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Utilizing Facebook Application for Disaster Relief: Social Network Analysis of American Red Cross Cause Joiners

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by

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Dedication

I dedicate my thesis to the memories of my beloved grandmother, Wong Mu-Chun, and my dear friend, Wong Ching-Man. I am utmost indebted to my grandmother for her selfless sacrifice to afford me the better opportunities in life – my life has been infinitely enriched by her unconditional love and unwavering support. Thank you, mah mah. I am also deeply grateful for my long-standing friendship with Ching-Man – she will always be my anchor for resilience through the challenging times. I miss you, my dear friend. The completion of my thesis would not have been possible without the ongoing reminders of their strength and endurance.

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Abstract

With the exponential growth of Facebook users worldwide, this platform for social network online has become a powerful tool to connect individuals and share information with each other. This study explores the phenomenal trend of utilizing a Facebook application called Causes to help users organize into online communities for a specific cause and mobilize their resources for disaster relief during the Haiti earthquake disaster. Two separate samples of 100 joiners each from the American Red Cross (ARC) Cause on Facebook were randomly selected before and after the Haiti earthquake disaster to examine the differences of the composition (i.e., attributes) and structure (i.e., relational ties) of each social network. The social network analysis performed for this thesis research intends to fill the gap of historical research literature on recruitment to activism and support provision following a disaster in the digital age of the 21st century. The results of this study show how understanding the membership size of online communities, salient identity for the cause through organizational affiliations, interpersonal ties among the joiners, density of the network as well as gender diversity can be crucial recruitment factors to leverage for disaster relief efforts. The findings reveal a beneficial partnership between disaster relief organizations and online social networks in mobilizing their resources for a speedy response to disasters.

Chapter 1: Introduction

In recent years, the Internet has offered researchers with access to massive samples, instantaneous communication, expedient data collection, 24-hour accessibility, lower cost for research, automatic categorizing of survey data, etc. in studying an organic community outside of the traditional (physical) environment (Christians & Chen, 2004). These advantages of data collection and processing in the digital age afford social researchers with limited resources to study the growing online communities. It also presents a unique opportunity for social researchers to study how popular social networks on the Internet, such as Facebook, can mobilize their users for disaster relief effort in an online environment.

According to a news report by CNN (2010), U.S. relief organizations raised a record-breaking $1.3 billion in disaster relief funds within a span of six months following the January 12, 2010 earthquake in Haiti. In fact, the American Red Cross (ARC) alone raised $468 million through conventional fundraising events as well as innovative approacheses through the Internet and mobile text messages. It is undeniable the emergence of the "new media" or mass media on such digital platforms as the World Wide Web, electronic mail, chatrooms, Web-based publications, etc., introduces a new form of interaction and structure for online social networks. Consequently, these online social networks can be leveraged to mobilize their members for disaster relief efforts and the formation of disaster communities made up of victims and non-victims working towards a specific cause.

Even though online social research has continued to gain momentum in studying online communities, only a very limited number of studies focus specifically on disaster communities on the Internet. As a result, researchers are not fully aware of how online social networking Websites can be used to recruit members for social movements or to mobilize members for disaster relief. The emerging opportunities to study these online disaster communities should also generate interest in the factors that predict recruitment to online disaster relief efforts (e.g., personal attitudinal affinity, referral from friends or organizations they belong to, and relational ties). Moreover, other analytical techniques such as network analysis should also be considered in order to understand the structural properties of the network (i.e., how connected individuals are within the community they join through interpersonal or organizational ties) and the composition of the network (i.e., characteristics of the users or the organizations they belong to).

The Haiti earthquake disaster on January 12, 2010 caught worldwide attention with the magnitude of earthquakes from 6.5 to 7.3 and a death toll of over 230,000 people as estimated by the Haitian government (Associated Press, 2010). The devastation of earthquake in Haiti generated an outpouring of support for the disaster victims through both conventional and innovative means of fundraising. The advancement of technology offered the general public instantaneous ways to make donations online or by text from their mobile phones, which were the two methods ARC used to collect their donations for the Haiti disaster relief effort. Online social networks such as Facebook and Twitter also played a critical role in raising awareness of fundraising and disaster relief.

In this thesis, I plan to draw on the literatures that have examined recruitment to social movements on the one hand, and social tie activation in a disaster context, on the other, to guide my research on the formation of online disaster communities. I select the ARC Joiners of Facebook's Causes application for my research given its versatility to organize a community on the Facebook platform. The sample is limited to a random selection of joiners to the ARC Cause during a specific time period. Two separate samples of the ARC Joiners were drawn: one before the January 12^{th} earthquake in Haiti, and the other after. In each case, the joiners were randomly selected to study the structural and compositional differences of the two networks as defined by relational ties between the sampled joiners as well as the other causes to which these sampled joiners belong.

Chapter 2 begins by reviewing past research literatures on recruitment to social movements and on support provision from the disaster community. After summarizing these literatures, I provide a background overview of Facebook, including the Causes application that is used to organize the online communities. In the last sections of Chapter 2, I describe the analytical technique of social network analysis for one-mode and two-mode networks as well as the sample selection process of the Facebook members who join the ARC Cause on Facebook. Chapter 3 uses data collected from 1) members' Facebook profiles to describe the characteristics of these samples and 2) their profiles on Causes to capture all the causes they belonged to. Finally, I present the results of the social network analysis of the two samples before and after disaster. In Chapter 4, I focus on their network composition, and in Chapter 5 I focus on the two-mode network structure of ARC Joiners and their Facebook Causes. In Chapter 6, I examine the one-mode network structure of ARC Joiners and their Facebook Causes. Finally, I will discuss the implications of the findings on how they can potentially help ARC or other disaster relief organizations to tailor their recruitment efforts for disaster preparation or relief. I also comment on the study's limitations and highlight areas in which further research is needed on online disaster communities.

Chapter 2: Literature Review and Background

What factors motivates individuals to join or participate in specific causes or social movements? Is it their own ideological beliefs or their structural position for activism (e.g., education, gender, income, etc.)? Perhaps it is due to influences from other individuals or the types of organizations they belong to? If there are strong causal influences that lead to activism, is there a model of recruitment factors that can predict participation in social movements? The insights into these questions can offer emergency response organizations, such as the American Red Cross, assistance in targeting their effort in encouraging activism for disaster preparation (in the event of natural disaster when advance warning is possible) and aiding disaster victims in their recovery process. Past research on social movement analysis as well as disaster research guide the direction on what historically influenced individuals to participate in social movement or disaster relief (specifically interpersonal or organizational ties) and how such findings may have evolved in the age of online social networks.

Recruitment for Social Movements

One of the most examined research topics on social movements is differential recruitment, i.e., why do some individuals get involved while others are inactive? Some of the individual attributes cited as most correlated to activism are strong attitudinal affinity with the goal of the movement and/or set of grievances consistent with the movement ideology. However, McAdam (1986) indicated the study of social movements in the recent decades pointed to structural availability as being more important than attitudinal affinity in encouraging activism. In fact, McAdam further examined the arguments for the structural perspective by exploring the types of “prior contact” that could make a difference with activism; for example, he examined the role of informal friendship networks compared to formal organizational affiliations and the effect of "weak ties" on recruitment compared to "strong ties" in his research on the recruitment to high-risk activism of the 1964 Mississippi Freedom Summer project.

McAdam criticized movement scholars for their tendency to oversimplify the recruitment process and movement participation by not clearly distinguishing the differences between participants/non-participants, activism/inactivism and members/non-members of social movements. While it can be challenging to define the aforementioned differences, he argued that it is possible to distinguish between low risk/cost and high risk/cost forms of activism at the minimum. The reference to "cost" is related to the expenditure of time, money and energy devoted to activism; for example, signing a petition is considered a relatively low cost activity while volunteering in a movement for the homeless is a high cost activity in terms of time and energy. Also, the reference to "risk" refers to anticipated danger such as legal, social, physical, financial, and political risks. In such case, signing a petition could potentially be high risk during the McCarthyism era, but volunteering in a movement for the homeless would be relatively risk-free.

McAdam also pointed out that prior contact with a recruiting agent can be a significant factor in low risk/cost activism – the prior contact with a recruiting agent refers to the networks, relationships or communities that "pull" the individual into activism. There were three different agents he identified for the recruitment process: 1) organizations that serve as the associational network for a new movement, 2) merger of existing groups of established organizations known as "bloc recruitment" and 3) individual activists as the single activist who introduces the recruit to the movement. An example to illustrate how a prior contact with a recruiting agent pulls the individual into low risk/cost activism is the idea that a potential recruit is more likely to join a rally with a friend's urging in order to not disappoint or lose the friend's respect given the low cost/risk of the rally. However, the "biographical availability", which refers to the personal constraints such as full-time employment, marriage and family obligations, may increase the costs and risks of the movement participation using the same example of the aforementioned rally. On the other hand, the correlates of high risk/cost activism include the history for activism, deep commitment to the ideology/goals of the movement, integration into the activist networks and freedom from personal constraints that would make participation risky.

For the purpose of his research on recruitment to high-risk activism, McAdam used the 1964 Mississippi Freedom Summer project. This campaign was clearly a high risk/cost form of activism for hundreds of mostly White college students from the North to help with the civil rights movement throughout the South during a violent time when there were instances of kidnapping and murder of volunteers by renegade segregationists. Moreover, these students were asked to volunteer for two months of their summer without pay. Prior to joining the movement, these prospective volunteers were asked to complete a detailed application on their organizational affiliations, college activities, reasons for volunteering and record of any previous arrests. These applicants were then categorized into three groups: 1) rejects, 2) participants (accepted to the project and participated) and 3) non-participants (accepted to the project but later withdrew). In total, there were 1,068 applicants that included 55 rejects, 720 participants, 239 non-participants along with 54 with unknown status. McAdam used the data collected from these applications to compare the characteristics of the participants and non-participants of the high risk/cost activism of the Freedom Summer project.

McAdam studied how the various types of prior contacts may differentiate the participants from the non-participants. The participants belonged to more organizations than non-participants: specifically, participants belonged to an average of 2.4 organizations compared to an average of 1.9 organizations for non-participants. The participants were also members of more explicitly political organizations than non-participants – 50% of participants were affiliated with civil rights organizations as compared to 40% of non-participants. McAdam also studied the interpersonal ties between applicants since they were asked to provide a list of at least ten people the applicants wished to keep informed of their summer activities (as part of the public relations efforts of the project). In this exercise, the participants provided many more names of other participants or known activists than non-participants – the listing of names of other participants was twice as long and the names of the other known activists were three times as long from the participants compared to the number of names provided by the non-participants.

Finally, McAdam examined the biographical availability to measure the relative costs and risks associated with participation, and the findings did not support the hypothesis that those with less time or more personal responsibilities were less likely to participate. Three constraints of marital status, employment and education were analyzed for their relationship to participation but being married and employed full-time actually enhanced participation; and education was the only variable with negative effect on participation as anticipated – the 1964 graduates were much more likely to participate in the project than the graduate students at the time. When McAdam assessed the combination of various factors on the likelihood for the applicants to participate in the project, there were four important factors that drove participation: 1) attitudinal affinity, 2) integration into activist networks, 3) prior history of activism and 4) absence of personal constraints on participation.

In summary, McAdam's study on the recruitment factors of high risk/cost activism showed participants scored higher on both organizational and interpersonal measures of integration into activist network than non-participants. It can be interpreted from the results, that while attitudinal affinity for the movement and biographical constraint are important factors to consider, but the extent of the structural pull from prior history of activism and integration into the supportive networks best accounted for participation in the Freedom Summer project. In other words, ideological identification of the movement can lead the individual in the direction of participation and prior history of activism along with integration into the supportive networks can pull the individual into participation.

In 1988, Fernandez and McAdam teamed up and narrowed their research on the structural factors for recruitment to social movements specifically on the network contact with recruitment agents that "pull" the individuals into participation. The focus on network analysis became prominent for the study of recruitment to social movement as increasing evidence indicated the importance of structural factors such as the ties among the social movement organizations to mobilize resources. In fact, ties formed through overlapping membership among these organizations known as "multiorganizational fields" became the focus of the research for Fernandez and McAdam on the recruitment for the Freedom Summer project. Rather than studying the role of the number of social movement organizations in which the recruits were involved, they focused on the effects of the pattern of overlapping memberships in organizations on recruitment at two particular universities (i.e., University of California at Berkeley and the University of Wisconsin at Madison) that participated in the Freedom Summer project.

The activists at University of California at Berkeley (UCB) had a long history of civil rights activism, and the students recruited for the Freedom Summer project mostly came from the activist subculture. On the other hand, the University of Wisconsin at Madison (UWM) had no presence of any major civil rights organization on campus – the activist community was small and not well organized. Indeed, Fernandez and McAdam had purposely selected Berkeley and Madison because of the sharp difference between the two colleges' activist cultures. The dependent variable of the analysis was participation vs non-participation – Berkeley had 31 participants and 9 non-participants; and Madison had 10 participants and 13 non-participants. The analysis for predicting activism included two steps: 1) the use of a prominence measure (which is explained further in the next page) to examine the potential effect of structural positions of individuals within multiorganizational fields; then 2) the study of independent effects of structural positions on individual activism such as parental income, years of education, gender, past level of civil rights movement and major area of study.

The method of network analysis was also used to study the multiorganizational fields for applicants to the Freedom Summer project from these two universities. The data were limited to the 40 applicants from Berkeley and 23 applicants from Madison to examine a small-group network process in social movement. Fernandez and McAdam used the organizational affiliations listed on the application to create two people-by-organizational affiliations matrices with 23 people by 17 organizations for Madison and 40 people by 36 organizations for Berkeley. Also, people-by-people matrices were created to analyze overlapping organizational affiliations – the entries were the number of organizations each pair of individuals shared. These interpersonal ties can likely affect an individual decision to participate online for social support. Among the Berkeley applicants, the density of the organizational overlap was .166 among participants and

.055 among non-participants. Among the Madison applicants, the density of the organizational overlap was .200 among participants and .026 among non-participants. Density refers to the number of ties among the individuals as a proportion of the number of possible ties. The network among non-participants from both schools was less dense than the network among participants which demonstrated that network factors were related to participation in the Freedom Summer project amongst applicants.

In addition to measuring density, network “prominence” was also measured to describe each individual’s position in relation to other individuals in the Berkeley or Madison network. Prominence refers to a measure of centrality which distinguishes among individuals who appear to be equally central (i.e., who are tied to the same number of others in the network) on the basis of the centrality of individuals to whom they are tied. Sharing the same number of organizational affiliations is not as relevant as being linked to more centrally located individuals in the network of overlap because more central individuals are more likely to experience social influence, and therefore, are more committed to recruit others. There was a tendency for more prominent individuals in the multiorganizational fields to be participants in the Freedom Summer project for both networks in Berkeley and Madison.

Finally, the results of the independent effects of structural positions on individual activism showed the pattern of higher family income, higher mean level of past activism and male applicants tended to yield higher overall rate of participation. The recruitment model on using structural positions within the multiorganizational field to predict participation in the Freedom Summer project has important implications: the effects of structural or independent variables on participation is dependent on the overall recruitment context, and the specifics involved between structural positions and individual-level background leading to activism can be complex in developing a precise recruitment model.

McAdam and Paulsen followed up in 1993 with another research study to specify the relationship between social ties and activism given the increasing attention to social movement literature on the role of social ties in movement recruitment. They identified three sources of theoretical and empirical imprecision from the reported findings by past literatures: 1) the lack of theory in explaining the effects of social ties on activism; 2) the lack of understanding of how and why the social ties are important; and 3) the lack of acknowledgement to the extent of organizational or associational network or individual relationship that can lead social pressure in joining a movement. As a result, a recruitment model focused on interpersonal ties and membership in organizations was developed to determine the causal effects on the decision to participate in a movement. Interpersonal ties refer to knowing someone already involved in social movement activity; and membership in organizations refers to an extension of interpersonal ties through meeting people and being exposed to subsequent opportunities to be pulled into social movement activities.

McAdam and Paulsen examined these social ties in movement recruitment by studying the Freedom Summer project. In addition to using data collected from the detailed applications completed by the interested applicants about their organizational affiliations, past civil rights activities and reasons for volunteering, more information was also collected from a follow-up survey on their alma mater, parents' address, school major and other such information. A total of 212 participants and 118 non-participants completed the follow-up survey, and another 40 participants and 40 non-participants took part in the in-depth interviews for the research study.

The first area of analysis on the relationship between social ties and movement recruitment was the support applicants received for participation from parents, friends, civil rights organizations, other volunteers (i.e., participants and non-participants) and religious groups. The dependent variable was the participation of the Freedom Summer project. The independent variables were the multiple ties that may influence an individual to participate in movement as listed above. The persons reported directly on the application as individuals who “positively influenced your decision to apply to the Freedom Summer project” were coded as strong ties and those not reported by the individuals but linked to them by way of a strong tie were considered the weak ties. The results showed that the rate of participants reporting support from their parents were doubled that of non-participants, and support of strong ties from other volunteers was 75% greater than non-participants. The logistic regression predicting participation of the Freedom Summer project also showed, in the aggregate, participants did receive greater support from their parents and peers. It was also concluded that the strength of a social tie played a significant role as a predictor of activism.

The second area of analysis was the salience of the social tie to assess its impact on volunteers’ decision to participate in the project. The open-ended question of why they “would like to work in Mississippi this summer” were coded into five categories for organizational context – the teachers, religious communities, socialists/leftists, liberal democrats and civil rights movements along with a “no discernable group” category. Over four-fifths of those with an identifiable recruitment community participated while only three-fifths of those without an identifiable recruitment community participated. The strong causal influence indicated a high degree of salience for the identification with the recruitment communities, and subsequently these communities provided strong support to link their identity with participation of the Freedom Summer project.

McAdam and Paulsen concluded that the recruitment model for an individual to participate depended on four factors: 1) the recruitment attempt that led to their application to participate in the project; 2) the linkage between the movement and identity, i.e., their willingness to apply due to some salient identity to which the recruitment community they belonged; 3) the support of the linkage by others who can sustain the identity and further sets participants apart from the non-participants; and 4) the absence of strong opposition for the identity. Their findings also showed a stronger effect of organizational ties rather than individual ties to pull into collective action. The individual ties were nonetheless important but it was more influential in an organizational context for participation.

Disaster Community and Support Provision

Contrary to popular belief held by the general public that disasters often lead to looting, social disorganization and deviant behaviors, the communities impacted by the disaster actually often suspend previous conflicts and unite in providing mutual support to one another. Tierney (2007:510) best summarizes this insight in her extensive summary of the sociology of disaster literature:

> *"Research accounts emphasized that disasters generate broad consensus regarding the value of life, property, and community and that affected populations are invariably more generous and helpful than during nondisaster times."*

The mass media has played a significant role in promoting disaster myths of heightened social conflicts through reports of exaggerated severity of looting and lawlessness, as was widely reported in the aftermath of the Hurricane Katrina disaster (Tierney et al., 2006; Voorhees et al., 2007).

The emerging platform of social networks on the Internet has offered an outlet for individuals impacted by the disastrous event to join in social cohesion to dispute the inflated reports of social disorganization. In studying the wealth of literature on disaster research that focused on communities, Kirschenbaum (2004) incorporated the various elements of these communities and expanded the definition of a “disaster community” beyond the physical and geographic boundaries within which a disaster occurred. Kirschenbaum emphasized that concept of a disaster community is, first and foremost, a social community made up of networks that were directly or indirectly affected by the disaster rather than only a physical event. Moreover, the Internet has expanded the geographic boundaries of such disaster communities to beyond the actual physical site of the disaster.

The fundamental characteristic of a disaster community is the social cohesion formed through the feelings of dependency, trust and support of one another for physical and emotional safety which would intensify with the threat of disasters. More importantly, disaster can draw in people who are not directly or physically affected by the actual disaster into the disaster community, i.e., uniting both victims and non-victims. Erikson (1994:235) suggested that trauma can be a source that creates a community based on spiritual kinship and a sense of identity. A “stage of euphoria” can ensue after a disastrous event which binds unconnected persons together to develop a form of fellowship – Erikson wrote:

> *“The energy with which rescuers work and the warmth with which neighbors respond act to reassure victims that there is still life among the wreckage, and they react with an outpouring of communal feeling, an urgent need to make contact with and even touch others by way of renewing old pledges of fellowship.”*

Moreover, Nilson’s (1985) description of such “therapeutic” or “altruistic” communities includes disaster victims providing emotional support to each other that can last from a few short days to a few years, depending on the remnants of the experience. During the recovery period, a disaster community can offer emotional and physical support to one another based on a network of victims or possibly non-victims volunteering their time and resources for emergency relief and to help the victims return to pre-disaster conditions quickly.

Haines et al. (1996) explored a model of support provision in the natural disaster context for 1) personal characteristics of the provider, 2) characteristics of their personal networks and 3) characteristics of the community in which they live – these factors are based on early findings found to affect provision and reception of social support. In fact, disaster victims tended to become resources in providing support to other victims rather than become helpless and dependent themselves. The model was tested using data collected on the preparation and recovery phase of the Hurricane Andrew disaster in order to gain an understanding of the determinants of helping behavior during natural disasters.

The data of this study were collected specifically from the two Louisiana parishes that were severely impacted when Hurricane Andrew struck the Gulf Coast in August of 1992. The substantial damage to housing, businesses and personal/economic injury in these two parishes totaled nearly $40 million. However, since there was minimal disruption to the telephone services, the data for this study were collected between October to December of 1992 by telephone with 594 respondents. The information collected include network data (i.e., asking the respondents to name up to five individuals with whom they discussed important matters in the past six months prior to Hurricane Andrew), personal characteristics of the providers (i.e., gender, education, etc.) and characteristics with the respondents (i.e., closeness of the tie). Additionally, Census data of the two parishes and the block groups of areas surrounding the towns were used as measures for community context.

The four measures of social support included: 1) whether respondents provided material aid during the preparation phase; 2) the number of individuals they assisted; 3) whether respondents provided recovery assistance during the short-term recovery phase; and 4) the number of individuals they assisted. For the prediction of support provision during the preparation phase of Hurricane Andrew, only one provider characteristic, i.e., age was significant – the older individuals were less likely to have provided support than younger individuals. There was no significance for any of the personal network variables. The length of residence was a significant variable for community context characteristics – the greater the length of residence, the greater the probability that support would be provided. For the prediction of the number of people supported during the preparation phase, family income had a significant positive effect that financial resources allowed for support provision.

When examining support provision during the *short-term recovery phase* of Hurricane Andrew, age had the same effect as was noted in the preparation phase, and house damage had a negative effect on providing support. There was one significant variable for personal network characteristics (i.e., residential proximity) and two significant variables for community context (i.e., trust in the local government and owner occupancy in the area). Consistent with past research on disaster community, gender had a significant positive effect with men providing more support than women in the recovery phase (though not found to be significant in the preparation phase). Furthermore, individuals in gender-diverse network have greater access to support provision resources. Also, other characteristics for community context such as membership in fraternal organizations, service organizations or other organizations had positive effect on the number of individuals helped.

Haines et al. found three sets of characteristics, i.e., personal characteristics of providers, personal networks and community context, affected support provided in the preparation and short-term recovery phases of the Hurricane Andrew disaster, and especially on the timing when such social support was provided. Past disaster research found support was most prominent during short-term recovery when presence of stress in terms of “index of need for support” is greatest. However, the determinants for long-term recovery phase may vary depending on the level of resources depleted during the short-term recovery phase. Further understanding of these factors for support provision could be useful in identifying and targeting potential providers for future disaster preparation and recovery efforts.

In 2000, Hurlbert et al. followed up on the research for support provision by examining how social network structures allocated resources for activation in the context of social support. This research study intended to bridge the gap by linking activated ties with the network structures rather just limiting attention to the dyadic relationship between the individuals and activated ties. Moreover, the results could provide a better understanding of how routine interpersonal environments can activate ties from pre-existing social networks (e.g., core networks) for social resources (such as informal support) in non-routine situation (e.g., natural disasters such as Hurricane Andrew). Social support researchers have argued that core networks that have strong and homophilous (or sharing similar characteristics) ties have better access to social support. According to Hurlbert et al. (2000), “core networks constitute key sectors of routine interpersonal environments that serve as primary loci of interpersonal contacts.”

For the purpose of this study, the four aspects of network structure considered to be influential in the support context include 1) network density, 2) network size, 3) diversity dimension of network range (e.g., geographic dispersion and gender diversity) and 4) network composition. For network density and size, it was hypothesized that, the higher the density or the larger the core network, the greater the ties from the core network to activate for informal recovery support and the more likely informal support will be provided from within the core network. For the network diversity on geographic dispersion, it was hypothesized that greater geographic dispersion would reduce the proportion of core network ties to activate for informal recovery support and the less likely informal support will be provided from inside the network. For the network diversity on gender, it was hypothesized that greater the representation of men in the core network, the greater proportion of core network ties that will be activated for informal support, although with a caveat that the gender effect will be minimized as the proportion of men in the network increases.

The results showed that a denser core network did increase the ties activated, and these individuals turned to core network ties for informal support in a non-routine situation in both the preparation and recovery phase of Hurricane Andrew. For the effect of the network size, smaller core network ties activated for informal support within a larger core network. There was no effect observed for geographic dispersion. For gender diversity, the findings showed that core network with higher proportion of men increased the degree of network ties activated; however if a core network is composed entirely of men then it would decrease the ties activated. Finally for network composition, having younger individuals and kin increased the degree of core network ties activated. The proportion of support providers from within the core network was greater when the core network prior to the disaster had a higher density, was larger in size, and included men and women and kin. These analyses confirmed that core network structure affected both core network ties activated for informal support and the degree to which individuals activated these ties from within the core network. For social resources in non-routine situation, the composition of the core network also served as a key determinant of core network ties activated.

Based on these research findings on recruitment factors for social movement and network characteristics for support provision over the past several decades, the landscape for disaster communities in the digital age has undoubtedly evolved. I will draw on the research findings of these literatures to inform the changes of disaster communities in the age of online social media. Prior to social networking Websites, individual involvement in disaster community was mostly limited to physical participation. However, online social networks offer a new space for participation as the next section on Facebook will describe. This new segment of online disaster community is not well researched at all, and this thesis research is intended to address that problem by examining this new segment of disaster community as an online social network.

Facebook

Facebook is arguably the most popular social networking Website today with more than 500 million active users worldwide as of July, 2010 (active users are defined as users who have returned to the site in the last 30 days). Founded in 2004m this social networking platform helps people communicate more efficiently with their friends, family and coworkers. However, Petersen (2010) reported the origin of Facebook has not always been so inclusive of different users. Indeed, in its early days, Facebook was limited to persons affiliated with Harvard (specifically users with a Harvard email address) who more than likely already knew one another prior to joining Facebook (unlike the other popular social network Websites such as MySpace or Friendster which were designed for users to connect with both friends and strangers online).

Facebook extended its registration in December, 2004, by opening to Stanford, Columbia and Yale. In 2005, membership was extended to high school and international school networks, and in 2006, it was again extended to work networks. Finally, in September, 2006, Facebook lifted its elitist status and opened its site to anyone who wanted to join. From less than 1 million active users at the end of 2004, Facebook grew to over 12 million active users by the end of 2006. According to the Press Room Statistics on Facebook (2010), this online social networking site grew exponentially in the following years. The membership base of over 50 million active users in October 2007 doubled to over 100 million active users in August 2008 and then tripled to over 350 million active users in 2009.

The concept of this wildly popular online social network originated from the freshman “facebook” that colleges traditionally distribute to incoming students with a photo of each classmate and their general profile. Facebook has been able to leverage the versatility of the Web platform over the years to make a number of key enhancements to the communication feature of the Website, including (but not limited to): the “Wall,” which is essentially the space on each user’s profile page to share his/her status by responding to the question “What’s on your mind?” or to post messages on other users’ walls; “Publisher,” a main feature of Facebook for users to post information and messages on their own Wall or their friends’ Walls; “News Feed,” which resembles a personalized wire service that highlights activities of their Facebook friends such as profile changes, upcoming events, birthdays, and messages exchanged between the walls of the Facebook friends; and “Photos,” which is a popular application that allows users to upload photos, tag friends (the photos would then be linked to that tagged user’s profile), and leave comments on the photos.

The user-friendly navigation of the Website and versatility of staying in constant touch with other users in a variety of ways contribute to the drawing power of Facebook. Moreover, Facebook is easily accessible by the users through the computer as well as mobile devices wherever they go. In fact, over 100 million active users access Facebook through their mobile devices, and these users are typically more active than non-mobile users of Facebook. The Home page of Facebook allows easy access to the core functions such as Messages, Events (calendar), Photos, Friends (list), Applications, Games, etc. The users can also perform administrative maintenance on the homepage by managing the Friend request (confirming or ignoring incoming requests as Facebook friend), adding a friend through a suggested list of new friends (linked through existing friends) or sending a message through a suggested list of existing friends that users may not have been in touch for awhile. The Profile page hosts the Wall, Info, Photos, etc. along with sponsored ads to the right of the navigation panel – the Profile page is related specifically to the Facebook user while the Home page hosts information about the friends of the user (see Figure 1 for an example of the Facebook Profile of the American Red Cross). The Account page allows the users to manage their privacy setting to control the information they share and with whom they share it with.

Figure 1: User Profile Page for ARC Cause on Facebook

Causes

Facebook offers users more than 500,000 active applications to play games, interact with friends, or to form individual groups with a specific purpose, e.g., for business, education, entertainment, utilities, etc. Seven of every 10 Facebook users engage in at least one application every month. One of the most popular applications on Facebook is Causes, which is ranked second in its popularity with over 125 million monthly active users as of August 2010. According to the homepage of Causes (Facebook, 2010):

> *"Causes strive to empower people from all walks of life to have a positive impact on the world in which they live. We allow Facebook users to organize into communities of action focused upon specific issues or non-profit organizations."*

Among the various organizations and groups utilizing this application, one of the most prominent disaster relief organizations to use Causes to reach the masses is the

American Red Cross (ARC) with over 64,000 members as of March, 2010. According to the ARC homepage on Causes (Facebook, 2010):

> *"The American Red Cross is where people mobilize to help their neighbors—across the street, across the country, and across the world—in emergencies. Each year, in communities large and small, victims of some 70,000 disasters turn to neighbors familiar and new—the more than half a million volunteers and 35,000 employees of the Red Cross."*

ARC had raised over $35,000 through the Causes application, and has shown steady increase in membership over the years.

With the increasing popularity of Facebook, individual activists or organizations have seized the opportunity to mobilize their network of Facebook friends toward a collective cause for disaster victims. In fact, the "Causes" application on Facebook was built in 2007 with the purpose to draw support for a specific cause and is been utilized by over 35 million active users to form online communities for disseminating important information, sharing experiences, signing petitions, making donations, etc. (see Figures 2-4 for ARC on Facebook Causes). These online communities are comprised of groups of individuals interacting with each other using communication tools such as emails, online social networks, instant messages and online discussion boards for social, professional, educational, philanthropic or other purposes. Not surprisingly, such emerging online communities have become an important channel of communication and support for disaster victims in their recovery process.

Figure 2: Homepage for ARC Cause on Facebook - Cause Bulletin

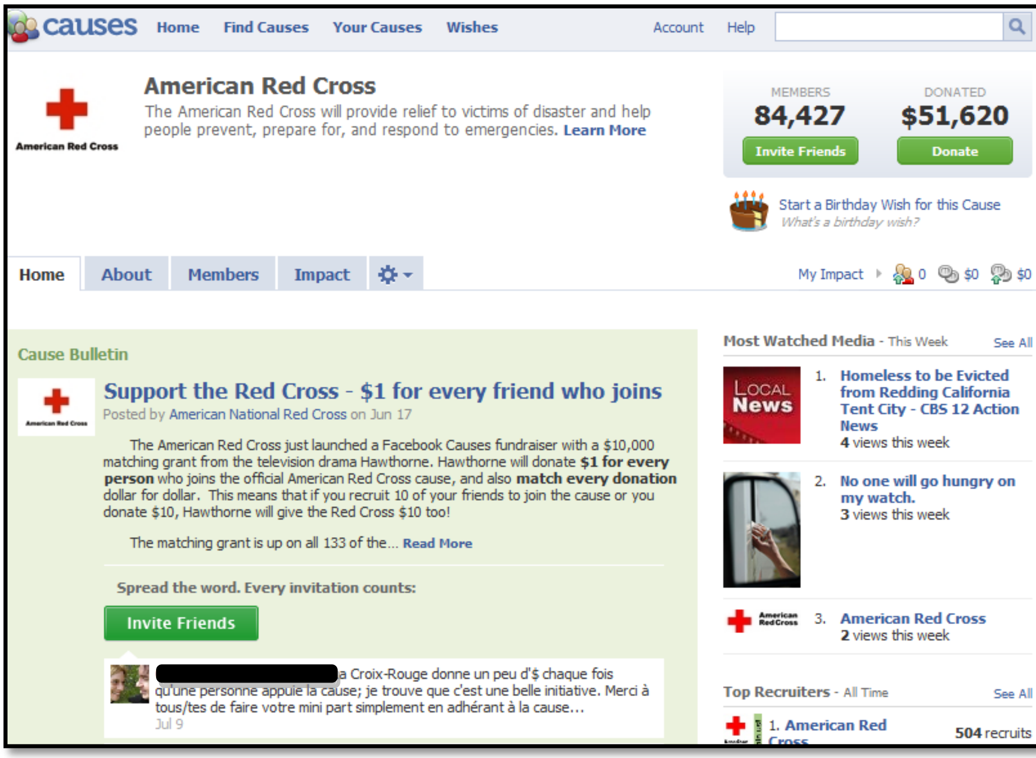


Figure 3: Homepage for ARC Cause on Facebook - Fundraising Activity

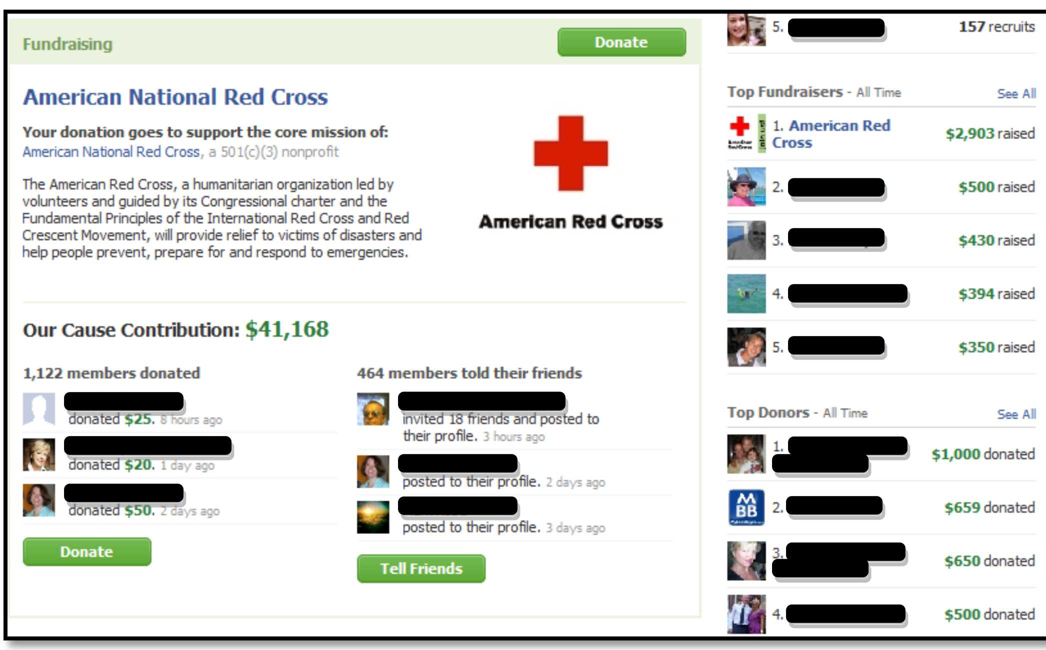
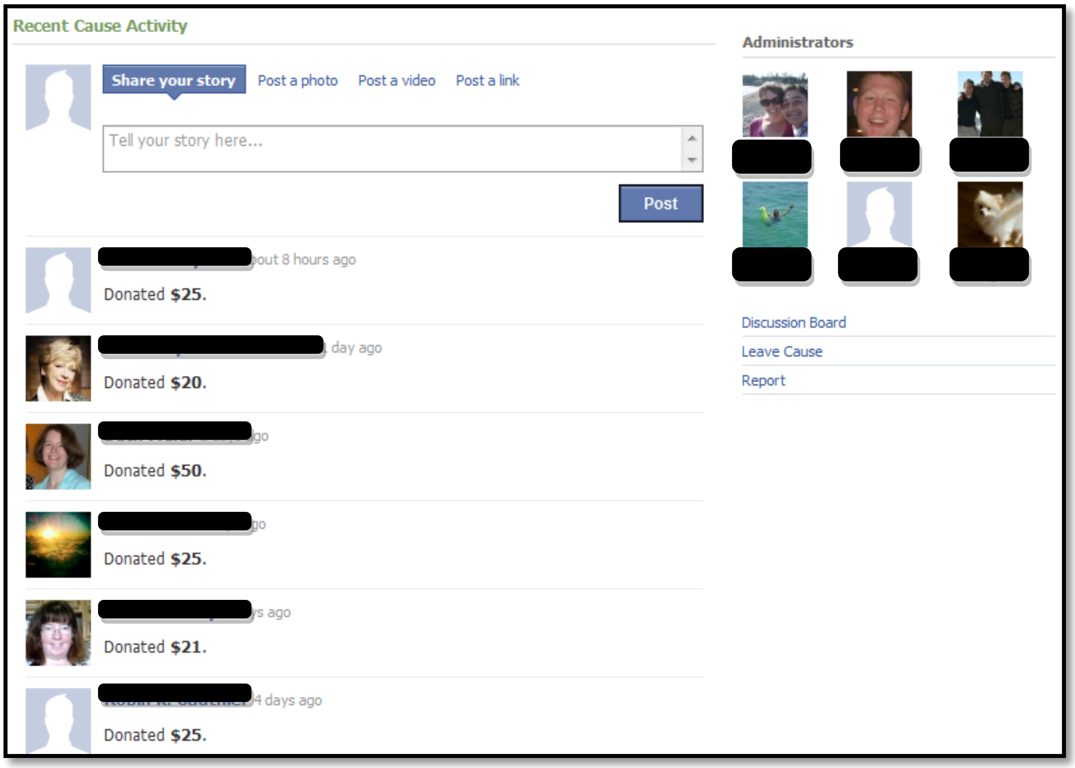


Figure 4: Homepage for ARC Cause on Facebook - Recent Cause Activity



Social Network Analysis

Given the popularity in recent years of online social networks in general and of Facebook in particular, researchers have displayed growing interest in the analysis of online community network structures. Social network analysis can help researchers seek answers to the fundamental question of how autonomous individuals are connected to one another in a community structure. In recent decades, researchers from a variety of applied fields outside of social sciences, such as management consulting, public health, crime and war/fighting have also used this analytical technique to examine relations within a group or population. Some examples include: helping organizations leverage knowledge and capabilities with its members for knowledge management, stopping the spread of infectious diseases to provide better health care and social support for public health,and fighting organized crime or terrorist groups for national security (Borgatti et al., 2009).

Social network analysis enables sociologists to examine the relations between individuals in the community and the varying properties of how these ties account for differences in the outcome for the individuals or the community. For a traditional social research data set, the two different sets of entities typically include persons (i.e., cases) and the attributes (i.e., variables) which is considered a 2-way 2-mode matrix. For a social network data set, both sets of entities are typically persons or nodes (rather than persons and attributes) which are considered a 2-way 1-mode matrix. Simply put, the traditional data focus on actors and attributes, and network data primarily focus on actors and relations. The data allow social researchers to examine the choices that individuals make in joining or affiliating with a particular group and how the groups themselves may affect the choices of the individual to join.

According to Wasserman and Faust (1994), the actor (discrete individual, corporate, or collective social units), the group (the collection of all actors on which ties are to be measured) and the relations (the collection of ties of a specific kind among members of a group) are the major concepts in network analysis:

> *"A social network consists of a finite set or sets of actors and the relation or relations defined on them. The presence of relational information is a critical and defining feature of a social network."*

Social network data include two types of variables: 1) structural variables, which defined as measurements on ties (linkage of actors to one another) among the social units such as association or affiliation: for example, joining the same social club, or for the purpose of this thesis research, the same Facebook Cause; and 2) composition variables, which are defined as measurements on characteristics at the level of individual actors (attributes of actors) such as age, gender, race, size of collective actors, etc. or at the level of groups.

The centrality concept for actors is also important for social network analysis in illustrating social power by means of relations between actors or the entire population (Hanneman,and Riddle, 2005). Centrality highlights the actors who are extensively “involved” or have relational ties with other actors in the network. In other words, a central actor would be involved with many ties with no distinction between receiving and sending, i.e., nondirectional relations (Wasserman and Faust, 1994). Furthermore, different measures of centrality are used to reflect the actors at the “center” of the set of actors which include degree (actors with the most ties to other actors in the network), closeness (how close an actor is to other actors in the network) and betweenness (two nonadjacent actors may depend on other actors who are between the two actors for interaction).

Given that network measurements focus on the use of structural or relational information of actors or groups for analysis, the traditional analytical methods of testing significance of relationship between two variables such as correlations, multiple regressions, *t*-tests, etc. are not applicable for some aspects of the analysis (Wasserman & Faust, 1994). However, other standard descriptive statistical techniques such as univariate, bivariate, or multivariate analysis can be used to describe and summarize social network data (Hanneman, 2005). In fact, a separate set of network analytical methods was developed to consider the relational tie among the actors or groups as well as their attributes. The key distinction between traditional social research analysis and social network analysis can best be summarized by Borgatti et al., (2009):

> *"Whereas traditional social research explained an individual's outcomes or characteristics as a function of other characteristics of the same individual (e.g., income as a function of education and gender), social network researchers look to the individual's social environment for explanations, whether through influence processes (e.g., individuals adopting their friends' occupational choices) or leveraging processes (e.g., an individual can get certain things done because of the connections she has to powerful others)".*

Another key component of social network analysis is to visually illustrate the various network properties that characterize the structures, positions and dyadic properties (connectedness of the structure) and the overall distribution of ties (Borgatti et al., 2009). UCINET is a specialized software commonly used for social network analysis to visualize data.

Social researchers can consider different types of social networks for analysis depending on the data structure and the number of sets of actors to analyze. Furthermore, the analysis can also include different types of actors (also known as social entities) which can be people, subgroups (usually made up of people), organizations (usually made up of subgroups of people), or collectives/aggregates such as communities or nation-states (usually made up of many organizations and subgroups). Wasserman and Faust (1994) defined the mode of a network as the social entities (actors or events) which structural variables are measured, and the number of modes derives from the number of distinct types of social entities within the network. The most common types are one-mode networks which involve a single set of actors (such as Facebook members), followed by two-mode networks which could be comprised of two distinct sets of actors or one set of actors and one set of events (such as Facebook members and the causes to which they belong).

One-Mode Network

One-mode network involves only one set of actors to measure one or more types of relations among them. Like actors, there are also different types of relations to study such as individual evaluation (measuring sentiments such as liking, respect, etc.), transfer of material resources (measuring transactions such as exchange of gifts, donations, etc.) transfer of non-material resources (measuring communication such as sending or receiving messages), interaction (measuring their presence in the same place at the same time), kinship (measuring relations such as marriage, descent, etc.). In addition to studying the relations of the set of actors, the attributes of the actors can also be studied such as age, gender, race, socioeconomic status, etc. which is similar to traditional social research.

Wasserman and Faust (1994) used Krackhardt's study of a single set of actors (i.e., 21 high-tech managers) in a small manufacturer that produces high-tech machinery as a classic example of a one-mode network. The objective of the analysis was to examine the managers' perceptions on the structure of the network, specifically on seeking informal advice and forming friendships as well as their reporting relationships. The data also included actor attributes for age, tenure (length of time employed by the company), level (level in the corporate hierarchy) and department. These managers were given a questionnaire to self-report who they would go to for advice at work and who was their friend from a roster of names of the other managers. Figure 5 shows the relational data set of two-way one-mode for "advice" which includes the set of 21 high-tech managers (actors) with dichotomous data – for example, manager ID #1 indicated that he/she would go to manager ID #2, #4, #8, #16, #18 and #21 for advice.

Figure 5: Krackhardt's One-Mode Network Matrix for Advice Relation

Matrix #1: ADVICE

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	0	1	0	1	0	0	0	1	0	0	0	0	0	0	0	1	0	1	0	0	1
2	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
3	1	1	0	1	0	1	1	1	1	1	1	1	0	1	0	0	1	1	0	1	1
4	1	1	0	0	0	1	0	1	0	1	1	1	0	0	0	1	1	1	0	1	1
5	1	1	0	0	0	1	1	1	0	1	1	0	1	1	0	1	1	1	1	1	1
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
7	0	1	0	0	0	1	0	0	0	0	1	1	0	1	0	0	1	1	0	0	1
8	0	1	0	1	0	1	1	0	0	1	1	0	0	0	0	0	0	1	0	0	1
9	1	1	0	0	0	1	1	1	0	1	1	1	0	1	0	1	1	1	0	0	1
10	1	1	1	1	1	0	0	1	0	0	1	0	1	0	1	1	1	1	1	1	0
11	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
13	1	1	0	0	1	0	0	0	1	0	0	0	0	1	0	0	0	1	0	0	0
14	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	1
15	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
16	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0
17	1	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
18	1	1	1	1	1	0	1	1	1	1	1	0	1	1	1	1	0	0	1	1	1
19	1	1	1	0	1	0	1	0	0	1	1	0	0	1	1	0	0	1	0	1	0
20	1	1	0	0	0	1	0	1	0	0	1	1	0	1	1	1	1	1	0	0	1
21	0	1	1	1	0	1	1	1	0	0	0	1	0	1	0	0	1	1	0	1	0

Two-Mode Network

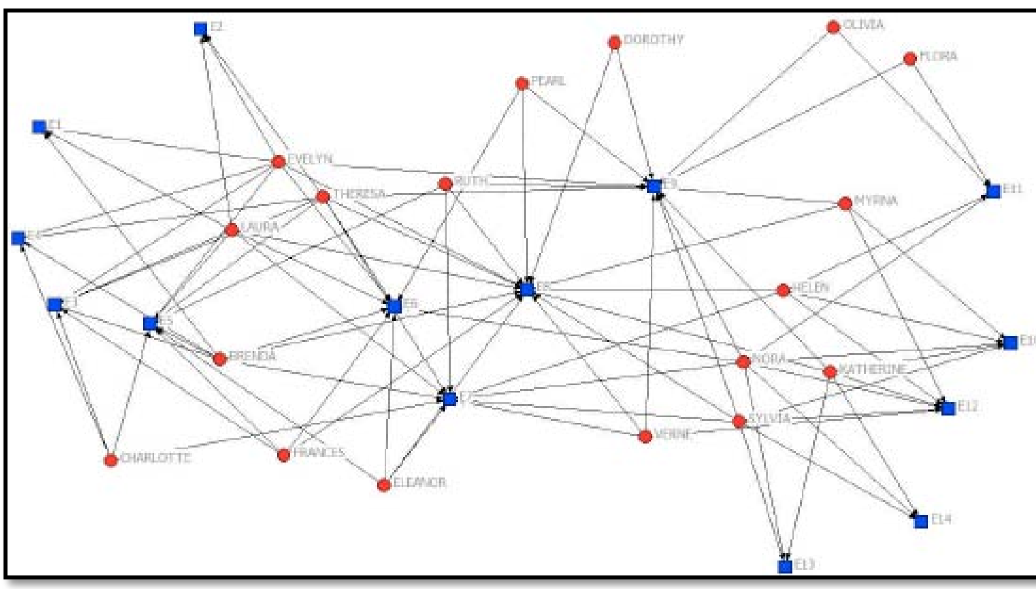
Two-mode network can involve two sets of actors or a single set of actors and a set of events. The types of actors, relations and attributes for one-mode network can also be applied to a two-mode network. For the two-mode network with two sets of actors, there can be unique attributes for each set of actors and should measure at least one relation between the two sets of actors (relations can also be measured within the set of actors). The focus of this thesis research will be on another type of two-mode network which involves one set of actors and one set of events. This type of network is also known as an affiliation network – the second mode is a set of events with which the first mode of actors is affiliated. The affiliation is based on a subset of actors who are related to each other through one or more common events, and these events can be membership in clubs or voluntary organizations, attendance at social events, etc. In addition to actor attributes, the events can also have attributes included in the data set such as size of the membership for the club/organization (or event), years of establishment, etc.

A classic example of a two-mode network analysis was conducted by Davis, Gardner, and Gardner (DGG) in studying the social activities of 18 women in a Southern city (Davis et al., 1941). The social events (e.g., social club meetings, church events, parties, etc.) that these women attended were recorded using newspaper records and interviews over a period of nine months. The objective of the analysis was to examine whether the women have social relations with other women within their own social classes. The first mode consisted of the 18 women and the second mode consists of the 14 events attended by these women. Figure 6 shows the woman-by-event matrix which includes the set of 18 women (actors) affiliated with the social functions that these women attended in the binary measurement – for example, Evelyn (CASE ID #1) attended Events #1, #2, #3, #4, #5, #6, #8 and #9. Figure 7 visualizes the 2-mode data using a graph with the actors and events as the nodes and the lines connecting the actors to the events (no lines connecting the actors or events directly).

Figure 6: DGG's Two-Mode Network of Women-by-Event Matrix

		1E	2E	3E	4E	5E	6E	7E	8E	9E	10E	11E	12E	13E	14E
1	EVELYN	1	1	1	1	1	1	0	1	1	0	0	0	0	0
2	LAURA	1	1	1	0	1	1	1	1	0	0	0	0	0	0
3	THERESA	0	1	1	1	1	1	1	1	1	0	0	0	0	0
4	BRENDA	1	0	1	1	1	1	1	1	0	0	0	0	0	0
5	CHARLOTTE	0	0	1	1	1	0	1	0	0	0	0	0	0	0
6	FRANCES	0	0	1	0	1	1	0	1	0	0	0	0	0	0
7	ELEANOR	0	0	0	0	1	1	1	1	0	0	0	0	0	0
8	PEARL	0	0	0	0	0	1	0	1	1	0	0	0	0	0
9	RUTH	0	0	0	0	1	0	1	1	1	0	0	0	0	0
10	VERNE	0	0	0	0	0	0	1	1	1	0	0	1	0	0
11	MYRNA	0	0	0	0	0	0	0	1	1	1	0	1	0	0
12	KATHERINE	0	0	0	0	0	0	0	1	1	1	0	1	1	1
13	SYLVIA	0	0	0	0	0	0	1	1	1	1	0	1	1	1
14	NORA	0	0	0	0	0	1	1	0	1	1	1	1	1	1
15	HELEN	0	0	0	0	0	0	1	1	0	1	1	1	0	0
16	DOROTHY	0	0	0	0	0	0	0	1	1	0	0	0	0	0
17	OLIVIA	0	0	0	0	0	0	0	0	1	0	1	0	0	0
18	FLORA	0	0	0	0	0	0	0	0	1	0	1	0	0	0

Figure 7: DGG's Two-Mode Network of Southern Women and Social Events



Chapter 3: Data and Methods

Research Questions

The first set of research questions for this thesis research is to investigate the compositional differences of the social networks among the Facebook members sampled from the ARC Causes before the Haiti earthquake disaster as compared to after the disaster. Specifically, I want would like to examine the differences between the two samples on the following: 1) the rate of Facebook members joining the ARC Cause; 2) the average number of other Facebook Causes these sampled ARC Joiners belonged to; 3) the average size of the Facebook Causes not related to ARC that ARC Joiners belonged to; 4) the types of Facebook Causes these joiners belonged to and 5) the gender diversity of two samples. The second set of research questions is to investigate the structural differences of the social network of the ARC joiners sampled before and after the disaster. Specifically, I want to examine the differences between the two samples on the 1) relational ties of the ARC Joiners and Facebook Causes; and 2) the density of the networks for ARC Joiners and Facebook Causes.

Research Methods

The sample of the Facebook members was selected from the ARC Causes "Members" section which listed all the members who joined the cause in real-time. In order to further assess how an actual disaster event may impact the participation of these Facebook members on ARC Causes, I randomly selected[1] 100 members out of the 553 total members who joined during a ten-day period before the Haiti earthquake disaster (i.e., between January 2, 2010, and January 11, 2010) and another 100 members out of the 4,386 total members who joined during a ten-day period after the disaster (i.e., between January 12, 2010, and January 21, 2010.   In addition, I recorded the other causes that each sampled joiner belonged to and coded the data into 8 categories (i.e., administrative, animal protection, disaster relief, game, memorial, philanthropy, political, religion and social services). This sampling method allows for comparison of any differences of the social networks of the sampled members before and after the Haiti earthquake.

I collected all the causes each sampled member belonged to which ranged from as few as one cause (i.e., the ARC cause) to as many as 118 causes (see Figure 8 for the format of the required data collected in the Excel spreadsheet) as well as the membership size of the cause. The data on the causes were collected during the time frame of April 14, 2010, to April 18, 2010, which was approximately four months after the Haiti earthquake disaster. The interpretation of results in Chapters 4 to 6 took the following assumptions into consideration: 1) the majority of the causes to which the sampled Facebook members belonged were joined before they joined the ARC Cause; 2) the rate of joining these other causes after they joined the ARC Cause is not significantly different from before they joined the ARC Cause. This is discussed further in Chapter 7 Conclusion.

[1] The random selection entails using SPSS to randomly select 100 cases out of the all the Facebook members joined the ARC Cause during the specified period. I then copied and pasted the required data of the randomly selected sampled members from the "Members" section on the ARC Causes page to an Excel spreadsheet.

The two samples belong to a total of 1,281 causes, and the number of causes to which members belonged before the disaster (625) is fairly equal to the number of causes to which they belonged after the disaster (664). Additionally, I also collected the demographic characteristics (i.e., gender) of the 200 sampled members to the extent allowed the privacy settings allowed from their Facebook profile pages.

Figure 8: Sample of Data Format for Actors and Events

	A	B	C	D
1		NAME	CAUSE1	CAUSE2
2	1	Tangela	Mandatory Life Sentences for Pedophiles & Child Molesters, Death for Child Killers.	A Real Man Never Hits A Woman!
3	2	Anthony	American Red Cross	
4	3	Masa	Abuse Against Women	International Justice Mission
5	4	Barbara	A World Without Breast Cancer	Breast Cancer "The Pink Cause"
6	5	Claire	Aflac Cancer Center and Blood Disorders Service of Children's Healthcare of Atlanta	ADD MORE LEVELS TO FARMTOWN
7	6	Wendy	Support and Save the Philly Fire Dept.	Amber Alert on Facebook
8	7	Shannon	A Real Man Never Hits A Woman!	Aflac Cancer Center and Blood Disorders Service of Children's Healthcare of Atlan
9	8	Carol Ann	Abolish Abortion	American Red Cross
10	9	Jeffery	Amber Alert on Facebook	KEEP sex offenders OFF
11	10	Maria	Abused Kids and Youth	Autism Awareness & Support - The greatest needs of anyone coping with Autism_
12	11	Linda	"STOP" killing innocent Animals	911 - We'll never forget - Will you fly a flag in memory of the lives lost?
13	12	Barbara	Find a cure for Multiple Sclerosis	Avon Breast Cancer Foundation
14	13	Sandra	"Rascal Sense Gratification" - Please.. Protect India's Cows	Autism Service Dogs of America
15	14	Dana	"The Cove" - Save Japan Dolphins	Canton for Senior Vice President of GreenWill and Isabel for Junior Vice Presiden
16	15	Jillian	"Pretty in Pink" Breast Cancer Support	Death Penalty For Cop-Killers
17	16	Isabel	ALS Research - help us fight for a cure!	Allow God in School
18	17	Debbie	*Support Children in Need - Meir Panim Relief Centers In Israel.	American Diabetes Association
19	18	Jeanna	911 - We'll never forget - Will you fly a flag in memory of the lives lost?	Fight Cancer: Support the American Cancer Society
20	19	Trevor	!!!Get one FarmVille dollar every day!!!	Ban Horse Slaughter In Canada
21	20	Marian	(FARMVILLE) Stop limiting the number of neighbors who we can send gifts to every day!	FORT WORTH BURRITO PROJECT
22	21	Nate	Allow God in School	Keep fine arts in our schools!
23	22	Michelle	All child sex offenders have penis cut off while conscious	Abused Kids and Youth
24	23	Donald	100 Days of Prayer for President Obama AND Beyond	PREVENT ABUSE AGAINST CHILDREN
25	24	Jessica	"MAFIA WARS" GAIN 1 ENERGY POINT IN EVERY 1 MIN!	Amnesty International: Support & Defend Human Rights Worldwide
26	25	Caly		Campaign for Cancer Prevention

Ethics for Online Social Research

Generally, individuals corresponding in public chat rooms or discussion groups could perceive the setting of their conversations to be private and research on these individuals would require the researcher to get informed consent from the subject under observation. However, public lists or discussion boards only require proper citation for materials used in the discussion (Barnes, 2004). The Facebook Website is considered to be a public forum, and the social networks on the Causes platform permits any Facebook members to join, so informed consent should not be required under these circumstances. However, in an effort to protect the privacy of the Facebook members in this study, only first name will be referenced to ensure complete privacy of their identity.

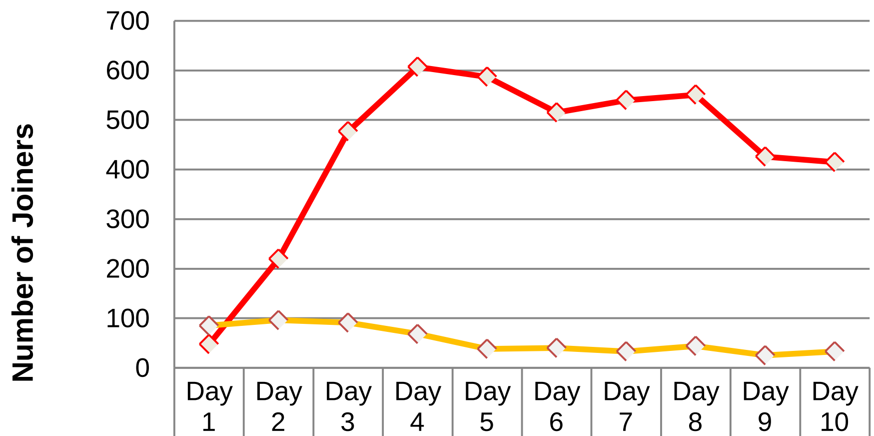
Chapter 4: ARC Network Composition Before and After Haiti Earthquake Disaster

The fundamental data structure of social networks includes two types of variables: compositional and structural. Compositional variables refer to attributes of actors from sources other than the network itself (e.g., how many people joined an organization at a given time? What is the gender of the people in the organization?). Structural variables can be used to measure the ties between pairs of actors (i.e., connection between the actors or the organizations). Depending on the objective of the analysis, these variables are commonly used as measures for social network data. This chapter will focus on comparing the composition of the network before and after the Haiti earthquake disaster including the trend of joining the ARC Cause, the average number of Facebook Causes not related to ARC that ARC Joiners belonged to, the average size of the Facebook Causes not related to ARC, the types of Facebook Causes the ARC Joiners belonged to and the gender diversity of the networks.

Trend of Joining the ARC Cause

Figure 9 clearly illustrates the drastic increase of Facebook members joining the ARC Cause in the period of ten days after the disaster compared to the period of ten days prior. The average number of joiners of the ARC Cause was 55 per day within the ten days before the disaster, and the average nearly increased tenfold to 439 per day within the ten days after the disaster. Moreover, the difference between these periods is more than tenfold for Day 4 through Day 10 in comparing the days before and after the disaster. The spike of this trend can be attributed to a variety of influences such as media coverage by the major outlets (e.g., traditional media of television and radio as well as emerging media of the Internet accessible on different platforms). However, the forthcoming findings from the other composition variables also lead to evidence of influences from the members and causes of Facebook mobilizing their resources to recruit others to join the ARC Cause after the disaster.

Figure 9: Number of Facebook Members Joining the ARC Cause

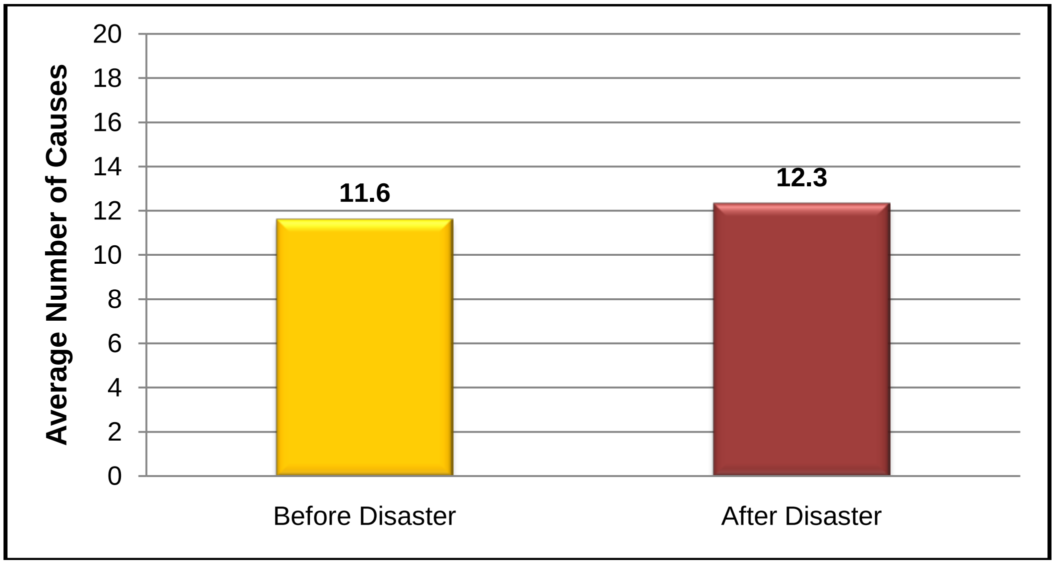


	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
After Disaster	48	220	477	607	587	515	540	551	426	415
Before Disaster	85	96	91	68	38	40	33	44	25	33

Organizational Affiliations of ARC Joiners

Figures 10 and 11 illustrate the differences of attributes of the two samples of ARC Joiners before and after the disaster. In comparing the number of Facebook Causes the sampled ARC Joiners belonged to, Figure 10 shows a slightly higher average number of Facebook Causes after the disaster (12.3 causes) than before the disaster (11.6 causes). Note the ARC Cause was excluded from the calculation of the average number of causes. It is also important to note the outliers of this average within the two different samples: there were as few as one cause (i.e., the Facebook members belonged to the ARC Cause only) and as many as 118 causes some of these joiners belonged to. However, Figure 11 illustrates the differences with the distribution of Facebook Causes for the two samples of ARC Joiners. While the differences of the overall average number of Facebook Causes the sampled ARC Joiners belonged to can be considered small or perhaps not meaningful, there are clear differences with the joiners before and after the disaster when analyzing the Facebook Causes at the incremental level. For Figure 11, 14 joiners before the disaster belonged to ARC Cause only compared to 8 ARC Joiners after the disaster, suggesting that the ARC Joiners sampled after the disaster were more active in terms of other causes they belonged to other than ARC. Similarly, these joiners sampled after the disaster belonged to more Facebook Causes (i.e., 13 ARC Joiners belonged to 25 or more Facebook Causes) compared to the joiners before the disaster (i.e., 10 ARC Joiners belonged to 25 or more Facebook Causes). The distribution of higher incremental numbers of Facebook Causes the ARC Joiners belonged to can indicate Facebook members sampled after the disaster were more active in disaster relief or philanthropic causes which will be further explored later in this chapter.

Figure 10: Average Number of Facebook Causes for ARC Joiners



Note: The ARC Cause was excluded from the calculation of the average number of causes.

Figure 11: Distribution of Facebook Causes for ARC Joiners

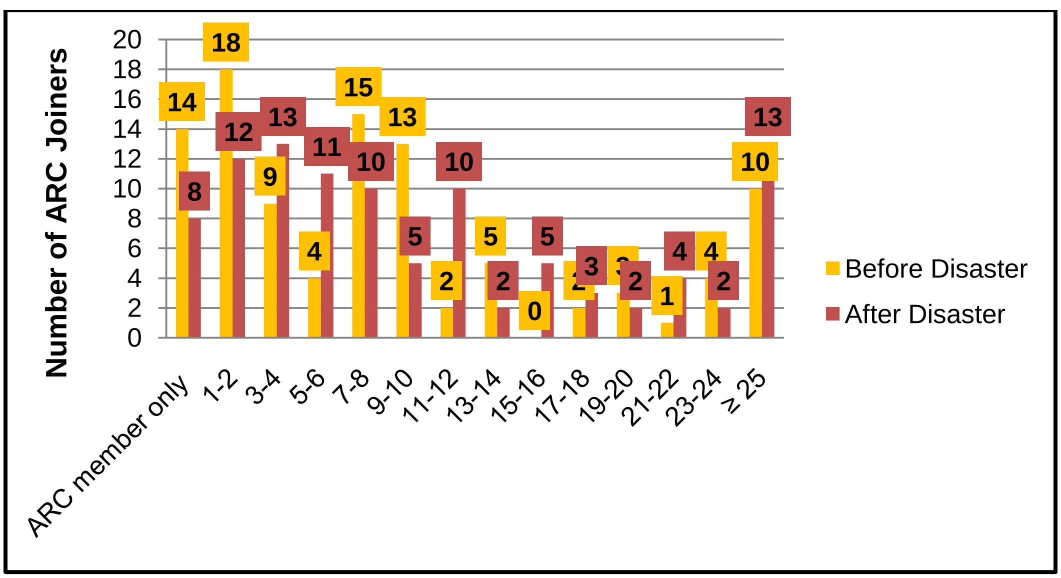
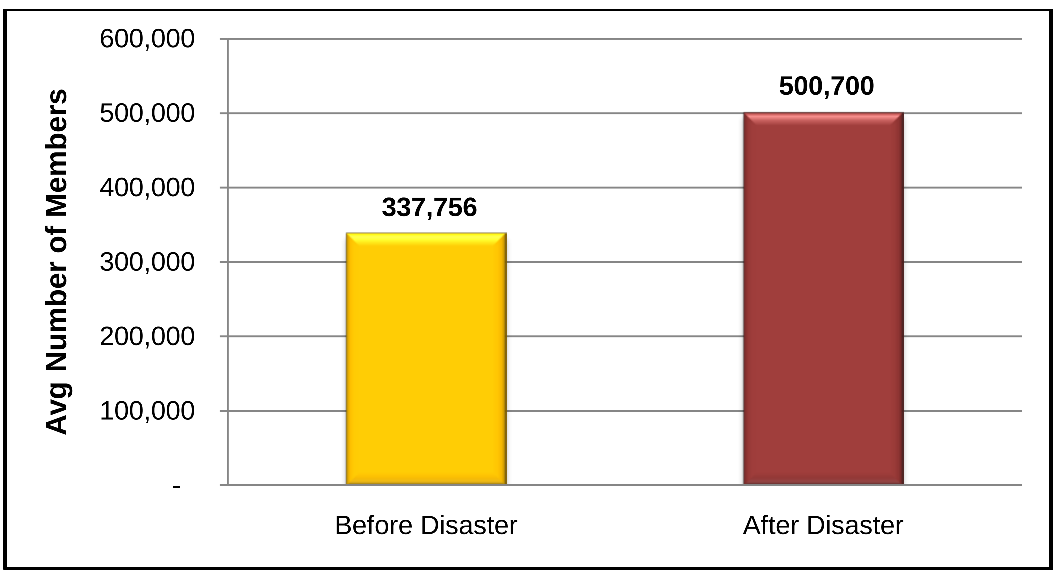


Figure 12 shows the average size of the causes collected from the sampled ARC Joiners. Note the ARC Cause was excluded from the calculation of the average size of causes. There is a sizeable difference of 162,944 Facebook members when comparing the average membership size of causes before and after the disaster (i.e., 500,700 Facebook members after the disaster and 337,756 before the disaster). For the causes that sampled ARC Joiners belonged to before the disaster, the membership size ranged from as few as 6 Facebook members to as many as 6,176,464 Facebook members. Similarly, for the causes that sampled ARC Joiners belonged to after the disaster, the membership size ranged from as few as 1 Facebook members to as many as 6,158,144. While the range of the membership size of the two samples is similar, the drastic difference between the average number of Facebook members can indicate the causes with larger membership size or causes that joined in forces (i.e., bloc recruitment) were more successful in recruiting new members after the disaster by mobilizing their active members to recruit others.

Figure 12: Average Membership Size of Facebook Causes



Note: The ARC Cause was excluded from the calculation of the average number of Facebook members.

Identifiable Recruitment Community

Following up from the previous finding that sampled ARC Joiners after the disaster belonged to more Facebook causes than the joiners before the disaster, Figures 13 and 14 show the types of causes to which they belong. The ARC Joiners sampled after the disaster belonged to almost twice as many disaster relief causes compared to the joiners sampled before the disaster. Figure 13 shows that 4% of the Facebook Causes the sampled ARC Joiners belonged to after the disaster are related to disaster relief (i.e., 24 out of 658 total causes), and Figure 14 shows that 2% of the causes the joiners belonged to before the disaster are related to disaster relief (i.e., 14 out of 614 total causes). Note the number of Facebook Causes coded differs from the original sample size (i.e., 614 vs. 625 before the disaster and 658 vs. 664 after the disaster) due to the fact that a fraction of these causes were disabled since the sample was drawn, so the disabled causes could not be coded and subsequently included in the calculation. Over half of these disaster relief causes are related to the Haiti earthquake such as Feed Hungry Children in Haiti, Help Earthquake Survivors in Haiti, Help Haiti Now !!!, Hope for Haiti Now: A Global Benefit for Earthquake Relief, etc.

In addition to the increase of Facebook Causes related to disaster relief, the causes related to philanthropy also increased from 45% before the disaster (i.e., 273 out of 614 total causes) to 50% after the disaster (i.e., 330 out 658 total causes). This indicates that ARC Joiners sampled after the disaster were more likely to come from philanthropic causes such as child abuse, diseases/illnesses, domestic violence, environment, military, etc. – the more prominent examples in terms of membership size include A World Without Breast Cancer, Amber Alert on Facebook, Free Postage For All Families of Deployed Military, Society

Against Child Abuse, Stop Global Warming, etc. On the other hand, there is a decrease of Facebook Causes related to games from 18% before the disaster (i.e., 108 out of 614 total causes) to 12% after the disaster (i.e., 82 out of 658 total causes). The most popular causes for games by far were related to Farmville, with over 70% of all causes related to games have "Farmville" in the name of the cause both before and after the disaster. The diminished share of these causes for games could result from the greater proportion of causes related to disaster relief and philanthropy as these causes were more likely to recruit new ARC members when the salience of disaster relief is heightened by the Haitian episodes.

Figure 13: Proportion of Types of Facebook Causes for ARC Joiners Before Disaster

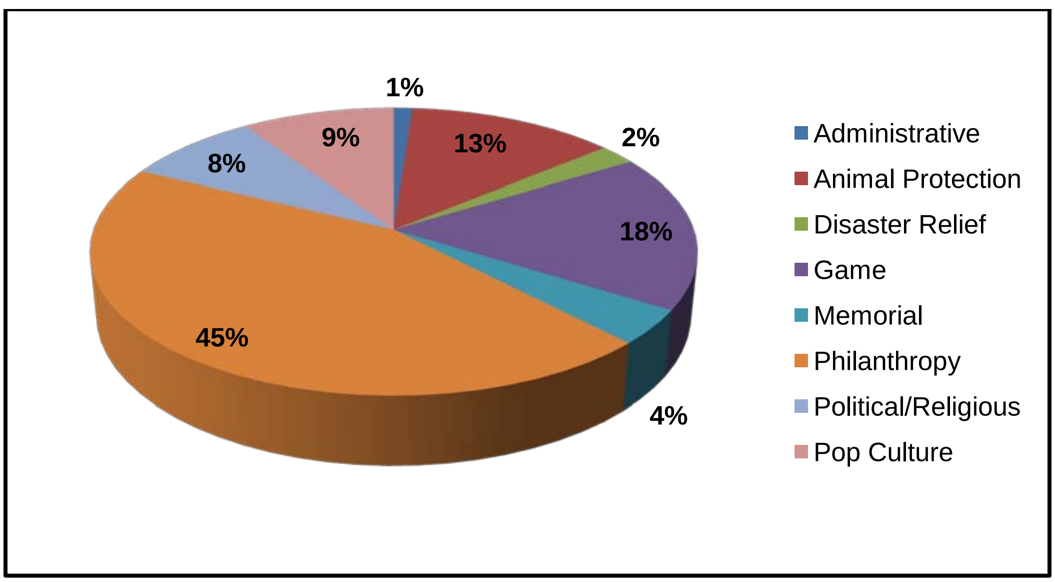
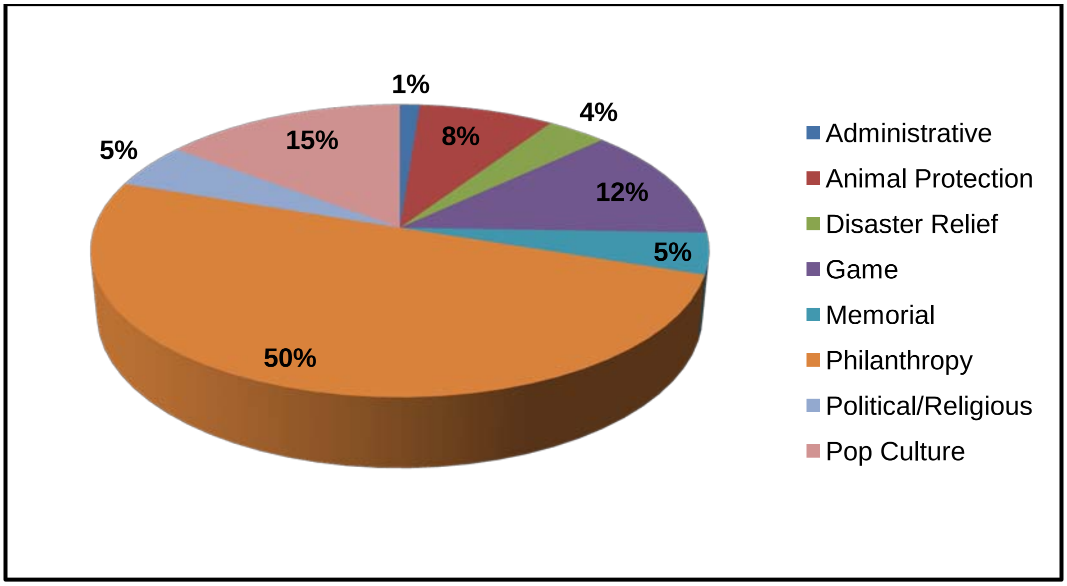


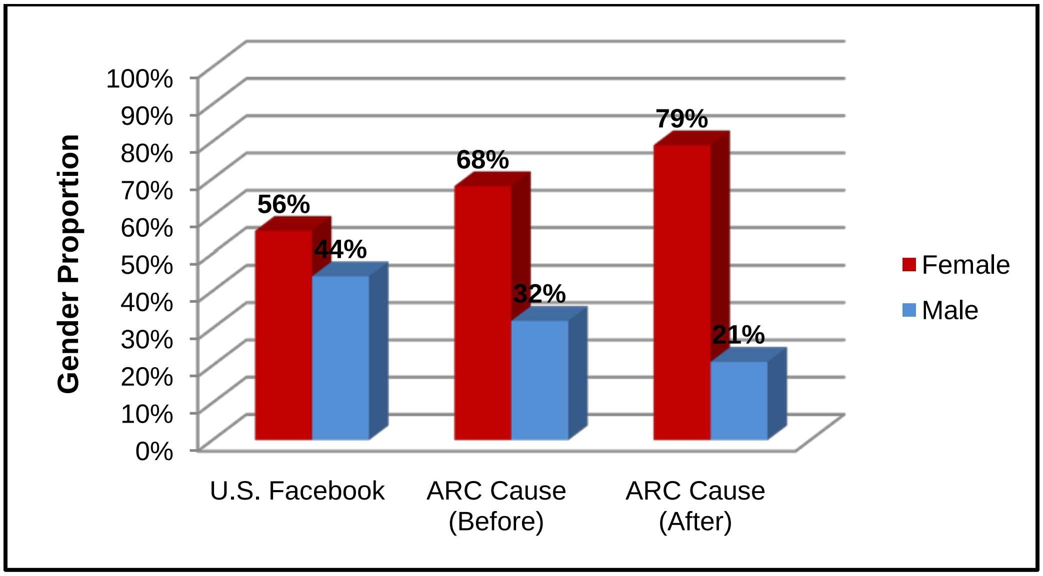
Figure 14: Proportion of Types of Facebook Causes for ARC Joiners After Disaster



Gender Diversity

Interestingly, when comparing the gender composition of the networks before and after the disaster in Figure 15, female joiners of the ARC Cause dominated the sample after the disaster with 79% compared to 21% of male joiners. Moreover, there is an increase of 11% of these female joiners sampled after the disaster when compared with the proportion of female joiners sampled before the disaster (i.e., 68%). The proportion of female joiners of the ARC Cause sampled before and after the disaster also exceeded the proportion of female members of the Facebook population in the U.S. (i.e., 56%) by 12% before the disaster and 23% after the disaster. Historically, the disaster research literature consistently reported men providing more support than women in the event of a disaster. However, this finding may indicate a new trend in the digital age that women are more likely than men to participate in low cost/low risk form of activism on the Internet in providing emotional support rather than physical support.

Figure 15: Gender Diversity of ARC Joiners



Chapter 5: Two-Mode Network of Sampled ARC Joiners and Their Facebook Causes

Following Fernandez and McAdam's (1988) research study on the role of multiorganizational fields in recruitment to social movements, this chapter will examine the structural factors that may "pull" the sampled ARC Joiners into a specific cause by evaluating the Facebook causes they belong to. The multiorganizational fields are defined as "ties formed by overlapping memberships among organizations" (Fernandez and McAdam, 1988: 358). The ties among these Facebook causes can potentially be leveraged to mobilize their resources (i.e., existing members) in recruiting others to their cause. The focus of this chapter is on the description of multiorganizational fields of the Facebook Causes the sampled ARC Joiners belonged to before and after the Haiti earthquake disaster and any clusters of joiners or causes apparent from the network illustrations. Further analysis of network density will be discussed in Chapter 6.

The method of network analysis is used to examine the multiorganizational fields of the sampled ARC Joiners, and it is limited to the interpretation on the pattern of overlapping organizational membership given no other data are available to verify any particular pattern of relational ties. Social network analysts typically use matrices or graphs to represent network data to illustrate patterns of ties among the actors. When a network data set has one set of actors and a set of events or organizations to which the actors belong, it is a type of two-mode network known as the affiliation network (the two modes are actors and events). The primary interest of this data set is to understand the macro-micro relationship, i.e., the Facebook Causes the sampled ARC Joiners belong to (micro-structure) and how the Facebook Causes may influence the decision to join their cause (macro-structure). The Facebook Causes of each sampled ARC Joiner belonged to were collected before and after the disaster – two people-by-organizational-affiliation matrices were created for the two two-mode networks: 100 sampled ARC Joiners by 625 Facebook Causes before the disaster, and 100 sampled ARC Joiners by 664 Facebook Causes after the disaster.

Table 1 is an example an ARC Joiner-by-Facebook-Cause matrix with 100 sampled Facebook members joined the ARC Cause ten days before the disaster by the pool of Facebook Causes they all belonged to. The two-mode network data are arranged in a rectangular data matrix of actors (rows) by events (columns). The first mode in an affiliation network (or sometimes known as membership network) is a set of actors and the second set is a set of events (or organizations) they affiliate with. Each Facebook Cause is a variable, and a binary measurement is used to indicate whether a specific ARC Joiner belonged to the cause. The only requirement is the actors must be affiliated with one or more organizations. The entry of "1" indicates the sampled ARC Joiner belongs to the Facebook Cause adjacent to it, otherwise it will be coded as "0" for not being affiliated with that particular cause. For example, ARC Joiner #1 (Tangela) belonged to 25 Facebook Causes (including the ARC Cause) which is coded as a "1" for Cause #1-25. The horizontal elements highlighted in red show which causes Tangela belonged to. Also, the vertical elements highlighted in red show all the ARC Joiners that belonged to the specific cause. For example, all the sampled ARC Joiners belonged to Cause # 4, the ARC Cause, which is coded a "1" for ARC Joiner #1-100.

Table 1: Two-Mode Network Matrix of ARC Joiners and Facebook Causes Before Disaster

		1 M	2 A	3 A	4 A	5 A	6 A	7 F	8 H	9 I	10 J	11 S	12 P	13 T	14 S	15 K	16 T	17 R	18 P	19 S	20 S	21 K	22 J	23 S	24 P	25 N	26 I	27 P	28 S	29 B	30 C	31 I	32 T	33 A	34 A	35 A	36 C	37 D	38 F	39 F	40 F	41 F	42 N	43 K	44 R	45 S	46 H	47 T	48 P	49 S	50 s	51 –	52 S	53 R	54 O	55 A	56 A	57 P	58 A	59 A	60 A	61 C	62 F	63 F	64 S	65 L	66 N
1	Tangela N. Price	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	Anthony Michael Vitrano	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	Masa Kaneko	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	Barbara	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	Claire	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
6	Wendy	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0
7	Shannon	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	1	1	1	1	1	1	1
8	Carol Ann Case Lauck	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	Jeffery Cleon Lott	0	0	0	1	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
10	Maria Basham	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	Linda Posso	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	Barbara Callahan	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	1	0	1	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0
13	Sandra	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
14	Dana	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	Jillian Gray	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
16	Isabel Brainstorm	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	Debbie Godshall Clemens	0	0	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	Jeanna Burns Gillihan	0	0	1	1	0	0	1	0	0	0	0	1	0	1	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0
19	Trevor Ash	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
20	Marian Walker Adams	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	Nate Dendinger	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	Michelle Gurin Reeves	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0
23	Donald R Alvey	0	0	0	1	0	0	1	0	0	0	0	0	1	1	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
24	Jessica Perris	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
25	Caly Chu	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
26	Nicole	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
27	Ana Legazcue	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
28	Josh Rousseau	0	1	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
29	Christophee Stone	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
30	Elise Lorene Ash	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31	Samantha Fey	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
32	Lina Letoe	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33	Donna Smulski MacDougall	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
34	Atosha Newsome Harden	0	1	1	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	1	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
35	Jammie Jacobson	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
36	Shauna Augusta Denecke	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
37	Fluffy McAllister	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
38	Alan Ho	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
39	Marie Strupatis	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
40	David Crozier	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
41	Bernadette Fouquet	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
42	Armando Macias Rodriguez	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0
43	Julie Ann Leavitt	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
44	Wayne Allen	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
45	Chrissy Freund	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
46	Gayle Velez	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	[illegible]

Note: The data on the causes were collected from April 14, 2010 to April 18, 2010.

Figures 16 and 17 present the graphs used to visualize the two-mode data in which both actors (sampled ARC Joiners) and events (Facebook Causes) are treated as nodes. The lines are used to show the ties between the joiners and the causes. As Figure 16 shows, the graph before the disaster has 724 nodes (100 nodes of joiners illustrated in red circles and 624 nodes of causes illustrated in blue squares). As Figure 17 shows, the graph after the disaster has 763 nodes (100 nodes of joiners and 663 nodes of causes). Note the ARC Cause was excluded from the individual sample of these graphs. The isolates on the left of the graphs are the sampled ARC Joiners that belonged only to the ARC Cause and not affiliated with any other causes or joiners (a total of 14 isolates from the sample before the disaster and 8 from after the disaster).

Figure 16: Two-Mode Network Graph of ARC Joiners and Facebook Causes Before Disaster

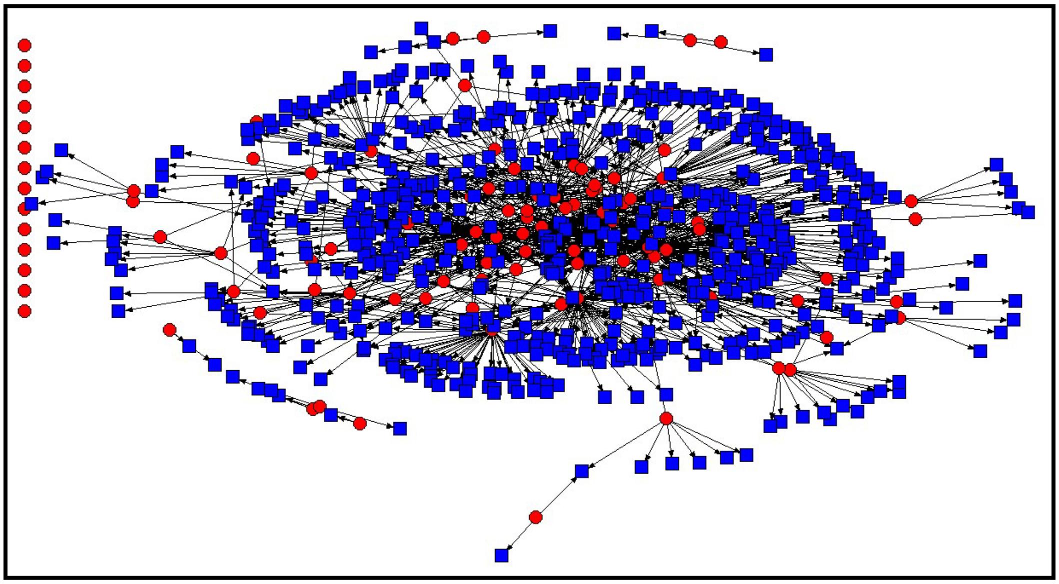
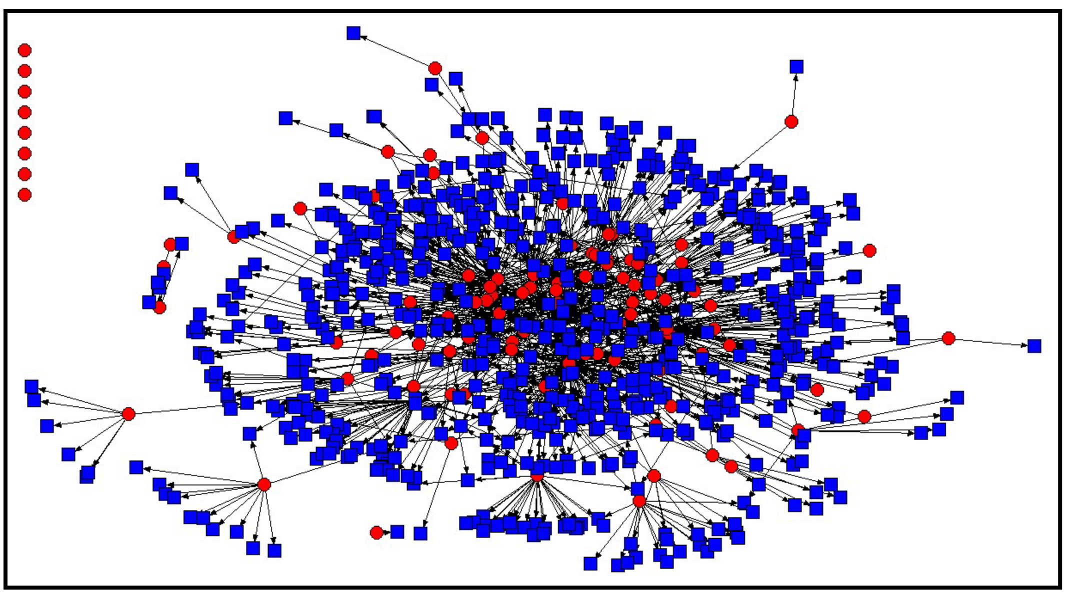


Figure 17: Two-Mode Network Graph of ARC Joiners and Facebook Causes After Disaster



In evaluating the graphs of the two-mode networks of ARC Joiners and Facebook Causes before and after the disaster (Figures 16 and 17), there does not seem to be any apparent pattern of clusters of causes or joiners in common though it is difficult to observe the pattern of connections or social significance with over 700 nodes given how closely they are clustered together. In fact, the causes and joiners are mostly clustered in a single network rather than broken out into clusters that can be visually apparent. As a result no further analysis is conducted for the two-mode networks. However, these networks can be converted into two one-mode data sets and examine relations within each mode separately. In Chapter 6, an actor-by-actor data set was created to measure the ties between each pair of actors by the number of Facebook causes these sampled ARC Joiners belonged to and connection between these causes. An event-by-event data set was also created to measure the ties between each pair of causes by the number of sampled ARC Joiners they have and connection between these joiners. The analyses for these one-mode networks include the relational ties of the sampled ARC Joiners/Facebook Causes at various levels of relations before and after the disaster as well as the density of the overall network and each level of relations within each network.

Chapter 6: One-Mode Network of Sampled ARC Joiners and Their Facebook Causes

To further examine the role of multiorganizational fields from the last chapter, the two-mode network of ARC-Joiners-by-Facebook-Causes is converted into two one-mode networks of ARC-Joiners-by-ARC-Joiners and Facebook-Causes-by-Facebook-Causes in order to study each network separately. Furthermore, this chapter also takes into consideration McAdam's (1986) argument for the need to distinguish the varying forms of activism (i.e., cost and risk) in relation to the responsibility of the "prior contact with a recruiting agent" (i.e., networks, relationships or communities) that pull the individual into activism.

The act of joining a Facebook cause can justifiably be considered a form of low cost/low risk activism following the same definition as McAdam for cost in terms of time, money and energy required for activism; and risk in terms of anticipated danger or behavioral consequences (of being perceived negatively). The membership for Facebook and joining the ARC cause is free (donation to the ARC is at the discretion of the joiner), and the level of participation is also dependent on the joiner (e.g., posting wall messages, recruiting other members, making donations, fundraising, etc.). It is also relatively risk-free to participate given all activities are completely Web-based so there should be minimal danger posed for financial, physical or social harm (unlike the 1964 Freedom Summer project). Moreover, the ARC has the reputation of being the nation's premier emergency response organization so joining its cause should not have bear any negative perceptions.

Historically, prior contact is a strong predictor of participation in low cost/low risk activism. To study this further with the two ARC samples in the digital age of online social movement, the relational ties (i.e., linkage between a pair of actors) of a one-mode network of ARC Joiners before and after the disaster are used to examine how connected they are. The analysis of the network can start with the number of ties (or connections) among each sample of ARC Joiners. Any differences of how connected they are before and after the disaster can be a potential indicator of heightened recruitment by "prior contact" of the sampled ARC Joiners towards a common cause (based on liberal interpretation of data available).

The adjacency matrix (or sociomatrix) is the most common form of matrix for one-mode network – the rows and columns of the actors in the network are in identical order. The matrix to illustrate the one-mode network of ARC Joiners before and after the disaster consists of rows and columns of the names of these ARC Joiners. The entries in the matrix represent the number of Facebook Causes each ARC Joiner has in common with the other ARC Joiners in each sample. The graphic display of network analysis uses points to represent the actors in the network and lines to represent ties or relations among the actors. The ties illustrated in the graph between the ARC Joiners in each sample show the circle labeled with their names and connection to each other through one or more Facebook Causes – the collection of ties can also be illustrated of a specific relation such as the set of ARC Joiners with more than one Facebook Causes in common (other than the ARC Cause).

One-Mode Network of Sampled ARC Cause Joiners

Table 2 is the ARC-Joiner-by-ARC-Joiner one-mode network matrix with 100 sampled Facebook members who joined the ARC Cause ten days before the disaster – these ARC Joiners are the set of actors for this data set. There are as many rows and columns as the number of actors in the data set (which is not all shown in the table illustrated). The primary interest of this data set focuses on the relational ties among these sampled ARC Joiners to examine how many other causes (in addition to the ARC Cause) they co-joined. The elements (score in the cells) of the matrix indicate the tie between each pair of actors, i.e., number of Facebook Causes co-joined. Note these ARC Joiners belonged to at least one cause in common (i.e., the ARC Cause). The diagonal elements highlighted in red show the number of Facebook Causes each ARC Joiner belongs to. For example, ARC Joiner #1 (Tangela) belonged to a total of 25 Facebook Causes (including the ARC Cause) and connected to ARC Joiners #2-4 (Anthony, Masa and Barbara) through the ARC Cause only. However, Tangela shared membership of two Facebook Causes with ARC Joiner #5 (Claire), the ARC Cause and one other.

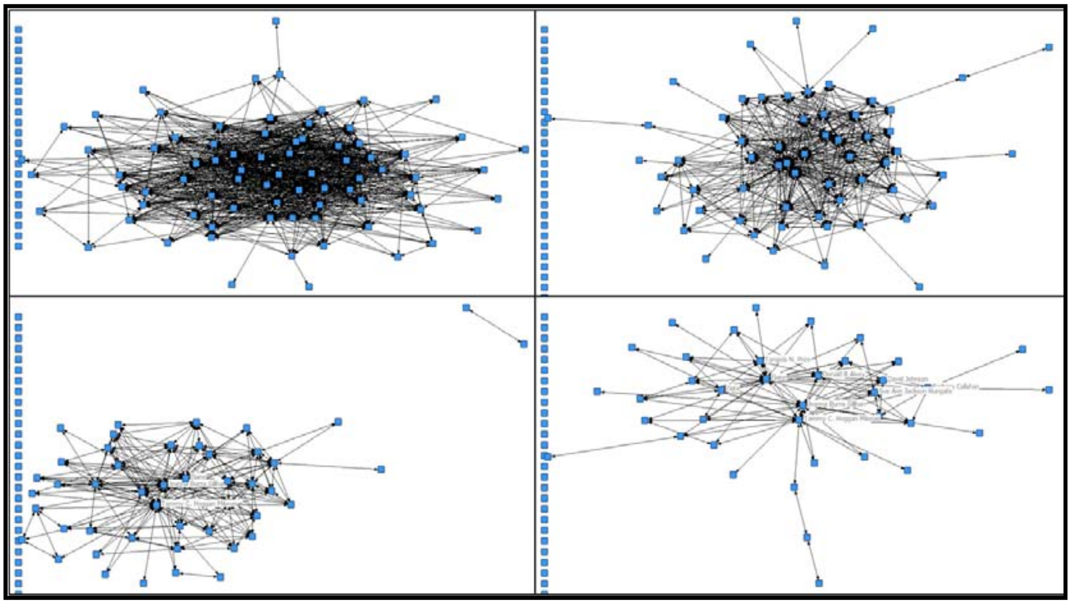
Table 2: One-Mode Network Matrix of ARC Joiners Before Disaster

		1 Tan	2 Ant	3 Mas	4 Bar	5 Cla	6 Wen	7 Sha	8 Car	9 Jef	10 Mar	11 Lin	12 Bar	13 San	14 Dan	15 Jil	16 Isa	17 Deb	18 Jea	19 Tre	20 Mar	21 Nat	22 Mic	23 Don	24 Jes	25 Cal	26 Nic	27 Ana	28 Jos	29 Chr	30 Eli	31 Sam	32 Lin	33 Don
1	Tangela N. Price	25	1	1	1	2	1	1	1	3	2	1	3	2	4	4	1	3	8	1	3	2	3	6	1	2	1	1	4	1	1	5	1	2
2	Anthony Michael Vitrano	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
3	Masa Kaneko	1	1	4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
4	Barbara	1	1	1	5	1	1	2	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	2	1	1	1	1	1	1	1	2	1	1
5	Claire	2	1	1	1	24	2	2	1	1	2	1	14	1	2	3	1	3	6	1	4	4	2	3	1	1	1	1	2	1	1	2	1	3
6	Wendy	1	1	1	1	2	5	2	1	1	1	1	3	1	1	2	1	1	2	1	2	2	2	2	2	1	1	1	1	2	1	1	1	1
7	Shannon	1	1	1	2	2	2	29	1	2	1	1	3	2	1	1	1	3	4	2	2	1	2	1	4	1	2	1	1	1	2	3	1	1
8	Carol Ann Case Lauck	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
9	Jeffery Cleon Lott	3	1	1	1	1	1	2	1	9	1	1	2	1	2	2	1	2	4	1	2	1	1	2	1	1	1	1	2	1	1	1	1	1
10	Maria Basham	2	1	1	1	2	1	1	1	1	3	1	2	1	2	1	1	1	2	1	2	2	2	2	1	1	1	1	1	1	1	2	1	2
11	Linda Posso	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
12	Barbara Callahan	3	1	1	1	14	3	3	1	2	2	1	25	1	2	5	1	2	5	1	5	4	3	4	1	1	1	1	1	1	1	2	1	3
13	Sandra	2	1	1	1	1	1	2	1	1	1	1	1	8	1	1	1	1	2	1	1	1	1	1	1	1	1	2	2	1	1	1	1	1
14	Dana	4	1	1	1	2	1	1	1	2	2	1	2	1	11	2	1	2	5	1	2	2	3	3	2	1	1	1	2	1	1	4	1	2
15	Jillian Gray	4	1	1	1	3	2	1	1	2	1	1	5	1	2	23	1	1	5	1	2	2	4	5	2	1	1	1	1	2	1	3	1	2
16	Isabel Brainstorm	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	6	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
17	Debbie Godshall Clemens	3	1	1	1	3	1	3	1	2	1	1	2	1	2	1	1	11	4	1	1	1	1	2	2	1	1	1	3	1	1	2	1	1
18	Jeanna Burns Gillihan	8	1	1	2	6	2	4	1	4	2	1	5	2	5	5	1	4	41	1	4	5	5	9	2	1	1	2	4	1	1	5	1	4
19	Trevor Ash	1	1	1	1	1	1	2	1	1	1	1	1	1	1	1	1	1	1	10	1	1	2	3	1	1	4	1	2	1	1	1	1	1
20	Marian Walker Adams	3	1	1	1	4	2	2	1	2	2	1	5	1	2	2	1	1	4	1	11	3	2	3	1	1	1	1	1	1	1	2	1	2
21	Nate Dendinger	2	1	1	1	4	2	1	1	1	2	1	4	1	2	2	1	1	5	1	3	8	3	4	1	1	1	1	1	1	1	2	1	3
22	Michelle Gurin Reeves	3	1	1	1	2	2	2	1	1	2	1	3	1	3	4	1	1	5	2	2	3	10	4	2	1	1	1	2	2	1	3	1	2
23	Donald R Alvey	6	1	1	2	3	2	1	1	2	2	1	4	1	3	5	1	2	9	3	3	4	4	39	2	1	2	1	2	2	1	3	1	3
24	Jessica Perris	1	1	1	1	1	2	4	1	1	1	1	1	1	2	2	1	2	2	1	1	1	2	2	10	1	1	1	1	2	2	2	1	1
25	Caly Chu	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	3	1	1	2	1	1	1	1	1
26	Nicole	1	1	1	1	1	1	2	1	1	1	1	1	1	1	1	1	1	1	4	1	1	1	2	1	1	9	1	1	1	1	1	1	1
27	Ana Legazcue	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	2	1	1	1	1	1	1	1	1	32	1	1	1	1	1	1
28	Josh Rousseau	4	1	1	1	2	1	1	1	2	1	1	1	2	2	1	1	3	4	2	1	1	2	2	1	2	1	1	10	1	1	1	1	1
29	Christophee Stone	1	1	1	1	1	2	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	2	2	2	1	1	1	1	2	1	1	1	1
30	Elise Lorene Ash	1	1	1	1	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	9	1	1	1
31	Samantha Fey	5	1	1	2	2	1	3	1	1	2	1	2	1	4	3	1	2	5	1	2	2	3	3	2	1	1	1	1	1	1	10	1	2
32	Lina Letoe	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
33	Donna Smulski MacDougall	2	1	1	1	3	1	1	1	1	2	1	3	1	2	2	1	1	4	1	2	3	2	3	1	1	1	1	1	1	1	2	1	8
34	Atosha Newsome Harden	9	1	1	1	2	1	2	1	4	2	1	2	2	4	3	1	3	7	1	2	3	4	3	1	1	1	2	4	1	1	4	1	2
35	Jammie Jacobson	4	1	1	1	2	1	1	1	1	2	1	2	2	3	2	1	1	5	1	2	2	3	2	1	1	1	2	1	1	1	3	1	2
36	Shauna Augusta Denecke	2	1	1	1	3	2	2	1	3	1	1	5	2	1	3	1	3	3	1	2	2	1	3	1	1	1	1	2	1	1	1	1	2
37	Fluffy McAllister	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
38	Alan Ho	1	1	1	1	1	2	3	1	1	1	1	2	1	1	1	1	2	2	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1
39	Marie Strupatis	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
40	David Crozier	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
41	Bernadette Fouquet	4	1	1	1	2	1	2	1	1	2	1	2	1	3	2	1	1	4	1	2	2	3	3	1	1	1	2	1	1	2	4	1	2
42	Armando Macias Rodriguez	3	1	1	1	2	2	3	1	3	1	1	3	1	1	4	1	3	5	1	2	1	2	4	2	1	1	1	1	2	1	2	1	1
43	Julie Ann Leavitt	1	1	1	1	2	1	1	1	2	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1
44	Wayne Allen	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	2	1	1	1	1	1	1	1	1	1	1
45	Chrissy Freund	1	1	1	1	1	1	2	1	1	1	1	1	1	1	1	1	2	2	1	1	1	1	1	1	1	1	1	1	1	1	3	1	1
46	Gayle Velez	1	1	1	1	2	3	2	1	1	1	1	2	1	1	3	1	1	2	1	1	1	2	2	2	1	1	1	2	2	1	1	1	1
47	Debbie Ryder Register	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	3	1	1	1	1	2	1	1	1	1	1	1	1	1	1	1

Note: The data on the membership were collected from April 14, 2010 to April 18, 2010.

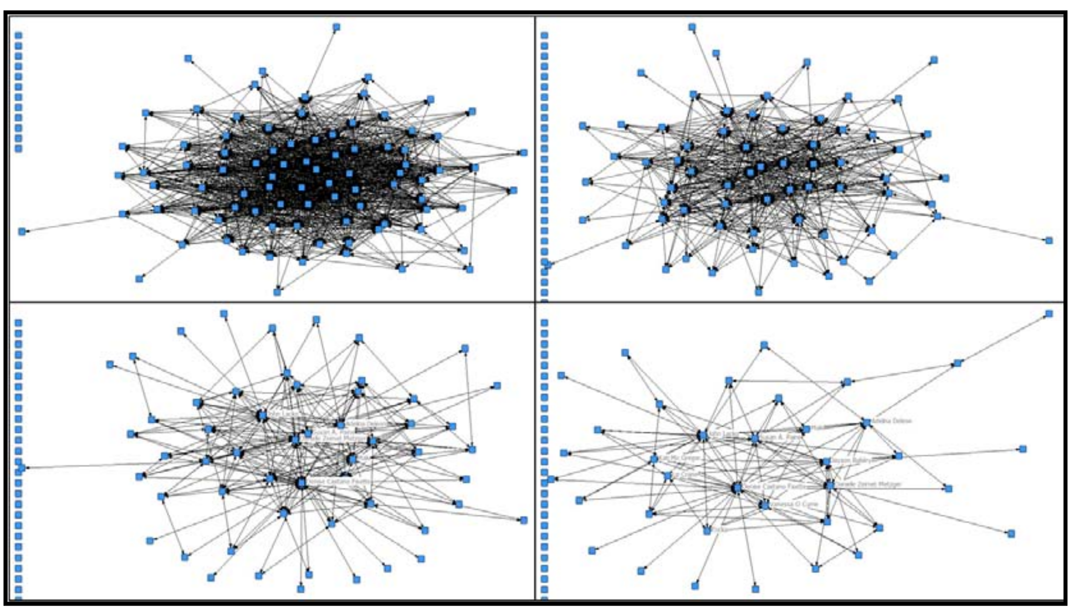
Figure 18 and 19 are the graphical presentation of ties at each level of relations between pairs of ARC Joiners for the samples before and after disaster. The four graphs for each sample show the collection of ties for a specific relation among the ARC Joiners, i.e., more than one Facebook Cause in common with other ARC Joiners; more than two Facebook Causes in common with other ARC Joiners; and so on. The stand-alone points (or nodes) on the left of the graph separated from the rest of the network are isolates which have less than the cut-off number of causes in common with any other joiner. In particular, the first graph with a cut-off value of two causes shows that a number of joiners have only the ARC Cause in common with the others in the sample.

Figure 18: One-Mode Network Graph of Relational Ties of ARC Joiners Before Disaster



Note: Top-left shows the ARC Joiners with greater than one relation, top- right shows greater than two relations, bottom-left shows greater than three relations and bottom-right shows greater than four relations.

Figure 19: One-Mode Network Graph of Relational Ties of ARC Joiners After Disaster



Note: Top-left shows the ARC Joiners with greater than one relation, top- right shows greater than two relations, bottom-left shows greater than three relations and bottom-right shows greater than four relations.

According to Table 3, there was greater number of relational ties, i.e., linkage between pairs of ARC Joiners after the disaster compared to before the disaster. For ARC Joiners with more than one Facebook Cause in common, there were 2,614 ties (i.e., 1,307 dyads or pairs of actors with ties between them) after the disaster compared to 2,114 ties (i.e., 1,057 dyads) before the disaster. There were also consistently more linkages after the disaster for ARC Joiners with more than four Facebook Causes in common after the disaster. Moreover, 22% (22/100 = 0.22) of the ARC Joiners sampled before the disaster had no relational tie to other ARC Joiners outside of the ARC Cause itself (i.e., isolates) compared to the 12% (12/100 = 0.12) isolates sampled after the disaster. Note that 8 out of the 22 isolates in the sample before the disaster belonged to more than one cause but only had a relational tie to other sampled joiners through the ARC Cause only. The remainder of the isolates did not belong to any other causes other than the ARC Cause as illustrated in Figure 18. Similarly, note that 4 out of the 12 isolates in the sample after the disaster belonged to more than one cause but had a relational tie to other sampled joiners through the ARC Cause only. The remainder of the isolates did not belong to any other causes other than the ARC Cause as illustrated in Figure 19. These results indicate the ARC Joiners were more connected to each other after the disaster compared to before the disaster which may be attributed to heightened recruitment efforts by prior contacts for these ARC Joiners, It should be acknowledged, however, that other factors such as attitudinal affinity for disaster recovery, constant media coverage of the disaster, etc. may also increase the connection among the ARC Joiners.

Table 3: Relational Ties of ARC Joiners Before and After Disaster

	Ties	
Relations	**Before**	**After**
Isolates	22	12
>1 relation	2114	2614
>2 relations	882	1062
>3 relations	430	476
>4 relations	202	218

Network density, measured by the number of ties among the actors as a proportion of the number of possible ties, can provide an index of the degree of dyadic connection in a population. For example, information about network density can be leveraged to assess the speed at which information can be shared within the network based on how connected the actors are. For the samples of the ARC Joiners before and after the disaster, the density of the network can contribute to how quickly existing ARC members recruit others to join the ARC Cause. The density of a graph can be computed by dividing the sum of all ties by the number of possible ties, and the maximum possible ties depend on the number of nodes (or actors in the network). For the ARC Joiners in the graphs illustrated in Figures 18 and 19, there is a total of 4,950 possible ties [100(100-1)/2 = 4,950].

The most dense relation in the two samples is among the ARC Joiners after the disaster. The density for the network with ARC Joiners after the disaster is consistently higher for the four levels of relations detailed in Table 4. The density for ARC Joiners with more than one Facebook Causes in common after the disaster is 0.26 (1,307/4,950 = 0.26) compared to 0.21 (1,057/4950 = 0.21) for ARC Joiners before the disaster. This indicates that 26% of all possible ties are present for the sample after the disaster compared to 21% for the sample before the disaster. The gap of the density between the two samples becomes closer for ARC Joiners with more than four Facebook Causes in common after the disaster (109/4,950 = 0.022) compared to before the disaster (101/4,950 = 0.020). The density for the entire network of ARC Joiners after the disaster is 1.48 compared to the network of ARC Joiners before the disaster of 1.41 (including the ARC Cause in the calculation of density). Unlike the density referenced previously on the proportion of ties present in a dichotomized matrix at a specific cut point (of relational ties), the density referenced here indicates the average number of common organizational affiliations in each 100 X 100 matrix of sampled ARC Joiners.

Table 4: Relational Density of ARC Joiners Before and After Disaster

	Ties	
Relations	**Before**	**After**
>1 relation	0.21	0.26
>2 relations	0.09	0.11
>3 relations	0.04	0.05
>4 relations	0.02	0.02

In addition to examining the one-mode network of the sampled ARC Joiners, the Facebook Causes each of these joiners belonged to can also be analyzed on how connected these organizations may be to one another before and after the disaster. For the one-mode network of the Facebook Causes, the rows and columns of the actors in the network are the pool of organizations (or Facebook Causes) the sampled ARC Joiners belonged to – the sampled joiners belonged to a pool of 625 Facebook causes before the disaster and the joiners sampled after the disaster belonged to a pool of 664 Facebook causes. These sampled joiners can belong to as few as one cause (i.e., ARC Cause) or over a hundred other causes from the pool of aforementioned Facebook Causes. The matrix to illustrate the one-mode network of Facebook Causes the ARC Joiners belonged to before and after the disaster is consisted of rows and columns of the name of these causes. The entries in the matrix represent the number of sampled ARC Joiners these causes have in common with each other. The graphic display illustrates the ties between these Facebook Causes in each sample – the collection of ties can also be illustrated of a specific relation such as the set of Facebook Causes with more than one sampled ARC Joiner in common.

One Mode Network of Facebook Causes (of Sampled ARC Joiners)

Table 5 is an example of a one-mode network matrix with 625 Facebook Causes the sampled ARC Joiners belonged to ten days before the disaster – these Facebook Causes are the set of events for this data set. There are 625 rows and 625 columns in the data set (which is not all shown in the table illustrated). The primary interest of this data set focuses on the relational ties among these Facebook Causes to examine how many other ARC Joiners they shared. The diagonal elements highlighted in red show the number of ARC Joiner each cause had. The entry of “0” indicates the two causes adjacent to each other do not have any members in common. However, if the entry is greater than or equal to one, then they share at least one ARC Joiner in common. For example, Facebook Cause #4 (“American Red Cross”) has a hundred sampled ARC Joiners in the entry given the entire sample was selected from the ARC Cause. Moreover, the ARC Cause also shared four ARC Joiners with the cause called “Mandatory Life Sentences for Pedophiles and Child

Molesters, Death for Child Killers", five ARC Joiners with "A Real Man Never Hits A Woman" and nine ARC Joiners with "Allow God in School".

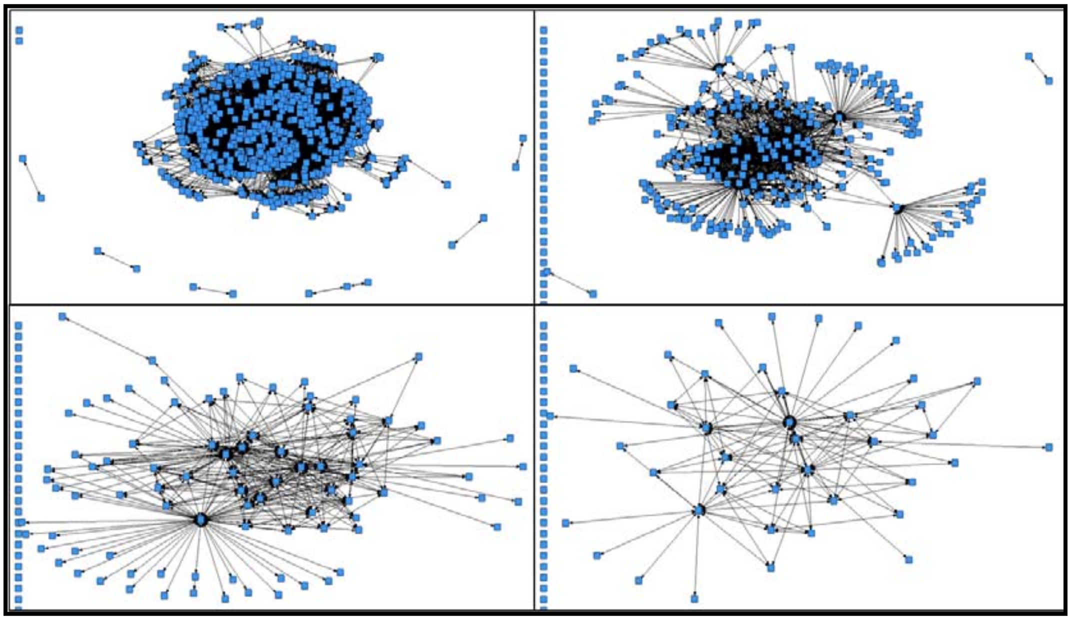
Table 5: One-Mode Network Matrix of Facebook Causes Before Disaster

	1 Man	2 A R	3 All	4 Ame	5 Ang	6 Awa	7 Fre	8 Hel	9 I'm	10 JES	11 Soc	12 Put	13 The	14 STO	15 KID	16 Tel	17 Req	18 P.U	19 SAY
Mandatory Life Sentences for Pedophiles & Child Molesters, Death for Child Killers.	4	1	1	4	1	1	1	1	1	1	1	1	2	1	1	1	1	1	3
A Real Man Never Hits A Woman!	1	5	3	5	1	1	2	2	1	1	1	3	3	3	1	1	2	1	3
Allow God in School	1	3	9	9	2	1	2	1	1	1	1	5	3	2	1	1	2	1	4
American Red Cross	4	5	9	100	4	1	14	3	1	1	4	8	11	11	1	1	7	1	19
Angel Hugs for Childhood Cancer	1	1	2	4	4	1	1	2	1	1	2	1	1	2	1	1	1	1	1
Awareness for Breast Cancer	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Free Postage For All Families of Deployed Military	1	2	2	14	1	1	14	2	1	1	2	3	5	5	1	1	4	1	6
Help stop DOG-FIGHTING	1	2	1	3	2	1	2	3	1	1	2	1	2	4	1	1	2	1	2
I'm Worth It - TRUE LOVE WAITS	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
JESUS CHRIST-our 1st LOVE and PRIORITY, ABOVE everyone and everything else	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Society Against Child Abuse	1	1	1	4	2	1	2	2	1	1	4	1	2	2	1	1	1	1	2
Put Christ Back Into Schools	1	3	5	8	1	1	3	1	1	1	1	8	3	2	1	1	2	1	4
The Breast Cancer site is having trouble getting enough people to click...	2	3	3	11	1	1	5	2	1	1	2	3	11	4	1	1	3	1	7
STOP CHILD PORNOGRAPHY	1	3	2	11	2	1	5	4	1	1	2	2	4	13	1	1	7	1	7
KIDS V CANCER	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Tell Everyone about how Awesome God is	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Require Amber Alerts to be issued for any child missing more than 5 hours	1	2	2	7	1	1	4	2	1	1	1	2	3	7	1	1	7	1	4
P.U.S.H.--Pray Until Something Happens!!!	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
SAY NO TO FACEBOOK BECOMING A PAYSITE	3	3	4	19	1	1	6	2	1	1	2	4	7	7	1	1	4	1	19
Stop Baby Momma Drama and Save Fatherhood	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
KEEP sex offenders OFF	2	3	4	25	2	1	8	3	1	1	3	4	6	11	1	1	6	1	12
JOIN THE FIGHT TO STOP DISHONORING THE PRESIDENT	1	3	2	4	1	1	2	2	1	1	1	2	3	3	1	1	2	1	3
Support to find a CURE for CF	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Pray for the Soldiers and Families at Ft. Hood	1	2	3	6	1	1	3	1	1	1	2	2	3	2	1	1	1	1	5
National Council of Negro Women(Palm Beach Chapter)	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
International Justice Mission	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Polaris Project	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Students Who Support NATO	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Breast Cancer "The Pink Cause"	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Campaign for Cancer Prevention	0	0	0	4	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1
I WORK FOR JESUS- "I Will Spread the WORD of GOD"	0	0	0	2	0	0	1	0	0	0	0	0	1	1	0	0	1	0	0
The Susan G. Komen Breast Cancer Foundation	0	0	1	2	0	0	1	0	0	0	0	1	0	1	0	0	1	0	1
Abuse Against Women	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ADD MORE LEVELS TO FARMTOWN	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Amber Alert on Facebook	2	1	2	14	0	0	5	1	0	0	0	1	3	4	0	0	2	0	4
Cure Childhood Cancer	0	0	0	3	0	0	1	0	0	0	0	0	1	0	0	0	0	0	1
Death Penalty For Cop-Killers	0	0	1	5	0	0	2	0	0	0	0	2	1	0	0	0	0	0	0
Fallen Fire Fighters	0	0	0	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Feel Your Boobies Foundation	0	0	1	6	1	0	2	0	0	0	0	0	0	0	0	0	0	0	0
Fight Childhood Cancer - Alex's Lemonade Stand Foundation	0	0	0	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Free Phone Calls for Soldiers	0	0	1	7	0	0	4	0	0	0	0	0	2	1	0	0	1	0	2
National Transplant Society	0	0	0	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Kidney Donation	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Remember September 11th	0	1	1	3	0	0	2	1	0	0	0	1	1	3	0	0	2	0	2
Save a Life -- Be Aware Motorcycles are Everywhere!	0	0	1	4	0	0	0	0	0	0	0	2	1	0	0	0	0	0	0
Help Keep CHRIST in Christmas	1	2	3	8	1	0	1	1	0	0	0	1	4	2	0	0	1	0	3
Thank A Soldier	1	1	2	16	0	0	8	1	0	0	0	1	3	5	0	0	3	0	7
PETITION TO CHANGE PORN SITES TO HAVE A DOT XXX URL ADDRESS ENDING TO PROTECT CHILDREN	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Note: The data on the causes were collected from April 14, 2010 to April 18, 2010.

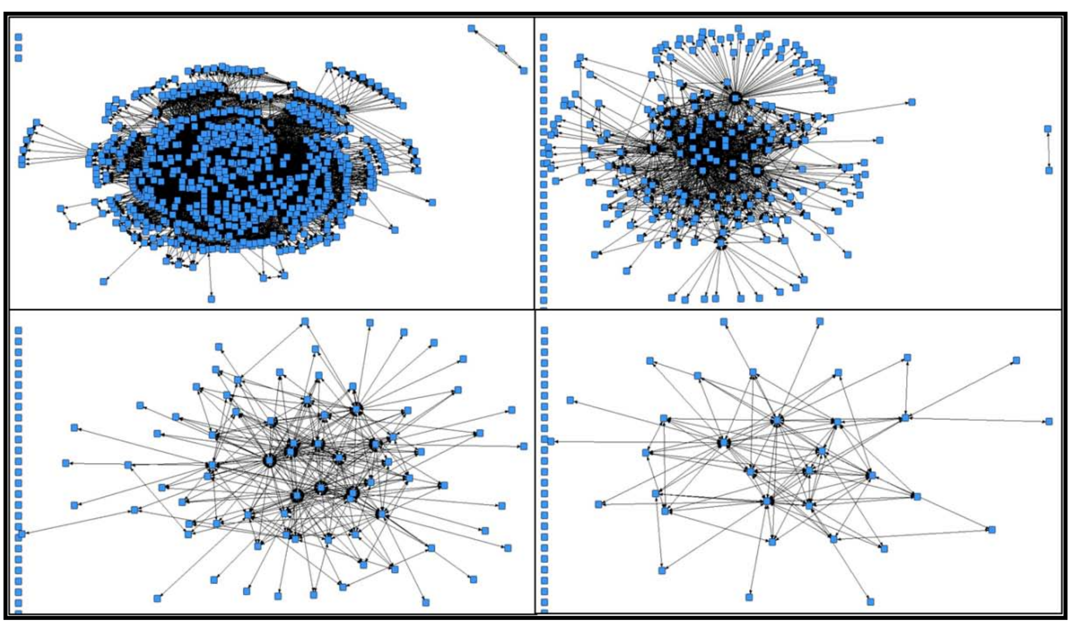
Figure 20 and 21 are the graphical presentation of ties at each level of relations between pairs of Facebook Causes the sampled ARC Joiners belonged to before and after disaster. The four graphs for each sample show the collection of ties for a specific relation among the Facebook Causes (excluding the ARC Cause), i.e., no ARC Joiner in common with other cause (no relation at all); more than one ARC Joiners in common with other causes (more than one relation); and so on. The isolates on the left of the graph separated from the rest of the network are the Facebook Causes that do not have any sampled ARC Joiners in common with another cause.

Figure 20: One-Mode Network Graph of Relational Ties of Facebook Causes Before Disaster



Note: Top-left shows the Facebook Causes with zero relation, top- right shows greater than one relation, bottom-left shows greater than two relations and bottom-right shows greater than three relations.

Figure 21: One-Mode Network Graph of Relational Ties of Facebook Causes After Disaster



Note: Top-left shows the Facebook Causes with zero relation, top- right shows greater than one relation, bottom-left shows greater than two relations and bottom-right shows greater than three relations.

Contrary to the networks of the ARC Joiners, there were more relational ties, i.e., linkage between pairs of Facebook Causes before the disaster compared to after the disaster according to Table 6. For the Facebook Causes with more than one ARC Joiner in common, there were 3,348 ties (i.e., 1,674 dyads or pairs of causes with ties between them) before the disaster compared to 2,344 ties (i.e., 1,172 dyads). Given that the network of Facebook Causes (excluding the ARC Cause) before the disaster was slightly smaller than the network after the disaster (625 vs. 664), this could increase the chances of connection between pairs of causes for the network before the disaster since the sampled ARC Joiners had a smaller pool of causes to share. There were also consistently more linkages before the disaster for Facebook Causes with zero to three ARC Joiners in common after the disaster. Moreover, only two out of all the Facebook Causes before the disaster had no relational tie to other causes compared to the three isolates after the disaster. The minimal number of isolates for Facebook Causes can indicate most of these causes are connected to each other one way or another.

Table 6: Relational Ties of Facebook Causes Before and After Disaster

	Ties	
Relations	**Before**	**After**
Isolates	2	3
>0 relation	38,420	31,964
>1 relations	3,348	2,344
>2 relations	682	594
>3 relations	228	206

Note: The ARC Cause was excluded from the calculation of the relational ties of Facebook Causes.

For the Facebook Causes in the graphs illustrated in Figures 20 and 21, there is a total of 195,000 possible ties [625(625-1)/2 = 195,000] before the disaster and a total of 220,116 possible ties [664(664-1)/2 = 220,116] after the disaster. The most dense relation in the two samples is among the Facebook Causes before the disaster. There is smaller difference for the density of the networks with Facebook Causes before the disaster at each of the four levels of relations detailed in Table 7 compared to the causes after the disaster. The density of the Facebook Causes with more than one sampled ARC Joiner in common before the disaster is 0.0085 (1,665/195,000 = 0.0085) compared to 0.0053 (1,172/220,116 = 0.0053) for ARC Joiners sampled after the disaster. This indicates that 1% of all possible ties are present for the network of causes before the disaster compared to less than 1% for the network of causes after the disaster. The gap of the density between the two samples becomes insignificant for the networks of Facebook Causes with more than two or three Facebook Causes in common. The density for the entire network of Facebook Causes before the disaster is 0.1159 compared to the network of Facebook Causes after the disaster is 0.0858 – this indicates the overall network of Facebook Causes before the disaster is more connected which can potentially be more influential in recruitment dependent on how active their members may be. Again, the density referenced here indicates the average number of common ARC Joiners in each 625 X 625 or 664 X 664 matrixes of Facebook Causes that ARC Joiners belonged to.

Table 7: Relational Density of Facebook Causes Before and After Disaster

	Ties	
Relations	**Before**	**After**
>0 relation	0.0985	0.0726
>1 relations	0.0085	0.0053
>2 relations	0.0017	0.0014
>3 relations	0.0005	0.0005

Note: The ARC Cause was excluded from the calculation of the density of Facebook Causes.

Chapter 7: Conclusion

There are two undeniable realities for emergency response organizations to take into consideration going forward with their disaster relief effort – 1) the magnitude and impact of disasters are often unpredictable and require speedy response to fulfill basic humanitarian needs for disaster victims; and 2) the users of online social networks (whether it is Facebook or another platform) will likely continue to grow exponentially in size and use the platform of online social networking sites as a real time communication tool with other online users. .Given the unpredictable nature of natural and man-made disasters, the capability to expedite the mobilization of resources for disaster relief is critical in saving lives and helping the disaster victims with the response/recovery process. Therefore, it is crucial for disaster relief organizations to target their recruitment effort of these resources by leveraging the online social networks to activate interpersonal or organizational ties from the disaster communities globally.

In order to fill the gap of research on the relational ties of the disaster communities organized through the social networks online, the analyses from Chapters 4 to 6 presented empirical evidence of unique differences of the Facebook members joining the ARC Cause (an online platform for disaster community) before and after the Haiti earthquake disaster. The results from this thesis research are not directly comparable to the research findings from McAdam et al. on social movement analysis or Hurlbert et al. on utilizing networks for social resource provision in the context of a disaster, but they do provide insights into the predictors of successful recruitment to social movements, specifically disaster relief efforts, based on network composition and structure.

Network Size Does Matter

Comparing the sampled joiners of ARC Cause before and after the Haiti earthquake disaster reveals that the average membership size of the Facebook Causes that sampled joiners belonged to after the disaster is 48% greater than before the disaster (500,700 members after the disaster compared to 337,756 members before the disaster). This finding indicates the Facebook Causes with larger membership sizes can potentially be more successful in mobilizing their resources to recruit other Facebook members to their cause. Additionally, analyzing the distribution at the incremental level reveals that the sampled joiners after the disaster also belonged to more Facebook Causes than they did before the disaster. As illustrated in Figure 11, 41% of the ARC Joiners sampled after the disaster belonged to 11 or more Facebook Causes compared to only 27% of the ARC Joiners sampled before the disaster. This is consistent with the findings of McAdam (1986) who reported that participants of the Freedom Summer project (high cost/high risk form of activism) had a greater number of organizational affiliations than the non-participants (i.e., those accepted to the project but later withdrew). As my analyses reveal, Facebook members who joined the ARC Cause (low cost/low risk form of activism) after the disaster may share similar characteristics in support of a specific cause.

Linkage Between Identity and Action

The sampled joiners of ARC Cause after the disaster belonged to twice as many Facebook Causes related to disaster relief than sampled joiners before the disaster (4% of Facebook Causes related to disaster relief after the disaster compared to 2% before the disaster). Similarly, the ARC Joiners sampled after the disaster also belonged to more Facebook Causes related to philanthropy than sampled joiners before the disaster (50% of Facebook Causes related to philanthropy after the disaster compared to 45% before the disaster). For the Freedom Summer project, McAdam and Paulsen (1993) also reported the participants not only belonged to more organizations but ones such as civil rights organizations, teacher associations, etc. – the Facebook members who joined the ARC Cause after the disaster can also be compared in the same vein in linking their identity with action through salience of organizational affiliations.

Mobilizing Women Online for Support Provision

Among the sampled joiners of the ARC Cause, women dominated the network after the disaster by a ratio of four to one, compared to a ratio of three to one before the disaster. The Haiti earthquake disaster "pulled" substantially more women to the social networks online for support provision, a finding that is contrary to the results of past research on differential participation in disaster communities and the results of Haines and Hurlbert (1996), who reported that higher proportions of men provide support in disaster relief compared to women. It is likely that women can now leverage online social networks to provide informal support of disaster relief efforts, something that was not possible in the physical sense prior to the popularity of social networks online. In fact, Figure 15 shows the differential participation of women over men in the general population of Facebook in the U.S. (56% women compared to 44% men). The disaster pulled an even greater proportion of women into disaster relief networks, with 68% of women joining the ARC Cause before the disaster and 79% of women joining after the disaster.

Stronger Effect of Interpersonal Ties for Recruitment

The sampled joiners of ARC Cause are more connected to each other after the disaster than the sampled joiners before the disaster. When analyzing the relational ties of the ARC Joiners after the disaster at the incremental level, they consistently have more relational ties from greater than one relation to greater than four relations as detailed in Table 3. However, when analyzing the relational ties of the Facebook

Causes before and after the disaster, the causes before the disaster consistently have more relational ties from greater than one relation to greater than four relations as detailed in Table 6. This indicates a heightened (or more effective) recruitment through activating interpersonal ties among ARC Joiners sampled after the disaster rather than organizational ties among Facebook Causes. Since there is a slightly higher number of Facebook Causes that sampled joiners belonged to after the disaster compared to before the disaster (664 Facebook Causes after the disaster compared to 625 before the disaster), this could potentially impact the number of relational ties to consider in the calculation.

News Travels Faster in a Dense Network

The sample of ARC joiners after the disaster has a greater density of relational ties at each incremental level compared to the joiners sampled before the disaster. According to Fernandez and McAdam (1988), the density of a network can predict participation, and moreover, the density of a network can offer insights into the speed of information diffusion among its members. This suggests that ARC Joiners may be recruited faster after the disaster as a result of their participation in a denser network with more joiners connected to each other. On the other hand, the Facebook Causes of the ARC Joiners before the disaster has greater density of relational ties at each incremental level (though the differences become more minimal with the higher level of increments). This should also take into consideration the higher number of Facebook Causes in the sample after the disaster as discussed in the previous section.

This study was conducted in hopes of offering insights to emergency response organizations such as the American Red Cross on tailoring their recruitment effort of activists and expediting the mobilization of readily available resources (in particular online) for emergency assistance in a moment's notice. While the findings from this thesis research may not be directly comparable to the historical findings cited in earlier chapters, the differences between the two samples selected before and after the Haiti earthquake disaster are mostly consistent on recruitment factors based on number of organizational affiliations, linkage to identifiable recruitment communities, interpersonal ties and density of network. There is also unique distinction for highly differential participation of female Facebook members joining the ARC Cause compared to historical support for stronger male presence in the disaster community.

Limitations and Future Research

The data collected for this study can be considered more observational than self-reported (except for the gender of the ARC Joiners was self-reported from their profile). A follow up study to further explore the motivation to participate (such as attitudinal affinity, personal relations or organizational affiliations) and other attributes (such as age, education, income, etc.) can confirm the conclusions based on the observational data. Another limitation is the data collection period of the attributes and organizational affiliations occurred after four months (April 14, 2010 to April 18, 2010) when the Facebook members first joined the ARC Cause in January, 2010. Their organizational affiliations for other Facebook Causes they may have joined after they joined the ARC Cause may differ from when they first joined the ARC Cause. Unfortunately, there was no way to differentiate the causes joined after becoming an ARC Joiner compared to before they joined the ARC since the date on which they joined is not indicated by the Causes application on Facebook.

Given the wealth of administrative data available through Facebook, future research can explore how the larger Facebook Causes may join forces in mobilizing their resources in recruiting others for disaster relief effort (i.e., bloc recruitment). Another area to explore further is how “Cause profiling” (i.e., targeting the Facebook members belonging to greater proportion of disaster relief or philanthropic causes) may be leveraged as the stronger ties in recruiting others to join their cause. This can potentially maximize the effort for disaster relief organization to mobilize their resources for recruitment in the event of a disaster. Furthermore, knowing that information can spread quicker in a more dense network, fundraising effort can also be targeted to these Facebook Causes in order to raise donations needed for disaster victims in a speedy manner. Although this thesis research only scratched the surface of the data mining opportunities possible with observational data alone, it does reveal encouraging findings of a beneficial partnership between emergency response organizations and online social networks working towards a common cause of helping to rebuild the lives of disaster victims.

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About the Author

Jennie Wan Man Lai was born in Hong Kong and earned a B.S. degree in Multinational Business Operation, Marketing with specialization in Marketing Research, and Finance from the College of Business at Florida State University. She has been working in the field of survey research methodology for The Nielsen Company since 2001; and experienced in the areas of media and consumer research. She is also active in participating and presenting at the American Association of Public Opinion Research (AAPOR).