SOCIAL MEDIA AND EXTREMIST GROUPS ONLINE: AN EXAMINATION OF METHODS OF RADICALIZATION AND ITS IMPLICATIONS

by

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ABSTRACT

RYAN FERTAKOS. Social Media and Extremist Groups Online: An Examination of Methods of Radicalization and Its Implications. (Under the direction of DR. JUSTIN CONRAD)

This thesis studies the relationship between extremist groups, their presence online, their ability to radicalize individuals, and the implications of this relationship. Data was collected from Twitter related to two significant events claimed by ISIS or ISIS supporters: the 2015 terrorist attacks in Paris and the 2017 Battle of Marawi in the Philippines. The sample of tweets was then broken down into four different "phases" of radicalization by using key indicator terms of each phase. Using both an analysis of time-series trends and negative binomial regression I examine the relationship between the temporal proximity to each event and the number of tweets in each phase of radicalization. The results are inconclusive: there are few clear trends in the time-series analysis, and no statistically significant relationships. I offer possible explanations for the absence of significant relationships, and I conclude that the results nonetheless demonstrate the potential of this type of analysis in the future. Extremist groups continue to operate online and understanding how they do so may be key to stopping them from radicalizing more individuals.

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CHAPTER 1: INTRODUCTION

As social media has become more and more prevalent in everyday life, it has also created new challenges for society to face. Misinformation can often be strife on such platforms and depending on if they are your only source of news, you may take this information as fact. They also provide for a way for individuals who may not have never been in contact with one another to do so, and while this is by and large a positive thing, the potential negative aspects of these interactions are very real as well. In this case, individuals representing extremist groups online can contact people who they identify as a potential recruit to their cause. Through propaganda and other means, there is the potential for these identified individuals to become radicalized through social media, without ever having to physically meet with the representative of the group. These methods of radicalization, and whether there is an identified pattern that can be seen by examining social media data, is what this thesis aims to address.

CHAPTER 2: THEORY AND HYPOTHESIS

Terrorism is a large problem facing the modern world, and terrorist's ability to enact real-word political violence through the radicalization of individuals online is a dangerous reality society must face. They have, in some ways, solved the collective action problem; that is, through their propaganda spread online, they are radicalizing individuals, and those individuals are taking real world action. Each of these three concepts, terrorism, radicalization, and collective action and the ensuing collective action problem, need to be defined in order to better understand the framework in which this thesis is operating. In Combs (2018) textbook, she has an entire chapter dedicated to the discussion of the definition of Terrorism. While creating a universally accepted definition of terrorism has proved to be quite difficult up to this point, it is possible to identify certain features common to it (Combs, 2018). These features are as follows and are derived from the varying definitions of terrorism used by differing domestic and international organizations that do exist today. Whatever is being considered as terrorism must have been, "an act of violence, designed to create a mood of fear in an audience, for [a] political/social motive, and be targeting people not engaged in combat." (Combs, 2018). As such, for the purposes of this thesis, Terrorism is defined **"as a synthesis of war and theatre – a dramatization of the most proscribed kind of violence – that which is deliberately perpetrated on civilian noncombatant victims – played in front of an audience in the hopes of creating a mood of fear, for political purposes."** (Combs, 2018).

Radicalization, for the purposes of this thesis, is defined as the four-step process in which an individual becomes capable of carrying out a terrorist act. Each step of this process, those being "It's Not Right, It's Not Fair, It's Your Fault, You Are Evil," are further defined in the literature, and expanded upon within its review. Collective Action refers to, in this case, the willingness for someone, as a member of a group, to act in benefit to the group in some way, while the Collective Action Problem, on the other hand, is the question in which one has to determine how these individuals become motivated enough to act in the interest of the group in the first place. The scope of this thesis examines how extremist groups attempt to solve this problem. How do they radicalize individuals enough so that they are willing to carry out extremist acts in the name of the group?

Collective Action, and the related collective action problem is not something that only extremist groups are trying to solve and has been extensively researched in multiple fields of study. Olson, (1971), explores this topic at length, and while his approach focuses mostly on economics, the ideas presented can apply to the social sciences as well. One that is particularly relevant to this thesis are his suggestions regarding small groups and the behavior of such groups. Explaining them to be much more effective than larger groups in pushing individuals into acting, he offers a potential explanation for the effectiveness of extremist communities on social media platforms (Olson, 1971). Because of their smaller nature, participants avoid the potential problem in feeling as if their contributions to the group may not make a significant impact (Olson, 1971). Extremists can capitalize on this "small group feeling," and emphasize the potential importance of a radicalized individual's actions.

There is also historical precedent within the Arab community of individuals willing to take collective action, as made evident by the Arab Spring. In that instance, many individuals were able to solve the collective action problem and convince people to protest repressive governments in their home countries. Steinert-Threlkeld examines how individuals were mobilized in the Arab Spring by looking at the impact "core" players had on getting people to protest, when compared to individuals on the "periphery." (Steinert-Threlkeld, 2017). "Core" players are those who are centralized and well connected, often at the center of a social network, while the "peripheral" individuals are those observed by others in a social network more directly, while not being as central to the network (Steinert-Threlkeld 2017). His results were that, contrary to what one might expect, these "periphery" individuals had a statistically significant effect on protest activity, while "core" individuals did not (Steinert-Threlkeld, 2017).

Social media plays a significant role in collective action now that it has become so mainstream. Kende *et al.* explore this in their article examining how social affirmation through social media effects collective action. They do this through two separate studies. The first is of a group of university students that took part in a 6-week protest regarding government higher education policy (Kende *et al,* 2016), and the second was through 261 university students that participated in an in-lab experiment for course credit (Kende *et al,* 2016). The results of the first study were that use of social media for social affirmation of individuals active in the protests led to an increased rate of participation both offline and online for the duration of the protest activities (Kende *et al,* 2016). Study two had similar results, indicating that engagement in social media motivated individuals to engage in collective action (Kende *et al,* 2016).

Spier also examines social media's impact on collective action and has findings particularly relevant when discussing its potential for use by extremist groups. He states that, “social media can help people overcome difficulties of coordination, organization, and communication in large groups; these difficulties are often the obstacles that prevent people from fulfilling their needs, motivation, and goals through collective action.” (Spier, 2017). Social media provides the platform in which ideas with the potential to cause collective action can be shared. With enough communal buy in of these ideas, it is possible the collective action problem can be solved, at least in certain instances.

The collective action problem, that being how to motive an individual enough to take collective action, is something that many different groups face. They need to motivate individuals enough to make the benefits of acting outweigh the costs. In the case of extremist groups, they do this through a process of radicalization in individuals that lowers the costs of action, or raises the costs of inaction, depending on the perspective they are trying to instill in an individual. These extremist groups also offer potential metaphysical rewards, which may also come into play. Their promises of a blessed afterlife, or the taking care of their families in the case they become a martyr to the cause, are physical and metaphysical benefits that other groups also attempting to incite collective action may not be able to offer. By convincing a potential actor that inaction might result in personal loss, or that their action would have tangible gain, ISIS can persuade individuals to act. The radicalization process is a multi-step endeavor that leads individuals down a path towards violence, as shown by Combs in her book.

These four steps of radicalization are, “It’s Not Right, It’s Not Fair, It’s Your Fault, You Are Evil.” Each step is linked to the way an individual might compare themselves to others. It’s not right that you have more than me, it’s not fair that you have more than me, it’s your fault that you have more than me, and then, finally, you are evil because you have more than me. This final step is the one in which action against those this individual deems as their "evil" might become acceptable (Combs, 2018).

Understanding this radicalization process is key to grasp this entire thesis, and as such, further explanation is warranted to cement that understanding. Combs (2018), breaks down these four steps that she mentions as being the radicalization process and elaborates on each using a consistent example throughout. The first step, that being "It's Not Right," is explained through this consistent example, that being an individual who lives in an impoverished area. This individual might get angry about this, looking inwardly and saying to themselves "It's Not Right" that they must suffer the way they do. They become angry at this, but this anger lacks direction, at least in this stage (Combs, 2018).

The second stage of the radicalization process, "It's Not Fair," begins when this angered individual starts to compare themselves to others around the globe that are not experiencing the same struggles that they are. Seeing these individuals who aren't, in this example, starving, or in fact, have more food then they need, begins to give direction to their anger. This results in our example individual stating that "It Isn't Fair" that those other people have more then what they need, and they, on the other hand, are starving. This anger, however, is often not directed fully at these individuals with more than they need; rather it is directed at this impoverished individuals' leaders, seeing them at fault, especially when compared to the leaders of those with too much to eat, rather than too little (Combs, 2018).

The third stage, "It's Your Fault," arises when the individual suffering feels the need to place fault on an individual or group for their suffering. In this example case, someone to blame for our example individual starving. “Savvy leaders,” (Combs 2018), will be able to direct this anger towards those with these overabundant resources, food, in our case. They might say things like, ‘While you, and your loved ones starve due to lack of resources, other countries and those that live in them complain of having too much.’ This anger can result in violence; however, this violence is often specific in its goals, employed to obtain something that is lacking, food, in our case. Globalization allows for these comparisons to be made among different people throughout the world, and while this is still not the phase in which terrorism can become an option appealing to those suffering individuals, they are very close to being fully radicalized (Combs 2018).

The fourth and final step of this radicalization process, “You Are Evil,” is where the line is crossed, and individuals become capable of carrying out radical acts. Rather than viewing those who they see as oppressing you as human, a radicalized individual would see them as a monster, something not human, something unable to be reasoned with. This dehumanization allows for true acts of terrorism to be carried out, as the killing of those viewed as ‘evil’ is considered more an obligation, or a righteous cause, rather than a crime (Combs 2018).

Each of these four steps take time to progress through, and the later stages are not something you are exposed to naturally. You may get mad at an individual or another group of people, and in turn blame them for your plight, but being pushed towards acting out against those individuals usually requires some sort of outside force to further radicalize you. That is where extremists’ groups step in, and through their use of social media, have a much easier time doing it. Without having to be physically present in a susceptible individual’s life, they can infiltrate it through the internet instead. By doing that, they establish a much wider reach, and can contact individuals they otherwise would not have been able to.

With the definition of terrorism for the purposes of this thesis, and an understanding of the radicalization process and collective action established, the literature examined then moves to where the bulk of this thesis's actual analysis lies; how does the use of social media by extremist groups lead individuals to take real world action? There is a myriad of literature on this subject, and those articles provided here establish a solid base to work from. Most examine either online extremism directly or look at methods in which to counter it. The former is where this thesis will begin, as there is more literature to review involving it, then that literature discussion countering online extremism will follow.

Singer discusses how societal fears have obscured how we perceive terrorists to be using the internet, when compared to how they are using it. Singer begins with pointing out the flaws in the discussion around cyber-terrorism, pointing out that many times we consider "any nonviolent mischief," to also be something that we should consider cyber-terrorism (Singer, 2012). The reality is that, as put by George R. Lucas Jr., a professor at the U.S. Naval Academy and quoted by Singer, pulling off a mass-scale action using cyber means "simply outstrips the intellectual, organizational and personnel capacities of even the most well-funded and well-organized terrorist organizations." (Singer, 2012). In that case, then, one might wonder why this focus on cyber-terrorism should continue, if groups aren't realistically able to commit acts through cyber means that would have violent results. Singer points out that terrorist groups use the internet like many of us do, and that can be particularly dangerous. Singer makes the comparison to an individual on a dating site. Like that person looking to meet someone, so too are extremist groups on the internet looking to meet likeminded individuals who share their ideals, or at least find information or propaganda that appeals to these ideals (Singer, 2012). This can eventually lead to the radicalization of these individuals to an extremist's group's cause, and in turn, create a lone-wolf terrorist.

This then brings up another question. Who are these individuals, and what leads to their exposure? Costello, Hawdon, Ratliff, and Grantham explore this question in their article. By surveying 1034 American youth and young adults, the authors examine how many had encountered negative views about a group online, how they would describe the negative material, and what that negative material pertained to (Costello *et al,* 2016). Their results showed that over 65% of their survey respondents had encountered hate material, and that most of those individuals exposed saw it accidentally. Much of this hate material was encountered on Facebook, with YouTube being the leading source behind that, then Twitter behind that (Costello *et al,* 2016). This study shows that, even amongst American users, who one may not expect to be the target of many of these extremist groups, plenty of hate material exists, and the majority of those focused on in this study, encountered it in some shape or form.

Relating to the previous article, Cao, Zheng, Vorobyeva, Song, and Johnson (2018) work to identify patterns in the direction individuals take towards supporting extremist groups online. In their article, they analyze a dataset pulled from VKontakte, which was once "the primary online social media source for ISIS propaganda and recruiting before moderator pressure forced activity toward encrypted alternatives such as Telegram in late 2015." (Cao *et al,* 2018). Their focus was on 91,781 VKontakte users who were members of at least one online pro-ISIS group at the start of the study or became a member during the study (Cao *et al,* 2018). To measure trajectory, the authors used moderator bans as an indicator. Of those 91,781 accounts, 7,707 would eventually develop such extremist views as to eventually result in a ban from VK (Cao *et al,* 2018). The authors are then also able to identity "dynamical patterns" in the online trajectories of these individuals, showing that it is, in fact, quantifiably possible to do so (Cao *et al,* 2018).

In the next article by Awan, the author highlights the ways in which ISIS has been waging cyber war. Citing "slick videos, online messages, and even an app," ISIS uses each to radicalize individuals online to push them towards action (Awan, 2017). Awan analyzed both Facebook and Twitter in his work to examine how those platforms were being used by ISIS, and his findings were twofold. While there are also strong negative sentiments towards ISIS throughout the social media data he examined, there was also a narrative present throughout that glorified ISIS (Awan, 2017). Awan also points out, through his research, seven different characteristics that make an individual more likely to support this ISIS narrative (Awan, 2017). He lays out why social media has become such a powerful tool for ISIS, and how it continues to affect those that make use of social media.

These articles have all been chosen because of their focus on Twitter in specific, as each provide varying insights as to why Twitter is and has been so impactful in terms of ISIS's presence within it. The first is by Benigni, Joseph, and Carley. In their work, Benigni *et al.* identify what they call online extremist communities, or OECs for short, and focus on the one within Twitter (Benigni *et al,* 2017). Firstly, through vertex clustering and classification (IVCC), the authors develop a way, through network analytics, to identify extremists through social media. They also perform a case study of that OEC within Twitter and offer multiple findings that also support the idea that IVCC can be used to support both diplomatic and defense initiatives regarding identifying extremist communities (Benigni *et al,* 2017).

Ferrara, Wang, Varol, Flammini, and Galstyan (2016) offer their own methods of extremist identification amongst social media in their article. Through the leveraging of a machine prediction framework and a large dataset derived from Twitter, they identify three tasks related to online extremism within Twitter: the detection of extremist users, the prediction of adoption of extremist content, and the forecasting of interaction reciprocity between regular users and extremists. The authors then propose a machine prediction framework to accomplish these tasks (Ferrera *at al,* 2016). Their conclusions show the power of this machine prediction framework, as well as some of the significant features of tweets, such as the retweet to tweet ratio, or average number of retweets per user, as indicators of high predictive power (Ferrera *at al,* 2016).

As the previous two articles suggest, being able to identify or predict the way ISIS's narrative will affect individuals on social media has the potential to play a big part in countering it. These different attempts at countering terrorism can come in many forms. In Warrington's paper, she analyzes the tweets from the "Average Mohammad" profile, a twitter account operated by an American-Somali man with the intention of countering what he sees as misrepresentations of Islam (Warrington, 2017). Given the way Twitter is structured, it is impossible to asses a concrete impact of the Average Mohammad profile (Warrington, 2017), however, her results show the potential in what

“Average Mohammad” had been doing. By providing a different message countering that which was being provided by extremists online, the potential is shown for including civil society actors in these counterterror activities (Warrington, 2017)

Mitts (2017) discusses in her article the impacts of community engagement events held in the United States by the Department of Homeland Security that aim to reduce radicalization in at risk communities. How effective these programs are is a key factor in assessing whether they are worth continuing, and this is something that Mitts looks to address (Mitts, 2017). Using an algorithm run through her data from Twitter, Mitts can identify 47,000 ISIS supporting accounts in the network that operated within the United States (Mitts, 2017) This algorithm used by Mitts to identify the geolocation of those ISIS supporting individuals on Twitter was developed by Jurgens (2013). By making inferences based on the social network of Twitter users, Jurgens can identify the geolocation of individuals present within the network (Jurgens, 2013). Mitts, in turn, then looks to see how these accounts are affected by these community engagement events and finds that these community engagement events do reduce the amount of pro-ISIS rhetoric amongst those previously identified ISIS supporting twitter accounts (Mitts, 2013). Why this is relevant is that by showing that these community engagement events are effective, so too does Jurgens exemplify that individuals can be influenced one way or another by outside actors. Rather than community engagement events, ISIS engages individuals online to radicalize them.

Finally, Shaikh documents interactions with ISIS and its followers through Twitter (Shaikh, 2015) Shaikh focused on North American, Western European, or Australian Muslims who were either recent converts, or “born again” Muslims who had become “hyper religious.” Shaikh then interacted with these individuals through social media, using a variety of different tones in the messaging between them. (Shaikh, 2015). The author’s approach in taking a more personal touch is in line with the previous article, and exemplifies the potential need for “micro-engagement, along with macro-approaches that relate to countering violent extremism.” (Shaikh, 2015).

These groups and their operations online, in addition to the eventual action that they have the potential to cause, has become a problem policy makers and emergency managers need to address. Ever since the 9/11 attacks on the World Trade Center, terrorism, and combating it, has become a very prominent issue among Homeland Security policymakers, and the response to it among Emergency Managers. Waugh, in his article, examines the National Emergency Management Network, which is a country wide network made up of:

> “FEMA, its state and local counterparts, emergency response agencies (e.g., fire departments, emergency medical services agencies, and search and rescue units), The American Red Cross and other general purpose nonprofit organizations, regional and local charities and civic organizations, and firms that provide services ranging from emergency planning to debris removal to psychological counseling.” (Waugh, 2003).

Waugh argues that this network of emergency management and other professionals needs to be employed when dealing with the potential threat of terrorism (Waugh, 2003). This network needs to evolve as extremist groups do to continue to be effective against them, and that includes the acknowledgement and adaptation to their presence online.

Congleton, in his examination of terrorism as “interest group politics,” their methods, and the impact they have on policy, derives several different interesting conclusions. Beyond the distinction in the differences between terrorist groups when comparing them to other political interest groups, cost benefit analysis of the types of resources allocated to combatting terror indicate that, “devoting substantial resources to detect, punish, discourage, and prevent terrorist acts is warranted, but the proper extent of such efforts has to be judged relative to the resources devoted to reducing other risks that we confront on a day-to-day basis.” (Congelton, 2002). He also discusses the consideration for the first amendment, which is particularly relevant to the ideas present within this thesis. Social media is a form of expression like many others defending by this amendment, however, there might need to be a line drawn in some cases when these platforms are used by extremist groups. He argues that this should be done within our current constitutional framework, and that dramatic change in policy may not be necessary (Congleton, 2002). It is also important when reading this article to consider the time in which it was written. Published in the summer of 2002, the 9/11 attacks were still fresh on the minds of many, including the author.

Based on the literature presented here, it’s clear that there is at least some sort of relationship between an extremist group’s activity online and their ability to affect the mindset of vulnerable individuals, which in term leads them down the steps of radicalization towards eventually enacting real world political violence. Propaganda and other forms of communication spread throughout different social media channels has a global reach, and that alone is dangerous. ISIS and similar groups are also very effective in their efforts, as made evident by recent lone-wolf attacks, such as the Pulse Night Club

Shooting or the London Bridge attack in 2017, in the United States and Europe. Emergency Managers and Policy Makers will also need to continue adapting to this evolving threat, and plan accordingly to counteract it. This, in turn, makes clear the hypothesis this thesis aims to address: A pattern of radicalization of individuals by extremist groups online can be determined through the examination and analysis of social media data.

CHAPTER 3: RESEARCH DESIGN

The hypothesis being tested is that **a pattern of radicalization of individuals by extremist groups online can be determined through the examination and analysis of social media data.** The use of Twitter, in this case, by extremist groups in order to spread their propaganda is hypothesized to aid them in pushing radicalized individuals in to acting. To test this hypothesis, I rely on an original data project that collects and codes extremist messages on Twitter, gathered using the Twitter API. Data was collected through this API, and a team including a data scientist, language and subject matter experts, and myself culled and collected the data to eventually create a useable database for analysis. If there is support for my hypothesis, I will see observable evidence of radicalization increasing leading up to real world events carried out by ISIS affiliated actors.

With the team in place and the data in a state in which it could be analyzed, I next discussed with them exactly what we were trying to examine within this project, and landed on the following as a goal: Can an increase in the social media presence of an extremist group, ISIS, in this case, be tracked leading up to two major events involving that group, those events being terror attacks in Paris, France, on November 13th, 2015, and the Battle of Marawi in the Philippines, which lasted from May 23rd to October 23, 2017. These two events were chosen for two reasons: their innate differences, as one is a clandestine attack committed by a single terror cell, and the other is a more traditional insurgency event, and the impacts they had on the social media-sphere. From these two events, date ranges were decided on, and then used to scrape tweets using the Twitter API. A set of terms and a date range for the API to search that would zero in on the 2015

Paris attacks and the same for the lead up to and the first half of the Battle of Marawi in 2017 was created with the help of subject matter experts on the research team, and can be referenced in Appendix A.

These terms and date ranged are input in to the Twitter API, and then it returns a collection of tweets tweeted out in these indicated date ranges, which contain the words or word combinations specified. To clarify between the use of OR/AND in the search terms:

- In the case of the use of OR, a tweet could contain either of those words, so, for example, any tweet that contain Muhajir OR Muhajirin, which is a term from the second twitter pull.
- In the case of the use of AND, a tweet had to contain both indicated terms, so, for example, and tweet that contained the words Marawi AND jihad, also from the second set of terms.

Because it is also important to understand the extremist group focused on primarily in this thesis and the research supporting it, it is worth going in to greater detail on the Islamic State of Iraq and the Levant, often referred to as either ISIS or ISIL. To establish an understanding of the group itself, McCants (2015) is used to provide background and contextual information about the group, its motivations, and its inner workings.

McCants, in his book, goes in to detail about how ISIS came to be, its impact on the world, and the lasting impressions it has made past its "demise," as he puts it. He argues that it is likely that some jihadists do follow the ISIS playbook, as "Large-scale violence heightens the appeal of apocalyptic narratives, particularly in areas mentioned in the prophecies, and it creates the political vacuums in which armed groups can flourish."

(McCants, 2015). ISIS, even as its presence throughout the Arab world begins to dwindle, has, and will continue to, have a lasting impact on the region, and other individuals inclined to continue their mission. This is where the value in understanding how they spread information throughout social media is derived and contributes to the causal reason for this thesis's focus in trying to accomplish that. Without this understanding, or at least an attempt to accomplish that objective, counterterror operations will be behind the curve.

ISIS has demonstrated that their use of social media to spread their propaganda, and in turn radicalize individuals, can have real world results, which was why they were chosen for this study. To use two attacks that occurred in the United States as an example, the Pulse Nightclub Shooting and San Bernardino Shooting were both carried out by ISIS supporting individuals that declared allegiance to the organization. Omar Mateen, the individual who perpetrated the Pulse Nightclub attack, pledged his allegiance on a 911 call he made during the attack, before he was eventually shot and killed by police. Rizwan Farook and Tashfeen Malik, the male and female individual responsible for the shooting in San Bernardino, had been radicalized through consumption of online propaganda, according to FBI Director at the time James Comey, and both pledged their allegiance to ISIS as well. Both attacks are clear examples of how dangerous ISIS being able to spread their messages online through social media can be, and why it is important to understand if it is as effective as this thesis hypothesizes.

Following the data collection phase, the next step was to translate the data scraped from Twitter. The Twitter API pulled tweets from a variety of languages, so after an examination of the results, I decided to translate and use the tweets gathered in Arabic, English, French, and German, largely because the research team had someone in house who could translate those tweets. Many tweets pulled from these two date ranges were also in Indonesian, but our lack of ability to translate those tweets resulted in putting them to the wayside in the interest of completing the project in a timely manner, an unfortunate, but unavoidable limitation on the project. In conjunction with the translation work, a list was also compiled of terms that would indicate a tweet as being considered in one of the four phases of radicalization discussed earlier in this thesis, if said tweet contained the term. These four phases, and the related terms, can be found in Appendix B. An additional consideration was made for those tweets that might contain terms from multiple phases that followed each other, I.E. a tweet containing a term from phase 1 and 2, phase 2 and 3, and phase 3 and 4. This tweets that contained terms from two phases were separated into their own categories and labeled as "transitionary" tweets, as their inclusion of tweets from multiple phases is hypothesized to indicate a transition from one phase to another of radicalization.

With the actual data now collected and translated, the next step involved determining which data was and was not relevant enough so that it was in a usable state for analysis. Our data scientist used a series of subset functions in the R programming language to filter out unneeded observations that did not contain the related terms regarding the radicalization phases outlined in Appendix B. She then used a series of if/else statements to sort the observations into their intended radicalization phases. With that finished, I now had a clean dataset of roughly 20,000 observations and could transition into the data analysis phase. The observations will be analyzed through several lenses: the date and time in which they were tweeted out, the phase of radicalization, and the interaction between these two variables. It is hypothesized that as time passes along each indicated date range and the date of the actual event becomes closer, I will see an increase in both general twitter presence and tweets indicated as being in the later stages of radicalization, while earlier tweets will be less frequent and will more likely be indicated as being in the earlier stages of radicalization, and through the use of negative binomial regression analysis and models provided by R, this will be shown to be, or not to be, the case.

CHAPTER 4: RESULTS AND ANALYSIS

The results of the time series analysis have some interesting interpretations, some of which support the main hypothesis presented in this thesis, but most support other conclusions. The first, and likely most noticeable trend when first examining the data plotted on a line graph, is the apparent decline in tweets in general that contain our key phrases leading up to both events. This decline begins in earnest at the t-3 week mark for the Paris event, and the t-4 week mark for the Marawi event. This aggregated Paris data can be seen below:

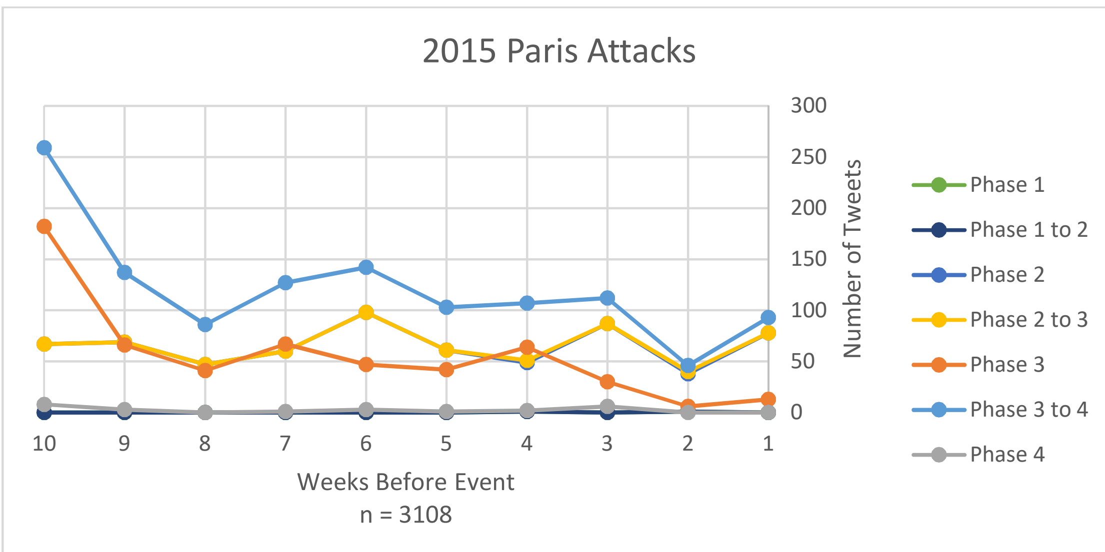

FIGURE 1: Paris Dataset Timeline

This decline was partially expected, especially among tweets categorized in to Phase 4. As individuals become more radicalized, and they are identified as potential actors by extremist groups, further conversations are likely taken to more private methods then public facing tweets, such as a private Telegram or WhatsApp channel, or direct messages between the Twitter accounts themselves, which could not be scraped by the Twitter API I had access to.

One aspect of the data that was explored were what was considered “transitionary tweets.” These tweets, all unique from others in the dataset, were tweets that contained terms from more than one phase of radicalization. These tweets, especially among those leading up to the Paris event, actually made up a fair bit of those that were identified as being radical, the most prevalent in that particular event being those in transition from Phase 3 to Phase 4, seen below, which does line up with our main hypothesis, and might also explain the drop in the amount of tweets in those final few weeks before the event occurred.

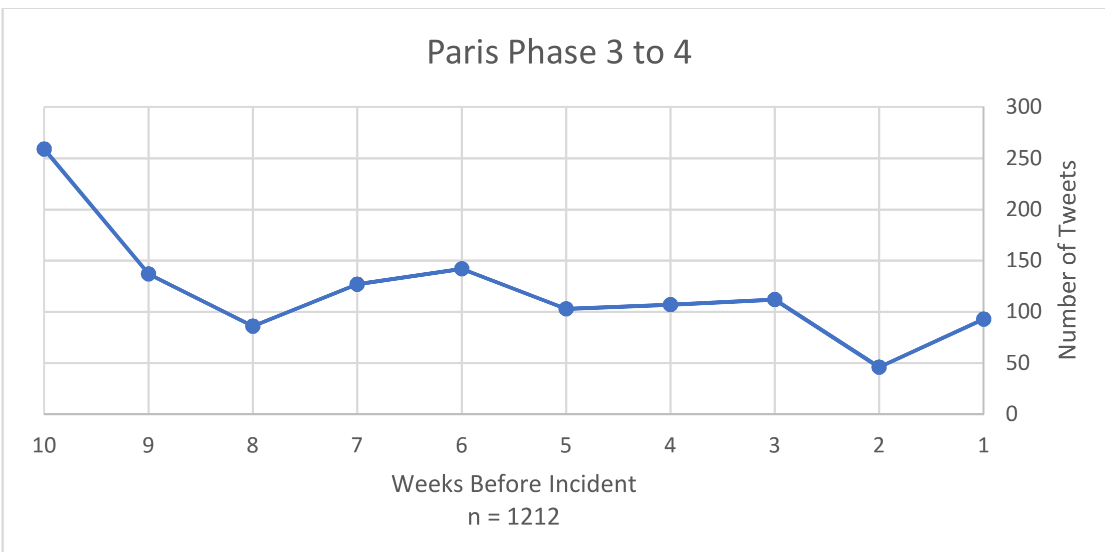

FIGURE 2: Paris Radicalization Phase 3 to 4 Timeline

As mentioned previously, conversations might have been taken offline or to more private channels in the weeks closer to the attack, and the greater presence of these tweets in the data, while there being a lack of the Phase 4 tweets, suggests that change to private channels might take place in that period between Phase 3 and Phase 4. Another interesting aspect of our results was the general lack of tweets considered to be in Phase 1. The general expectation was that there would be a larger number of tweets categorized in to this phase, considering that this was the least radical of the four phases. However, our list of terms for this phase might have also come in to play, and as such, a change in research design might be necessary to better capture this first phase. This might also be something to consider for the other phases, and a potential change across the board; equalizing the amount of key terms for each phase would likely make up for some of the discrepancy found between the numbers of tweets in each phase.

The Marawi set of tweets, of which the aggregated trend lines can be found below, showed some stark differences to the Paris tweet set, especially in the number of tweets in each phase.

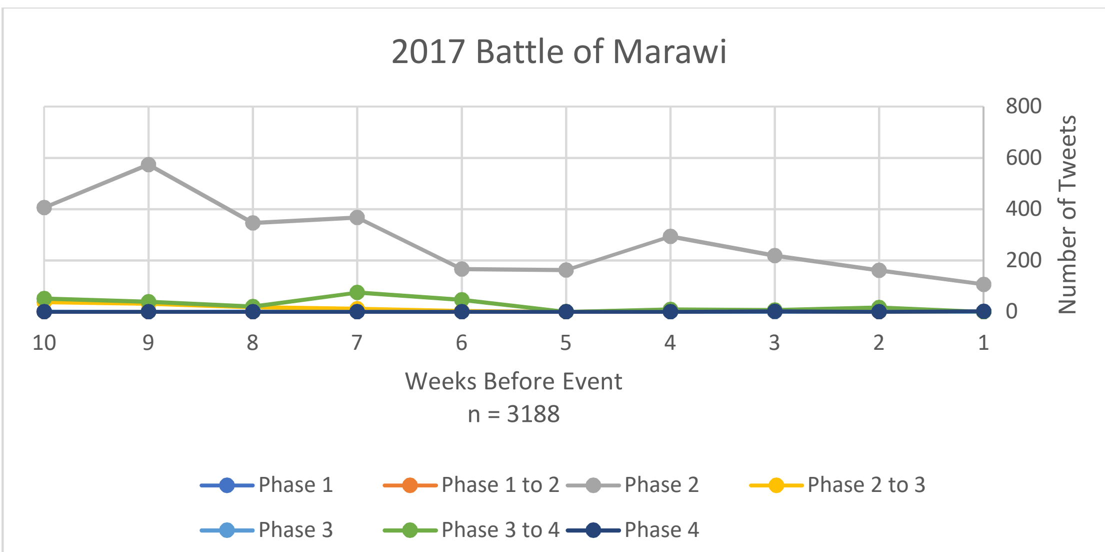

FIGURE 3: Marawi Dataset Timeline

As seen here, most tweets in the Marawi dataset were in the second phase of radicalization, while some also falling into the transition between Phase 2 to Phase 3, or Phase 3 to Phase 4. There isn't a clear explanation for this result, at least after careful consideration of why this may have occurred. Perhaps in that region of the world, rather than those Tweets involving the Paris attacks, the terminology used for the Phase 2 keywords were much more common in regular discourse on the Twitter platform, especially among individuals that I attempted to target. There might be a difference in the discord among social media users as well.

In both cases, the main hypothesis of this thesis, however, is not supported. My expectation was that there would be a reasonably visible upward trend in the number of tweets leading up to either event, and that the more time there was between the event and the time of the tweet, the less radical that tweet would be. Clearly, that isn't the case. Rather than what I expected, I found that the further you are from the start of an event, the more tweets there were that contained our set of keywords. In the Paris event tweets, there was a greater spread of the tweets among the different phases, with Phase 2, Phase 2 to 3, and Phase 3 all having about 600 unique tweets in each, while the Phase 3 to 4 transitionary tweets totaled to 1212. The tweets related to the Marawi dataset were not nearly as spread out between the phases as they were with the Paris tweets. Most of the tweets in that set landed in Phase 2, with some categorized into the transitionary phase between Phase 2 and Phase 3, and Phase 3 and Phase 4.

To further test the relationship between the amount of time before each example event, and the number of tweets, I ran a series of negative binomial regression tests, with the dependent variable being the number of tweets per phase, and the independent variable being the amount of time before the event. I ran this type of test largely because of the nature of the twitter data, and its ability to account for overdispersion of the data. As can also been seen by the number of tweets in each Phase for each event, not all phases were able to be tested this way; essentially, if the sample size of the phase was above 100, it was decided that was enough to run the negative binomial test to check for any significant relationships. The results of this analysis of all phases with a large enough sample size showed one single instance of statistical significance, from Week 2 of the Paris Dataset tweets in the 3rd Phase of radicalization, seen in Appendix I. This being the only significant result still does not provide enough evidence to support this thesis's hypothesis.

CHAPTER 5: IMPLICATIONS AND CONCLUSIONS

As made evident by the time trend and negative binomial regression analysis, the relationships hypothesized to exist between the amount of time before an extremist attack, and there being an identifiable pattern of radicalization over time through Twitter, was not the case. In the time period that I examined for both events, while there was a presence of tweets with the key phrases identified as indicators of radicalization, there wasn’t much in terms of clear, identifiable trends. What trends did exist go against what was hypothesized to be the relationship between time before the event and the number of tweets per phase. In the case of the Paris attacks, what phases had enough tweets to identify anything showed that the number of tweets decreased as the actual event got closer. The same was the case with the tweets related to Marawi, though there was a spike in the presence of Phase 2 tweets 4 weeks out before the event.

The lack of statistically significant results from the negative binomial regression analysis, outside of the single week of a single phase in the Paris dataset, further exemplifies the apparent lack of a relationship between the tested variables. Even when testing those Phases of radicalization that had enough counts to run the test in the first place, only a single significant relationship was found. At this point, a discussion of the implications of these findings, and some posits at what might have caused them, are in order. Firstly, this lack of a relationship might, in fact, be by design, to a degree. The individuals I am trying to examine in this data from Twitter, by their nature, do not want to be found. Many are breaking all sorts of laws in acting on the behalf of these extremist groups, and as such, may avoid posting their more radical thoughts on such a public facing form of social media. The previously mentioned more private methods, such as a private Telegram or WhatsApp channel, might be where more radicalized individuals gather to exchange ideas. The difference in the types of communication around each event might also be at play. Since the attacks in Paris were isolated, random incidents, while the Battle of Marawi was a longer, more traditional insurgency, perhaps communication is taken to different channels that are harder to track at different times, depending on the type of event.

Another possible explanation for the lack of any significant results is the research design. The data we collected has some limitations that impact the statistical significance of the results. A single instance of a significant relationship between the amount of time before an event and the number of tweets in each radicalization phase makes that clear. If given the chance to further refine the data collection process, a much more statistically significant dataset may be the result. This data would, in turn, better support the hypothesis of this thesis. This kind of research into how actions on social media effect individuals is very important and impacts multiple fields and should be continued.

What, however, this research shows the potential benefit that this kind of research may have, and the need for projects of this type to continue. It is a known fact that extremist groups are using social media and other online platforms to radicalize individuals. The rise of lone-wolf terrorism in the United States may be partially attributed to this. Islamic terror groups are not the only groups using these methods as well; white nationalist and other right-wing extremist groups are very present online and radicalize individuals on similar platforms. With a different approach and a more refined research design, more concrete results may be possible. There is also a need for this kind of information amongst policy makers in the public sector, especially those involved with law enforcement and emergency management. Human-made disasters, such as terrorism, are becoming more and more of a concern in today's geopolitical climate, and both policy makers and emergency planners alike must take them into consideration. Being able to effectively respond to these kinds of disasters will be key when emergency management officials are involved in them. If they can use this kind of research to better predict the types of attacks they are dealing with, they will be able to plan for them more effectively. Policymakers may benefit in a similar way, as the information gained from this kind of research might help them when they consider the types of policy, they might implement in Homeland Security or elsewhere.

The first amendment implications of these new policies and procedures are also important. The creation and evolution of social media presents some interesting challenges when considering the right to free speech, to that of public safety. Social media gives individuals platforms to express their ideals in a very public and far reaching way, and while that inherently isn't a bad thing, depending on their message, it could be. These extremist groups using social media to spread their message is a great example of the potential negative effects it can have. Law enforcement needs to be able to combat these and other groups to try and prevent them from inciting violence. The implications of this, however, and what does and does not constitute a violation of free speech, will need to be determined moving forward.

The potential for great strides in understanding the way extremist groups operate online is there and will be extremely important as technology continues to advance. Being able to radicalize and train an individual from the other side of the world through a computer, rather than a training camp, provides an extremely dangerous challenge for both academics to understand, and for law enforcement to try and combat. By improving on and continuing this type of research, academics have the potential to aid both law enforcement and policymakers in this endeavor. This research, while having insignificant results at this stage, should be iterated on further. Discovering why that was the case with this dataset and to, potentially, begin to identify trends online in how extremist groups are radicalizing individuals is something many different groups may benefit from. Future research, if able to identify these trends, could make a large difference in the combating of terrorism across the globe.

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APPENDIX A: TWITTER DATE RANGES AND SEARCH TERMS

- **The lead up to and the immediate aftermath of the 2015 Paris Attacks**
  - **Date Range:** June 29th, 2014 through November 29th, 2015
  - **Terms:**
    - (Abu Sayyaf) AND (bayah OR baiah)
    - Paris AND (daulahislamiyah OR daulaislam)
    - jihad AND (martyr OR martyrs OR syahid)
    - (bayah OR baiah) AND (caliphate OR Khilafah)
    - (hijra OR hijrah) AND (caliphate OR Khilafah)
    - Ansar Khilafah
    - bayah OR baiah
    - (Katibah Nusantara) AND (hijra OR hijrah)
    - jihad AND (daulahislamiyah OR daulaislam)
- **The lead up to and throughout the first half of the Battle of Marawi**
  - **Date Range:** March 11th, 2017 through July 11th, 2015
  - **Terms:**
    - Abu AND Sayyaf AND filibin
    - Marawi AND jihad
    - Muhajir OR Muhajirin
    - Tanzim AND al-dawlah AND al-islamiyah AND fi'l AND fil

APPENDIX B: PHASE OF RADICALIZATION INDICATOR TERMS

Phase 1: It's Not Right

- blessings of Allah (be upon you)
- Recommendation
- Lecture
- Talks
- Discussion
- course taught
- writings
- sufficient

Phase 2: It's Not Fair

- Ansar and Muhajirin
- Muhajir
- muhajirin
- mujahid
- Mujahadin
- bayah
- bay'ah
- baia
- baiah
- brother(s)
- aqida
- aqeeda
- aqidah
- aqeedah
- waiting
- remaining
- abiding and remaining
- Salaf
- salafi
- Akhi

Phase 3: It's Your Fault

- mother & martyr
- Martyr
- Martyrdom
- coward(s)
- traitor(s)
- idolator
- taghut
- taghuti
- apostate(s)
- Murtadd
- Amir
- Ameer
- Osama bin Laden
- shaykh al-islam
- the shaykh
- Ansar & Mujahadin
- Repentence
- The Prophet
- Ansar
- Muhajirin
- Kafir
- Tauba
- Taubah
- black banner(s)
- bayah
- baia
- oppressors
- Brussels
- Bruxelles
- Caliph
- Caliphate
- Charlie Hebdo
- dawlah
- daulah
- Hizb Allat
- hypocrite
- karahah
- unbelievers
- kuffar
- baqiyah family

Phase 4: You Are Evil

- fard'ayn
- booty
- ghanima
- ghanimah
- loot
- stranger(s)
- ghuraba
- gharib
- hadd
- haddi
- kill
- hadud
- hijra
- hijrah
- lone wolf
- jihad
- fard
- manhaj
- muharribin
- one who fights God
- surrender
- mission or vision

APPENDIX C: MARAWI PHASE 1 NEGATIVE BINMOIAL REGRESSION ANALYSIS RESULTS

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval Lower	95% Wald Confidence Interval Upper	Hypothesis Test Wald Chi-Square	Hypothesis Test df	Hypothesis Test Sig.
(Intercept)	-28.203	443673.7566	-869612.787	869556.381	.000	1	1.000
[week=1]	5.501E-5[a]	.	.	.	.	.	.
[week=2]	5.501E-5[a]	.	.	.	.	.	.
[week=3]	28.203	443673.7566	-869556.381	869612.787	.000	1	1.000
[week=4]	5.501E-5[a]	.	.	.	.	.	.
[week=5]	5.501E-5[a]	.	.	.	.	.	.
[week=6]	5.501E-5[a]	.	.	.	.	.	.
[week=7]	5.501E-5[a]	.	.	.	.	.	.
[week=8]	5.501E-5[a]	.	.	.	.	.	.
[week=9]	5.501E-5[a]	.	.	.	.	.	.
[week=10]	0[b]	.	.	.	.	.	.
(Scale)	1[c]						
(Negative binomial)	1[c]						

Dependent Variable: total_tweets

Model: (Intercept), week

a. Hessian matrix singularity is caused by this parameter. The parameter estimate at the last iteration is displayed.

b. Set to zero because this parameter is redundant.

c. Fixed at the displayed value.

APPENDIX D: MARAWI PHASE 2 NEGATIVE BINMOIAL REGRESSION ANALYSIS RESULTS

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	6.006	1.0012	4.044	7.969	35.988	1	.000
[week=1]	-1.334	1.4184	-4.114	1.446	.884	1	.347
[week=2]	-.919	1.4173	-3.697	1.859	.420	1	.517
[week=3]	-.617	1.4167	-3.394	2.159	.190	1	.663
[week=4]	-.323	1.4163	-3.099	2.453	.052	1	.820
[week=5]	-.913	1.4173	-3.690	1.865	.415	1	.520
[week=6]	-.888	1.4172	-3.666	1.889	.393	1	.531
[week=7]	-.098	1.4160	-2.874	2.677	.005	1	.945
[week=8]	-.157	1.4161	-2.933	2.618	.012	1	.912
[week=9]	.346	1.4157	-2.428	3.121	.060	1	.807
[week=10]	0[a]	.	.	.	.	.	.
(Scale)	1[b]						
(Negative binomial)	1[b]						

Dependent Variable: total_tweets

Model: (Intercept), week

a. Set to zero because this parameter is redundant.

b. Fixed at the displayed value.

APPENDIX E: MARAWI PHASE 2 TO 3 NEGATIVE BINMOIAL REGRESSION ANALYSIS RESULTS

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval Lower	95% Wald Confidence Interval Upper	Hypothesis Test Wald Chi-Square	Hypothesis Test df	Hypothesis Test Sig.
(Intercept)	3.638	1.0131	1.652	5.623	12.893	1	.000
[week=1]	-32.160[a]	.	.	.	.	.	.
[week=2]	-2.944	1.5894	-6.060	.171	3.432	1	.064
[week=3]	-2.944	1.5894	-6.060	.171	3.432	1	.064
[week=4]	-1.846	1.4809	-4.748	1.057	1.554	1	.213
[week=5]	-32.160[a]	.	.	.	.	.	.
[week=6]	-2.539	1.5361	-5.550	.472	2.732	1	.098
[week=7]	-1.240	1.4551	-4.092	1.612	.726	1	.394
[week=8]	-.747	1.4429	-3.575	2.081	.268	1	.605
[week=9]	-.204	1.4348	-3.016	2.609	.020	1	.887
[week=10]	0[b]	.	.	.	.	.	.
(Scale)	1[c]						
(Negative binomial)	1[c]						

Dependent Variable: total_tweets

Model: (Intercept), week

a. Hessian matrix singularity is caused by this parameter. The parameter estimate at the last iteration is displayed.

b. Set to zero because this parameter is redundant.

c. Fixed at the displayed value.

APPENDIX F: MARAWI PHASE 3 TO 4 NEGATIVE BINMOIAL REGRESSION ANALYSIS RESULTS

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	3.932	1.0098	1.953	5.911	15.162	1	.000
[week=1]	-31.906[a]	.	.	.	.	.	.
[week=2]	-1.159	1.4430	-3.987	1.669	.645	1	.422
[week=3]	-1.986	1.4705	-4.868	.896	1.824	1	.177
[week=4]	-1.735	1.4597	-4.596	1.126	1.412	1	.235
[week=5]	-31.906[a]	.	.	.	.	.	.
[week=6]	-.103	1.4288	-2.903	2.697	.005	1	.942
[week=7]	.386	1.4258	-2.409	3.180	.073	1	.787
[week=8]	-.936	1.4386	-3.756	1.884	.423	1	.515
[week=9]	-.268	1.4301	-3.071	2.535	.035	1	.851
[week=10]	0[b]	.	.	.	.	.	.
(Scale)	1[c]						
(Negative binomial)	1[c]						

Dependent Variable: total_tweets

Model: (Intercept), week

a. Hessian matrix singularity is caused by this parameter. The parameter estimate at the last iteration is displayed.

b. Set to zero because this parameter is redundant.

c. Fixed at the displayed value.

APPENDIX G: PARIS PHASE 2 NEGATIVE BINMOIAL REGRESSION ANALYSIS RESULTS

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval Lower	95% Wald Confidence Interval Upper	Hypothesis Test Wald Chi-Square	Hypothesis Test df	Hypothesis Test Sig.
(Intercept)	4.205	1.0074	2.230	6.179	17.419	1	.000
[week=1]	.152	1.4240	-2.639	2.943	.011	1	.915
[week=2]	-.567	1.4287	-3.367	2.233	.158	1	.691
[week=3]	.261	1.4235	-2.529	3.051	.034	1	.854
[week=4]	-.313	1.4267	-3.109	2.483	.048	1	.826
[week=5]	-.094	1.4252	-2.887	2.700	.004	1	.948
[week=6]	.380	1.4231	-2.409	3.169	.071	1	.789
[week=7]	-.110	1.4253	-2.904	2.683	.006	1	.938
[week=8]	-.355	1.4270	-3.151	2.442	.062	1	.804
[week=9]	.029	1.4246	-2.763	2.822	.000	1	.984
[week=10]	0[a]	.	.	.	.	.	.
(Scale)	1[b]						
(Negative binomial)	1[b]						

Dependent Variable: total_tweets

Model: (Intercept), week

a. Set to zero because this parameter is redundant.

b. Fixed at the displayed value.

APPENDIX H: PARIS PHASE 2 TO 3 NEGATIVE BINMOIAL REGRESSION ANALYSIS RESULTS

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	4.205	1.0074	2.230	6.179	17.419	1	.000
[week=1]	.152	1.4240	-2.639	2.943	.011	1	.915
[week=2]	-.516	1.4283	-3.315	2.284	.130	1	.718
[week=3]	.261	1.4235	-2.529	3.051	.034	1	.854
[week=4]	-.273	1.4264	-3.069	2.523	.037	1	.848
[week=5]	-.094	1.4252	-2.887	2.700	.004	1	.948
[week=6]	.380	1.4231	-2.409	3.169	.071	1	.789
[week=7]	-.110	1.4253	-2.904	2.683	.006	1	.938
[week=8]	-.355	1.4270	-3.151	2.442	.062	1	.804
[week=9]	.029	1.4246	-2.763	2.822	.000	1	.984
[week=10]	0[a]	.	.	.	.	.	.
(Scale)	1[b]						
(Negative binomial)	1[b]						

Dependent Variable: total_tweets

Model: (Intercept), week

a. Set to zero because this parameter is redundant.

b. Fixed at the displayed value.

APPENDIX I: MARAWI PHASE 3 NEGATIVE BINMOIAL REGRESSION ANALYSIS RESULTS

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	5.204	1.0027	3.239	7.169	26.934	1	.000
[week=1]	-2.639	1.4431	-5.467	.189	3.344	1	.067
[week=2]	-3.412	1.4738	-6.301	-.524	5.360	1	.021
[week=3]	-1.803	1.4279	-4.601	.996	1.594	1	.207
[week=4]	-1.045	1.4217	-3.832	1.741	.540	1	.462
[week=5]	-1.466	1.4245	-4.258	1.326	1.060	1	.303
[week=6]	-1.354	1.4236	-4.144	1.436	.904	1	.342
[week=7]	-.999	1.4214	-3.785	1.787	.494	1	.482
[week=8]	-1.490	1.4247	-4.283	1.302	1.094	1	.296
[week=9]	-1.014	1.4215	-3.800	1.772	.509	1	.475
[week=10]	0[a]	.	.	.	.	.	.
(Scale)	1[b]						
(Negative binomial)	1[b]						

Dependent Variable: total_tweets

Model: (Intercept), week

a. Set to zero because this parameter is redundant.

b. Fixed at the displayed value.

APPENDIX J: MARAWI PHASE 3 TO 4 NEGATIVE BINMOIAL REGRESSION ANALYSIS RESULTS

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	5.557	1.0019	3.593	7.521	30.760	1	.000
[week=1]	-1.024	1.4194	-3.806	1.758	.521	1	.471
[week=2]	-1.728	1.4232	-4.518	1.061	1.474	1	.225
[week=3]	-.838	1.4187	-3.619	1.942	.349	1	.555
[week=4]	-.884	1.4189	-3.665	1.897	.388	1	.533
[week=5]	-.922	1.4190	-3.703	1.859	.422	1	.516
[week=6]	-.601	1.4181	-3.380	2.178	.180	1	.672
[week=7]	-.713	1.4184	-3.493	2.067	.252	1	.615
[week=8]	-1.102	1.4197	-3.885	1.680	.603	1	.437
[week=9]	-.637	1.4182	-3.416	2.143	.202	1	.653
[week=10]	0[a]	.	.	.	.	.	.
(Scale)	1[b]						
(Negative binomial)	1[b]						

Dependent Variable: total_tweets

Model: (Intercept), week

a. Set to zero because this parameter is redundant.

b. Fixed at the displayed value.