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MEASURING SENTIMENT RESPONSE TO COLLECTIVE VIOLENCE THROUGH SOCIAL MEDIA

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MEASURING SENTIMENT RESPONSE TO COLLECTIVE VIOLENCE THROUGH SOCIAL MEDIA

by

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December 2018

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The rise in the popularity of social media platforms along with the increased global access to communication technologies presents a unique opportunity to study the interaction between violence and the sentiment of social media users. With the availability of vast amounts of open-source data, through mediums such as Twitter, this study examines the effects of civil conflict between state and non-state actors on the sentiment of Twitter users in the countries of Nigeria, Pakistan, and the Philippines from August 1, 2013, to July 31, 2014. With the continued rise of the megacity, a focus area of this study examines the expressed sentiment within the megacities of Lagos, Karachi, and Manila and analyzes how this can be used to predict sentiment expressed in the rest of the country. From this research, we conclude that collective violence produces emotionally charged sentiment within social media toward both the state and non-state actors across various types of civil conflict. Furthermore, we find that this polarizing sentiment varies among the ethnic groups present in each country. This research also concludes that the sentiments expressed in a megacity can serve as a useful predictor of sentiments expressed throughout the rest of the country.

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ABSTRACT

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LIST OF ACRONYMS AND ABBREVIATIONS

ASG	The Abu Sayyaf Group
BIFM	The Bangsamoro Islamic Freedom Movement
BLF	The Balochistan Liberation Front
BLA	The Balochistan Liberation Army
BRA	The Balochistan Republican Army
CPP	The Communist Party of the Philippines
DARPA	The Defense Advanced Research Projects Agency
DLIFLLC	The Defense Language Institute Foreign Language Center
GECON	Geographically-based Economic Database
GED	Georeferenced Dataset
IMU	The Islamic Movement of Uzbekistan
IS	Islamic State
LeJ	Lashkar-e-Jhangvi
MILF	The Moro Islamic Liberation Front
MIM	The Moro Independence Movement
MNLF	The Moro National Liberation Front
NLTK	National Language Toolkit
NPA	New People's Army
NPS	Naval Postgraduate School
TTP	Tehrik-e-Taliban Pakistan
UBA	United Baloch Army
UCDP	Uppsala Conflict Data Program
UN	United Nations

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I. INTRODUCTION

Advances in technology give individuals, states and organizations access to global communication tools, providing them the ability to communicate and share ideas through multiple mediums in near–real time. One of the more well-known advances has taken shape in the form of social media, which enables a wide variety of individuals to share opinions and ideas widely. This intimate yet impersonal view provides an unprecedented volume of insight into how individuals and groups perceive their environments. It also presents the opportunity to analyze and understand population sentiment, and sentiment shifts over time via social media output. Pragmatically, this abundance of information has the potential to be harnessed to support decision makers with an enhanced understanding of the environment.

The information environment of a megacity—a city that has ten million or more inhabitants—offers robust infrastructures that support both mass media outlets and social media platforms. These two forms of media contribute to how various groups within a megacity perceive an event, issue, or action, which could influence the behaviors of its inhabitants. Information sharing within a megacity can create unity among its citizens, but also can divide or cause conflict between the various actors within it.

The U.S. military has historically tried to avoid operating within urban environments, but it has yet to encounter the challenges of operating within a megacity. From a military standpoint, megacities offer unique challenges such as ethnic, cultural, religious, economic, linguistic, and social diversities. Inhabitants of megacities can readily access a wide range of communication and information-sharing capabilities, some of which can positively and negatively impact military operations. Within conflict areas, especially those involving low-intensity conflict or those in denied areas, leveraging sentiment analysis can assist the military in gaining situational awareness to predict how diverse megacity populations will respond to violent events, and in doing so, how that response affects their loyalties toward state or non-state actors.

The goal of this research is to understand the relationship between conflict and population sentiments. The megacity provides a powerful lens to examine this, due to its high population density and diverse communities. Current methodologies for understanding rapidly shifting popular sentiments are inadequate, however, due to the complex cultural and linguistic diversity exhibited within megacity environments. This research presents an approach that seeks to overcome these obstacles.

This research sought to the answer the question, *can social media content measure changes in population sentiment toward state and non-state actors caused by violent events of civil conflict?* This study advances the field of social media sentiment analysis through the creation of an emoji co-occurrence methodology in which commonly used emotional symbols in social media guide the creation of multi-lingual sentiment dictionaries unique to multiple countries. Through quantitative analysis, these lexicon dictionaries were used to examine the sentiment of tweets posted on days of violent events and evaluate the various characteristics of civil conflict that can influence the sentiment expressed toward state and non-state actors. This analysis considers several variables that may influence the sentiments of social media users, including the number of violent events, the state and non-state actors involved in violence, and the number of casualties resulting from the violent event. This analysis finds that through the use of dictionaries created through the emoji co-occurrence methodology, social media sentiment content can be emotionally categorized and changes observed as a population reacts to violence caused by state and non-state actors.

II. LITERATURE REVIEW

A. LOW-INTENSITY CONFLICT, VIOLENCE, AND POPULATION

In developing states mired in low-intensity conflicts, be it rebellion, insurgency or civil war, there are many actors involved in the interplay of international relations and domestic politics. These actors can be categorized as the state authority, internal rebel groups, and external actors.[1] Despite a wide array of disagreements, there are some key tenets broadly accepted amid the breadth of literature on political violence in low-intensity conflict. This research generally accepts that stability can be achieved should two key conditions be met: first, the state must achieve a monopoly on violence; and second, the population must accept, willingly or through coercion, that the state is the authority.[2] Despite the agreement on the importance of these tenets, developing strategies to apply these notions toward a desired resolution has proven a wanting task.[3] At the heart of properly addressing the issue is the need to properly understand and influence the sentiment of the population.

When examining the actors within a particular conflict setting, a close analysis of their espoused narrative can provide insight as to why the groups view the need for conflict in the first place. The conflict studies literature extensively covers the importance of the narrative, and why winning the battle of the information domain remains just as essential as victory in the various physical domains. Supporting this claim, Gergen and Gergen assert that the narrative must establish a “goal state” or endpoint. Doing so allows the group to explain events or actions taken in an attempt to reach their desired end state. Additionally, the authors suggest that how well a group’s actions coincide with their narrative relates to

[1] Nathan Constantine Leites and Charles Wolf Jr, *Rebellion and Authority: An Analytic Essay on Insurgent Conflicts* (Chicago: Markham Publishing Company, 1970), https://www.rand.org/pubs/reports/R0462.html.

[2] Alejandro Hernandez, Julian Ouellet, and J. Nannini, “Circular Logic and Constant Progress: IW Assessments in Afghanistan,” in *Assessing War: The Challenge of Measuring Success and Failure*, ed. Leo Blanken, Hy Rothstein, and Jason Lepore (Georgetown University Press, 2015), 218; Leites and Wolf Jr, *Rebellion and Authority: An Analytic Essay on Insurgent Conflicts*.

[3] Colin Gray, “The Strategist as Hero,” *Joint Force Quarterly*, no. 62 (July 2011): 37–45.

how close the group comes to achieving their expressed end state.[4] Groups often construct their narratives to explain their actions and how they perceive their identity. For instance, Sarbin describes the narrative as a means for a group to justify their actions as well as provide an explanation to those outside of the group, which thrust the group into action.[5]

The literature on narratives stresses their strategic significance within conflict. Arquilla and Ronfeldt assert that narratives are strategically important to a networked organization, in that they provide a tie that holds the organization together.[6] Moreover, Arquilla and Ronfeldt claim that, just as important as winning the physical war, the battle for the narrative victory is of equal importance. A combatant within the conflict requires a victory of the narrative if he wants to achieve victory in the overall military campaign.[7] The development and delivery of the strategic narrative differs depending on the actor. National policymakers within a state structure their narrative differently from that of a non-state actor, such as a terrorist organization. In her study on narrative wars, Archetti identifies the uniqueness of the strategic narrative from the terrorist perspective, in that it is created through collective construction from those within the group.[8] Supporting the concept of the importance of a non-state actor's use of the narrative to strengthen their follower's conviction, H.J. Ingram argues that groups such as Al-Qaida and the Islamic State (IS), use their narratives to project in-group and out-group identities.[9] The careful construction of the narrative, Ingram argues, allows these organizations to shape the lens

[4] Kenneth J. Gergen and Mary M. Gergen, "Narrative Form and the Construction of Psychological Science," in *Narrative Psychology*, ed. Theodore R. Sarbin (New York: Praeger Publishers, 1986), 25–26.

[5] Theodore R. Sarbin, "The Narrative as a Root Metaphor for Psychology," in *Narrative Psychology*, ed. Theodore R. Sarbin (New York: Praeger Publishers, 1986), 9.

[6] John Arquilla and David Ronfeldt, "Afterword (September 2001): The Sharpening Fight for the Future," in *Networks and Netwars*, ed. John Arquilla and Ronfeldt (RAND, 2001), 328, https://www.rand.org/pubs/monograph_reports/MR1382.html.

[7] Arquilla and Ronfeldt, 330.

[8] Cristina Archetti, "Narrative Wars: Understanding Terrorism in the Era of Global Interconnectedness," in *Forging the World: Strategic Narratives and International Relations*, ed. Alister Miakimmon, Ben O'Loughlin, and Laura Roselle (Ann Arbor, MI: University of Michigan Press, 2017), 236.

[9] Haroro J. Ingram, "An Analysis of Inspire and Dabiq: Lessons from AQAP and Islamic State's Propaganda War," *Studies in Conflict and Terrorism* 40, no. 5 (August 2016): 358, https://doi.org/10.1080/1057610X.2016.1212551.

through which their followers view both themselves and out-groups, which may increase the polarization of their views.[10]

The effectiveness of these actors is judged by their respective domestic populations. The challenge of measuring the sentiment of these populations, who eventually determine the success or failure of the various actors, through support or acquiescence, is very difficult. Tremendous resources are invested into ascertaining population sentiment; paradoxically, the tools available are limited at best and at worst provide a misleading view. Addressing this contradiction is paramount to any effort seeking a desired outcome within a low-intensity conflict.[11]

B. THE MEGACITY

Megacities present an interesting security situation in which the likelihood of conflict (both low-intensity and conventional military conflict) continues to increase due to rising competition and violence in these economically important, globally connected cities. Social media platforms serve as mediums through which megacity populations share information during conflict and crises as well as offer actors the mechanism to employ targeted messaging to diverse populations. Recent and notable examples of social media use in megacities, specifically Twitter and how it was used to coordinate collective action and disseminate information, include Cairo during the 2011 Arab Spring, and the Paris bombings and hostage taking in November 2015.[12] Existing research on megacities suggests two main points of view about the nature of these cities (i.e., densely populated, and diverse) and the impact they have on their populations. On one hand, several scholars emphasize the potentially positive impact that megacities have on populations, such as

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[10] Ingram, 358–59.

[11] Jack D. Kem, "Assessment: Measures of Performance and Measures of Effectiveness," *Military Intelligence Professional Bulletin* 35, no. 2 (April 2009): 48–50; Seth G. Jones, *Counterinsurgency in Afghanistan* (Santa Monica, CA: RAND Corporation, 2008), 7, https://www.rand.org/content/dam/rand/pubs/monographs/2008/RAND_MG595.pdf.

[12] "How the Paris Attacks Unfolded on Social Media," Online News, BBC, November 17, 2015, https://www.bbc.com/news/blogs-trending-34836214; Axel Bruns, Tim Highfield, and Jean Burgess, "The Arab Spring and Social Media Audiences: English and Arabic Twitter Users and Their Networks," ed. Zeynep Tufekci and Deen Freelon, *American Behavioral Scientist* 57, no. 7 (2013): 871–98, https://doi.org/10.1177/0002764213479374.

access to better government services, greater economic opportunities for the lower class, and opportunities to capitalize on "green" initiatives. On the other hand, several experts argue the challenges of living in such densely populated and heterogeneous populations leave many behind economically, and expose segments to violence and crime.

Those who view the impact of megacities in a more opportunistic manner focus on the megacity as a hub for economic and technological advancement.[13] These authors see the benefits of advancement outweighing the negative impacts, such as poverty, violence, and crime that often occur in megacities. Similar literature argues not to view the dense populations, disenfranchisement of lower classes, and environmental effects in a negative manner, as advancement overall provides better government services, economic opportunities for the lower class, and best opportunity to capitalize on green initiatives.[14]

In the study of violence in megacities, the literature argues that dense populations of impoverished residents in a megacity do not promote the well-being of the city, but perpetuate violence instead.[15] Even with the economic progress that megacities offer, some scholars argue that the disparity of wealth creates enclaves and socio-economic segregation of the city, which can lead to violent unrest.[16] Within the research on the risks of the megacity, the literature highlights the vast risks associated with the continued increase in the growth of the megacity. This area of study claims the characteristics of the megacity,

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[13] Edward L. Glaeser, *Triumph of the City: How Our Greatest Invention Makes Us Richer, Smarter, Greener, Healthier, and Happier* (New York: Penguin Books, 2012); Karima Kourtit and Peter Nijkamp, "In Praise of Megacities in a Global World," *Regional Science Policy & Practice* 5, no. 2 (June 2013): 167–82, https://doi.org/10.1111/rsp3.12002.

[14] Jonathan Kalan, "Think Again: Megacities," *Foreign Policy* 206 (2014): 69–73.

[15] Kees Koonings and Dirk Kruijt, eds., *Megacities: The Politics of Urban Exclusion and Violence in the Global South* (London; New York: Zed Books, 2009), https://ebookcentral.proquest.com/lib/ebook-nps/detail.action?docID=482400#.

[16] David Harvey, *Rebel Cities: From the Right to the City to the Urban Revolution*, Paperback ed (London: Verso, 2013); George Bugliarello, "Megacities and the Developing World," *The Bridge* 29, no. 4 (2009): 19–26; Manuel Castells, "Why the Megacities Focus? Megacities in the New World Disorder," in *Urban Innovations at the Intersection of Poverty and Environment: Mega-Cities Case Studies*, vol. 18 (Hartford, CT: The Mega-Cities Project, 1998), 1–16, http://janice-perlman.com/pub_2.php; Joel Kotkin, "Urban Legends," Foreign Policy, August 6, 2010, https://foreignpolicy.com/2010/08/06/urban-legends/.

including overpopulation and lack of adequate infrastructure and resources, leave it exceptionally vulnerable to violence, pollution, epidemics, and natural disasters.[17]

The existing military literature also highlights the importance of megacities but does so in terms of their relevance to U.S. strategic interests. The megacity represents the potential for the most complex and difficult form of urban operations yet experienced by the U.S. military. The potential for this problem prompted the Army Chief of Staff, General Mark Milley, to authorize a study to examine what difficulties the U.S. Army could face during conflict in a megacity. The published findings of the report "Megacities and the United States Army: Preparing for a Complex and Uncertain Future" examine the strategic importance, dynamics, and potential for conflict through case studies of megacities of the "global north" and "global south." The report concludes that the megacities of the world represent centers of vast strategic importance and interest of the United States, and environments which the United States joint force must prepare to operate within.[18] These studies of the megacity acknowledge the hybrid, irregular, and asymmetric challenges the megacities present to security issues.[19]

Contrasting this view, several other experts suggest megacities are not as central to U.S. strategic interests as some believe. In "The Case Against Megacities," for example, Evans argues that megacities do not represent the environment around which planning efforts should revolve; instead, the military's strategic focus should be on numerous "middleweight" cities. Additional research acknowledges the importance of large cities, but those that do not fit the criteria of a megacity, in terms of military preparation. Others have argued that preparing for conflict in megacities will also adequately prepare for combat operations in the smaller sub-megacities, however.[20]

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[17] Buglliarello, "Megacities and the Developing World"; Frauke Kraas, "Megacities as Global Risk Areas," in *Urban Ecology: An International Perspective on the Interaction between Humans and Nature*, ed. John M. Marzluff et al. (New York: Springer Science + Business Media, 2008), 583–96, https://link.springer.com/content/pdf/10.1007%2F978-0-387-73412-5.pdf.

[18] Kevin Felix and Frederick Wong, "The Case for Megacties," *Parameters* 45, no. 1 (2015): 19.

[19] David Kilcullen, "The City as a System: Future Conflict and Urban Resilience," *The Fletcher Forum of World Affairs* 36, no. 2 (July 26, 2012): 19–29.

[20] Michael Evans, "The Case Against Megacities," *Parameters* 45, no. 1 (2015): 33–43.

While the existing literature extensively covers the drivers of risk to a megacity's social-economic and cultural well-being, it rarely addresses security-related issues regarding low and high-intensity conflict. Moreover, scant research exists pertaining to a military's ability to shape a population's sentiment.

C. SOCIAL MEDIA AND SENTIMENT ANALYSIS

With the astronomical rise of social media over the last decade, a massive store of data has emerged that may provide a source of insight into population sentiment. Elements of social media include social networking, bookmarking, social news, media sharing, and microblogging and blog forums. These forums provide a vast array of data that can be mined and analyzed at unprecedented speeds, creating a swell of opportunity and challenges as the fields of advertisement, political campaigning, finance, academics, and government attempt to navigate and understand population sentiment through social media.[21] The bulk of this work tends to be focused on Western developed states, and is inclined to concentrate on market analysis, consumer trends and electoral preferences.[22] Significantly less work has been invested in the developing world, where low-intensity conflict is more prominent.

Social media platforms, such as Twitter and Facebook, provide a conduit into users' opinions through their public posting regarding topics ranging from product review to political issues. The existing literature on the topic of sentiment analysis, and in particular social media-based sentiment analysis, provides a broad range of differing approaches to the line of inquiry. Because Twitter, as a micro-blog, is immediately available through open source media, it serves as a unique platform for social media sentiment analysis. This broad and deep sample presents an opportunity to advance sentiment analysis, and has gathered a great deal of interest from the private, and to a lesser extent, the public sectors.

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[21] Georgios Paltoglou, "Sentiment Analysis in Social Media," in *Online Collective Action: Dynamics of the Crowd in Social Media*, ed. Nitin Agarwal, Merlyna Lim, and Rolf T. Wigand (Vienna: Springer, 2014), 3–18, https://link.springer.com/content/pdf/10.1007%2F978-3-7091-1340-0.pdf.

[22] Ian Tunnicliffe and Steve Tatham, *Social Media- The Vital Ground: Can We Hold It?* (Carlisle, PA: Strategic Studies Institute and U.S. Army War College Press, 2007), 8, https://ssi.armywarcollege.edu/pubs/display.cfm?pubID=1349.

Sentiment analysis is the field of study that analyzes personal opinions, sentiments, evaluations, appraisals, attitudes, and emotions toward entities such as products, services, organizations, individuals, issues, events, topics, and their attributes. This type of analysis resides within the discipline of natural language processing, which involves the study of various aspects of language through mathematical and computational methods.[23] Researchers can employ a variety of techniques when conducting sentiment analysis. Determining the sentiment of text can occur at the document-level or sentence-level and is not limited to a single opinion or topic but can focus on multiple aspects of a text.[24] The two main computationally-based approaches for sentiment analysis use various techniques of machine learning and lexicon-based approaches.[25] The machine-learning method involves using a set of pre-annotated data to train an algorithm as to the characteristics of given text. Once the text characterization has been learned, the algorithm then can be applied to the test set of data for classification. The lexicon-based approaches reference a pre-determined list of words and then compare the content of a given text to determine the positive and negative terms on the list to define semantic orientation of the text.[26] Both methods produce promising results; they continue to face challenges, however, particularly in analysis of text outside the scope of formal writing.

The study of sentiment analysis continues to develop as social media's popularity continues to rise. Twitter serves as a convenient platform for mining social media content, in that all of the messages posted by its members are available for anyone to view. It provides those studying sentiment analysis with a large data set, a wide range of topics,

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[23] Aravind K. Joshi, "Natural Language Processing," *Science* 253, no. 5025 (1991): 1242, https://doi.org/10.1126/science.253.5025.1242; Bing Liu, *Sentiment Analysis and Opinion Mining*, Synthesis Lectures on Human Language Technologies (San Rafael, CA: Morgan & Claypool, 2012), 1, 10.2200/S00416ED1V01Y201204HLT016.

[24] Ronen Feldman, "Techniques and Applications for Sentiment Analysis," *Communications of the ACM* 56, no. 4 (April 2013): 82–89, https://doi.org/10.1145/2436256.2436274.

[25] Pollyanna Gonçalves et al., "Comparing and Combining Sentiment Analysis Methods," in *COSN'13 Proceeedings of the First ACM Conerence on Online Social Networks* (Boston, MA: Association for Computing Machinery, 2013), 27–38, https://doi.org/10.1145/2512938.2512951.

[26] Peter D. Turney, "Thumbs Up or Thumbs Down? Semantic Orientation Applied to Unsupervised Classification of Reviews," in *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics* (Philadelphia, PA: Association for Computational Linguistics, 2002), 417–24, https://portalparts.acm.org/1080000/1073083/fm/frontmatter.pdf?ip=205.155.65.226.

and a diverse and global audience.[27] Additionally, with 335 million monthly active users worldwide, the opportunity exists to gain insight into timely and relevant topics in real time, all over the world.[28] Recent studies of Twitter sentiment analysis have utilized various approaches to classifying sentiment based on presence of a positive or negative emotion, human annotation of sentiment based on tweet content, and presence of sentiment words drawn from a sentiment lexicon dictionary.

The scholarship of sentiment analysis in social media has largely focused on topics such as politics, the stock market, and consumer reviews.[29] What is important to note is that many of the existing studies of sentiment analysis have been largely limited to the English language.[30] Many of the sentiment analyzers currently available work only with English text, and will therefore miss many of the native languages of the 267 million

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[27] Alexander Pak and Patrick Paroubek, "Twitter as a Corpus for Sentiment Analysis and Opinion Mining," in *Proceedings of the Seventh Conference on International Language Resources and Evaluation*, ed. Nicoletta Calzolari et al. (Valletta, Malta: European Languages Resources Association (ELRA), 2010), 27–37, https://pdfs.semanticscholar.org/ad8a/7f620a57478ff70045f97abc7aec9687ccbd.pdf.

[28] "Twitter Inc, Q2 2018 Letter to Shareholders," July 27, 2018, https://investor.twitterinc.com/static-files/610f4a82-5b52-4ed9-841c-beecbfa36186.

[29] Andranik Tumasjan et al., "Predicting Elections with Twitter: What 140 Characters Reveal about Political Sentiment," in *Proceedings of the Fourth International AAAI Conference on Weblogs and Social Media* (Menlo Park, CA: The AAAI Press, 2010), 178–85, https://www.aaai.org/ocs/index.php/ICWSM/ICWSM10/paper/download/1441/1852; Brendan O' Connor et al., "From Tweets to Polls: Linking Text Sentiment to Public Opinion Time Series," in *Proceedings of the Fourth International AAAI Conference on Weblogs and Social Media* (Menlo Park, CA: The AAAI Press, 2010), 122–29, https://www.aaai.org/ocs/index.php/ICWSM/ICWSM10/paper/viewFile/1536/1842; Johan Bollen, Huina Mao, and Xiaojun Zeng, "Twitter Mood Predicts the Stock Market," *Journal of Computational Science* 2, no. 1 (March 2011): 1–8, https://doi.org/10.1016/j.jocs.2010.12.007; Mahesh Joshi et al., "Movie Reviews and Revenues: An Experiment in Text Regression," in *HLT '10 Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics*, ed. Ron Kaplan et al. (Los Angeles, CA: Association for Computational Linguistics, 2010), 293–96, https://dl.acm.org/citation.cfm?id=1858037; Sitaram Asur and Bernardo A. Huberman, "Predicting the Future with Social Media," in *WI-IAT '10 Proceedings of the 2010 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology*, ed. Xiangji Huang et al. (Piscataway, NJ: IEEE Computer Society Conference Publishing Services, 2010), 492–99, https://arxiv.org/pdf/1003.5699.pdf.

[30] T. Camber Warren, "The Technology of Statecraft in the Age of Social Media: Idioms of Authority and Radicalization in Nigerian Social Communication" (San Francisco, CA: Annual Meeting of the American Political Science Association, 2016), 5.

international monthly active users on Twitter.[31] Sentiment analysis studies that include non-English text often rely on the limited sentiment analysis tools available in languages other than English or conduct a machine translation approach. Approaches to sentiment analysis or sentiment lexicons have been developed for languages such as Spanish, German, Chinese, French, and Arabic; they do not represent a multi-lingual solution that can be easily adapted to a broader diversity of languages, however.[32] Limited cross-lingual or multi-lingual approaches have been conducted within the field of sentiment analysis, but often rely on machine translations of known sentiment words in a given language, such as English, to determine the sentiment of the non-English term. These studies require the use of a pre-annotated sentiment text corpus in a given language or parallel corpora, with one known language, in order to determine sentiment of a target language.[33]

The military has significant interest in social media content and its relevance to conflict across the globe. The Defense Advanced Research Projects Agency (DARPA) conducted technical research in the form of a competition to discover how to identify and protect against influence bots. The study concluded that a semi-supervised approach, which

[31] Mohammad Salameh, Saif Mohammad, and Svetlana Kiritchenko, "Sentiment after Translation: A Case-Study on Arabic Social Media Posts," in *Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies* (Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Denver, Colorado: Association for Computational Linguistics, 2015), 767, https://doi.org/10.3115/v1/N15-1078; "Twitter Inc, Q2 2018 Letter to Shareholders," 2.

[32] Kia Dashtipour et al., "Multilingual Sentiment Analysis: State of the Art and Independent Comparison of Techniques," *Cognitive Computation* 8, no. 4 (August 2016): 757–71, https://doi.org/10.1007/s12559-016-9415-7.

[33] Jordan Boyd-Graber and Phillip Resnik, "Holistic Sentiment Analysis Across Languages: Multilingual Supervised Latent Dirichlet Allocation," in *Proceedings of the Conference on Empirical Methods in Natural Language Processing*, ed. Eric Fosler-Lussier (Stroudsburg, PA: The Association for Computational Linguistics, 2010), 45–55, http://aclweb.org/anthology/D10-1000; Carmen Banea et al., "Multilingual Subjectivity Analysis Using Machine Translation," in *Proceeding of the 2008 Conference on Empirical Methods in Natural Language Processing*, ed. Sebastian Pado (Stroudsburg, PA: Association for Computational Linguistics, 2008), 127–35, http://www.aclweb.org/anthology/D08-1000; Honglei Guo et al., "OpinionIt: A Text Mining System for Cross-Lingual Opinion Analysis," in *Proceedings of the 19th ACM International Conference on Information and Knowledge Management - CIKM '10* (the 19th ACM International Conference, Toronto, ON, Canada: ACM Press, 2010), 1199, https://doi.org/10.1145/1871437.1871589; Xinfan Meng et al., "Cross-Lingual Mixture Model For Sentiment Classification," in *Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics: Long Papers*, ed. Maggie Li and Michael White, vol. 1 (Stroudsburg, PA: Association for Computational Linguistics, 2012), 572–81, https://dl.acm.org/citation.cfm?id=2390605.

involves human involvement in bot detection and identification, is most effective.[34] The Naval Postgraduate School (NPS) has produced two thesis projects on the topic: the first, *Assessing Sentiment in Conflict Zones Through Social Media*, compared polling data to social media trends, demonstrating that under certain conditions, social media can supplement or replace surveys; the second, *Understanding Violence Through Social Media*, demonstrated how social media sentiment analysis can be used to predict the outbreak of violence under specific circumstances.[35]

Much of the literature regarding the role of social media and the military focuses on the strategic impact of social media and less on techniques and tools through which to implement social media analysis. In a non-mission-focused setting, the military uses social media to disseminate information, managing the force and as a tool for recruitment.[36] With a more mission-focused approach, the RAND Cooperation study, *Monitoring Social Media*, highlights that social media can support the U.S. military's information operations by "providing a window into the perspective, thoughts and communications of a wide range of relevant audiences."[37] From a technical aspect the study recommends that the military seek out open source technologies, as commercial products withhold the information as to how they analyze the data.[38] As noted, many of the studies in social media sentiment analysis conducted research in a single language, often English. This approach is problematic because it limits insights into portions of the population that do not speak the dominant language, which prohibits researchers from understanding varying sentiments among populations that experience conflict. Moreover, this limitation is exacerbated when

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[34] V.S. Subrahmanian et al., "The DARPA Twitter Bot Challenge," *Computer* 49, no. 6 (June 2016): 38–46, https://doi.org/10.1109/MC.2016.183.

[35] Andrew K. Bourret, Joshua D. Wines, and Jason M. Mendes, "Assessing Sentiment in Conflict Zones through Social Media." (Master's thesis, Naval Postgraduate School, 2016), http://hdl.handle.net/10945/51650; Evans, Frost, and Hodges, "Understanding Violence Through Social Media: Twitter & Violence in Iraq," 2017.

[36] Ryan G. Walinski, "The U.S. Military and Social Media" (Maxwell AFB, AL: Air University, Air Command and Staff College, 2015), 36, http://www.dtic.mil/dtic/tr/fulltext/u2/a626009.pdf.

[37] William Marcellino et al., *Monitoring Social Media: Lessons for Future Department of Defense Social Media Analysis in Support of Information Operations* (Santa Monica, CA: RAND Corporation, 2017), 7, https://www.rand.org/pubs/research_reports/RR1742.html.

[38] Marcellino et al., 69.

a geographic area contains a megacity with a population that speaks many diverse languages. Consequently, this study contributes to the field of sentiment analysis by incorporating a new multi-lingual approach.

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III. BACKGROUND

A. COUNTRY SELECTION

A multitude of factors may lead to violence in megacities and other larger urban centers worldwide. Some of these factors range from substantial poverty and urbanization, to ethnic, cultural, and religious diversity. These are common issues that affect most nations; three countries possess important characteristics that make them useful case studies for this research, however, namely Pakistan, Nigeria, and the Philippines. Specifically, these countries have faced significant and repeated violence over the last decade, and they possess at least one megacity that is under threat of one or multiple non-state actors that pose challenges to the legitimacy and survivability of the state.[39]

B. PAKISTAN

Pakistan is a country of vast multicultural heritages plagued by years of violence within its borders and concerns of uprisings by more prominent counter-state actors including Tehrik-e-Taliban Pakistan (TTP), the Taliban, Al Qaeda, and the Balochistan Liberation Army (BLA). Violence regularly occurs throughout much of Pakistan, impacting both large urban areas and modest rural regions. Common forms of violence occurring in these large cities take shape in the form of burglaries, muggings, and robberies; organized violence, however, namely in the megacity of Karachi, is notably associated with targeted assassinations tied to political affiliates and terrorism.[40] Where difficult to combat, violence in sprawling Pakistani cities creates challenges for local and federal governments. Violence often creates insecurity among a populace as well as

[39] The content of the following non-state actors is not an exhaustive description of all non-state actors within each country. Those listed in the text are the most common and have caused extensive harm within their respective countries. A more in-depth analysis and summarization of a complete list can be found through the Stanford University's Mapping Militant Organizations, http://web.stanford.edu/group/mappingmilitants/cgi-bin/ and Uppsala Conflict Data Program, http://www.ucdp.uu.se/.

[40] Sobia Ahmad Kaker, "Enclaves, Insecurity and Violence in Karachi," *South Asian History and Culture* 5, no. 1 (2014): 93–107, https://doi.org/10.1080/19472498.2013.863016.

entrenching a gap in the level of trust a society places in their governing body.[41] This combination of insecurity and lack of trust can breed anti-government sentiment within a population, which often degrades opportunities for economic development and jeopardizes political stability.[42]

1. Tehrik-e-Taliban Pakistan

As a result of varying challenges and conflicts within the region, the Tehrik-e-Taliban Pakistan (TTP) formed in December 2007 to serve as an echelon of authority over a multitude of similar militant groups throughout tribal regions of Pakistan. United by common goals and driven by jihadi principles, the TTP has established its base in the direction of performing operations to achieve three goals essential to their platform. Their goals are to create an atmosphere whereby Sharia law is the primary rule of law, target U.S and allied forces in Afghanistan to obstruct coalition efforts, and fight the Pakistani military through waging jihad to establish an Islamic state in Pakistan.[43] Due to the requirements of what achieving their goals entails, and acknowledging Afghanistan as operating terrain, most TTP violence occurs within Pakistan's northwestern regions.[44] Additionally, it is worth noting that, while conducting acts of violence toward the state and allied partners, the TTP is extremely diverse, composed of multiple ethnicities including Arab, Uzbek, Afghan, Chechen, Punjabi, and a majority of Pashtun militants.[45]

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[41] Daniel Esser, "The City as Arena, Hub and Prey Patterns of Violence in Kabul and Karachi," *Environment and Urbanization* 16, no. 2 (October 2004): 31–38, https://doi.org/10.1177/095624780401600219.

[42] Esser.

[43] Qandeel Siddique, "Tehrik-E-Taliban Pakistan: An Attempt to Deconstruct the Umbrella Organization and the Reasons for Its Growth in Pakistan's North-West" (Copenhagen, Denmark: Danish Institute for International Studies, 2010), http://pure.diis.dk/ws/files/104682/RP2010_12_Tehrik_e_Taliban_web.pdf; "Tehrik-i-Taliban Pakistan (TTP)," Project on Violent Conflict, 25 2015, https://www.start.umd.edu/baad/narratives/tehrik-i-taliban-pakistan-ttp; "Tehrik-E Tailban Pakistan (TTP)," Counter Terrorism Guide: Terrorist Groups, accessed October 22, 2018, https://www.dni.gov/nctc/groups/ttp.html#.

[44] Syed Raza Hassan, "India, Afghanistan Gave Help to Pakistani Taliban, Says Group's Ex-Spokesman," *Reuters*, April 26, 2017, https://www.reuters.com/article/us-pakistan-militants/india-afghanistan-gave-help-to-pakistani-taliban-says-groups-ex-spokesman-idUSKBN17S1VN.

[45] "Tehrik-i-Taliban Pakistan," Mapping Militant Organizations, August 6, 2017, http://web.stanford.edu/group/mappingmilitants/cgi-bin/groups/view/105.

2. The Taliban

Primarily a Sunni Muslim group, the Taliban found its footing in Afghanistan in the mid-1990s, establishing itself as an Islamic group dedicated to the creation of an Islamic state and the overthrow of the existing Afghan government.[46] To gain control of the country, the Taliban began by focusing on the region south of the Afghan capital of Kabul. The group initially targeted warlords, which at the time the Afghan government viewed as favorable given it saw many of the targeted warlords as a threat.[47] By eradicating these groups from the south, the Taliban was in a key position to seize control of vital terrain in Kandahar, Helmand, and Zabul Provinces, all of which were Pashtun tribal territory. The Taliban continued to gain prominence in Afghanistan and eventually overthrew the central government. Many countries blamed Pakistan for the Taliban's rise to power because they provided the group with material support essential to its efforts.[48] In late 2001, after the September 11th attacks on U.S. soil, the United States with the support of anti-Taliban warlords removed the Taliban from power. Upon their removal, the Taliban often sought refuge in Pakistan, utilizing the country's western and northern borders with Afghanistan as launching points to refit and conduct offensive operations toward coalition forces in Afghanistan.

3. The Balochistan Liberation Army

Strongly opposed to Pakistan's central government, the Balochistan Liberation Army (BLA) is one of several militant groups that occupies portions of Balochistan Province in western Pakistan. Due to a multitude of factors, predominantly economic oppression and non-representation through the government, insurgent uprisings have swelled in the region among Baloch tribal sects and have been met with Pakistani military

46 Zachary Laub, "The Taliban in Afghanistan," Council on Foreign Relations, July 4, 2014, https://www.cfr.org/backgrounder/taliban-afghanistan; Omer Aziz, "The ISI's Great Game in Afghanistan," Diplomat, June 8, 2014, https://thediplomat.com/2014/06/the-isis-great-game-in-afghanistan/.

47 "Taleban," UCDP, accessed October 23, 2018, http://ucdp.uu.se/#/actor/303.

48 Aziz, "The ISI's Great Game in Afghanistan."

force to suppress the movements.[49] Additionally, the BLA is consistent in their belief that ethnic identity is more important than religious identity, a controversial thought among Islamic regions. The opposing stance that the state of Pakistan takes on this further ignites resistance and conflict between the state and the non-state actor, as does their beliefs that Pakistan does not view the Baloch as equal and unevenly distributes wealth from natural resources in the area to ethnic Punjabis.[50] Of note, three additional non-state actors with ties to the BLA, the Balochistan Liberation Front (BLF), The Balochistan Republican Army (BRA), and United Baloch Army (UBA) have taken similar positions in line with those of the BLA, but have rarely impacted state affairs within Pakistan.

4. Al Qaeda

As a product of the Mujahedeen fight against the Soviet Union in Afghanistan in the 1980s, Al Qaeda emerged as a loosely organized structure to represent oppressed and victimized Muslims around the world as a result of alleged illegitimate occupation of Muslim lands by western and non-Muslim powers. Al Qaeda's founding member, Abdullah Azzam, with support from Usama bin Laden, emphasized the group to serve as a base for all oppressed Muslims to serve and fight against the struggle put before them, formally recognizing the group in 1988.[51] Primarily a Sunni Muslim group, Al Qaeda's main goal stressed the importance of expelling all non-Islamic ideas, practices, and behaviors viewed as secular to bring back true Islam to the Muslim world. Usama bin Laden emphasized that in order to achieve this goal, attacks on western targets, especially those in the United States and on U.S. citizens wherever found, were essential and mandated.[52] Today, due to efforts to eradicate terrorist organizations through the war on

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[49] Karlos Zurutuz, "Understanding Pakistan's Baloch Insurgency," *Diplomat*, June 24, 2015, https://thediplomat.com/2015/06/cracking-pakistans-baloch-insurgency/.

[50] Scott Gates and Kaushik Roy, *Unconventional Warfare in South Asia: Shadow Warriors and Counterinsurgency* (Farnham, Surrey, England ; Burlington, VT: Ashgate, 2014), 199, https://ebookcentral.proquest.com/lib/ebook-nps/reader.action?docID=1580878&query=.

[51] Bruce O. Riedel, *The Search for Al Qaeda: Its Leadership, Ideology, and Future* (Washington, DC: Brookings Institution Press, 2008), 46, https://ebookcentral.proquest.com/lib/ebook-nps/reader.action?docID=513999&query=.

[52] Dan Rassler and Vahid Brown, *The Haqqani Nexus and the Evolution of Al-Qa'ida* (West Point, NY: Combating Terrorism Center, 2011), http://www.dtic.mil/dtic/tr/fulltext/u2/a560977.pdf.

terror after the events of September 2001, Al Qaeda has been decentralized in a majority of its former territories. Some pockets of the organization still remain centrally intact in contested areas of Afghanistan, however, as well as some protected areas of Pakistan.

Throughout Pakistan, additional groups play minor roles in the overarching scheme to transition the shape and structure of the government. Rebel groups such as The Islamic Movement of Uzbekistan (IMU), Jamaat-ul-Ahrar, and Lashkar-e-Islam have all attempted to impose their influence on the state through inflicting violence, but their efforts have been minimal and ineffective in achieving their goals.

C. NIGERIA

Throughout the nation's history, Nigeria has evolved from years spent under British colonial rule to become a primary economic contributor due to its coastal port facilities and key location of Lagos, one of the largest and most economically developed cities on the African continent. Today, Nigeria's rapid rate of modernization and contributions in the western and central regions of Africa have been overshadowed by challenges associated with groups advocating different and violent ideologies. Although somewhat physically and geographically contained, Boko Haram, formally known as Jama'atu Ahlis Sunna Lidda'awati Wal-Jihad ("People Committed to the Propagation of the Prophet's Teachings and Jihad"), has created turmoil and chaos through much of Nigeria's northern, central, and eastern states.[53] Relatively isolated to certain sections of the country, their impact has been felt both internally and across international boundaries. In addition to Boko Haram as the main and most commonly known non-state actor in Nigeria, large urban centers such as Lagos have struggled with an influx of localized extremist groups known as Confraternity Cults, which are increasingly spreading their beliefs, influence, and traditions to many other countries abroad.

[53] "Who Are Boko Haram?" *BBC News*, November 24, 2016, https://www.bbc.com/news/world-africa-13809501.

1. Boko Haram

For nearly a decade, Boko Haram has intensified its attacks against the Nigerian government and civilians in a quest to create a completely Islamic state. Prior to 2009, however, Boko Haram was not intent on defeating the Nigerian government and creating mass exposure as an extreme terrorist organization. The group's founder, Mohammed Yusuf, an Islamic cleric and trained Salafist, focused on the spread of radical jihad and fundamental Islam, ridding Nigeria of western ideas and secular activities as Nigeria is almost split evenly between Christian and Muslim followers.[54] Since the group's beginning, more than 15,000 individuals have joined its ranks for an assortment of reasons.[55] These reasons have contributed to solidifying the group's identity among its members and increasing resolve for their cause. The most significant of these reasons rests with common religious beliefs, with Islam as the foundation, but overlaid with extreme jihadist teachings and anti-west sentiment. These strong religious ties are predominant in the country's central and northern states of Borno, Yobe, and Kano primarily, where the majority of individuals are impoverished Muslims and have very little opportunity for progressive lifestyles.

2. The Divide between Christians and Muslims

Nigeria's internal conflict between Christians and Muslims has been ongoing for years, long before the establishment of Boko Haram. Islam was first introduced to what is now present-day Nigeria through the Trans-Sahara trade routes and interactions with North African and Arab persons further introducing the region to the Islamic faith. Eventually, the northern Nigerian states would convert to Islam as the primary religion in the eleventh century. The migration of the Islamic faith to include its ideologies, teachings, and political practices would filter out across other Northern states, creating an Islamic identity for the northern half of Nigeria.[56]

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[54] Claire Felter, "Nigeria's Battle with Boko Haram," Council on Foreign Relations, August 8, 2018, https://www.cfr.org/backgrounder/nigerias-battle-boko-haram.

[55] "Boko Haram at a Glance," Amnesty International, January 29, 2015, https://www.amnesty.org/en/latest/news/2015/01/boko-haram-glance/.

[56] "Islam in Nigeria," Religious Literacy Project, 2018, https://rlp.hds.harvard.edu/faq/islam-nigeria.

Christianity, on the other hand, was introduced through European powers as early as the Fifteenth Century in coastal regions of West Africa, eventually spreading into western and southern areas of present-day Nigeria. While Nigeria is mainly a nation split between two religions associated with the North and South, Christianity becomes further complex as the southern half of Nigeria is divided into eastern and western societies. The West consists of Yoruba and Edo tribes, while the East is made up of Igbo, Efik, and a handful of other smaller tribes.[57] Similar tribes such as the Hausa-Fulani in the Islamic North contributed to religious irregularities and differences throughout the country, all in favor of their separate and distinct political, judicial and administrative associations that have provided a path to the current conflicts of today. The various beliefs these two religions offer contribute to their own distinct social identities creating diverse in-groups among the multiple ethnicities that subscribe to the teachings and ideologies within the Christian and Muslim faiths.

3. Nigerian Confraternities

Consisting of nearly 21,000,000 citizens, Lagos is not only Nigeria's largest city but the largest in Africa as well.[58] Developing at a record pace and with its prime location as a port city on the Nigerian coast, Lagos is seen as a coveted location for economic and personal opportunity. Like most megacities, however, Lagos is no stranger to challenges posed by criminal activity and antagonist groups. Far from the scale of Boko Haram, Lagos is home to groups of Confraternities, which are similar to gangs, but made up of individuals who wish to be part of brotherhoods or groups that portray enticing social characteristics. These groups, unlike more politically organized violent actors, typically commit violence toward each other or other non-state groups, rather than opposing the central government or state entities.

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[57] Bulus Galadima and Yusufu Turaki, "Christianity in Nigeria," *Africa Journal of Evangelic Theology* 20, no. 1 (2001): 87.

[58] United Nations, Department of Economic Affairs, *World Urbanization Prospects: The 2014 Revision* (New York: United Nations, 2015), 93.

When Confraternities were first established, the original cause that joined individuals together was to create social and religious opportunities for minority groups at universities and tertiary institutions. As time progressed, the cause has shifted, putting emphasis on oppression, intimidation, and conducting brutal acts of violence toward rival groups, all which were formed under similar premises.[59] Aside from organizing violent groups within Nigeria's education system, it is a growing concern that these groups adopt a cult-like mindset, instilling ideologies in young persons, easily influenced and willing to adapt to a growing sense of cultism. Contributing reasons behind this cult growth are similar to that of many other gangs or social groups abroad. Strong influence by peers, lack of parental guidance, and abundant free time throughout their educational experiences are factors that enable youth to steer toward association with these groups.[60]

Although numerous groups exist, the most prominent of these groups, the Black Axe or the Neo-Black Movement of Africa and Eyie, are of critical concern due to mounting acts of violence against competing cults and their coercive recruitment styles, often using force to encourage others to join their ranks.[61] The characteristics of these groups differ greatly from organizations such as Boko Haram, ISIL, and al Shabab, in terms of a distinct identity that connects them. Whereas these more extreme terrorist organizations are all spread over various geographic regions and do not directly collaborate operationally with one another on a regular basis, they all have similar goals or objectives which unify their efforts, bringing together a resolve for what they believe to be a righteous cause. Although Confraternities form and grow on similar premises, they find it challenging to accept one another's goals or position within the region, setting conditions for warring in-group, out-group competition and violence in the megacity.

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[59] Evelyn Usman, "The Increasing Menace Cultism: How I Was Forced into Eiye Confraternity," *Vanguard News*, June 23, 2016, https://www.vanguardngr.com/2016/09/increasing-menace-cultism-forced-eiye-confraternity/.

[60] Elizabeth Uwandu, "Cultism among Nigerian Students," *Vanguard News*, September 23, 2016, https://www.vanguardngr.com/2016/09/cultism-among-nigerian-students/.

[61] "Nigeria: The Black Axe Confraternity, Also Known as the Neo-Black Movement of Africa, Including Their Rituals, Oaths of Secrecy, and Use of Symbols or Particular Signs; Whether They Use Force to Recruit Individuals (2009-November 2012)" (Ottawa, Ontario, Canada: Canada: Immigration and Refugee Board of Canada, December 3, 2012), http://www.refworld.org/docid/50ebf7a82.html.

D. PHILIPPINES

For decades, various non-state actors have violently opposed the government of the Republic of the Philippines for control of the southern area of Mindanao. The root cause of conflict between these groups centers on either autonomous or independent rule by the island's Muslim population, known as the Moros. The conflict within the southern Philippines traces its origins back to Spanish colonization during the 16th century.[62] During Spanish rule over the Philippines, the Muslim population in the south was politically, economically, socially, and religiously discriminated against by the Christian population in the north.[63] Land reform within the Philippines during the 1920s allowed for the granting of land in Mindanao to settlers from the north. This loss of land further marginalized the native Muslim inhabitants of Mindanao.[64] Post-World War II, the Muslim population in the south sought exclusion from the now independent Philippines in an effort to establish self-rule. This failed effort and continued marginalization from the Philippine government throughout the 1960s set the conditions for the emergence of armed counter-state groups who sought to fight for self-governance.[65] The Moro National Liberation Front (MNLF), the Moro Islamic Liberation Front (MILF), the Bangsamoro Islamic Freedom Movement (BIFM), the Abu Sayyaf Group (ASG), and the Communist Party of the Philippines (CPP) are five of the most active and influential counter-state groups fighting for independence within the Philippines. These counter-state actors in the

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62 Diana Rodriguez and Soliman M. Santos Jr., "Introduction," in *Primed and Purposeful: Armed Groups and Human Security Efforts in the Philippines* (Geneva, Switzerland: Small Arms Survey, 2010), 4, http://www.smallarmssurvey.org/fileadmin/docs/D-Book-series/book-12-Philippines/SAS-Armed-Groups-Human-Security-Efforts-Philippines.pdf.

63 Soliman M. Santos Jr., "War and Peace on the Moro Front: Three Standard Bearers, Three Forms of Struggle, Three Tracks (Overview)," in *Primed and Purposeful: Armed Groups and Human Security Efforts in the Philippines* (Geneva, Switzerland: Small Arms Survey, 2010), 58, http://www.smallarmssurvey.org/fileadmin/docs/D-Book-series/book-12-Philippines/SAS-Armed-Groups-Human-Security-Efforts-Philippines.pdf.

64 Sietze Vellema, Saturnino M. Borras Jr, and Francisco Lara Jr, "The Agrarian Roots of Contemporary Violent Conflict in Mindanao, Southern Philippines: The Agrarian Roots of Conflict in Mindanao, Southern Philippines," *Journal of Agrarian Change* 11, no. 3 (July 2011): 298–320, https://doi.org/10.1111/j.1471-0366.2011.00311.x.

65 Mark Turner, "Terrorism and Secession in the Southern Philippines," *Contemporary Southeast Asia* 17, no. 1 (June 1995): 1–19.

country's south each possess unique qualities, often leveraged through violent armed struggle, to achieve legitimacy and regional control.

1. The Moro National Liberation Front

The Moro National Liberation Front (MNLF) emerged as one of the early non-state actors that entered into armed conflict against the Philippine government. The MNLF formed after the disbanding of the Moro Independence Movement (MIM) in 1970, sustaining a continued desire for self-governance among the people.[66] Additionally, the creation of the MNLF developed from the aspiration of the inhabitants of Mindanao to have a separate national identity, as well as from grievances regarding continued socio-economic issues.[67] Building the group's sense of identity, the MNLF adopted the term "Moro," which was originally an ethnic slur used against them. This further assisted in the group's self-categorization, as an autonomous people, who were different from the Filipinos in the north.[68] Over time, the group began a shift from an armed counter-state actor to a political organization. The MNLF became more secular in nature as it wanted to be seen as a legitimate political party that could govern autonomously over Mindanao. The MNLF reinforced this identity through their peace agreement with the Philippine government in 1996, which recognized it as the legitimate representative of the Moro people.[69] In viewing itself as the legitimate representative of the Moro people in Mindanao, as per the 1996 peace agreement with the government, subsequent agreements between the government and other Islamic independence groups forced the MNLF to once again strongly assert this identity.[70] To reinforce their self-identified role as the legitimate party,

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[66] Lela Garner Noble, "The Moro National Liberation Front in the Philippines," *Pacific Affairs* 49, no. 3 (1976): 405, https://doi.org/10.2307/2755496.

[67] Noble.

[68] Charles O. Frake, "Abu Sayyaf: Displays of Violence and the Proliferation of Contested Identities among Philippine Muslims," *American Anthropologist* 100, no. 1 (March 1998): 47.

[69] Santos Jr., "War and Peace on the Moro Front: Three Standard Bearers, Three Forms of Struggle, Three Tracks (Overview)," 66.

[70] "MNLF: Framework Abrogates 1996 Peace Treaty," *Philippine Star*, June 27, 2014, https://www.philstar.com/headlines/2014/01/27/1283435/mnlf-framework-abrogates-1996-peace-treaty.

the MNLF leader, Nur Misuari, declared independence of the Bangsamoro Republic, and once again shifted to an armed counter-state actor.

As important as their ability to conduct acts of violence against the Philippine government, so too was their ability to conduct information campaigns. As with all narratives, the MNLF's narrative required an end state that their actions sought to achieve. The end state envisioned for the MNLF was that of an autonomous state under the sovereignty of the Philippines.[71] With the founding of alternate independence groups within the Philippines, such as the MILF, the MNLF continued to press the narrative that the 1996 peace agreement's framework made them the legitimate ruling party in Mindanao.[72] The MNLF used this important aspect of their narrative to justify the reemergence of violence against the government.

2. The Moro Islamic Liberation Front

Much like the MNLF, the Moro Islamic Liberation Front (MILF) also sought self-governance in the southern Philippines. Key to the MILF's identity was that they categorized themselves into a group based on independence, not autonomous rule, which the MNLF seeks.[73] The concept of community represented another aspect of the social group that members of the MILF further identified with. The MILF's members closely associated themselves on communal and familial ties. These ties assisted the MILF in recruiting, with children often joining the organization due to their family ties.[74] These communal aspects, as well as their emphasis on members being of the Maguindanao ethnicity also sought to further define the group's uniqueness.[75] The MILF's identity

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[71] Astrid S. Tuminez, "This Land Is Our Land: Moro Ancestral Domain and Its Implications for Peace and Development in the Southern Philippines," *SAIS Review* 27, no. 2 (2007): 81, https://doi.org/10.1353/sais.2007.0044.

[72] "MNLF: Framework Abrogates 1996 Peace Treaty."

[73] Alpaslan Özerdem, Sukanya Podder, and Eddie L. Quitoriano, "Identity, Ideology and Child Soldiering: Community and Youth Participation in Civil Conflict – A Study on the Moro Islamic Liberation Front in Mindanao, Philippines," *Civil Wars* 12, no. 3 (September 2010): 309, https://doi.org/10.1080/13698249.2010.509566.

[74] Özerdem, Podder, and Quitoriano, 310–15.

[75] Santos Jr., "War and Peace on the Moro Front: Three Standard Bearers, Three Forms of Struggle, Three Tracks (Overview)," 63.

heavily resided in its adherence to Islam, that is non-secular nature, and a determination to achieve self-rule as an independent state.

The MILF's narrative, until fairly recently, espoused its desire for an independent Bangsamoro as its end state. The organizational narrative differentiated itself from that of the MNLF, in that the MILF did not recognize the constitution of the Philippines and therefore declared that it would not live under rule by the government. As the MNLF attempted to assert its role as the representative entity in the southern Philippines through peace negotiations, the MILF contested this role, stating that they would continue to fight against the government until it had achieved their desired end state.[76] The MILF claimed that within this narrative, the group justified its violent actions because "[t]he Bangsamoro Mujahedeen are strictly following the teachings of Islam. As such, they do not commit any crime."[77] Like other groups within the southern Philippines, such as the MNLF, the MILF began to shift its demands after years of conflict with the government. The MILF's use of armed action against the government filled the void left by the MNLF when it negotiated for peace with the state, causing the MILF to rise to the front as the legitimate representative of the Moro people. In 2014, the group shifted its narrative to support the peace agreement it negotiated with the Philippine government. Even though it agreed to autonomous rule and not independent rule, the MILF leadership claimed the agreement was "the crowning glory of our struggle."[78]

3. The Bangsamoro Islamic Freedom Movement

Derived as a fragmented section of the Moro Islamic Liberation Front, the Bangsamoro Islamic Freedom Movement (BIFM) was founded in 2011 determined to establish an Islamic state for Filipino Muslim minorities in Mindanao, independent of

[76] Zachary Abuza, "The Moro Islamic Liberation Front at 20: State of the Revolution," *Studies in Conflict & Terrorism* 28, no. 6 (November 2005): 455, https://doi.org/10.1080/10576100500236881.

[77] "Interview with MILF Leader, Sheikh Salamat Hashim," *Nida'ul Islam*, April 1998, https://www.islam.org.au/articles/index.htm.

[78] Rosemarie Francisco, Manuel Mogato, and Will Dunham, "Philippines, Muslim Rebels Sign Final Peace Deal to End Conflict," *Reuters*, March 27, 2014, https://www.reuters.com/article/us-philippines-rebels/philippines-muslim-rebels-sign-final-peace-deal-to-end-conflict-idUSBREA2Q1W220140327.

control from the central government.[79] Initially, BIFM was formed out of failed negotiations between the MILF and the Philippine government as armed conflict between the two entities raged for years. It has been a constant stance of BIFM that negotiations with the government are unwelcome and unable to achieve their goals of an independent Islamic state without the use of violence and armed struggle to validate their cause.[80] Since the BIFM's inception, the main targets of their aggression have been armed wings of the Philippine government, namely military and police forces seen as a challenge to their positions. In an effort to undermine the government's legitimacy and break down any types of peaceful attempts brokered by the MILF and the central government, however, the BIFM has been known to leverage attacks on civilian targets in order to continue to achieve their objectives through armed conflict.[81]

4. The Abu Sayyaf Group

The Abu Sayyaf Group (ASG), founded by Abdurajak Abubakar Janjalani in 1991, seeks to establish an independent Islamic State in the southern Philippines, specifically in Mindanao and the island chain of Sulu.[82] The rise of ASG began with either un-attributed attacks or attribution by rumor in the early 1990s. The group increased its commitment to achieving an Islamic state through the increase of violent events throughout the 1990s.[83] Dissatisfied with the MNLF and its cooperation with the government, Janjalani and other members of the MNLF broke away from the group and started ASG.[84] These former MNLF members built the identity that the group would operate under, and continue to do so under future leaders. The unique identity that the members formed for ASG centers on

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[79] Peter Chalk, "The Bangsamoro Islamic Freedom Fighters: The Newest Obstacles to Peace in the Southern Philippines?" *CTC Sentinel* 6, no. 11–12 (November 2013): 25–27.

[80] Chalk.

[81] "Peace Talks Resume after Deadly Attacks," *Rappler*, August 7, 2012, http://www.rappler.com//nation/10032-peace-talks-resume-after-deadly-rebel-attacks.

[82] "Abu Sayyaf Group," Mapping Militant Organizations, July 20, 2015, http://web.stanford.edu/group/mappingmilitants/cgi-bin/groups/view/152?highlight=al+qaeda.

[83] Turner, "Terrorism and Secession in the Southern Philippines," 6.

[84] Rommel C. Banlaoi, "The Abu Sayyaf Group: From Mere Banditry to Genuine Terrorism," *Southeast Asian Affairs*, no. 33 (2006): 248.

the concept of conducting jihad to achieve their outcomes. The group finds its uniqueness in this, because unlike the other separatist groups, ASG uses violence as the sole means to achieve their end state without any attempts at a political solution.[85] ASG's identity also differs from other counter-state groups in that they do not self-categorize as Moros, and view those who do as not practicing Islam correctly.[86] The ASG's avoidance of the term Moro reinforces their group identify and allows them to assign out-group membership to other counter-state groups that proudly use the term Moro, as indicated by their group names.

5. The Communist Party of the Philippines

Established in the mid-1960s, the Communist Party of the Philippines (CPP) has continuously sought communist rule in the country by ousting the existing government through use of force and armed aggression.[87] Originating from a former communist faction, founding members developed the CPP to adhere to a more profound and fundamental approach to communist principles once inspired through previous uprisings in China and Cuba. In addition, U.S. presence in the Philippines was viewed as an encroachment on Filipino values, further igniting the cause for the up-and-coming communist party.[88] Utilizing the group's armed front through the New People's Army (NPA), the CPP has been able to conduct military-style attacks for decades in both rural and urban settings throughout the Philippines with its main objective to institute policy changes in what they see as an illegitimate political environment.

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[85] "Abu Sayyaf Group."

[86] Banlaoi, "The Abu Sayyaf Group: From Mere Banditry to Genuine Terrorism," 251.

[87] "The Communist Insurgency in the Philippines: Tactics and Talks," International Crisis Group, February 14, 2011, https://www.crisisgroup.org/asia/south-east-asia/philippines/communist-insurgency-philippines-tactics-and-talks.

[88] "Program for a People's Democratic Revolution (1968) Ratified by the Congress of Reestablishment of the Communist Party of the Philippines December 26, 1968," December 26, 1968, http://www.bannedthought.net/Philippines/CPP/1960s/ProgramForPeoplesDemRev-681226.pdf.

IV. RESEARCH METHODS

A. HYPOTHESES

This research intends to further the field's understanding of the relationship between violence and how a population expresses their sentiments about violence through social media. In other words, it seeks to understand the impact of violence in relation to how it either promotes or impedes the salience of a conflict actor's narrative. We hypothesize that, if a violent event occurs, social media messages expressing positive sentiment about the state will decrease and messages expressing negative sentiment about the state will increase (Hypothesis 1a). Additionally, we hypothesize that if the number of civilian casualties increases we will find similar patterns, with the positive sentiment toward the state decreasing and negative sentiment increasing (Hypothesis 1b). Additionally, if a violent event occurs, we expect that messages expressing positive sentiment about the non-state actor will increase and messages expressing negative sentiment about the non-state actor will decrease (Hypothesis 2a). If civilian casualties increase, however, we expect to find similar patterns to that of the government, with the positive messages about the non-state actor decreasing and negative messages about the non-state actor increasing (Hypothesis 2b). When examining the megacity, we hypothesize that sentiments expressed in a megacity will influence the sentiments expressed on the following day in the rest of the country (Hypothesis 3).

B. DATA AND METHODS

1. Constructing a Multi-lingual Sentiment Dictionary

Social media sentiment analysis often uses sentiment dictionaries to search within a list of terms that have been scored with a positive or negative sentiment score. To capture the sentiment of the messages occurring within conflict areas, this study uses a sentiment dictionary. Unlike previous research, much of which used existing English sentiment dictionaries, however, the multi-lingual nature of this project prohibits the use of existing lexicon dictionaries. As no all-inclusive, multi-lingual sentiment dictionary exists from which to draw sentiment search terms, this study sought to form a dictionary through the use of words that most frequently co-occur with popular emojis and emoticons. The NPS-licensed Twitter archive provided the social media content for this study. The Twitter corpus contains 40 terabytes of data, which contains over three billion tweets. The archive's data contains a random sample of 10 percent of the tweets posted from August 1, 2013 through July 21, 2014.

We used Novak et al.'s Emoji Sentiment Ranking Lexicon to build a multi-lingual sentiment dictionary from all of the tweets in the NPS Twitter Archive.[89] The Emoji Sentiment Ranking Lexicon consists of 751 emojis ranked by frequency of use from a data set of 1.6 million tweets. These emojis have been assigned a sentiment score ranging from -1 to 1, with -1 being most negative, 0 being neutral, and 1 being most positive. From the available 751 emojis, we selected the top 10 most frequently used positive and negative emojis as starting point for building our multi-lingual sentiment dictionary.[90] We also included the most commonly used emoticons, using the emoticons listed in the popular NLTK Sentiment Analyzer.[91]

To determine the subset of messages that referenced the conflict actors within each country, native speakers of Pashtu, Urdu, and Tagalog at the Defense Language Institute Foreign Language Center (DLIFLLC) translated the names from English, to include slang and abbreviations, of the conflict actors identified in the Uppsala Conflict Data Program's (UCDP) Georeferenced Event Dataset (GED) within Pakistan and the Philippines. The United States Embassy in Nigeria provided the translations for the conflict actors as identified in the UCDP's GED within Nigeria from English to Yoruba and Igbo. The conflict actor list excluded common acronyms used by multiple groups to ensure the search returned only conflict actors relevant to each country. Using the list of emojis and emoticons, we conducted a search for terms within the NPS Twitter Archive that co-

[89] Petra Kralj Novak et al., "Sentiment of Emojis," *PLoS ONE* 10, no. 12 (December 7, 2015): 22, https://doi.org/10.1371/journal.pone.0144296.

[90] The parameters used to select emojis mirror those in the study conducted by Kyle Foster presented in the article *Classifying Arabic Sentiment Like a* ناطق بها كلغتك الأم.

[91] Md Rakibul Islam and Minhaz F. Zibran, "Leveraging Automated Sentiment Analysis in Software Engineering," in *Proceedings, 2017 IEEE/ACM 14th International Conference on Mining Software Repositories (MSR)*, 2017, 230, https://doi.org/10.1109/MSR.2017.9.

occurred most frequently with these popular sentiment symbols. The expanded list of sentiment terms derived from this search were used to construct a robust sentiment lexicon dictionary for each county. We bounded searches by the geographic area of each country to ensure we captured native language sentiment terms.

2. Text Processing of Social Media Data

Pre-processing of the text is common in research involving the analysis of natural language, including tweets. Pre-processing involves steps such as normalizing the case of the text for ease of analysis and tokenizing the ext. Prior to tokenization, this study first normalized the tweets to lowercase in order to prevent the double counting of words or letters and avoided the same word being counted as separate words for example, "The" and "the."[92] Tokenizing the tweet splits the entire messages into words or phrases based on criteria established to meet the researcher's intent.[93]

The tokenization step typically involves using tools such as the Natural Language Toolkit (NLTK) library function of breaking the words on "white space."[94] The tokenization process used here first split all of the tweets on white space, but the study required additional rules for splitting the text due to its distinctive multi-lingual characteristics. While tokenization based on white space works well for Latin, Greek, and Cyrillic-based languages, ideographic languages such as Chinese, Japanese, or Korean cannot apply this technique due to the lack of white space between characters. One- and two-character words make up the vast majority of the Chinese language, while few compounds of three or four characters exist.[95] Following a similar lexical characteristic,

[92] Steven Bird, Ewan Klein, and Edward Loper, *Natural Language Processing with Python*, 1st ed (Cambridge, MA: O'Reilly, 2009), 107.

[93] Bird, Klein, and Loper, 7.

[94] "Nltk.Sentiment Package — NLTK 3.3 Documentation," accessed October 23, 2018, https://www.nltk.org/api/nltk.sentiment.html.

[95] Bolin Yu et al., "STM Capacity for Chinese and English Language Materials," *Memory & Cognition* 13, no. 3 (May 1985): 202, https://doi.org/10.3758/BF03197682.

the majority of Japanese words typically consist of two characters.[96] To account for the appearance of tokens in character form, the tokenization process split words on multiples of three- and four-byte strings to account for languages that use ideographic characters. This step kept words that had a minimum length of three characters, and a maximum phrase length of six words. As with the Bourret et al. study, our approach also utilized a parallelized in-memory database application developed through the CODA Lab at NPS.[97] The process utilized swarms of parallel computational workers to operate in tandem allowing it to avoid "resource conflicts, without the need for hierarchical control structures." [98]

The search process first applied the pre-processing rules, and then searched the NPS Twitter archive based on the previously outlined functions for co-occurring matches with the initial sentiment dictionary to develop a more robust multi-lingual sentiment dictionary. The next step in the process calculated the *match probability* (the number of matches to a given search category divided by the total number of tweets in each country), the *token probability* (the count of a given token divided by the total number of tweets in each country), and the *joint token-match probability* (the count of messages containing both a given match category and a given token divided by the total number of messages in each country). These values were used to calculate the ranking of the negative and positive sentiment words. First, extremely frequent tokens, with token probability greater than 0.15 were excluded, as tokens that appear so broadly offer limited leverage for separating positive and negative sentiments. In addition, extremely rare tokens, seen less than 10 times in an entire country, were excluded as they had insufficient information for accurate rankings. Then we calculated metrics similar to Pointwise Mutual Information (PMI) scores, equal to the joint token-match probability, divided by the match probability. For each token, a positive score was calculated based on the rate of co-occurrence (the joint

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[96] John Morton et al., "The Organization of the Lexicon in Japanese: Single and Compound Kanji," *British Journal of Psychology* 83, no. 4 (November 1992): 521, https://doi.org/10.1111/j.2044-8295.1992.tb02456.x.

[97] Bourret, Wines, and Mendes, "Assessing Sentiment in Conflict Zones through Social Media.," 19.

[98] Warren, "The Technology of Statecraft in the Age of Social Media, 96.

token-match probability) with positive emojis, and a negative score was calculated based on the rate of co-occurrence with negative emojis. The final score for each token was then calculated by subtracting the negative score from the positive score. Upon completion of the co-occurrence search, the top 100 positive and 100 negative tokens were used to create the separate narrative sentiment dictionaries for the countries of Nigeria, Pakistan, and the Philippines.

3. Tweet Mining

Following the construction of the sentiment dictionaries, the study then conducted a search of the NPS Twitter Archive for tweets containing tokens from the sentiment dictionaries within Nigeria, Pakistan, and the Philippines from August 1, 2013 through July 31, 2014. In addition to creating a data set of the tweets from the entire country, a sub-dataset was also created that contained tweets from the urban agglomeration of the megacities of Karachi, Lagos, and Manila. The urban agglomeration was selected as it is the concept of cities used in determining population by the UN Urbanization Prospect Report 2014, which this study used to justify the selection of Karachi, Lagos, and Manila as megacities.[99] To understand the daily geospatial trends of tweet sentiment in relation to violence, uniform grid-squares with widths of approximately 22km were overlaid onto each country. The georeferenced violent events and tweets were then assigned to their corresponding grid-cell.

4. Dependent Variables

The three dependent variables in this study are: (1) the ratio of sentiment tweets to the total number of tweets in a grid-cell day, (Polarized Sentiment); (2) the ratio of positive sentiment tweets to the total number of tweets, (Positive Sentiment); and (3) the ratio of negative sentiment tweets to the total number of tweets, (Negative Sentiment). Each of these metrics are calculated in reference to each conflict actor within a given grid-cell day for the entire countries of Pakistan, Nigeria, and the Philippines. When testing the influence

[99] UN-HABITAT, *World Cities Report 2016: Urbanization and Development - Emerging Futures*, World Cities Report (United Nations, 2016), 1, https://doi.org/10.18356/d201a997-en.

of the megacity sentiment on the rest of the country, the dependent variable includes all of the tweets in the country except for those within the cities of Karachi, Lagos, and Manilla.

Population sentiment refers to the positive or negative sentiment regarding a conflict actor within Pakistan, Nigeria, or the Philippines. The population sentiment toward a particular actor, both positive and negative, reflects the total number of tweets that contain a word from the sentiment dictionary along with a word from the conflict actor narrative salience dictionary. Figures 1 through 3 depict the geo-referenced location of tweets within each country from August 1, 2013, through July 31, 2014 from the NPS Twitter Archive.

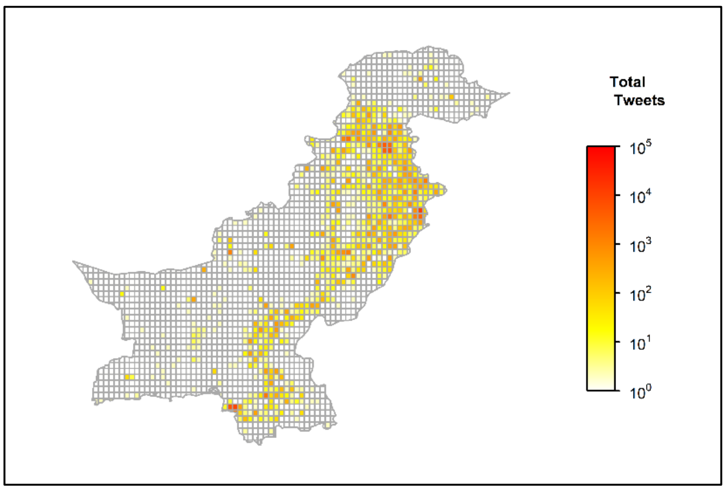

Figure 1. Pakistan Tweets August 2013–July 2014

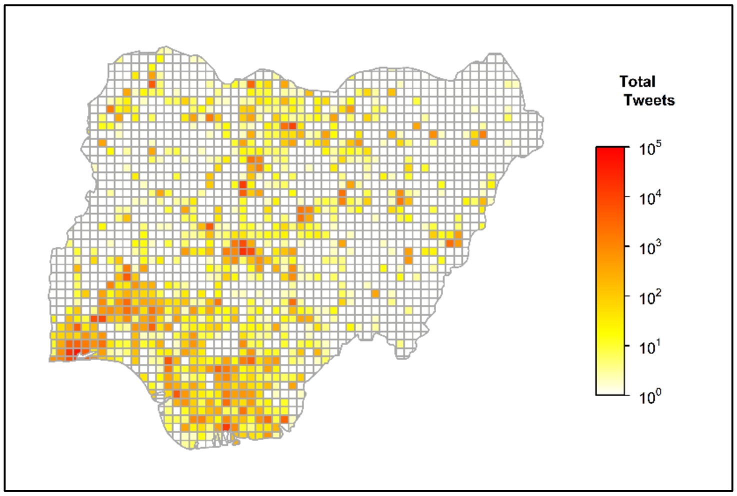

Figure 2. Nigeria Tweets August 2013–July 2014

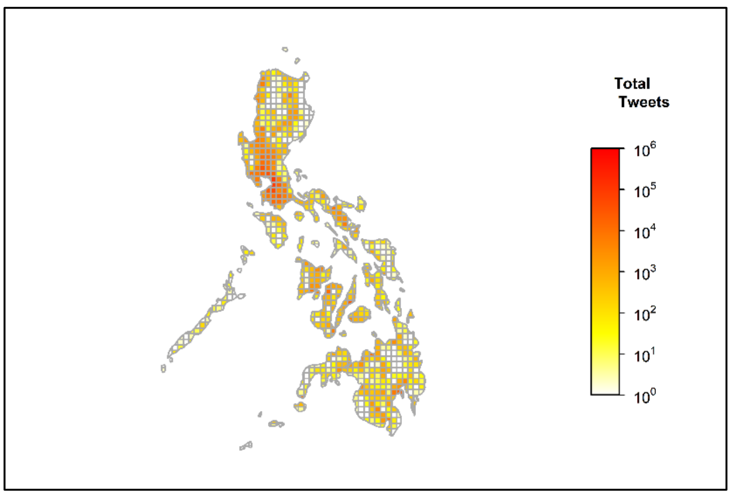

Figure 3. Philippines Tweets August 2013–July 2014

5. Independent Variables

To measure violence within each country, we used data for the countries of Pakistan, the Philippines, and Nigeria from the Uppsala Conflict Data Program Georeferenced Event Dataset (GED). The GED database identifies violent events by participating state and non-state actors, date, and the location of each event by longitude and latitude. The events recorded are those that met the threshold defined by UCDP, in that at least one death occurred in a single event, in the context of a civil conflict between a state and non-state actor. The GED base dataset contains over 135,000 events from the beginning of 1989 until the end of 2016. The dataset used in this study reduced the GED base set and focused on a timeframe from August 1, 2013, through July 31, 2014, to match the NPS Twitter dataset period used in this study. This dataset identifies 438 violent events in Nigeria, 157 violent events in the Philippines, and 296 violent events in Pakistan. Figures 4 through 6 illustrate the number of violent events from each country from August 1, 2013 through July 31, 2014.

The study uses the deaths of the conflict actors and civilians as a result from a violent event as independent variables to represent violence that occurs within each country. Gov't Pakistan Deaths, TTP Deaths and Civilian Deaths Pakistan represent the violence variables in Pakistan. Gov't Nigeria Deaths, Boko Haram Deaths, and Civilian Deaths Nigeria, represent the violence variables in Nigeria. Gov't Philippines Deaths, MNLF Deaths, and Civilian Deaths Philippines, represent the violence variables in the Philippines.

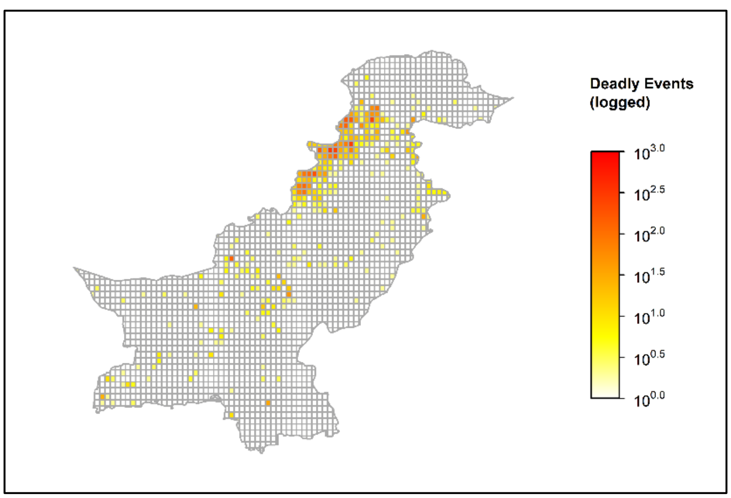

Figure 4. Pakistan Violent Events August 2013–July 2014

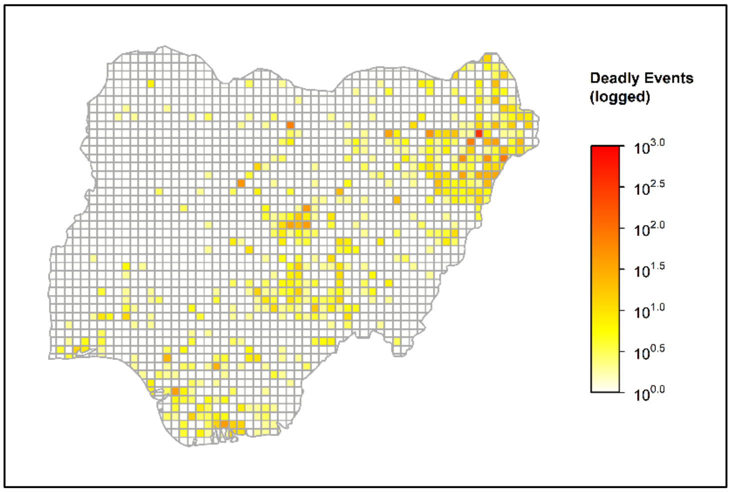

Figure 5. Nigeria Violent Events August 2013–July 2014

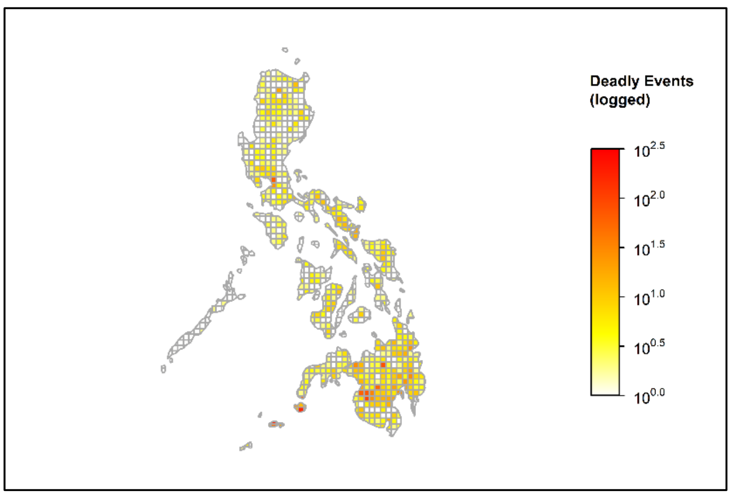

Figure 6. Philippines Violent Events August 2013–July 2014

To test the influence of the previous day's sentiment expressed within the megacity sentiment on the sentiment outside of the megacity, the variables include the ratio of sentiment tweets in the megacity to the total number of tweets in the megacity, Polarized Sentiment Karachi, Polarized Sentiment Lagos, and Polarized Sentiment Manila; the ratio of positive sentiment tweets in the megacity to the total number of tweets in the megacity, Positive Sentiment Karachi, Positive Sentiment Lagos, and Positive Sentiment Manila; and the ratio of negative sentiment tweets in the megacity to the total number of tweets in the megacity, Negative Sentiment Karachi, Negative Sentiment Lagos, and Negative

Sentiment Manila. Each of these variables is lagged by one day to capture the propagation of sentiment over time.

The study used the ETH Zürich Ethnic Power Relation Data Set, the relative ethnic relationship to examine if the various ethnic groups within a country react differently to violence. Figures 7 through 9 depict the ethnic breakdown within Pakistan, Nigeria, and the Philippines within the study's 2013–2014 timeframe at the 22km grid- cell. The ethnic group variables for Pakistan are Baluchi, Punjabi, Pashtun, and Sindhi. The ethnic group variables for Nigeria are Hausa, Igbo, Ijaw, Ogoni, Tiv, and Yoruba. The ethnic group variables for the Philippines are Christian, Indigenous, and Moro.

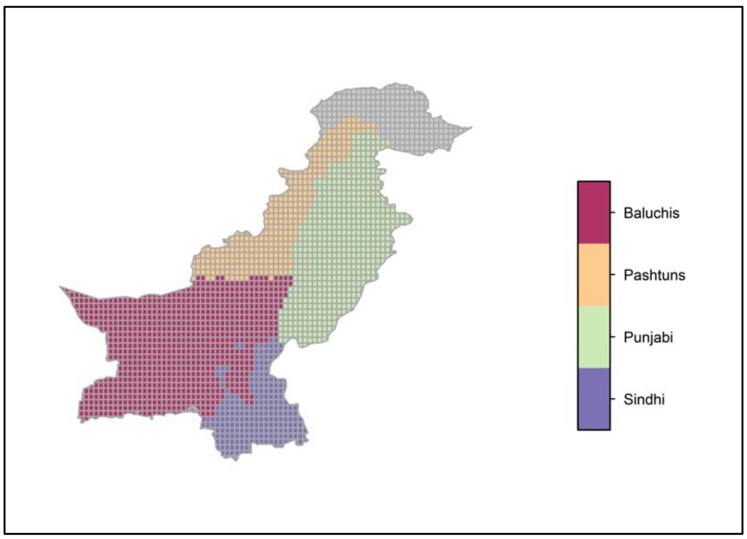

Figure 7. Pakistan Ethnicity Map

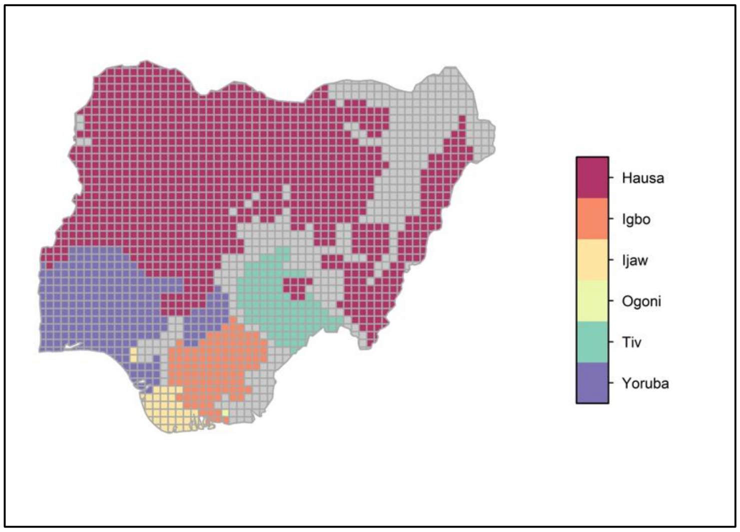

Figure 8. Nigeria Ethnicity Map

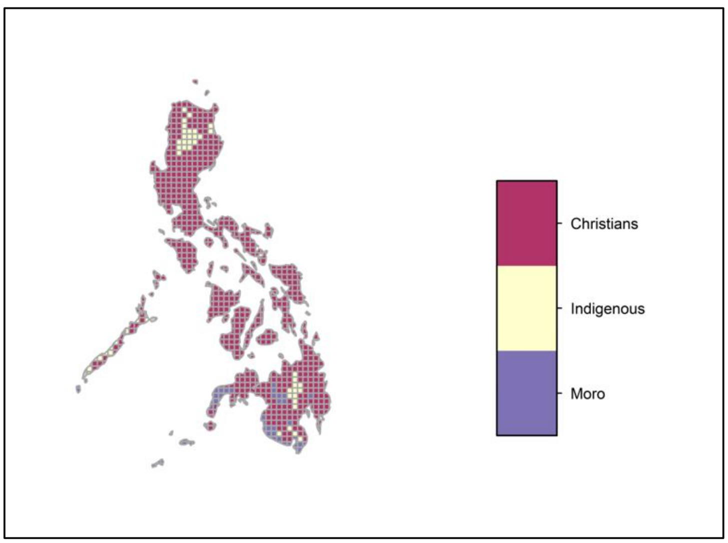

Figure 9. Philippines Ethnicity Map

6. Control Variables

This study controls for population density, GDP per-capita, tweets per-capita, total tweets, and the one-day-lag of each of the dependent variables. The population density and GDP per-capita variables were obtained using the Geographically Based Economic (GECON) database.[100] This study also controlled for the lag of each dependent variable as well as tweets per-capita.

C. REGRESSION ANALYSIS

This study utilized linear regression models, as the dependent variable consisted of continuous ratios of rates of sentiment expressions, with a unit of analysis of a 22 km grid-cell day. Our models aim to determine the relationship between a violent event and a population's reaction to the violent event within Twitter, and in doing so determine what impact social media can have in gaining situational awareness after violent events within the country.

[100] Nordhaus, W.D.; Chen, X., "Global Gridded Geographically Based Economic (G-Econ) Data Set, Version 4" (Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC), 2016), https://doi.org/10.7927/H42V2D1C.

V. RESULTS

The multi-lingual sentiment dictionary search produced three dictionaries unique to each country's communication patterns. From these search dictionaries, tweets were collected and categorized based on sentiment tokens, to include the number of positive and negative sentiment tweets and tokens when referencing a conflict actor. Following the collection of tweets matching the search criteria established in the methodology, three regression models for each country's government and non-state actors examined the relationship between violent events and the sentiment of tweets. The first model for each country examines the relationship between multiple independent variables and the ratio of sentiment tweets referencing the government or a non-state actor to that of *total* number of tweets in a grid-cell day. The second model examines the dependent variable of the ratio of *positive* sentiment tweets referencing the government or the non-state actor. The third model examines the dependent variable of the ratio of *negative* sentiment tweets referencing the government or the non-state actor.

A. MULTI-LINGUAL SENTIMENT DICTIONARY AND TWITTER SEARCH RESULTS

The results of the construction of the sentiment dictionary and Twitter search produced three significant findings regarding language, word frequency and the presence of a conflict actor's name in tweets. First, when examining the tokens returned from the construction of the multi-lingual sentiment dictionary, a large percentage of the tokens within each country's sentiment dictionary are in the English language. Even when bounding the searches to the borders of each country, the English language still prevailed in producing the most frequently occurring sentiment terms. This may indicate that Twitter users attempt to direct their tweets to an international audience of English speakers, the largest audience available on Twitter. These users, either speaking positively or negatively with regard to a certain conflict actor, may do so in an attempt to influence foreign audiences and gain support for their cause.[101] The sentiment dictionaries contain words in the native languages spoken in each country, but these were rarely seen. This could also suggest that the sentiment dictionaries may miss through the co-occurrence search process the less frequent sentiment terms of native speakers, which may indeed provide the best indicator of sentiment among the population, as the tweets expressed are not directed at external audiences, but toward others within the country. Second, frequently used words associated with neutral sentiment appear in all three countries' sentiment dictionaries, with the majority receiving a positive sentiment score. This resulted in some tweets' categorization as both positive and negative due to the presence of these frequently used words. This indicates the potential for the inclusion of false positives within the tweets counted as containing a positive or negative sentiment token, when in actuality they may contain no true sentiment-based statement and represent a neutral tweet.

Third, several groups' names did not appear in the data. The exclusion of the use of two- and three-letter acronyms may have impacted the results for capturing group conflict actors within the search. The possibility of associating groups that share the same acronym or abbreviation with the targeted conflict actor within tweets warranted their exclusion. Additionally, acronyms were excluded when they had alternate meaning associated with them, such as the Moro Islamic Liberation Front (MILF). Indeed, this likely resulted in missing what appears to be a method in which many individuals refer to these conflict actors in Twitter due to the imposed character limitations. If groups or organizations share a commonly used acronym to shorten their name, they may consider rebranding as a means to gain further name recognition and support, or risk being lost in the noise of social media. There also exist other explanatory reasons for the limited occurrence of some actors within the Twitter environment. Some of the conflict actors during the study's timeframe committed very few violent acts, which may not have warranted a response from Twitter users. For example, the limited number of violent events committed by the MILF during the study's timeframe, three, may have impacted their

[101] Clifford Bob, *The Marketing of Rebellion: Insurgents, Media, and International Activism*, Cambridge Studies in Contentious Politics (Cambridge; New York: Cambridge University Press, 2005), 14.

prevalence within Twitter as during this time they were in peace talks with the government of the Philippines on autonomous rule, and the eventual signing of the Comprehensive Agreement on Bangsamoro. The Twitter search for Nigeria yielded similar results to that of the Philippines. Similarly, when examining the tweets compiled for Nigeria, the Black Axe, Eyie, and the Supreme Vikings failed to yield a return of sentiment tweets of any significant volume. The Twitter conversations that did reference a conflict actor within Nigeria almost exclusively focused on Boko Haram due to the high-profile nature of their actions. This trend continued when examining the tweets referencing conflict actors in Pakistan, as Tehrik-i-Taliban Pakistan was the only group that yielded significant tweet returns as well. From the Twitter search with the expanded sentiment dictionaries, the MNLF, Boko Haram, TTP, and the government of each country returned a significant number of sentiment tweets to model the interaction between civil conflict and social media sentiment.

Figure 10 reflects population, violence, and Twitter statistics of the countries and megacities from this study. Notably, Twitter use is somewhat sparse in Nigeria and Pakistan, whereas the Philippines has a much higher usage spread out over a broader area in the country. Nigeria and Pakistan grid-cell days with no tweets were recorded 90% and 94% of the time, respectively. The Philippines was much lower at 68%.

	Nigeria	Pakistan	Philippines
Population	178,517,000	185,133,000	100,097,000
Megacity Population (Lagos, Karachi, Manila)	12,614,000	16,126,000	12,764,000
Violence			
Violent Events	438	296	157
Total Deaths	6,918	2,247	662
Government Deaths	359	385	143
Non-State Actor Deaths	2,668	962	199
Civilians Deaths	3,094	368	38
Twitter			
Total Tweets in Country	6,672,621	5,835,139	42,978,173
Avg Tweets in a *Grid-cell Day	9.16	7.05	118.22
Total Tweets in Megacity	258,079	3,700,310	24,928,218
Percentage of All Tweets from the Megacity	0.35%	36.59%	42.00%
Avg Tweets in the Megacity in a *Grid-cell Day	8.81	4.47	68.64
Total Tweets outside Megacity	6,414,542	2,134,829	18,049,955
Avg Tweets outside Megacity in a *Grid-cell Day	0.35	2.58	49.58
*Grid-cell = ~22km x 22km			

Figure 10. Country and Megacity Statistics

Figures 11, 12 and 13 represent the extent to which the dictionary was able to use tokens to differentiate the content of individual tweets. Notably, the dictionary was able to detect a larger number of tokens in Nigeria and Pakistan than was observed in the Philippines, despite the fact the Philippines had vastly more Twitter use. This can be reasonably explained, as the Philippines also had fewer violent events.

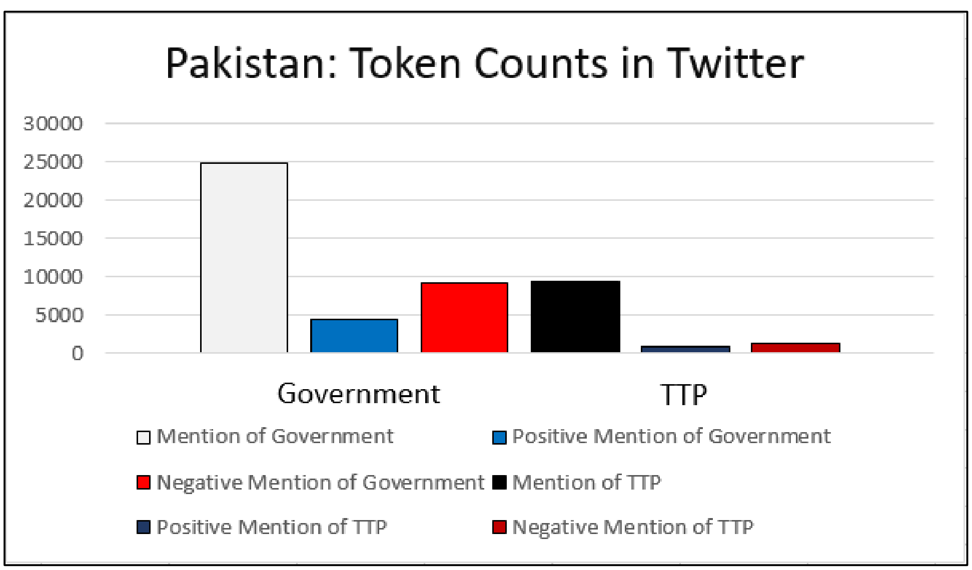

Figure 11. Pakistan Token Counts in Twitter

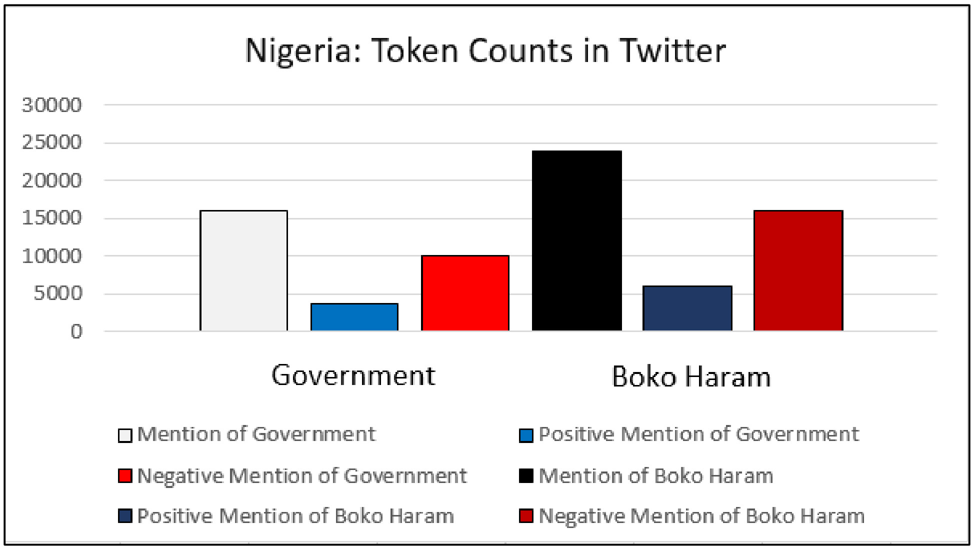

Figure 12. Nigeria Token Counts in Twitter

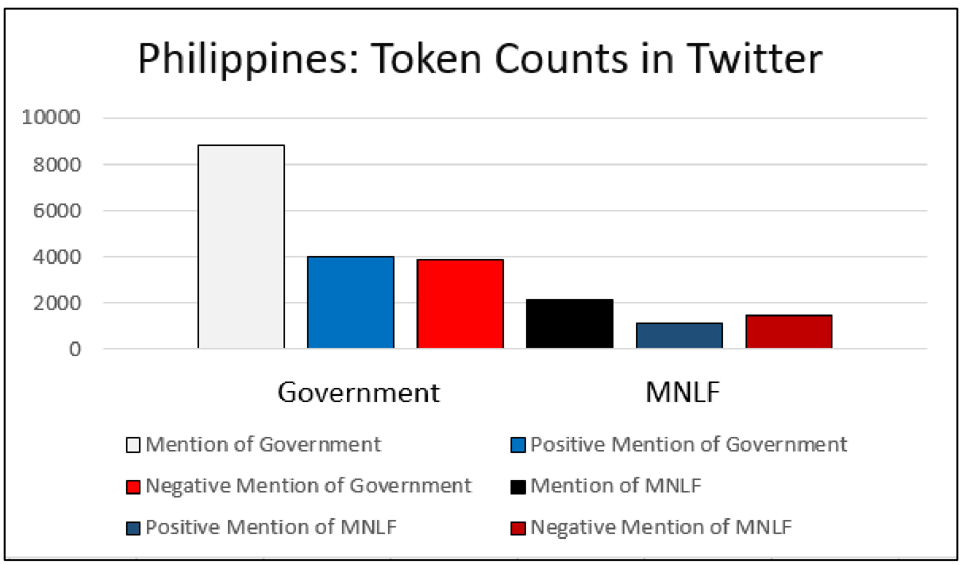

Figure 13. Philippines Token Counts in Twitter

B. REGRESSION RESULTS—PAKISTAN

1. Finding One—Polarized Sentiment toward Government of Pakistan Varies between Ethnic Groups

In Models 1 through 3, *Gov't Pakistan Deaths* demonstrate a highly statistically significant positive coefficient ($p<0.01$). This fails to support Hypothesis 1a, in that a decrease in *Positive Sentiment* toward the government was not observed as expected. This indicates that when violence results in the death of government forces, there is more polarizing sentiment expressed as opposed to an overall negative emotional reaction toward the government.

Similar to the findings for *Gov't Pakistan Deaths*, the resulting deaths of the TTP also have a polarizing effect on the population. The positive and highly significant coefficient for the variable *TTP Deaths* ($p<0.01$) in Model 2 indicates that when the government of Pakistan inflicts deaths upon the TTP, then *Positive Sentiment* toward the government increases. Model 3, however, shows that as *TTP Deaths* increase, *Negative Sentiment* also increases significantly ($p<0.05$).

When observing the sentiment expressed by the various ethnic groups within a grid-cell, Models 1 through 3 demonstrate a highly significant positive coefficient ($p<0.01$) for *Punjabi* locations. Similarly, Models 1 through 3 demonstrate a significant positive coefficient ($p<0.01$-0.05) for *Pashtun* locations. In contrast, *Sindhi* locations show significant negative coefficients ($p<0.01$-0.05) in all three models. These findings demonstrate that sentiments toward the government can be expressed in very different ways across different ethnic groups. Table 1 and Figure 14 detail these findings.

Table 1. Government of Pakistan Regression Models

	Dependent variable: Government of Pakistan		
	Polarized Sentiment (1)	Positive Sentiment (2)	Negative Sentiment (3)
Gov't Pakistan Deaths	0.002^{***}	0.001^{***}	0.001^{***}
	(0.0002)	(0.0001)	(0.0001)
TTP Deaths	0.0002^{**}	0.0001^{***}	0.0001^{*}
	(0.0001)	(0.00004)	(0.0001)
Civilian Deaths	0.0002^{*}	-0.00000	0.0002^{**}
	(0.0001)	(0.00005)	(0.0001)
Pashtuns	0.0002^{***}	0.00005^{**}	0.0001^{***}
	(0.00004)	(0.00002)	(0.00003)
Punjabi	0.0003^{***}	0.0001^{***}	0.0002^{***}
	(0.00005)	(0.00002)	(0.00003)
Baluchis	-0.00002	-0.00001	-0.00001
	(0.00004)	(0.00002)	(0.00002)
Sindhi	-0.0002^{***}	-0.0001^{**}	-0.0001^{***}
	(0.0001)	(0.00003)	(0.00003)
Population Density	0.000^{***}	0.000^{***}	0.000^{***}
	(0.000)	(0.000)	(0.000)
GDP- Per Capita	-0.00001	-0.00001	-0.00000
	(0.00001)	(0.00001)	(0.00001)
Tweets Per-Capita	3.433^{***}	1.094^{***}	2.427^{***}
	(0.157)	(0.077)	(0.102)
Total Tweets	0.00003^{***}	0.00001^{***}	0.00002^{***}
	(0.00000)	(0.00000)	(0.00000)
Polarized Sentiment (lag)	0.142^{***}		
	(0.001)		
Positive Sentiment (lag)		0.142^{***}	
		(0.001)	
Negative Sentiment (lag)			0.109^{***}
			(0.001)
Constant	0.00001	0.00001	0.00001
	(0.00004)	(0.00002)	(0.00002)
Observations	825,188	825,188	825,188
Log Likelihood	2,622,122.000	3,205,879.000	2,980,869.000
Akaike Inf. Crit.	-5,244,219.000	-6,411,731.000	-5,961,712.000
Note:			* p<0.1; **p<0.05; ***p<0.01

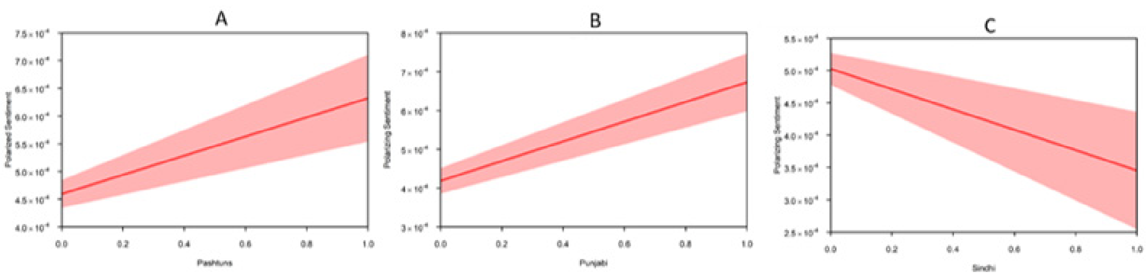

Figure 14. Predicted Effect of Polarized Sentiments (A) Pashtun, (B) Punjabi, (C) Sindhi

2. Finding Two—Civilian Deaths Produce a Negative Emotional Response toward the TTP

In Model 4, *Gov't Pakistan Deaths* produced a highly significant negative coefficient in relation to *Negative Sentiment*. This may suggest support for the TTP in that they are less critical of the group when a violent event results in the death of government forces. When observing the impact of *Civilian Deaths,* Model 4 demonstrates a highly significant positive coefficient ($p<0.01$) in relation to *Polarized Tweets*. Model 6 supports Hypothesis 2b, in that *Civilian Deaths* produced a highly significant positive coefficient ($p<0.01$) in relation to *Negative Sentiment,* and Model 5, a moderately significant negative coefficient in relation to *Positive Sentiment.* This indicates that the population in Pakistan is critical of non-state actors when their actions result in civilian deaths.

While most models did not produce a statistically significant finding in relation to ethnicity and sentiment expressed toward the TTP, Model 4 demonstrates a significant positive relationship ($p<0.05$) in respect to *Punjabi* grid-cells and *Polarized Sentiment* in response to violence. In Model 6, *Punjabi*, also produced a significant positive coefficient ($p<0.05$) in relation to *Negative Sentiment*. What this suggests is that there is significantly more negative sentiment toward the TTP expressed by the Punjabi ethnic group as opposed to that of the positive sentiment expressed. Table 2 details these findings.

Table 2. TTP Regression Models

	Dependent variable: TTP Tweets		
	Polarized Sentiment (4)	Positive Sentiment (5)	Negative Sentiment (6)
Gov't Pakistan Deaths	-0.0001	0.00003	-0.0001***
	(0.0001)	(0.00004)	(0.0001)
TTP Deaths	-0.00001	0.00000	-0.00001
	(0.00004)	(0.00002)	(0.00002)
Civilian Deaths	0.001***	-0.00005**	0.001***
	(0.00005)	(0.00002)	(0.00003)
Pashtuns	0.00002	-0.00000	0.00002
	(0.00002)	(0.00001)	(0.00001)
Punjabi	0.00005**	0.00002	0.00003**
	(0.00002)	(0.00001)	(0.00001)
Baluchis	-0.00000	-0.00000	0.00000
	(0.00002)	(0.00001)	(0.00001)
Sindhi	0.00002	0.00001	0.00001
	(0.00002)	(0.00001)	(0.00002)
Population Density	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
GDP- Per Capita	-0.00000	-0.00000	-0.00000
	(0.00001)	(0.00000)	(0.00000)
Tweets Per-Capita	0.818***	0.160***	0.646***
	(0.077)	(0.037)	(0.048)
Total Tweets	0.00001***	0.00000***	0.00001***
	(0.00000)	(0.00000)	(0.00000)
Polarized Sentiment (lag)	0.024***		
	(0.001)		
Positive Sentiment (lag)		-0.009***	
		(0.001)	
Negative Sentiment (lag)			0.051***
			(0.001)
Constant	0.00001	0.00001	0.00000
	(0.00002)	(0.00001)	(0.00001)
Observations	825,188	825,188	825,188
Log Likelihood	3,213,355.000	3,813,635.000	3,602,438.000
Akaike Inf. Crit.	-6,426,684.000	-7,627,245.000	-7,204,850.000
Note:			* p<0.1; **p<0.05; ***p<0.01

C. REGRESSION RESULTS—NIGERIA

1. Finding One—Ethnicity Influences the Polarization of Sentiment toward the Government of Nigeria

Model 7 through 9 fail to support Hypothesis 1a and 1b, in that *Gov't Nigeria Deaths, Boko Haram Deaths,* and *Civilian Deaths* produce no statistically significant findings in relation to the sentiment expressed on Twitter. Within Nigeria, several of the ethnic groups' sentiments toward the government seem to be predominantly expressed through less emotionally charged tweets. This is demonstrated with the highly significant negative coefficient for *Igbo* and *Ijaw*, a significant negative coefficient ($p<0.05$) for *Tiv*, and a moderately negative coefficient for *Hausa* and *Ogoni* ($p<0.1$). In Models 7 through 9, however, *Yoruba* demonstrated a highly significant positive coefficient ($p<0.01$). This relationship could be due to the amount of native Yoruba speakers in Nigeria's economically robust and heavily populated areas of the nation's south and coastal regions. Table 3 and Figure 15 detail these findings.

Table 3. Government of Nigeria Regression Models

	Dependent variable: Government of Nigeria		
	Polarized Sentiment	Positive Sentiment	Negative Sentiment
	(7)	(8)	(9)
Gov't of Nigeria Deaths	0.0002	0.00001	0.0001
	(0.0002)	(0.0001)	(0.0001)
Boko Haram Deaths	-0.00000	-0.00000	-0.00000
	(0.00002)	(0.00001)	(0.00001)
Civilian Deaths	0.00001	-0.00001	0.00002
	(0.00003)	(0.00001)	(0.00002)
Hausa	-0.0001*	-0.00003	-0.00004
	(0.00004)	(0.00002)	(0.00003)
Yoruba	0.0004***	0.0001***	0.0003***
	(0.0001)	(0.00003)	(0.00004)
Tiv	-0.0002**	-0.0001**	-0.0001**
	(0.0001)	(0.00003)	(0.00005)
Igbo	-0.0003***	-0.0001***	-0.0002***
	(0.0001)	(0.00004)	(0.0001)
Ijaw	-0.0003***	-0.0001**	-0.0002***
	(0.0001)	(0.00005)	(0.0001)
Ogoni	-0.001*	-0.0003	-0.001*
	(0.001)	(0.0003)	(0.0004)
Population Density	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
GDP Per-Capita	-0.00000	-0.00000	-0.00000
	(0.00000)	(0.00000)	(0.00000)
Tweets Per-Capita	-7.573***	-0.514***	-7.140***
	(0.198)	(0.088)	(0.137)
Total Tweets	0.00005***	0.00001***	0.00003***
	(0.00000)	(0.00000)	(0.00000)
Polarized Sentiment (lag)	0.206***		
	(0.001)		
Positive Sentiment (lag)		0.111***	
		(0.001)	
Negative Sentiment (lag)			0.201***
			(0.001)
Constant	-0.0001**	-0.00003*	-0.0001***
	(0.00003)	(0.00002)	(0.00002)
Observations	726,544	726,544	726,544
Log Likelihood	2,160,081.000	2,744,602.000	2,430,252.000
Akaike Inf. Crit.	-4,320,132.000	-5,489,173.000	-4,860,474.000
Note:			* p<0.1; **p<0.05; ***p<0.01

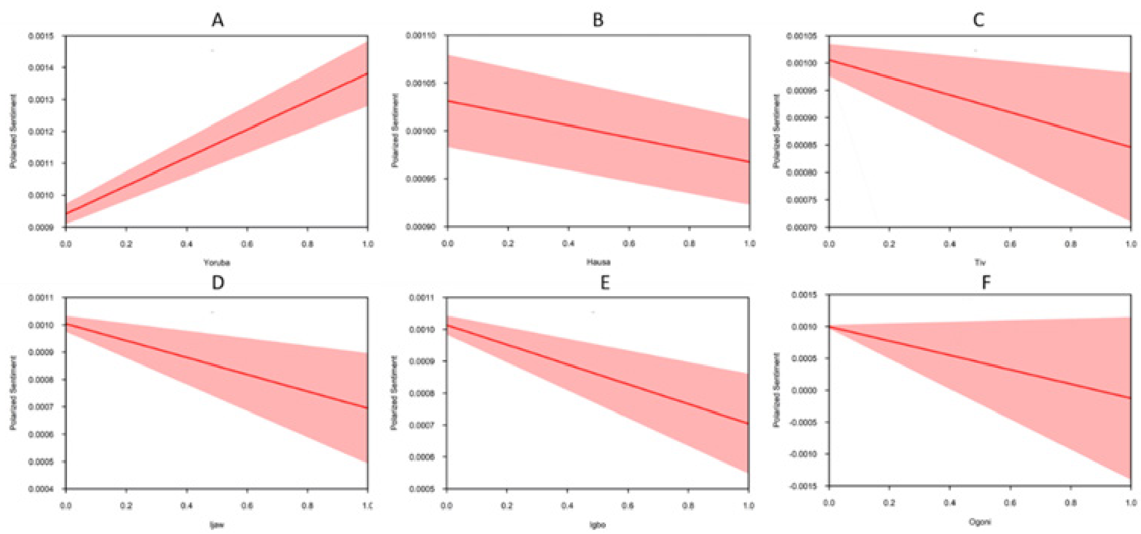

Figure 15. Predicted Effect of Ethnic Group Polarized Sentiment
(A) Yoruba, (B) Hausa, (C) Tiv, (D) Ijaw, (E) Igbo, (F) Ogoni

2. Finding Two—Ethnicity Influences the Polarization of Sentiment toward Boko Haram

Model 10 demonstrates a highly significant positive coefficient ($p<0.01$) in the relationship between *Gov't Nigeria Deaths* and *Negative Sentiment* regarding Boko Haram. This indicates that with an increase in violence resulting in the death of government forces, negative sentiment is being directed at Boko Haram. Negative sentiment is not solely being expressed by the population, however, in that there is a significant positive coefficient ($p<0.01$) in the relationship between *Polarized Sentiment* expressed toward Boko Haram and *Gov't of Nigeria Deaths*. This may indicate, while not statistically significant, that there may still be a small number of tweets, possibly by Boko Haram supporters, that express a positive sentiment reaction to the death of government forces, alongside the larger number of negative reactions.

Variance in the polarization of sentiment tweets toward Boko Haram are observed across ethnic boundaries. *Yoruba* shows a highly significant positive coefficient ($p<0.01$) in relation to *Polarized Sentiment*, *Positive Sentiment*, and *Negative Sentiment* expressed toward Boko Haram, indicating greater rates of emotionally charged sentiment tweets. In Model 10, however, *Tiv* displays a significant negative coefficient ($p<0.05$) in relation *Polarized Sentiment.* This demonstrates that those living in predominantly Tiv locations tend to generate less emotionally oriented tweets toward Boko Haram. Similarly, the *Hausa variable* also displays a significant negative coefficient ($p<0.05$) in relation to *Polarized Sentiment*, *Positive Sentiment*, and *Negative Sentiment* toward Boko Haram. *Igbo*, which demonstrated a moderately significant positive coefficient ($p<0.1$) in relation to *Positive Sentiment*, represents the only ethnic group that had a significant finding in a single direction of expressed sentiment. This indicates that the Igbo locations are more likely than others to express positive sentiments regarding Boko Haram. Table 4 details these findings.

Table 4. Boko Haram Regression Models

	Dependent variable: Boko Haram Tweets		
	Polarized Sentiment (10)	Positive Sentiment (11)	Negative Sentiment (12)
Gov't of Nigeria Deaths	0.0004**	0.00002	0.0004***
	(0.0002)	(0.0001)	(0.0001)
Boko Haram Deaths	-0.00001	0.00000	-0.00001
	(0.00002)	(0.00001)	(0.00001)
Civilian Deaths	-0.0001	-0.00002	-0.00003
	(0.00004)	(0.00002)	(0.00003)
Hausa	-0.0001**	-0.00005**	-0.0001**
	(0.00005)	(0.00002)	(0.00003)
Yoruba	0.0003***	0.0001***	0.0002***
	(0.0001)	(0.00003)	(0.00005)
Tiv	-0.0002**	-0.0001	-0.0001**
	(0.0001)	(0.00004)	(0.0001)
Igbo	0.0001	0.0001*	0.00004
	(0.0001)	(0.00005)	(0.0001)
Ijaw	-0.0002	-0.0001	-0.0001*
	(0.0001)	(0.0001)	(0.0001)
Ogoni	-0.001	-0.0004	-0.001
	(0.001)	(0.0004)	(0.001)
Population Density	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
GDP Per-Capita	-0.00000	-0.00000	-0.00000
	(0.00000)	(0.00000)	(0.00000)
Tweets Per-Capita	-6.727***	-1.055***	-6.147***
	(0.241)	(0.108)	(0.164)
Total Tweets	0.00003***	0.00001***	0.00002***
	(0.00000)	(0.00000)	(0.00000)
Polarized Sentiment (lag)	0.488***		
	(0.001)		
Positive Sentiment (lag)		0.360***	
		(0.001)	
Negative Sentiment (lag)			0.460***
			(0.001)
Constant	-0.00001	-0.00001	-0.00000
	(0.00004)	(0.00002)	(0.00003)
Observations	726,544	726,544	726,544
Log Likelihood	2,016,857.000	2,596,769.000	2,295,858.000
Akaike Inf. Crit.	-4,033,684.000	-5,193,507.000	-4,591,686.000
Note:			* p<0.1; **p<0.05; ***p<0.01

D. REGRESSION RESULTS: REPUBLIC OF THE PHILIPPINES

1. Finding One—Violence Increases Polarized Sentiments toward the Government of the Philippines

MNLF Deaths, in Models 13 through 15, show a highly significant positive coefficient ($p<0.01$) in its relationship to *Polarized Sentiment*, *Positive Sentiment*, and *Negative Sentiment* about the government of the Philippines. While *Gov't Philippines Deaths* demonstrated a significant positive coefficient ($p<0.05$) in relation to *Negative Sentiment*, and a moderately significant positive coefficient ($p<0.1$) in relation to *Polarized Sentiment* and *Negative Sentiment* expressed toward the government. This suggests that the population expresses a more polarized conversation regarding the government following the deaths of those conflict actors. In contrast, *Civilian Deaths* garnered no statistically significant findings toward the government of the Philippines. Additionally, the ethnic variables showed no statistical significance, signifying that ethnicity is not a driver of differences in sentiment tweets within the Philippines. These findings fail to support Hypothesis 1b, in that the presence of civilian deaths did not reduce the positive sentiment and increase the negative sentiment toward the government as initially expected. Table 5 details these findings.

Table 5. Government of the Philippines Regression Models

	Dependent variable: Government of the Philippines		
	Polarized Sentiment (13)	Positive Sentiment (14)	Negative Sentiment (15)
Gov't Philippines. Deaths	0.001*	0.001**	0.001*
	(0.001)	(0.0003)	(0.0003)
Civilian Deaths	-0.001	-0.0005	-0.0002
	(0.001)	(0.0004)	(0.0004)
MNLF Deaths	0.003***	0.002***	0.002***
	(0.0001)	(0.0001)	(0.0001)
Christians	-0.0001	-0.00003	-0.00004
	(0.0002)	(0.0001)	(0.0001)
Indigenous	-0.0001	-0.0001	-0.0001
	(0.0002)	(0.0001)	(0.0001)
Moro	-0.0002	-0.0001	-0.0001
	(0.0002)	(0.0001)	(0.0001)
Population Density	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
GDP Per-Capita	-0.00001	-0.00000	-0.00000
	(0.00003)	(0.00002)	(0.00002)
Tweets Per-Capita	4.413***	2.235***	2.306***
	(0.152)	(0.081)	(0.079)
Total Tweets	0.00000***	0.00000***	0.00000***
	(0.00000)	(0.000)	(0.000)
Polarized Sentiment (lag)	0.224***		
	(0.002)		
Positive Sentiment (lag)		0.203***	
		(0.002)	
Negative Sentiment (lag)			0.203***
			(0.002)
Constant	0.00000	-0.00000	0.00000
	(0.0002)	(0.0001)	(0.0001)
Observations	362,544	362,544	362,544
Log Likelihood	1,103,521.000	1,332,207.000	1,337,892.000
Akaike Inf. Crit.	-2,207,019.000	-2,664,390.000	-2,675,759.000
Note:			* p<0.1; **p<0.05; ***p<0.01

2. Finding Two—The Population Expresses Less Sentiment in Reaction to Civilian Deaths

In Models 16 through 18, the variables of *Gov't Philippines Deaths* and *MNLF Deaths* demonstrate a highly significant positive coefficient ($p<0.01$) in relation to *Polarized Sentiment*, *Positive Sentiment*, and *Negative Sentiment* about the MNLF. This indicates that violence in the Philippines results in an increase in emotional sentiment within the country about the MNLF as a result of deaths involving the conflict actors. The variable *Civilian Deaths* produced a highly significant negative coefficient ($p<0.01$) in relation to *Polarized Sentiment*, *Positive Sentiment*, and *Negative Sentiment* about the MNLF, however. The presence of civilian deaths had a suppressing effect on the sentiment expressed within Twitter. This lack of emotionally charged conversation may be due to the majority of the tweeting population not identifying with the civilians involved in conflict, which primarily takes place in the Southern Philippines and the fight for Moro autonomy. These findings fail to support Hypothesis 2b, in that it was thought that the presence of civilian deaths would have an adverse effect on the sentiment expressed toward the MNLF. Table 6 and Figure 16 detail these findings.

Table 6. MNLF Regression Models

	Dependent variable: MNLF Tweets		
	Polarized Sentiment (16)	Positive Sentiment (17)	Negative Sentiment (18)
Gov't Philippines Deaths	0.002***	0.001***	0.002***
	(0.0003)	(0.0001)	(0.0001)
Civilian Deaths	-0.004***	-0.002***	-0.002***
	(0.0004)	(0.0002)	(0.0002)
MNLF Deaths	0.005***	0.003***	0.002***
	(0.0001)	(0.00003)	(0.00003)
Christians	-0.00002		-0.00001
	(0.0001)		(0.00004)
Indigenous	-0.00002		-0.00001
	(0.0001)		(0.00005)
Moro	-0.00002		-0.00001
	(0.0001)		(0.00005)
Population Density	0.000**	0.000**	0.000***
	(0.000)	(0.000)	(0.000)
GDP Per-Capita	-0.00001	-0.00000	-0.00000
	(0.00001)	(0.00001)	(0.00001)
Tweets Per-Capita	1.658***	0.829***	0.902***
	(0.071)	(0.035)	(0.039)
Total Tweets	0.00000***	0.00000***	0.00000***
	(0.000)	(0.000)	(0.000)
Polarized Sentiment (lag)	0.611***		
	(0.001)		
Positive Sentiment (lag)		0.588***	
		(0.001)	
Negative Sentiment (lag)			0.603***
			(0.001)
Constant	0.00001	-0.00000	0.00001
	(0.0001)	(0.00001)	(0.00005)
Observations	362,544	362,544	362,544
Log Likelihood	1,377,506.000	1,636,180.000	1,600,599.000
Akaike Inf. Crit.	-2,754,988.000	-3,272,342.000	-3,201,175.000
Note:			* p<0.1; **p<0.05; ***p<0.01

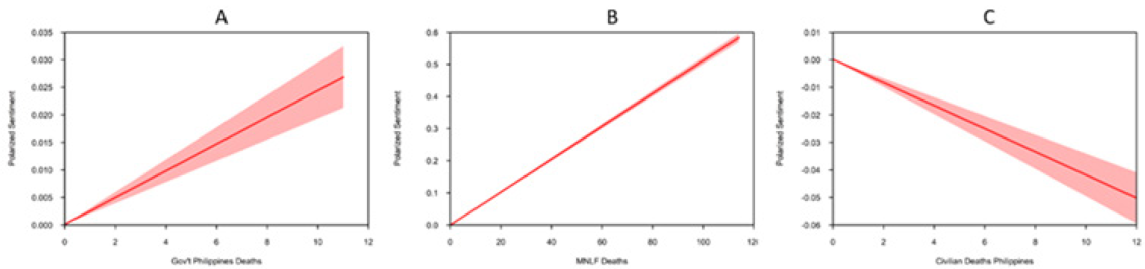

Figure 16. Predicted Effects of Polarized Sentiment (A) Philippines Gov't Deaths, (B) MNLF Deaths, (C) Civilian Deaths Philippines

E. REGRESSION RESULTS: THE MEGACITY

The next series of models seeks to examine the impact of the megacity's communication on the rest of the country. When examining the megacity, we hypothesize that sentiment of the tweets in the megacity influence the sentiments of the following day's tweets outside the megacity (Hypothesis 3).

1. Finding One—Karachi's Tweeting Sentiment Varies by Conflict Actor

Model 19 shows a highly significant positive coefficient ($p<0.01$) in the relationship between *Polarized Sentiment Karachi* and *Polarized Sentiment* regarding Government of Pakistan. Model 20 also demonstrates a highly significant positive coefficient ($p<0.01$) in the relationship between *Positive Sentiment Karachi* and *Positive Sentiment* regarding the Gov't of Pakistan. This indicates that the previous day's tweets in the megacity demonstrate the ability to predict the tweets outside of the megacity when they are expressing polarizing or positive sentiment about the government. This supports Hypothesis 3.

Models 22 through 24 produced no statistically significant findings regarding the relationship between the previous day's sentiment tweets in the megacity and the sentiment tweets outside expressed about the TTP, however. This may be due to the proximity of other influential area tweets regarding the TTP. While smaller than Karachi, the megacity of Lahore, may also influence Twitter sentiment throughout the country. The tweets originating from Islamabad may also serve as key influencers for the tweets throughout the country as it is a city in which policy originates, especially as it relates to the relationship of the Gov't of Pakistan and the TTP within the Federally Administered Tribal Areas of Pakistan. Table 7 and Figure 17 detail these findings.

Table 7. Megacity Regression Models—Karachi

	Dependent variable: Tweets Outside the Megacity					
	Polarized Sentiment Gov't (19)	Positive Sentiment Gov't (20)	Negative Sentiment Gov't (21)	Polarized Sentiment TTP (22)	Positive Sentiment TTP (23)	Negative Sentiment TTP (24)
Polarized Sentiment-Karachi-Gov't (lag)	0.0001***					
	(0.00004)					
Positive Sentiment-Karachi-Gov't (lag)		0.0002***				
		(0.00004)				
Negative Sentiment-Karachi-Gov't (lag)			0.0001			
			(0.00005)			
Polarized Sentiment-Karachi-TTP (lag)				0.00001		
				(0.00003)		
Positive Sentiment-Karachi-TTP (lag)					-0.00003	
					(0.00003)	
Negative Sentiment-Karachi-TTP (lag)						0.00005
						(0.00003)
Constant	-0.00001	-0.00001	-0.00000	0.00001	0.00001	0.00000
	(0.00003)	(0.00002)	(0.00002)	(0.00001)	(0.00001)	(0.00001)
Observations	824,824	824,824	824,824	824,824	824,824	824,824
Log Likelihood	2,722,868.000	3,304,886.000	3,072,776.000	3,388,155.000	3,990,326.000	3,755,373.000
Akaike Inf. Crit.	-5,445,708.000	-6,609,744.000	-6,145,525.000	-6,776,281.000	-7,980,624.000	- 7,510,717.000
Note: Control Variables behaved as expected, not included in table.						* p<0.1; **p<0.05; ***p<0.01

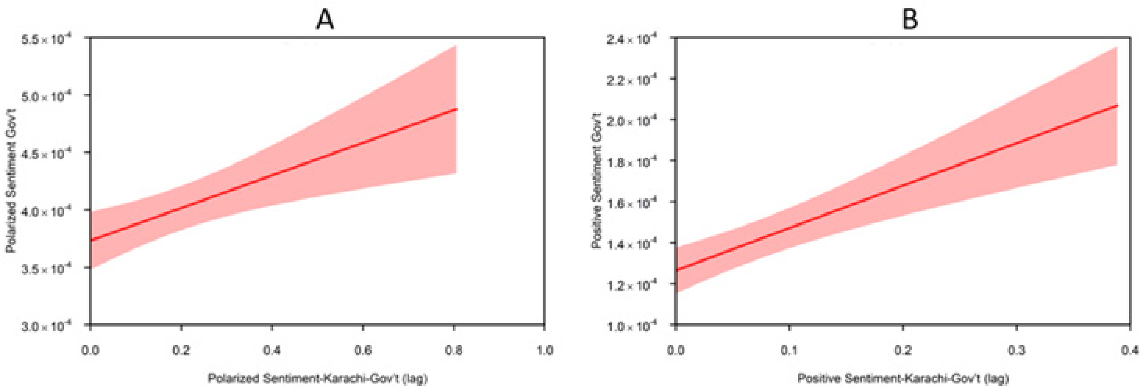

Figure 17. Predictive Effect of TTP Deaths (A) Polarized Sentiment, (B) Positive Sentiment

2. Finding Two—Lagos's Tweeting Sentiment Is a Predictor for the Rest of Nigeria

The ability to predict the following day's sentiment tweets outside of Lagos from the previous day's sentiment tweets within Lagos is demonstrated in the statistical significance of five out of the six models. Model 25 demonstrates a highly significant positive coefficient ($p<0.01$) in the relationship between *Polarized Sentiment Lagos* and *Polarized Sentiment* regarding sentiment expressed about the government. This is also seen in the sentiment expressed about the government in the relationship between *Positive Sentiment Lagos* and *Positive Sentiment*. When examining Models 28 through 30, all three models demonstrate a highly significant positive coefficient in the relationship between the *Polarized Sentiment Lagos*, *Positive Sentiment Lagos*, and *Negative Sentiment Lagos* and the following day's sentiment tweets outside of the megacity that reference Boko Haram. The findings support Hypothesis 3 and indicates that Lagos is a key influencer and communicator within the country. While no longer the country's capital, Lagos's continued influence, represented in this study through tweets, may be due to its vast economic importance and robust infrastructure. If those outside of Lagos view it as a model city for the rest of the country, this may provide insight as to why the sentiment expressed in Lagos can be used as a predictor for the rest of the Nigeria. Table 8 and Figure 18 detail these findings.

Table 8. Megacity Regression Models—Lagos

	Dependent variable: Tweets Outside the Megacity					
	Polarized Sentiment Gov't (25)	Positive Sentiment Gov't (26)	Negative Sentiment Gov't (27)	Polarized Sentiment Boko Haram (28)	Positive Sentiment Boko Haram (29)	Negative Sentiment Boko Haram (30)
Polarized Sentiment-Lagos-Gov't (lag)	0.0004**					
	(0.0002)					
Positive Sentiment-Lagos-Gov't (lag)		0.0004**				
		(0.0002)				
Negative Sentiment-Lagos-Gov't (lag)			0.0002			
			(0.0002)			
Polarized Sentiment-Lagos-Boko Haram (lag)				0.004***		
				(0.0001)		
Positive Sentiment-Lagos-Boko Haram (lag)					0.004***	
					(0.0001)	
Negative Sentiment-Lagos-Boko Haram (lag)						0.004***
						(0.0001)
Constant	-0.0001*	-0.00002	-0.00004*	-0.0003***	-0.0001***	-0.0002***
	(0.00004)	(0.00002)	(0.00002)	(0.00004)	(0.00002)	(0.00003)
Observations	726,180	726,180	726,180	726,180	726,180	726,180
Log Likelihood	2,169,115.000	2,754,186.000	2,438,762.000	2,025,171.000	2,605,786.000	2,303,817.000
Akaike Inf. Crit.	- 4,338,199.000	- 5,508,341.000	- 4,877,492.000	- 4,050,310.000	- 5,211,540.000	- 4,607,603.000

Note:
Control Variables behaved as expected, not included in table

*p<0.1; **p<0.05; ***p<0.01

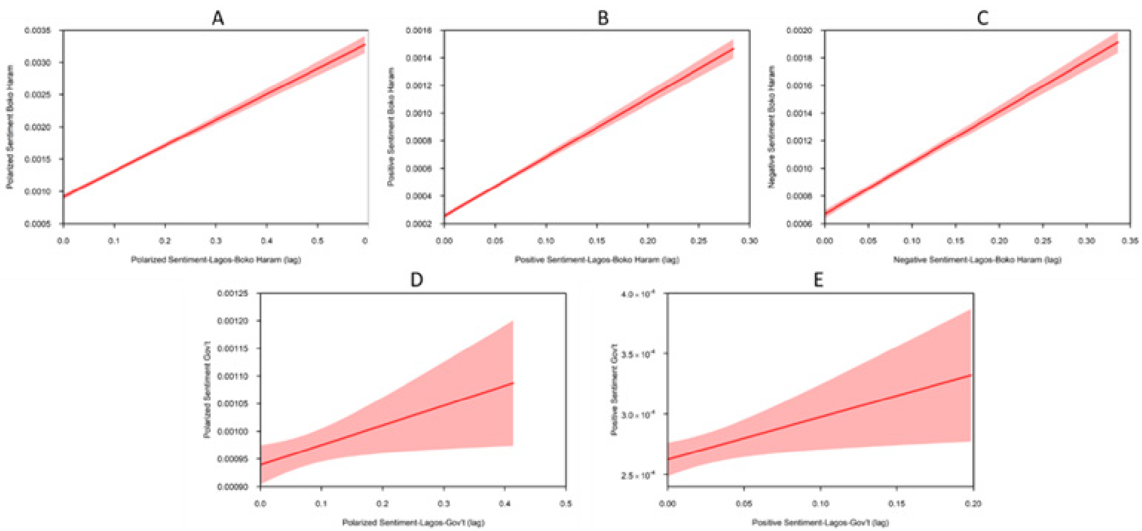

Figure 18. Predictive Effects of Lagos Sentiment on Nigeria
(A) Polarized Sentiment toward Boko Haram, (B) Positive Sentiment toward Boko Haram, (C) Negative Sentiment toward Boko Haram, (D) Polarized Sentiment toward Gov't, (E) Positive Sentiment toward Gov't

3. Finding Three—Manila's Tweeting Sentiment Is a Predictor for the Rest of the Philippines

The ability to predict the following day's sentiment tweets outside of Manila from the previous day's sentiment tweets within Manila is demonstrated by the statistical significance of all six models and supports Hypothesis 3. Models 31 through 33 describe a highly significant positive coefficient ($p<0.01$) in the relationship between *Polarized Sentiment Manila*, *Positive Sentiment Manila*, and *Negative Sentiment Manila* and the tweets expressing sentiment about the Gov't of the Philippines outside of the megacity. Similarly, Model 34 through 36 also describe a highly significant positive coefficient ($p<0.01$) in the relationship between *Polarized Sentiment Manila*, *Positive Sentiment Manila*, and *Negative Sentiment Manila* and the tweets expressing sentiment about the MNLF outside of the megacity. This demonstrates that one can leverage the sentiment expressed in Manila to predict the future. As the capital of the Philippines, the sentiment of influential communicators' tweets within the megacity can be seen as a predictor for the following day's tweets in the rest of the country. The Philippines' national capital region falls within the area that represents the megacity of Manila. This may provide insight as to why Manila's tweets can serve as a predictor of the next day's tweets in the rest of the country. Opinions expressed that originate from this area may be more emotionally and politically influential due to the co-location of the majority of Twitter users and followers as well as the country's political institutions. Table 9 and Figure 19 detail these findings.

Table 9. Megacity Regression Models—Manila

	Dependent variable: Tweets Outside the Megacity					
	Polarized Sentiment Gov't (25)	Positive Sentiment Gov't (26)	Negative Sentiment Gov't (27)	Polarized Sentiment Boko Haram (28)	Positive Sentiment Boko Haram (29)	Negative Sentiment Boko Haram (30)
Polarized Sentiment-Lagos-Gov't (lag)	0.0004**					
	(0.0002)					
Positive Sentiment-Lagos-Gov't (lag)		0.0004**				
		(0.0002)				
Negative Sentiment-Lagos-Gov't (lag)			0.0002			
			(0.0002)			
Polarized Sentiment-Lagos-Boko Haram (lag)				0.004***		
				(0.0001)		
Positive Sentiment-Lagos-Boko Haram (lag)					0.004***	
					(0.0001)	
Negative Sentiment-Lagos-Boko Haram (lag)						0.004***
						(0.0001)
Constant	-0.0001*	-0.00002	-0.00004*	-0.0003***	-0.0001***	-0.0002***
	(0.00004)	(0.00002)	(0.00002)	(0.00004)	(0.00002)	(0.00003)
Observations	726,180	726,180	726,180	726,180	726,180	726,180
Log Likelihood	2,169,115.000	2,754,186.000	2,438,762.000	2,025,171.000	2,605,786.000	2,303,817.000
Akaike Inf. Crit.	-4,338,199.000	-5,508,341.000	-4,877,492.000	-4,050,310.000	-5,211,540.000	-4,607,603.000
Note: Control Variables behaved as expected, not included in table					* p<0.1; **p<0.05; ***p<0.01	

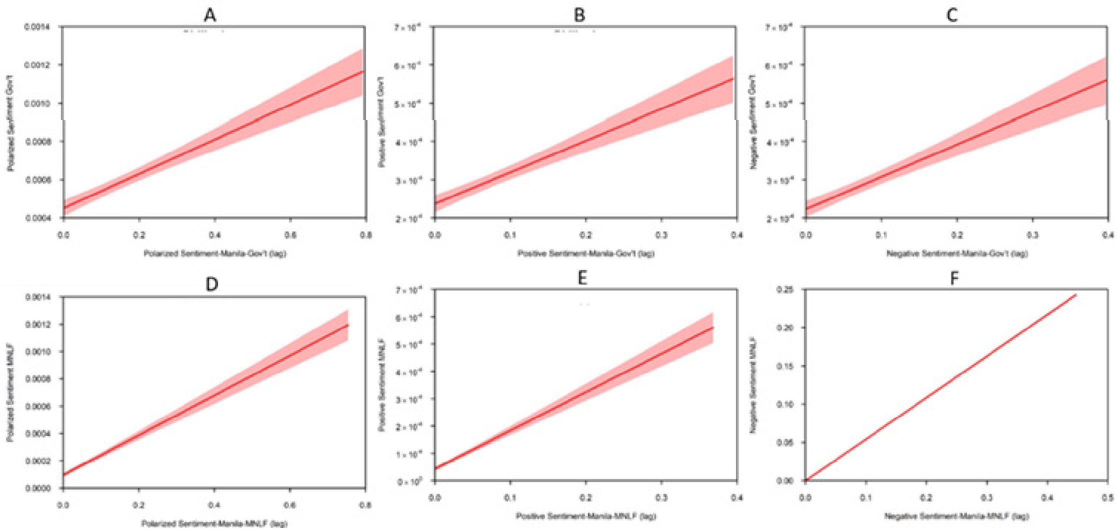

Figure 19. Predictive Effects of Manila Sentiment on the Philippines (A) Polarized Sentiment toward Gov't, (B) Positive Sentiment toward Gov't, (C) Negative Sentiment toward Gov't, (D) Polarized Sentiment toward MNLF, (E) Positive Sentiment toward MNLF, (F) Negative Sentiment toward MNLF

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VI. ADDITIONAL RESEARCH

Here we identify two areas for the potential continuation of this investigation in future research. They are continued development of a methodology for building a multi-lingual sentiment dictionary through co-occurrence patterns and additional variable considerations for use in the regression models to further explain sentiment reactions in Twitter.

A. MULTI-LINGUAL SENTIMENT AND NARRATIVE DICTIONARY DEVELOPMENT

Additional research is required to refine the rules for the co-occurrence sentiment word search to achieve a more accurate result. One area that requires focus is the elimination of commonly occurring words that appear with both positive and negative scores within the sentiment dictionary. Sentiment analysis studies often include removal of these common words, or stop words, but as this study utilized an approach for non-native language speakers, this would have been a difficult task, especially in less prevalent languages. Additionally, we recommend the development of rules that can account for the conflict actor's name in acronym form without including other groups that share the same acronym. This approach could leverage rules that include the acronym or abbreviation of the group name. This could produce a more robust return of tweets that contain a conflict actor as opposed to the few that use the whole or parts of the full name. Further efforts should focus on developing a process that captures more tokens in the native language of each country studied.

The development of a conflict actor narrative dictionary also provides another avenue that may provide further understanding of civil conflict and how actors may use violence to gain legitimacy. Following a similar methodology in the design and implementation of the sentiment dictionary, the development of a narrative dictionary using co-occurring words associated with the conflict actor within tweets could provide insight into how salient their message is within social media.

B. ADDITIONAL VARIABLE SELECTION

To understand the causes of sentiment reactions within Twitter better, additional variables could be added that may further explain the sentiment expressed within tweets after violent events. Information on the nature of the violent event may assist in this understanding. Individuals within social media may express sentiment differently if the violent event was a suicide bomber than they would if the event was an assassination of a political or religious figure. Additionally, the study could also provide a more in-depth analysis of the sentiment tweets within a megacity or dense urban area at a micro-level. Examining sentiment at a lower administrative level, such as by district or block could provide even greater insight for those seeking to understand the effects of violence on a particular city of interest. One could also consider adding variables that evaluate if demographic characteristics such as age and gender provide insight in identifying trends in tweeting following a violent event. Finally, this study focused on conflicts that involved actors internal to each country, but some actors have ties or elements that go beyond state boundaries. Selecting data that includes regional conflicts and external actor intervention may significantly change the sentiment of tweets based on how the population views the conditions that led to or sustain external intervention.

VII. CONCLUSION

This thesis sought to further the means of understanding the sentiment of a country's population and the impact of the megacity's influence on social media sentiment following violent events. Additionally, it sought to fill a gap in research related to multi-lingual social media sentiment analysis. We conducted this analysis focusing on violent events in Pakistan, Nigeria, and the Philippines from August 1, 2013, through July 31, 2014 and the Twitter sentiment responses that followed these violent events.

To analyze the sentiment of tweets within the selected countries and megacities, the study produced a sentiment dictionary respective to each country. As the countries spoke languages other than English, commonly available sentiment analyzers were not appropriate for this study. In order to capture the multiple languages spoken within each country, a co-occurrence methodology was implemented to capture the most frequently occurring sentiment terms in any languages within the country. The lexicon dictionaries produced from the co-occurrence searches enabled the gathering of tweets containing positive or negative sentiment words. The collected tweets allowed for the analysis of the sentiment of tweets preceding and following violent events in order to understand the impact these violent events have on the sentiments expressed toward state and non-state actors in social media.

The models produced from examining the interaction of the violent event and the sentiment expressed within Twitter produced four important findings. First, violence had a polarizing effect on the vast majority of messages expressing sentiment toward both the state and non-state actors within the countries studied. Second, the various ethnic groups responded differently to violence within each country. Identifying how ethnic groups expressed sentiment on social media can potentially provide greater insight into a group's perceived grievances against or expressed support of the state or non-state actors. Third, the sentiment expressed in the megacity is predictive of the sentiment of those who reside outside of the megacity. This is impactful in that it supports the concept that the megacity is key in influencing the social media environment within the country and can help assist in understanding how a country may respond to a significant event.

The results presented illustrate the importance of understanding how societies communicate on various mediums, and how individuals who choose to do so, express their sentiment among those within their society and to the greater international audience. This study provides a new approach to overcoming the obstacles presented in linguistically diverse populations, as well as a means and insight into how ethnically diverse populations respond to collective violence through social media.

APPENDIX. LEXICON SEARCH DICTIONARY

Emoji (POS)	Emoji (NEG)	Emoticons (POS)	Emoticons (NEG)
😂	😭	:-)	:L
❤	😟	:)	:-/
♥	😒	;)	>:/
😍	😔	:o)	:S
😚	😧	:]	>:[
😊	😢	:3	:@'
👌	🔫	:c)	:-(
💕	😦	:>	:[
🙌	😌	:]	:-||
😁	😪	8)	=L
		=)	:<
		:}	:-[
		^)	:-<
		:-D	=\\
		:D	=/
		8-D	>:(
		x-D	:(
		=-D	>.<
		=D	:'-(
		:-))	:'(
		:'-)	:\\
		:')	:-c
		:*'	:c
		:^*	:{
		>:P	>:\\
		:-P	;(
		:P	
		x-p	
		:-p	
		:p	
		=p	
		:-b	
		:b	
		:)	
		>;)	
		>:-)	
		<3	

Actor Names (Philippines)	Actor Names (Nigeria)	Actor Names (Pakistan)
Abu Sayyaf Group, Abu Sayyaf	Boko Haram, Boko Haram	Islamic Republic of Pakistan, Islamic Republic of Pakistan
Bangsamoro Islamic Freedom Movement, Bangsamoro Islamic Freedom Movement	Boko Haram, Eewo ni iwe kika	Islamic Republic of Pakistan, da Pakistan islami jumhoryat
Bangsamoro Islamic Freedom Movement, BIFF	Boko Haram, boko	Islamic Republic of Pakistan, اسلامی باکستان د جمهوریت
Bangsamoro Islamic Freedom Movement, BIFM	Boko Haram, Boko Boys	Islamic Republic of Pakistan, dirty land
Communist Party of the Philippines, Communist Party of the Philippines	Boko Haram, BH Boys	Islamic Republic of Pakistan, chatulistan
Communist Party of the Philippines, partido komunista ng pilipinas	Black Axe, Black Axe	Islamic Republic of Pakistan,چتلیستان
Communist Party of the Philippines, bagong hukbong bayan	Black Axe, Aake Dudu	Baluchistan Liberation Army, Baluchistan Liberation Army
Communist Party of the Philippines, taga-kaliwa	Black Axe, Ayee	Baluchistan Liberation Army, da Baluchistan Azadi Urdu
Communist Party of the Philippines, kaliwa	Black Axe, Black Movement	Baluchistan Liberation Army, اردو آزادي بلوچستان د
Communist Party of the Philippines, tagabundok	Eyie, Air Lord	Baluchistan Liberation Army, ای بی ای
Moro Islamic Liberation Front, Moro Islamic Liberation Front	Supreme Vikings, Supreme Vikings	Baluch Liberation Front, Baluch Liberation Front
Moro National Liberation Front, Moro National Liberation Front	Supreme Vikings, Egbe okunkun ori omo	Baluch Liberation Front, da Baluchistan Azadi Jubhuh
Moro National Liberation Front, MNLF	Supreme Vikings,Vikky	Baluch Liberation Front, جبهه آزادي بلوچستان د
MoroMulti, kapatid na muslim	Supreme Vikings, Sea Lord	Baluch Liberation Front, baluch sarmuchar
MoroMulti, kabaro na muslim	Black Axe, Ume Ake	Baluch Liberation Front, سرمچار بلوچ
MoroMulti, muklo	Black Axe, Ake Boyz	Baloch Republican Army, Baloch Republican Army
Republic Of the Philippines, Republic Of the Philippines	Black Axe, Aye Axe Men	Baloch Republican Army, آرمی ریپبلکن بلوچ

Republic Of the Philippines, Republika ng Pilipinas	Eyie, Eyie	Baloch Republican Army, پوځ جمهوری بلوچ
Republic Of the Philippines, pamahalaan ng Pilipinas	Eyie, Eyie Confraternity	Islamic Movement of Uzbekistan, da Uzbekistan Islami Harkut
Republic Of the Philippines, gobyerno ng Pilipinas	Supreme Vikings, Umu Viki	Islamic Movement of Uzbekistan, د ازبکستان حرکت اسلامي
Republic Of the Philippines, Sandatahang Lakas ng Pilipinas	Supreme Vikings, Viki Boyz	Islamic Movement of Uzbekistan, اے ای ٹی
Republic Of the Philippines, Hukbong Katihan ng Pilipinas	Government, government	Jammat-ul-Ahrar, Jammat-ul-Ahrar
Republic Of the Philippines, Hukbong Himpapawid ng Pilipinas	Government of Nigeria, Gwamnatin Nijeriya	Jammat-ul-Ahrar,جماعت الاحرار
Republic Of the Philippines, Pambansang Pulisya ng Pilipinas	Government of Nigeria, Ijoba ti Nigeria	Jammat-ul-Ahrar, TTP Shakh
Republic Of the Philippines, kasundaluhan	Government of Nigeria, Gọọmentị Nigeria	Jammat-ul-Ahrar, پی ٹی شاخ
Republic Of the Philippines, kapulisan	Government of Nigeria, Ìṣèlú ilẹ̀ Nàìjíríà	Lashkar-e-Islam, Lashkar-e-Islam
Republic Of the Philippines, sundalo	Government of Nigeria, Ndọrọ ọchịchị nke Nigeria	Lashkar-e-Islam,لشکر اسلام
Republic Of the Philippines, pulis	Government, Gwamnati	Lashkar-e-Islam,ای پی ال
Republic Of the Philippines, kawani	Government, Ijoba	Lashkar-e-Islam,ای ال
Republic Of the Philippines, mandirigma	Government, Gọọmentị	Tehrik-i-Taliban Pakistan, Tehrik-i-Taliban Pakistan
Republic Of the Philippines, lespu	Government of Nigeria, Ndọrọ ọchịchị nke	Tehrik-i-Taliban Pakistan, د پاکستان تحریک طالبان
Republic Of the Philippines, parak	Government of Nigeria, Ìṣèlú ilẹ̀	Tehrik-i-Taliban Pakistan,پی ٹی ٹی
Government, pamahalaan	Christians, Christians	Tariq Afridi,Tariq Afridi
	Christians, Kiristoci	Tariq Afridi,آفرید طارق
	Christians, Kristiani	Tariq Afridi, Commander Tariq Afridi
	Christians, Ndị Kraịst	Tariq Afridi,طارق کوماندان آفرید

	Muslims, Muslims	Tariq Afridi,طارق کوماندر آفرید
	Muslims, Musulumi	Tariq Afridi,طارق قوماندر آفرید
	Muslims, Alakụbaa	Tariq Afridi,طارق قوماندان آفرید
		United Baloch Army, United Baloch Army
		United Baloch Army, da Baluch Mutahid Lashkar
		United Baloch Army,د لشکر متحد بلوچ
		United Baloch Army,یو اے بی
		Islamic Republic of Pakistan, Jumhoryat Islami Pakistan
		Islamic Republic of Pakistan,اسلامی جمہوریہ پاکستان
		Islamic Republic of Pakistan,پاکستان
		Baluchistan Liberation Army, Azad Baluchistan Army
		Baluchistan Liberation Army,آرمی بلوچستان آزاد
		Baluch Liberation Front,فرنٹ لبریشن بلوچستان
		Islamic Movement of Uzbekistan, Islamic Movement of Uzbekistan
		Islamic Movement of Uzbekistan, Tehrik Islami Uzbekistan
		Islamic Movement of Uzbekistan,اسلامی دتحریک اُزبکستان
		Tehrik-i-Taliban Pakistan, Pakistan Taliban
		Tehrik-i-Taliban Pakistan, Taliban Pakistan

		Tehrik-i-Taliban Pakistan, Pakistan Taleban
		Tehrik-i-Taliban Pakistan, Taleban Pakistan
		Tehrik-i-Taliban Pakistan,طالبان پاکستان
		Tehrik-i-Taliban Pakistan,پاکستان طالبان
		Tehrik-i-Taliban Pakistan, Tehrik
		Tehrik-i-Taliban Pakistan, Tehreek
		Tehrik-i-Taliban Pakistan,تحریک
		Tehrik-i-Taliban Pakistan, Tehreek-i-Taliban
		Tehrik-i-Taliban Pakistan, Tehreek-e-Taliban
		Tehrik-i-Taliban Pakistan,طالبان تحریک پاکستان
		Tariq Afridi,آفریدی طارق
		Tariq Afridi, Commander TTP
		Tariq Afridi,طارق شہید آفریدی
		Tariq Afridi, Shahid Tariq Afridi
		Tariq Afridi,ٹی کمانڈر ثانی پی
		United Baloch Army, mutahid baluch army
		United Baloch Army,آرمی بلوچ متحدہ
		United Baloch Army,یو اے بی
		Government,حکومت

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