the Mumbai terrorist attack in 2008, (2) the Seattle café shooting incident in 2012, and (3) the Toyota recalls in 2010. The first two data sets represent man-made crises but with different scales and impacts, and the third data set deals with the business crisis of Toyota recalls.

These three types of incidents are appropriate for this research for two reasons. First, as the rumor literature suggests, large-scale crises offer optimal conditions for rumor-mongering. Second, analysis of data from three different types of social crisis will offer generalizable insights on the quality of social information produced by the online public.

Backgrounds of the Three Social Crises Under Analysis

The Mumbai Terrorist Attack in 2008

The Mumbai terrorist attack of November 2008 was arguably the worst terrorist incident in the history of India. A group of terrorists killed 165 and injured 304 people at the heart of India's financial capital, Mumbai, by using a combination of improvised explosive devices, grenades, and hand-held guns (Indian Ministry of External Affairs 2009). The unfolding tragedy was broadcast live through India's mainstream TV media and live web streaming for almost 60 hours without any restraint. The scenes were terrifying enough to create anxiety and confusion in the minds of the Indian people (Oh et al. 2011; Raman 2009).

Within minutes of the initial attack, a local Mumbai resident posted a stream of onsite pictures at a photo sharing site, Flickr. Almost concurrently, a group of people voluntarily formed a Twitter page with a link to the Flickr site, and spread eyewitness accounts of the terrorist attacks with texts, photos, and links to other sources. Through tweets, online users expressed condolences, encouraged blood donations, posted help line contacts, broadcast information about their safety to their family, reported eyewitness accounts of the unfolding situation, etc.

For active situational reports, some users added comments like "*twitter rocks – I am getting accurate and better information than MSM like Times Now!*" or "*CNN has been playing catch up to twitter :)*." However, despite the rapid dissemination of situational information, much confusion existed in the Twitter space due to too many rumors (Gahran 2008). As a result, many Twitter users expressed concerns regarding the reliability of news sources,[4] finger-pointed specific users as

[3]Directed message is a message sent to specific Twitter user by attaching "@" in front of the recipient's Twitter ID. It can be sent to a specified user. Therefore, conceptually it is close to publicly displayed private e-mail.

[4]Some exemplary tweets expressing concerns about rumors were "*#mumbai Please tweet only direct observations, RT rumors are just decreasing the signal/noise ratio*" and "*where did you get that info? its crap. all of this is live on TV. pls stop spreading such stuff without verifying #mumbai.*"

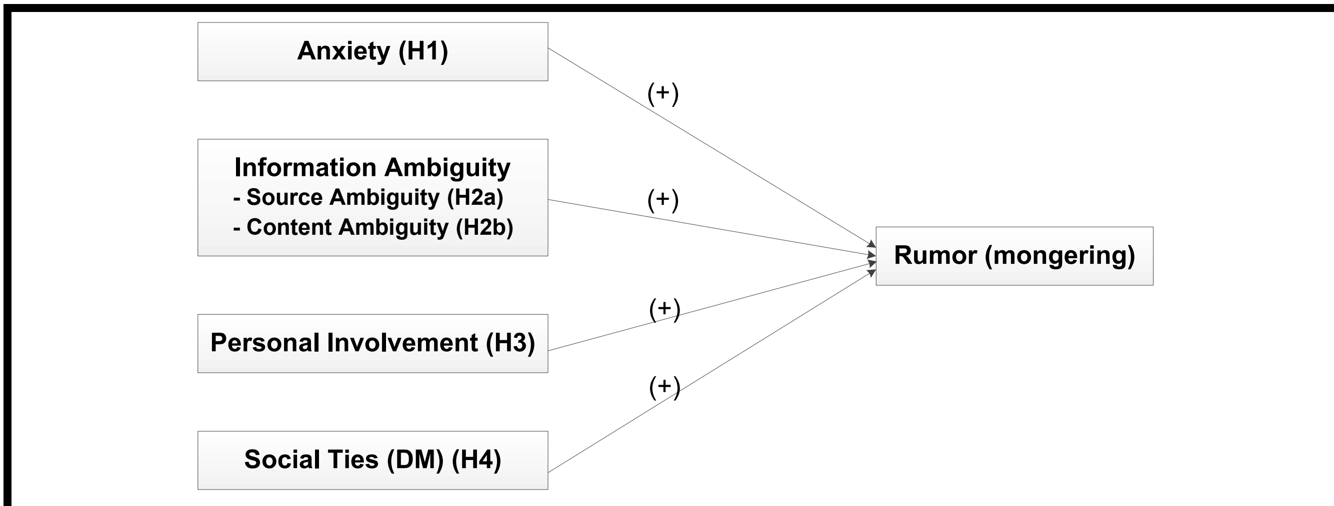

Figure 1. Proposed Research Model

abusers of the Twitter space, showed distrust in Twitter, or requested Twitter users to post only direct observations.

Seattle Café Shooting Incident in 2010

On May 20, 2012, a gunman in Seattle, Washington, killed five people and injured one person before committing suicide. It was reported that the gunman had gotten into fights with musicians at Café Racer and have been made to leave by a bartender. At that moment, he pulled out two handguns and shot at customers and employees. He fled the scene immediately, going to a parking lot in the downtown area where he killed a woman and hijacked her car. Later that afternoon, the gunman shot himself to death as the police approached him (CNN 2012; McNerthney 2012). During the search operation, the Mayor, the Seattle Police Department, and local news outlets (such as *Seattle Times*, Seattle PI, Komo News, etc.) were deeply involved in tweeting to broadcast the unfolding situation.

The police at first treated the shooting incidents at the café and the parking lot as separate crimes. The informational confusion and ambiguous situations about the shooters' whereabouts created discomfort in the minds of community members (Johnson 2012; Winter 2012). Many people expressed anxiety and doubted the quality of information circulating through Twitter. Example tweets included "*Twitter is not a great place to get reliable sourcing on #Seattle shootings right now. So many conflicting reports*," or "*#DowntownShooting #RooseveltShooting How does this make sense? Suspect Downtown was blond and suspect on Roosevelt was brown haired?*"

Toyota Recalls in 2010

Starting from the end of 2009 and throughout 2010, Toyota suffered from a series of recall nightmares. In September 2009, Toyota announced its biggest recall ever of more than 4 million vehicles for a problem related to accelerator pedals getting trapped in the floor mat. Four months later, in January 2010, they announced another large-scale recall of around 2.3 million vehicles in the United States for potentially faulty accelerator pedals (Allen and Sturcke 2010). In April 2010, they recalled around 600,000 minivans in the United States for potential corrosion problems in the spare tire carrier cable. In July 2010, they announced additional recalls of over 400,000 cars in the United States and Canada for more serious mechanical problems in the steering system, which could cause deadly road accidents (Reuters 2010).

Following the serial recalls, in May 2011, sales of Toyota declined by a third compared to May 2010. To make matters worse, along with the effect of the economic downturn affecting the overall U.S. car industry, the company faced a backlash from the mainstream and social media for their problematic safety checks, quality controls, and frequent recalls. Reflecting the impact of the business crises and its attendant consumer safety concerns, during the recall periods, Toyota became a trend word on Google and Twitter, mostly with negative comments (Wasserman 2011).

Data Collection

The data collection process for the three crisis incidents is detailed below.

Mumbai Terrorist Attack 2008

As soon as the Mumbai terrorist attack occurred on November 26, 2008, we manually collected 929 tweet messages and their user IDs. Subsequently, to increase the sample size, we read through the 929 tweet messages and collected additional user IDs embedded in the tweet messages as a form of directed message or retweets. Through this process, we identified total 602 IDs of users who might have posted messages during the Mumbai attack. By tracking back all Twitter messages of those 602 IDs,[5] we collected a total of 20,920 Twitter messages for the period November 26 to November 30, 2008. For our qualitative hand coding of the data, we randomly selected 7,000 Twitter messages out of the entire set of Twitter messages. One of the authors and two Master's students (who were familiar with the Mumbai scenario from personal experience) read through all the 7,000 tweets to remove thematically irrelevant tweets.

Toyota recalls 2010

Twitter data on the 2010 Toyota recalls was obtained from Stefan Stieglitz and Nina Krüger (2011).[6] The sample size that we received from Stieglitz and Krüger was 37,323 tweets, which were collected between March 21 and July 31, 2010, by using the keyword combination of "Toyota" and "recall." From the data we obtained, we randomly selected and read 5,000 tweets to check if they were relevant to the Toyota recalls. All tweets were relevant to the Toyota recalls and we saved them for pilot and actual coding for our study.

Seattle Café Shooting 2012

As soon as we heard the news about the shooting incident in Seattle, Washington, at 5:20 p.m. Central Time on May 30, 2012, we began data collection with four hashtagged keywords: #DowntownShooting, #SeattleShooting, #Seattle, and #RooseveltShooting. Those hashtagged keywords were determined by our monitoring of the live tweet messages through the Twitter search engine. We concluded our data collection at 2:00 p.m. Central Time on May 31, when we heard the official news that the shooter had committed suicide. We collected a total of 9,104 tweet samples during the period.

[5]To retrieve the archival Twitter messages, we created our own Twitter data collection application in compliance with Twitter API terms of service. The application is available from the authors on request.

[6] The authors thank Drs. Stieglitz and Krüger for generously allowing us to use their Twitter data for our study.

Unitizing

Bordia and DiFonzo (1999, 2004) suggest that, before content coding, a paragraph, sentence, or narrative should be dissected into a unit of one complete thought. They suggest that "a complete thought provides enough information so that it can be interpreted by others and can stimulate a reaction in them" (Bordia and DiFonzo 2004, p. 38). Given that the Twitter message has a maximum of 140 characters, our data sample was already unitized into a unit of one complete thought for coding.

Coding Scheme

We coded each tweet message to measure the effect of anxiety, information ambiguity (content ambiguity and source ambiguity), personal involvement, and direct message on rumor.

Detailed coding schemes for dependent and independent variables are attached as Appendix A. To develop the coding scheme for the dependent variable, *rumor*, we referred to various rumor definitions (Buckner 1965; Rosnow et al. 1988; Rosnow and Kimmel 2000). To create the coding scheme for independent variables, we modified the rumor interaction analysis systems (RIAS) to our research context (Bordia and DiFonzo 2004). The RIAS is a coding scheme to categorize communication postures represented in rumor text into 14 categories. Its purpose is to understand how interactive human communication changes over the life of a rumor to solve two problems (*anxiety* and *uncertainty*) implied in rumor. However, as the purpose of our study is to identify the rumor causing factors, we borrowed only those definitions relevant to our rumor model (Figure 1) (e.g., *apprehensive statement* for anxiety, *personal involvement statement*, and *interrogatory statements* for content ambiguity).

To code the dependent variable, rumor, we used Rosnow and Kimmel's (2000) rumor definition: "*Unverified* proposition or belief that bears *topical relevance* for persons actively involved in its dissemination" (p. 122, italics addedl). We also referred to the actual questionnaire items that Rosnow et al. (1988) used in their rumor research on the murder incident at a campus dorm of a local college: "any report, statement, or story that one may have heard for which there is *no immediate evidence to verify* its truth" (p. 32, italics added). Finally, to sharpen the relevance of theme in the Twitter messages, we employed Buckner's (1965) rumor definition: "*Unconfirmed* message passed from one person to another… that *refer[s] to an object, person, or situation* rather than an idea or theory" (p. 55, italics added).

In brief, these rumor definitions involve three dimensions: unverified proposition, topical relevance, and referents of the statement (that is, an object, person, or situation rather than an idea or theory). Therefore, in the Twitter context, three conditions have been applied to code a tweet as a rumor: (1) if the tweet message explicitly indicates a person (e.g., the prime minister of India), source (e.g., BBC, NDTV, link to web address, etc.), context, or known data to serve as proof or verification for the statement, AND (2) if the tweet is topically relevant to three types of crises under this study, AND (3) if the tweet statement refers to an object, person, or situation rather than an idea or theory (Bordia 1996; Rosnow et al. 1988; Rosnow and Kimmel 2000; Buckner 1965). Rumor and all independent variables were coded as dichotomous (either 1 or 0). Along with exemplary tweet messages, the full coding scheme for dependent and all independent variables is detailed in Appendix A.

All variables were coded as dichotomous because of the content analytic coding procedure used. Previous rumor studies in the off-line context have used survey or interview methods along with psychometric measurement scales as a means to measure the perceived level of different variables (e.g., anxiety, importance, ambiguity, etc.) on an interval scale (Anthony 1973; Buckner 1965; Rosnow et al. 1988). However, as our study involves reading and content coding for the unobtrusively collected tweet texts, we coded our variables as dichotomous by checking whether or not a tweet message contains traits of variables suggested in our research model.

Inter-Coder Reliability

We followed the steps for content coding and analysis suggested by Krippendorf (1980) and Landis and Koch (1977). For the content coding, two Master's and two undergraduate students were hired to separately code the Twitter data. Two Master's students with deep local knowledge of Mumbai, its surroundings, and the terrorist attacks separately coded the Mumbai terrorist attack data. Two other undergraduate students separately coded the Seattle café shooting incident data. After finishing the coding of those two data sets, one Master's and one undergraduate student independently coded the Toyota recall data.

To build a coding book (Appendix A), three meetings were held to understand the histories of the three different social crises and the role of Twitter during those crises situations. The authors were not involved in content coding. Hypotheses and measurement models were not shared with student coders, and they were not allowed to communicate with each other while coding. They were asked not to spend more than an hour each day coding the data in order to miminize coding errors due to fatigue.

Pilot data coding was carried out in two rounds for the Mumbai terror data, and in three rounds for the Seattle café shooting and Toyota recall data sets. Our goal for pilot coding was to repeat coding and refine the coding book until independent coding results reached the *kappa* value greater than .70, indicating a probability of agreed understanding between coders that is significantly higher than what can be obtained by chance (Krippendorf 1980; Landis and Koch 1977).[7]

The first pilot coding was to verify the level of mutual understanding of the coding book. For the first pilot coding, we used 100 tweet samples that we randomly selected from our original data sets. If the first pilot coding result did not reach the threshold *kappa* value of .70, then two authors and all student coders conducted video conferences to discuss the disagreed coding results. As Table 1 shows, the coding result for the Mumbai terrorist attacks exceeded the desired threshold *kappa* value of .70 at the first round of coding. Therefore, coders performed coding with 300 sample tweets. Coding for the other two data sets (Toyota recalls and Seattle café shooting) exceeded the threshold *kappa* value of .70 after the second round of coding. Therefore, we proceeded to the third round of coding for these two data sets with 300 sample tweets each. The final pilot coding results with 300 tweet messages confirmed that our coding book is robust, and therefore, one Master's and two undergraduate student coders proceeded to separately code the entire 3,500 tweet data samples of the three different social crises. We ensured that the pilot sample data (400 tweet sample for the Mumbai terrorist attacks and 500 tweet samples for the Toyota recalls and the Seattle shooting incident) were excluded from 3,500 sample data of three different incidents (total 10,500 tweets) that we used for our logistic regression analysis.

Analysis Method

Due to the dichotomous nature of the dependent variable (rumor), we employed logistic regression. Logistic regression is appropriate "with an outcome variable that is dichotomous and predictor variables that are continuous or categorical" (Field 2005, p. 218). It does not assume linear relationships

[7]Landis and Koch suggest that *kappa* value 0.21~0.40 is fair, 0.41~0.60 moderate, 0.61~0.80 substantial, and 0.81~1.00 almost perfect agreement between independent coders.

Table 1. Pilot Coding Results (Cohen's Kappa Values)

	Mumbai Terrorist Attack 2008		Toyota Recalls 2010			Seattle Café Shooting 2012		
	1st Coding	2nd Coding	1st Coding	2nd Coding	3rd Coding	1st Coding	2nd Coding	3rd Coding
Rumor	0.77	**0.84**	0.63	0.71	**0.79**	0.75	0.80	**0.89**
Anxiety	0.81	**0.82**	0.85	0.85	**0.82**	0.73	0.80	**0.86**
Personal Involvement	0.89	**1.00**	0.63	0.85	**0.83**	0.64	0.71	**0.96**
Source Ambiguity	0.75	**0.86**	0.63	0.82	**0.74**	0.59	0.71	**0.92**
Content Ambiguity	0.74	**0.81**	0.77	1.00	**0.85**	0.59	0.83	**0.94**
Social Ties	0.79	**0.99**	0.48	0.79	**0.89**	0.64	0.77	**1.0**
Sample Size	**100**	**300**	**100**	**100**	**300**	**100**	**100**	**300**

Table 2. Spearman's Correlations

Mumbai Terror Attacks 2008						
	Rumor	**Anxiety**	**Sorc Amb**	**Cont Amb**	**Per Inv**	**Soc Tie**
Rumor	1					
Anxiety	.182**	1				
Sorc Amb	.358**	.291**	1			
Cont Amb	.047**	.074**	.179**	1		
Per Inv	.239**	.328**	.360**	-0.01	1	
Social Tie	-.189**	0.012	0.011	.108**	-.038*	1
Toyota Recalls 2010						
	Rumor	Anxiety	Sorc Amb	Cont Amb	Per Inv	Soc Tie
Rumor	1					
Anxiety	.050**	1				
Sorc Amb	.301**	0.012	1			
Cont Amb	0.021	.083**	-0.021	1		
Per Inv	.060**	.259**	-0.005	.189**	1	
Social Tie	0.03	.156**	0.016	.041*	.228**	1
Seattle Shootings 2012						
	Rumor	**Anxiety**	**Sorc Amb**	**Cont Amb**	**Per Inv**	**Soc Tie**
Rumor	1					
Anxiety	.164**	1				
Sorc Amb	.280**	.378**	1			
Cont Amb	.045**	.162**	.180**	1		
Per Inv	.142**	.455**	.275**	.078**	1	
Social Tie	0.005	-0.004	.055**	.044**	-0.015	1

**Indicates correlation is significant at the 0.01 level (2-tailed).

*Correlation is significant at the 0.05 level (2-tailed).

Abbreviations: Sorc Amb - Source Ambiguity; Cont Amb - Content Ambiguity; Per Inv - Personal Involvement; Soc Tie - Social Ties between the dependent and independent variables, and independent variables need not be interval, nor normally distributed, nor linearly related (Tabachnick and Fidell 1996). Further, the results have direct interpretations as odds-ratios. The Spearman rank correlation test (Table 2) indicates that all correlations are less than 0.5, indicating that no significant multicollinearity problems exist (Kishore et al. 2004-2005). Also, the correlation between rumor and source ambiguity is not in the range of statistical concern (.358 for the Mumbai terrorist attacks, .301 for the Toyota recall, and .280 for the Seattle shooting incident). Note that the Twitter data are observable and explicit (as opposed to latent) that community members actually tweeted during the situation of social crises. We also ensure that our sample sizes (3,500 tweets from each crisis incident) are large enough to suppress the potential Type I and Type II errors. The concern of Type II errors can be suppressed with a large sample size, and the immunity of Type I error can be ensured by the significance of p-value (Larson-Hall 2010).

The rumor model tested is as follows:

$$P(\text{Rumor}) \approx \textit{Anxiety} + \textit{Source Ambiguity} + \textit{Content Ambituity} + \textit{Personal Involvement} + \textit{Direct Message}$$

As our Twitter data sets were collected over specific time periods, we performed Durbin-Watson tests to verify that the error terms in our data sets did not contain any first order autocorrelations. (Durbin and Watson 1951; Savin and White 1977). Values of the Durbin-Watson statistics (d) were 1.94, 1.96, and 1.99 at $p < .05$ for each of the three data sets (Mumbai, Toyota, and Seattle). As all of these values are between lower ($d_U = 1.93$) and upper ($4 - d_U = 2.07$) bound of critical values at $p < .05$, we do not detect any autocorrelations between the error terms, validating that the error terms are independent of each other (Murray 2005).[8]

[8]To test for the independence of error terms in the logistic regression model, a first order autocorrelation test was performed. The Durbin-Watson test and the resulting d-statistic are used to perform this test. If the d-statistic value is between lower and upper bound critical values (d_U) and $4 - d_U$ at $p < .05$, then no autocorrelation exists in the data set. If the d-statistic value is less than the lower bound critical value (d_L) at $p < .05$, then it confirms that positive autocorrelation exists in the data set. If the d-statistic value is greater than $4 - d_L$, then it indicates that negative autocorrelation exists in the data set. All d-statistic values in our data sets (1.94, 1.96, 1.99) were between the lower ($d_U = 1.93$) and upper ($4 - d_U = 2.07$) bound critical values, which indicate that error terms in our data sets are independent of each other (Murray 2005).

Results

Using logistic regression analysis, we estimated the probability of rumor-mongering for the five independent variables during the three different types of crisis incidents. Results of the regression analysis are presented in Table 3. The results indicate a good model fit for the Mumbai terrorist attacks data, $\chi^2 = 680.21$ ($p < .001$), for the Toyota recall data, $\chi^2 = 260.94$ ($p < .001$), and for the Seattle shooting incident data, $\chi^2 = 292.69$ ($p < .001$). Table 3 also shows that H1 is supported for the Mumbai terror case at the significance level of $p < .01$, and for the Seattle shooting incident case at the significance level of $p < .05$. However, H1 is only marginally supported for the Toyota recall data at $p < .10$. This implies that, during the Mumbai terrorist attacks, a Twitter message charged with anxiety is 1.406 times more likely to be a rumor than an anxiety-free message. In the Seattle shooting incident, the probability of an anxious Twitter message to be a rumor is 1.299 times higher than a non-anxious one. In the Toyota recalls, although the probability that an anxious Twitter message is likely to be a rumor is 1.59 times higher than a non-anxious one, its significance level is marginal at $p < .1$.

Table 3 shows significant effects of source ambiguity on rumor at $p < .01$ for all three crisis cases, leading to strong support for H2a. In other words, the probability that a Twitter message with an ambiguous source is likely to be a rumor is 4.237 times, 4.523 times, and 4.001 times higher than a Twitter message having source information for the cases of the Mumbai terrorist attacks, the Toyota recall, and the Seattle shooting, respectively. Table 3 also shows the significant effects of personal involvement on rumor for all three crisis cases but with slightly different significance levels. The probability that a message implying a feeling of personal involvement is likely to be a rumor is 1.699 times ($p < .01$), 2.15 times ($p < .01$), and 1.401 times ($p < .05$) higher than a message that does not imply a feeling of personal involvement for different cases, supporting H3.

A comparison of the coefficient values for each independent variable of the three supported hypotheses (H1, H2a, and H3) shows consistent patterns. In other words, all three different cases of social crises show that source ambiguity is the most important, personal involvement is next in importance, and anxiety is the least yet marginally important rumor causing factor. However, different from our expectation, we could not find effects of content ambiguity and social tie on rumor. Therefore, H2b and H4 are not supported.

Table 3. Results for the Independent Effects on Rumor (95% CI for Exp(b))

	Mumbai Terror 2008			Toyota Recall 2010			Seattle Shooting 2012			
	B(SE)	**Sig.**	**Exp(B)**	**B(SE)**	**Sig.**	**Exp(B)**	**B(SE)**	**Sig.**	**Exp(B)**	**Hypothesis**
Constant	-1.364 (.066)	0.000	.256	-1.799 (.078)	0.000	.165	-2.323 (0.079)	0.000	0.098	
Anxiety	.341 (.096)	0.000	**1.406*****	.464 (.257)	.071	1.59*	.262 (.123)	0.033	**1.299****	**H1: Partially Supported**
Source Ambiguity	1.444 (.086)	0.000	**4.237*****	1.509 (.088)	0.000	**4.523*****	1.387 (.103)	0.000	**4.001*****	**H2a: Supported**
Content Ambiguity	.1 (.108)	0.357	1.105	.194 (.201)	.337	1.214	-.104 (.19)	0.586	0.902	H2b: Rejected
Personal Involvement	.53 (.09)	0.000	**1.699*****	.766 (.28)	.006	**2.151*****	.337 (.149)	.0204	**1.401****	**H3: Supported**
Social Tie	-1.114 (.093)	0.000	.328	.142 (.284)	.619	1.152	-.114 (.284)	0.687	0.892	H4: Rejected
Model Fit	= 680.21, *df* =5 ($p < .001$)			= 260.94, *df* = 5 ($p < .001$)			= 292.69, *df* = 5 ($p < .001$)			

***Significant at the 0.01 level. **Significant at the .05 level. *Significant at the .10 level.

Discussion

Key Findings

The results of logistic regression indicate that, while content ambiguity does not contribute to rumormongering, source ambiguity does so very significantly. This result needs contextual interpretation from the view of collective communication behavior in virtual space during social crises.

Twitter messages coded for content ambiguity were mainly composed of questions seeking information on the crisis situation or doubts expressing suspicion on Twitter posts.[9] Questioning or doubtful statements explicitly display the subjective nature of the messages. The tone of the messages signals that they were not persuasive statements intended to make others believe and spread the received messages. As a result, contrary to H2b, the content ambiguity variable turned out to be a nonsignificant rumormongering factor. In contrast, messages in the category of source ambiguity frequently resembled third-person situation reports without sources being attached.[10] In their postures, these statements looked like news reports, but without clear source, data, or context described. This might have influenced their role as a rumormongering factor.

The nonsignificant effect of content ambiguity and the highly significant effect of source ambiguity on rumormongering highlights the nature of citizen-centric social reporting behavior under crises. As rumor studies tell, it is a spontaneous collective information processing behavior "to make sense of an unclear situation or to deal with a possible threat" (DiFonzo and Bordia 2007, p. 771). However, given that collective information diffusion and processing essentially go parallel with the collective sense-making process in the Twitter space, citizen reporting cannot lead to successful sense making without a sufficient number of messages being supported with trusted sources. This means that, unlike the mainstream media where professional reporters check information sources before publication, the shortage of reliable information in the social media space may be more likely to lead to questions seeking information, doubts expressing suspicions, subjective interpretations, or rumors.

Another important finding is that, contrary to the traditional rumor research in the offline context, the results in Table 3 show that the effect size of anxiety on rumoring is much lower than that of source ambiguity. As Rosnow's (1991) meta-analytic exploration of rumor studies shows, traditional rumor researchers have consistently reported that anxiety is normally the most influential rumormongering factor. However, in our case, the influence of anxiety (ranging from 1.299 to 1.59 in its coefficient values) on rumor was much lower than that of source ambiguity (ranging from 4.001 to 4.523 in its coefficient values).

[9]For example, "*Fact or fiction? Indian gov't trying to stop tweets about Mumbai?*" (from the Mumbai terrorist attacks data), or "*How does this make sense? Suspect [in] downtown was blond and suspect on Roosevelt was brown haired?*" (from the Seattle shooting incident Twitter data).

[10]"*#mumbai The terrorist attacked a hospital for women and children and took patients hostage*" (from the Mumbai terrorist attack data); "*Toyota Moving Forward With Recall, Multiple Factories Closed*" (from the Toyota recall data).

This reversed influence can be described by the characteristics of social relations and their attendant communication patterns, which are propelled by different modes of community. Traditional rumor studies have been built upon the idea of territorial community. That is, as triggers of rumor transmission, rumor theory has maintained that social crises cause collective anxiety and ambiguous situations, which are commonly experienced by people living in the adjacent territorial boundary of the crisis stricken community (Allport and Postman 1947; Festinger 1962; Shibutani 1966). Therefore, when rumor theorists argue that rumors tend to "avoid crossing social barriers and therefore have a restricted circulation" (Allport and Postman 1947, p. 35) or it cannot travel without social support (Festinger 1962), they assume a territorial community in close proximity, which is somehow sustained by repeated social relations, some level of affective trust, and enduring shared values. Therefore, the tightly knit territorial community is likely to impose social influences to accept the received message without checking facts or the source of the ambiguous information (Garrett 2011). That means, people tend to trust information they receive from those they know, and replace with affective trust their disbelief in the received information, even when its source is ambiguous. Therefore, in the traditional territorial community supported by affective trust and preexisting social relations, shared anxiety may have been the more important rumor-causing factor, compared to source ambiguity.

However, communication through the virtual space of Twitter has very different characteristics in terms of social relations and communication modes especially under social crises. As Twitter communications are rapidly improvised in response to the social crises, territorial community boundary, preexisting social ties, social influence, shared anxiety, and affective trust may be very weak or even almost absent. It is highly likely that (1) Twitter communication on the Mumbai terrorist attacks was improvised at the national level, (2) Twitter communication on the Seattle shooting incident was mainly made at the Seattle community level, and (3) Twitter communication on the Toyota recall case may not even imply any traits of traditional territorial community. Instead, they might have gathered on Twitter with temporary crisis issues to seek and share information on the unfolding crisis situations. Therefore, compared to the territorial community, the virtual Twitter space might have been an improvised, loose community where social relations are weak, affective trust is low, and hence little social pressure to accept ambiguous information. In other words, as the Twitter community has weaker social pressures, Twitter users do not easily accept dubious reports with ambiguous sources. A few exemplary tweet messages that express distrust for unreliable information are as follows:

> "*wish that people wouldn't clutter @mumbai with stupid speculation and half-baked opinions*" (from Mumbai terrorist attack data).
>
> "*I'm seeing conflicting information about how many are dead from #RooseveltShooting – is it 2,3, or 4? Male or female?*" (from Seattle shooting incident data).
>
> "*Is it true that the Lexus engine will explode? Who said that?*" (from Toyota recall data).

However, although aspects of the virtual community are dominant in Twitter, it does not necessarily mean that territorial traces are completely erased in a virtual community. The traces of territorial community are represented in the personal involvement statements[11] in that those statements may have been posted by Twitter users who were in close proximity to the physical location of Mumbai or Seattle.[12] However, the fact that the effect of personal involvement on rumor (from 1.401 to 2.151) is much lower than that of source ambiguity (from 4.001 to 4.532) shows that, in aggregate, the Twitter space is dominated by the virtual characteristics of online community.

As to social ties, which were measured by directed messages, we could not find its effect on rumors, hence H4 is rejected. According to our close reading of directed messages, the main reason for the insignificance of H4 is that online users used directed messages primarily to ask about personal safety, share anxious feelings with their acquaintances, and for short chats. It was very rare to use directed messages for situational information gathering and dissemination, hence they did not lead to rumor dissemination.

Finally, it is noteworthy to mention the result of descriptive statistics in Table 4. First, the very low frequency of anxiety in the Toyota recall data (2.20%), compared to that of the Mumbai terrorist attacks (22.35%) and the Seattle shooting incident (16.03%), confirms the insights of early rumor researchers that community crises (like war, terrorist attack, or natural disaster) involve high levels of anxiety at the community level (Allport et al. 1947; Oh et al. 2011; Oh et al.

[11]"*hearing navy sounds at the helipad near my house …*" (from Mumbai terrorist attack data); "*Dueling helicopters above our house. Shooting suspect was shot and killed. Which shooting is unknown. #downtownshooting #rooseveltshooting*" (from Seattle shooting incident data).

[12]Our appreciation goes to an anonymous reviewer who suggested the personal involvement variable.

Table 4. Frequency and Percentage of Each Variable of Different Social Crises

	Mumbai Terror 2008	Toyota Recall 2010	Seattle Shooting 2012
	Frequency (%) Percent	Frequency (%) Percent	Frequency (%) Percent
Rumor	1211 (34.61%)	1133 (32.38%)	649 (18.54%)
Anxiety	782 (22.35%)	77 (2.20%)	561 (16.03%)
Source Ambiguity	1670 (47.73%)	2136 (61.05%)	1512 (43.20%)
Content Ambiguity	537 (15.35%)	131 (3.74%)	163 (4.66%)
Personal Involvement	987 (28.21%)	69 (1.97%)	298 (8.51%)
Social Ties	1112 (31.78%)	63 (1.80%)	86 (2.46%)
Sample Size	**3,500**	**3,500**	**3,500**

2010; Rosnow et al. 1976; Shibutani 1966). Given that the Toyota recall case is more about a business crisis that is not attached to a physical community, it is understandable that the frequency of anxiety is very low (2.2%), and the effect of anxiety on rumor is only marginal at $p < .1$, but the effect of source ambiguity on rumor is very high at $p < .01$. It implies that, different from other community crisis situations, rumors under business crisis tend to be driven primarily by information problems and very marginally by collective anxiety. We can infer this reason from the fact that, while citizens facing the Toyota recalls have alternatives of not purchasing or not using the Toyota products, community crises like the Mumbai terrorist attacks and the Seattle shooting incident do not offer alternatives for citizens other than fleeing their communities. In addition, relative to the Toyota recall data (1.97%), the higher frequency of personal involvement in the cases of the Mumbai terrorist attacks (28.21%) and the Seattle shooting incident (8.51%) reveals that community disasters are more likely to exert direct effects on community members to consider them as personal problems. For the same reason, it is no wonder that the frequency of anxiety is lowest in the business crisis of the Toyota recall case.

Comparison of the two different community crises of the Mumbai terrorist attacks and the Seattle shooting incident show different patterns of communication. The frequencies of all variables (rumor, source ambiguity, personal involvement, anxiety, content ambiguity, and social ties) in the large-scale Mumbai terrorist attacks are consistently higher than the corresponding frequencies in the local scale of the Seattle shooting incident. As detailed in the previous section on the backgrounds of the three crises, the different frequencies reflect the differences in scales and impacts of the two community crises.

Theoretical Contributions

By extending the traditional rumor theory to the social media context, we identified key variables (source ambiguity, personal involvement, and anxiety) that explain rumor dissemin- on Twitter during diverse crisis events: the Mumbai terrorist attacks, the Seattle shooting incident, and the Toyota recalls.

The findings of our study reveal interesting patterns of collective information processing, similar to those observed in offline contexts in prior research, yet with different modes, scale, and implications. This result is contrary to findings of traditional rumor research in which anxiety is normally considered the most influential factor in rumor spread. To explain the changed order of influences on rumors in the Twitter space, we contrasted two different types of community: a tightly knit territorial community and an improvised virtual community for temporal emergency situations. Our interpretation is that, while the traditional territorial community replaces disbelief with affective trust for the ambiguous information, the improvised virtual community executes cognitive distrust for ambiguous information to understand uncertain situations and to reduce cognitive ambiguity. Also, the descriptive statistics in Table 4 confirmed that, while information of ambiguous provenance is a general rumor causing factor across business and community crises, the business crisis of the Toyota recalls show much lower levels of anxiety than the other two community crises in their collective reporting.

Practical Contributions

Many rumor researchers have warned that, unless properly managed, negative rumors can decrease morale and increase distrust in the capacity of the organization and government to protect their customers and citizens (Allport and Postman 1947; Rosnow and Fine 1976). Symptoms of these deleterious effects were actually visible in our data set as well:

> "*from karmayog #mumbai We are witnessing a lack of leadership from elected or appointed public representatives, bureaucrats, spiritual leader*" (from the Mumbai terrorist attack data).

> "*The mayor of #Seattle is a complete idiot. Guns don't kill people, people kill people.#fb*" (from the Seattle shooting incident data).

> "*Dear Toyota, it would be easier to let us know which cars we can keep as it seems like almost all of them has been recalled*" (from the Toyota recall data).

As Rosnow (1991) suggests, one important task for crisis response is to control rumors and obtain and distribute local and reliable information to the affected community as early as possible. The fact that source ambiguity is the most important rumor-causing factor across business and community crises provides an important implication for such responses. Under crisis situations, if there are too many situation reports with ambiguous or no information source, then we can surmise that rumor mills are being constructed. It may be a strong signal that people are desperately searching and sharing situational information through their social networks but without reliable information from authoritative sources.

We believe that emergency response teams, in firms or governments, need to understand the crisis communication patterns and rumormongering conditions. The descriptive statistics in Table 4 indicate that the low frequency of anxiety (2.20%) and high frequency of source ambiguity (32.38%) in the Toyota recall suggests that firms in a business crisis should pay attention to information issues to control rumor dissemination. In contrast, in cases of community disasters, emergency responders need to make extra efforts to distribute reliable information and, at the same time, control collective anxiety in the community to suppress rumor spread. That means, if unambiguous and localized situational information is not provided to the affected community in a timely manner, their collective information processing is very likely to encourage rumors. Therefore, emergency response teams need to put in place prompt response systems to refute the wrong information and provide citizens with timely, localized, and correct information through multiple communication channels such as website links, social network websites, RSS, e-mail, text message, radio, TV, or Retweets. In fact, given that the motivation of rumoring is fundamentally to deal with a possible threat (DiFonzo and Bordia 2007), provision of timely and certain information may lead to successful threat management in partnership with voluntary online citizens.

Future Research and Conclusion

To the best of our knowledge, this study is the first application of rumor theory to social media and community intelligence. As a result, our suggested model needs replication and refinement in different social media contexts. Further, as we coded all variables as binary data types, there could be information loss during coding and analysis. It was, however, an inevitable choice in the situation that coders should manually read and code all data of tweet texts for all variables. To overcome this limitation, development and use of richer measurement scales for all variables would be beneficial. Future studies can combine archival data of social media with survey response data of online users who are involved in social reporting under different crisis situations.

As the former national incident commander, Thad Allen, testified, it is almost certain that "there will never be a major disaster that won't involve public participation" (Berinato 2010, p. 78). This offers many opportunities for the IS community to contribute in solving crisis problems in business and society. Among many, we suggest two promising research opportunities.

First, unlike human response in traditional business contexts, much human response during crises is reflexive. Therefore, evidence from prior extreme events should be used to guide interventions and agency response during social crises. In the past, such research has been hampered by the lack of proximate data from social crises. However, the introduction of Twitter and other social media services has provided researchers with a precious window of data on information processing by concerned respondents, usually in the immediate aftermath of crisis incidents. In this regard, analysis of social media data on social crises will offer invaluable insight to enhance individual and institutional capability to monitor and identify threats, needs, and opportunities to solve many crisis problems.

Second, although many pundits have portrayed rosy pictures about the potential of online crowds for collaborative problem solving (Kazman and Chen 2009; Surowiecki 2005; Tapscott and Williams 2006), less attention has been paid to the information quality issues in the context of citizen-centric social media technologies. However, given that information quality and the perceived trust on online information are critical success factors for e-commerce (Gefen et al. 2008) and information systems (DeLone and McLean 2003), the quality of social information produced by a multitude of social media users is likely to determine the success of collaborative problem solving by the voluntary online public, especially under social crisis situations. This study will be a good starting point to understand the issue of social information quality.

Acknowledgments

The authors would like to thank the senior editor, associate editor, and the review team for their encouragement. We thank the referees for comments that have greatly improved the lucidity of the paper. We are also indebted to Stefan Stieglitz and Nina Krüger for making available the Toyota data set. We also thank the following for research assistance during the course of this study: Sahana Aranha, Sandesh Badarayani, Chris Bang, Masuma Dinani, Sathyanarayanan Gopalakrishnan, Shruti Jain, Yuvaraj Kondaswamy, Wen Luo, Himanshu Maheshwari, Srikanth Parameswaran, Shama Pillai, Lavanya Rao, Harish Shankara, Srikanth Venkatesan, Clayton Whitelaw, and Jinsoo Yeo. Finally, we also express our deep gratitude to Larry Brandt who set us off on this path. We acknowledge the National Science Foundation (NSF) for supporting this research in part through awards IIS 0926376, 0916612, 1134853 and 1227353. The usual NSF disclaimer applies. For this research, the last (corresponding) author was also supported by the World Class University program funded by the Ministry of Education, Science, and Technology through the National Research Foundation of Korea (R31-20002) and by the Sogang University Research Grant of 2011. We would like to dedicate this paper to all those who lost their lives in the 2008 Mumbai terrorist incident and the Seattle shooting incident of 2012.

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About the Authors

Onook Oh is an assistant professor with the Information Systems and Management Group at Warwick Business School, University of Warwick. His research interests are in the areas of new modalities of information exchange and social media, crowdsourcing, open collaboration, and use of social media in information assurance and extreme events. His papers have been published or are forthcoming in *Communications of AIS, Information Systems Frontiers, AIS Transactions on Human-Computer Interaction*, and *Information Systems Management*. He has also presented his papers at major national and international IS conferences. He completed his Ph.D. at SUNY Buffalo.

Manish Agrawal is an associate professor in the department of Information Systems and Decision Sciences of the College of Business Administration at the University of South Florida, Tampa, Florida. His current research interests include information security, software quality, and the use of IT during extreme events. His articles have appeared or are to appear in journals including *Management Science, Journal of Management Information Systems, MIS Quarterly, INFORMS Journal on Computing*, and *IEEE Transactions on Software Engineering*. His research received the Design Science Award from the INFORMS Information Systems Society. He completed his Ph.D. at SUNY Buffalo.

H. R. Rao (corresponding author) is a Distinguished Service Professor in the department of Management Science and Systems at SUNY Buffalo, with a courtesy appointment with Computer Science and Engineering as adjunct professor, and World Class University Visiting Professor in the Department of Global Service Management at Sogang Univeristy, South Korea. His interests are in the areas of management information systems, e-business, emergency response management systems, and information assurance. He received a Fulbright fellowship in 2004. His research is supported by the National Science Foundation and the Department of Defense. Dr. Rao has served as coeditor of special issues of *The Annals of Operations Research* and *Communications of the ACM*, as associate editor for *Decision Support Systems, Information Systems Research, ACM Transactions on MIS*, and *IEEE Transactions on Systems, Man and Cybernetics*, and coeditor-in-chief of *Information Systems Frontiers.* He has published over 150 papers in journals including *Decision Support Systems*, *Information Systems Research*, *ACM Transactions on MIS*, and *IEEE Transactions on Systems, Man and Cybernetics*. He completed his Ph.D. at Purdue University.

Appendix A

Coding Scheme

Variable	Definition	Data Type
Rumor (DV)	A Twitter message which does NOT explicitly indicate a person (e.g., the prime minister of Indian government), source (e.g., BBC, NDTV, website, etc.), context or known data to serve as a proof or verification for the message. The message MUST be topically relevant to the incidents under this study (Mumbai terrorist attack, Toyota recalls, and Seattle shooting incident), and it MUST refer to an object, person, or situation rather than an idea or theory (Bordia 1996; Buckner 1965; Rosnow et al.1988; Rosnow and Kimmel 2000). **Examples** 1. "stock markets a bit up n down. The Sensex has always risen after terror attacks in 1993 and 2006. Hope so this time too!" (coded as "1," indicating a rumor) 2. "Metro cinema attacked by grenades. All were killed b4 nsg [National Security Guard, authors added] storming" (coded as "1," indicating a rumor) 3. "Injured reports rise from 185 to 187 now. #mumbai CNN.com" (coded as "0," indicating not a rumor)	Binary
Source Ambiguity (IV)	A Twitter message which does not contain an external source (such as name of media or links to external media, video, picture, etc.) or/and a Twitter message that expresses distrust and/or ambiguity about the source. **Examples** 1. "#Mumbai IDesiTV.com Video stream link http://idesitv.com/starnews.php. Very <u>*spotty*</u> info about Oberoi/Trident and Santa Cruz Airport." (coded as "1," indicating that the message expresses ambiguity about the source) 2. "more hostages at the Cama hospital - #Mumbai" (coded as "1," indicating that the message does not provide information source) 3. "Live twitter news feed for Mumbai attacks http://tinyurl.com/6b4wjj" (coded as "0," indicating that the information source is not ambiguous)	Binary
Anxiety (IV)	A Twitter message "that express rumor related fear, dread, anxiety or apprehension, and statement that express a 'threatened' feeling" (Bordia 1996). **Examples** 1. "*Scared* to sleep not knowing what i'll wake up to #mumbai" (coded as "1") 2. "How will India bounce back? *Sadly* I have no faith in the leadership to take control and stop these heinous acts!" (coded as "1") 3. "Good going by the NSG .... we are proud of what you did in #mumbai ..." (coded as "0," indicating no anxious feeling)	Binary
Personal Involvement (IV)	A Twitter message "that describe[s] experiences of the person, in the context of the rumor" (Bordia 1996, p. 22). A Twitter message that expresses that s/he is personally involved in, committed to, or has some relationship to the event (McPhail 1991, p. 77). **Examples** 1. "hearing navy sounds at the helipad *near my house* ... still 90+ snaps to be uploaded. plan to catch up on TV now!" (coded as "1") 2. "im locked inside Vitthals restaurant with a few frnds. shutters down . this is *as close as* i can get to the action #mumbai" (coded as "1") 3. "Still blown away by the twitter response to Mumbai" (coded as "0")	Binary

Variable	Definition	Data Type
Content Ambiguity (IV)	A Twitter message that expresses ambiguity or distrust about the Twitter message content. A Twitter message that expresses that the given information is conflicting in nature. A Twitter message for which a person expresses distrust or confusion (Allport and Postman 1947). "Questions seeking information. This category does not include sarcastic remarks or persuasion attempts" (Bordia 1996). **Examples** 1. "Just received SMS/calls with info on further shootings in Marine Lines, Fountain and Princess Street; rumors? or true? #Mumbai" (coded as "1") 2. "what is #mumbai wisdom? Number of terrorists? No captured? No killed?" (coded as "1") 3. "Interview of Navy commando's in CNN IBN" (coded as "0")	Binary
Social Ties (Directed Messages) (IV)	A Twitter message directed to specific user account. **Examples** 1. "@xxxx @yyyyy Nick, apparently yes. For latest Mumbai tweets: http://tinyurl.com/55h2m8" (coded as "1") 2. "@yyyy is your family safe?" (coded as "1")	Binary

MIS Quarterly

SPECIAL ISSUE: DIGITAL BUSINESS STRATEGY

HOW A FIRM'S COMPETITIVE ENVIRONMENT AND DIGITAL STRATEGIC POSTURE INFLUENCE DIGITAL BUSINESS STRATEGY

Sunil Mithas
Robert H. Smith School of Business, University of Maryland, Van Munching Hall,
College Park, MD 20742 U.S.A. {smithas@rhsmith.umd.edu}

Ali Tafti
College of Business, University of Illinois at Urbana-Champaign,
Champaign, IL 61820 U.S.A. {atafti@illinois.edu}

Will Mitchell
Rotman School of Management, University of Toronto, Toronto, ON CANADA {william.mitchell@rotman.utoronto.ca}
and Duke University, Durham, NC 27708 U.S.A. {will.mitchell@duke.edu}

Appendix

Table A1. Firm Performance Model Showing the Effect of Current Year IT Investments on Tobin's q (Dependent Variable Is Tobin's q). Random Effects Panel Regression.

	(1) Tobin's q
IT_STRATPOSTURE (Industry Norm Minus Firm's IT investments)	-0.710 (1.517)
IT (current year)	3.653*** (1.182)
IT × INDTURB	-76.62*** (17.91)
IT × HHI	-16.12 (16.43)
IT × INDGROWTH	82.85** (36.89)
IT × COMPUNC	-14.77 (24.44)
Industry Turbulence (INDTURB)	-0.456 (0.950)
Herfindahl-Hirschman Index (HHI)	-0.754 (1.013)
Industry Growth (INDGROWTH)	6.640*** (2.227)
Competitive Uncertainty (COMPUNC)	0.913 (0.613)
Lag Investment (IT)	-1.249 (1.709)
Related Diversification	-2,901** (1,167)
Firm size: Log(Employees)	-0.0970 (0.0613)
ADV	-0.00294 (0.0378)
RD	-0.0404** (0.0204)
Tobin's q Industry Avg.	0.565*** (0.217)
Observations	1,018
Number of Firms	335
Hausman test comparison with Fixed Effects	8.93 (p = 0.78)
R^2	0.22
Wald χ^2	196.3***

Robust standard errors in parentheses; ***p < 0.01; **p < 0.05; *p < 0.10

The estimated model includes an intercept, physical capital intensity, market share, an indicator variable for regulated industry, and indicator variables for year and industry. Variables in interaction terms are mean centered. We rescaled several variables to produce meaningful coefficient decimal places: Competitive uncertainty (× 100), industry growth (× 10), free cash flow (× 10,000), related diversification (× 10,000). The Hausman test statistic suggests no significant difference from fixed-effects panel estimates.

Table A2. Effect of Outsourcing Strategic Posture on IT Investments (Dependent Variable Is IT Investments). OLS Regression Estimates.

	(1) IT Investments
OS_STRATPOSTURE	0.000573* (0.000313)
OS_STRATPOSTURE × INDTURB	-0.00145 (0.00206)
OS_STRATPOSTURE × HHI	-0.00100 (0.00128)
OS_STRATPOSTURE × INDGROWTH	-0.00182 (0.00341)
OS_STRATPOSTURE × COMPUNC	0.000786 (0.00316)
Industry Turbulence (INDTURB)	0.0218 (0.0308)
Herfindahl-Hirschman Index (HHI)	0.0120 (0.0169)
Industry Growth (INDGROWTH)	0.0144 (0.0471)
Competitive Uncertainty (COMPUNC)	0.0124 (0.0360)
Lag Investment (Outsourcing)	0.000590* (0.000335)
Related Diversification	-40.39** (18.71)
Firm size: Log(Employees)	0.00281*** (0.000900)
Market share	-0.0578*** (0.0209)
Observations	519
R^2	0.219
F stat	6.657***

Robust standard errors in parentheses. ***p < 0.01; **p < 0.05; *p < 0.10

The estimated model includes an intercept, free cash flow, and indicator variables for year and industry. Variables in interaction terms are mean centered. We rescaled several variables to produce meaningful coefficient decimal places: Competitive uncertainty (× 100), industry growth (× 10), free cash flow (× 10,000), related diversification (× 10,000).

Table A3. Seemingly Unrelated Regression (SUR) Estimates

Positive coefficient on IT_STRATPOSTURE or OS_STRATPOSTURE suggests convergence in IT investment or outsourcing, respectively; negative coefficient suggests divergence; positive interaction effects suggest stronger convergence due to environmental factors; and negative interactions suggest stronger divergence due to environmental factors.

	(1) IT Investment	(2) Outsourcing Pct. of IT
IT_STRATPOSTURE × INDTURB (H1 -)	-6.156*** (1.078)	
IT_STRATPOSTURE × HHI (H2 +)	-0.102 (0.701)	
IT_STRATPOSTURE × INDGROWTH (H3 +)	5.908*** (1.520)	
IT_STRATPOSTURE × COMPUNC	-2.485*** (0.707)	
OS_STRATPOSTURE × INDTURB (H1 -)		1.769 (1.313)
OS_STRATPOSTURE × HHi (H2 +)		0.673# (0.461)
OS_STRATPOSTURE × INDGROWTH (H3 +)		4.540*** (1.579)
OS_STRATPOSTURE × COMPUNC		1.233 (1.234)
Industry Turbulence (INDTUR)	0.0524* (0.0290)	20.77 (17.40)
Herfindahl-Hirshman Index (HHI)	-0.00292 (0.0179)	-24.85** (10.86)
Industry Growth (INDGROWTH)	-0.0174 (0.0390)	-38.69* (23.37)
Competitive Uncertainty (COMPUNC)	0.0115 (0.0285)	-8.715 (16.83)
Lag Investment (IT)	0.943*** (0.0596)	
Firm Size: Log(Employees)	0.00120 (0.000728)	0.0716 (0.433)
Related Diversification	0.668 (19.46)	21,839* (11,828)
Free Cash Flow	-0.00375 (0.00493)	3.758 (2.998)
Market Share	-0.0276 (0.0187)	12.13 (11.14)
IT_STRATPOSTURE (IT Strategic Posture)	0.0744 (0.0521)	
OS_STRATPOSTURE (Outsourcing Strategic Posture)		-0.0715 (0.0570)
Lag Investment (Outsourcing)		0.661*** (0.0632)
Observations	406	406
R^2	0.729	0.609
F stat	42.10***	24.51***

Standard errors in parentheses. ***p < 0.01; **p < 0.05; *p < 0.10; #p < 0.10 (one-tail)

The estimated models include an intercept and indicator variables for year and industry. Variables in interaction terms are mean centered. We rescaled several variables to produce meaningful coefficient decimal places: Competitive uncertainty (× 100), industry growth (× 10), free cash flow (× 10,000), related diversification (× 10,000).

Table A4. Robustness Checks (Including Controls for Diversification and Number of Industry Segments) Fixed-Effects Panel Regressions. Dependent Variable Is IT Investment.

	(1)	(2)	(3)	(4)	(5)
β_1: IT_STRATPOSTURE × INDTURB (H1 -)	-5.944*** (0.619)	-7.399*** (0.598)	-7.274*** (0.599)	-5.306*** (0.603)	-7.994*** (0.609)
β_2: IT_STRATPOSTURE × HHI (H2 +)	1.137* (0.642)	-0.104 (0.586)	-0.633 (0.631)	0.435 (0.624)	-0.392 (0.585)
β_3: IT_STRATPOSTURE × INDGROWTH (H3 +)	4.809*** (1.195)	3.018*** (1.139)	2.616** (1.151)	4.569*** (1.206)	3.029*** (1.129)
IT_STRATPOSTURE × COMPUNC	-4.344*** (0.818)	-2.177*** (0.781)	-2.508*** (0.793)	-5.608*** (0.758)	-2.110*** (0.770)
IT_STRATPOSTURE	0.0352 (0.0530)	-0.000771 (0.0479)	0.0320 (0.0500)	0.111** (0.0498)	0.0158 (0.0471)
NUM_SEGMENTS				0.000500 (0.00137)	0.000468 (0.00127)
IT_STRATPOSTURE × NUM_SEGMENTS					-0.128*** (0.0114)
TOTALDIVERSE		0.00861 (0.00532)	0.00863 (0.00530)		
IT_STRATPOSTURE × TOTALDIVERSE		-0.400*** (0.0381)	-0.459*** (0.0462)		
RELDIVERSE	-0.000799 (0.00636)	-0.00847 (0.00711)	-0.00968 (0.00712)	-0.00341 (0.00666)	-0.00202 (0.00619)
IT_STRATPOSTURE × RELDIVERSE	-0.272*** (0.0693)		0.177** (0.0794)		
INDTURB	0.0476* (0.0261)	0.0359 (0.0247)	0.0341 (0.0247)	0.0486* (0.0265)	0.0360 (0.0246)
HHI	0.202*** (0.0686)	0.173*** (0.0657)	0.164** (0.0657)	0.197*** (0.0695)	0.152** (0.0648)
INDGROWTH	0.0812** (0.0409)	0.0702* (0.0388)	0.0691* (0.0387)	0.0795* (0.0415)	0.0667* (0.0386)
COMPUNC (competitive uncertainty)	-0.00738 (0.0240)	-0.00975 (0.0227)	-0.00782 (0.0227)	-0.00200 (0.0242)	-0.00800 (0.0225)
1 yr Lag IT Investment	0.462*** (0.0657)	0.353*** (0.0603)	0.390*** (0.0624)	0.568*** (0.0606)	0.425*** (0.0577)
Firm size: Log(Employees)	0.000692 (0.00286)	-0.00131 (0.00272)	-0.00136 (0.00271)	0.00118 (0.00289)	-0.00138 (0.00269)
Free Cash Flow	-0.00358 (0.00524)	-0.00463 (0.00497)	-0.00469 (0.00496)	-0.00311 (0.00530)	-0.00502 (0.00493)
Market share	-0.0958 (0.0599)	-0.0725 (0.0572)	-0.0663 (0.0572)	-0.0948 (0.0606)	-0.0634 (0.0564)
Observations	1,225	1,225	1,225	1,225	1,225
E^2	0.530	0.580	0.583	0.521	0.587
Number of firms	400	400	400	400	400
F stat	47.90***	55.65***	53.50***	46.23***	57.13***

Standard errors in parentheses. ***$p < 0.01$; **$p < 0.05$; *$p < 0.10$

The estimated models include an intercept, and indicator variables for year and industry. Variables in interaction terms are mean centered. We rescaled several variables to produce meaningful coefficient decimal places: Competitive uncertainty (× 100), industry growth (× 10), free cash flow (× 10,000), related diversification (× 10,000).

Table A5. Robustness Checks (Controlling for Current Year and Prior Year Performance) Fixed-Effects Panel Regressions. Dependent Variable I IT investment.

	(1)	(2)	(3)	(4)
Tobin's Q (current year)		0.00101 (0.000745)		0.00101 (0.000753)
Tobin's Q (prior year)			1.42e-05 (0.000145)	-6.29e-06 (0.000149)
β_1 : IT_STRATPOSTURE × INDTURB (H1 -)	-5.291*** (0.601)	-5.327*** (0.637)	-5.336*** (0.638)	-5.328*** (0.639)
β_2 : IT_STRATPOSTURE × HHI (H2 +)	0.443 (0.623)	0.489 (0.670)	0.486 (0.670)	0.501 (0.674)
β_3: IT_STRATPOSTURE × INDGROWTH (H3 +)	4.546*** (1.203)	4.397*** (1.278)	4.415*** (1.280)	4.401*** (1.282)
IT_STRATPOSTURE × COMPUNC	-5.618*** (0.757)	-5.824*** (0.813)	-5.803*** (0.814)	-5.831*** (0.817)
IT_STRATPOSTURE	0.111** (0.0498)	0.109** (0.0530)	0.110** (0.0531)	0.110** (0.0533)
INDTURB	0.0478* (0.0263)	0.0636** (0.0311)	0.0640** (0.0311)	0.0636** (0.0313)
HHI	0.195*** (0.0692)	0.207*** (0.0774)	0.211*** (0.0774)	0.209*** (0.0780)
INDGROWTH	0.0812** (0.0413)	0.0825* (0.0467)	0.0878* (0.0467)	0.0823* (0.0469)
COMPUNC	-0.00242 (0.0242)	-0.00299 (0.0287)	-0.000133 (0.0289)	-0.00250 (0.0292)
1 yr Lag IT Investment	0.567*** (0.0605)	0.552*** (0.0648)	0.552*** (0.0650)	0.552*** (0.0651)
Firm size: Log(Employees)	0.00121 (0.00288)	0.000366 (0.00323)	2.85e-05 (0.00322)	0.000365 (0.00324)
RELDIVERSE	-27.39 (64.00)	-27.73 (71.52)	-26.16 (72.59)	-26.71 (72.87)
Free Cash Flow	-0.00324 (0.00529)	-0.00335 (0.00586)	-0.00367 (0.00791)	-0.00299 (0.00813)
Market share	-0.0935 (0.0604)	-0.0948 (0.0652)	-0.0928 (0.0650)	-0.0957 (0.0656)
Observations	1,225	1,071	1,066	1,062
R^2	0.521	0.526	0.525	0.526
Number of firms	400	348	344	343
F stat	48.84***	41.04***	40.84***	38.72***

Standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.10

The estimated models include an intercept, and indicator variables for year and industry. Variables in interaction terms are mean centered. We rescaled several variables to produce meaningful coefficient decimal places: Competitive uncertainty (× 100), industry growth (× 10), free cash flow (× 10,000), related diversification (× 10,000).

Table A6. Using Rolling Averages of Strategic Posture Fixed-Effects Panel Regressions. Dependent Variable Is IT Investment.

	(1) Base Model Same as Column 2 of Table 3	(2) Using Two-Year Rolling Average for IT Strategic Posture
β_1: IT_STRATPOSTURE × INDTURB (H1 -)	-5.291*** (0.601)	
β_2: IT_STRATPOSTURE × HHI (H2 +)	0.443 (0.623)	
β_3: IT_STRATPOSTURE × INDGROWTH (H3 +)	4.546*** (1.203)	
IT_STRATPOSTURE × COMPUNC	-5.618*** (0.757)	
IT_STRATPOSTURE	0.111** (0.0498)	
INDTURB	0.0478* (0.0263)	0.00915 (0.0275)
HHI	0.195*** (0.0692)	0.114* (0.0674)
INDGROWTH	0.0812** (0.0413)	0.0202 (0.0411)
COMPUNC	-0.00242 (0.0242)	0.0237 (0.0240)
IT	0.567*** (0.0605)	0.572*** (0.0546)
Firm size: Log(Employees)	0.00121 (0.00288)	0.00397 (0.00306)
RELDIVERSE	-27.39 (64.00)	-7.816 (67.70)
Free Cash Flow	-0.00324 (0.00529)	-0.00446 (0.00815)
Market share	-0.0935 (0.0604)	-0.0599 (0.0637)
SP 2 yr rolling × INDTURB		-5.979*** (1.801)
SP 2 yr rolling × HHI		-0.592 (0.785)
SP 2 yr rolling × INDGROWTH		13.42*** (1.969)
SP 2 yr rolling × COMPUNC		-2.634** (1.295)
SP 2 yr rolling = Avg(IT_STRATPOSTURE (t - 1), IT_STRATPOSTURE)		-0.302*** (0.0792)
Observations	1,225	731
R^2	0.521	0.628
Number of firms	400	273
F stat	48.84***	43.83***

Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

The estimated models include an intercept, and indicator variables for year and industry. Variables in interaction terms are mean centered. We rescaled several variables to produce meaningful coefficient decimal places: Competitive uncertainty (× 100), industry growth (× 10), free cash flow (× 10,000), related diversification (× 10,000).