



Measuring the Popular Resonance of Daesh's Propoganda

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Measuring the Popular Resonance of Daesh's Propaganda

Author Biography

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Abstract

We describe an innovative approach to social media analysis, combining corpus linguists and statistical methods to measure the resonance of Daesh's propaganda to a sample population (Egypt). The findings from this research effort demonstrate that: (1) Daesh's messaging is measurable and distinct from other Salafi groups, such as the Egyptian Muslim Brotherhood; (2) while Daesh's messaging generally do not resonate with Egyptians, its uptake increased in Upper Egypt and the Sinai regions during 2014; and (3) this method can be applied more broadly to measure the spread of violent extremist messaging across regional populations over time.

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Introduction

In June 2014, the Islamic State of Iraq and the Levant, often referred to by its Arabic acronym *daesh*, declared that it had established an Islamic Caliphate in the territory under its control.¹ This territory included areas surrounding Fallujah, Tikrit and Mosul, Iraq's second most-populated city after Baghdad. It also incorporated territory within Syria, especially near the city of Raqqa, which had become Daesh's headquarters. Soon thereafter, other violent extremists issued statements of support for Daesh and, in some instances, declared local *wilayat* (provinces) of the Islamic State. By September 2015, Daesh had recognized provinces in parts of Libya, Egypt, Algeria, Yemen, Saudi Arabia, Nigeria, Russia, and Afghanistan.² Suddenly, policymakers in the United States and elsewhere faced the dilemma of how to address the threat of Daesh's expansion.

Social media is a key factor in Daesh's global distribution of affiliates. Sophisticated social media propaganda generation and distribution have made the Internet an effective tool for generating recruits and coordinating efforts. Between 27,000 and 31,000 people traveled to Iraq and Syria to fight for IS and its affiliates. Social media was a decisive factor catalyzing of the flow of recruits in communities across the world and continues to be the primary recruitment tool in the Americas.³

This article addresses the national security dilemma posed by Daesh's social media-fueled expansion using Twitter data to measure the spread of Daesh's propaganda over time for local populations within Egypt, a country where secular, moderate Islamic and extremist ideologies are actively competing for the hearts and minds of its population. We call this resonance analysis in the

¹ Al Jazeera and agencies, "Sunni Rebels Declare a New Islamic Caliphate," June 30, 2014, available at: <http://www.aljazeera.com/news/middleeast/2014/06/isil-declares-new-islamic-caliphate-201462917326669749.html>.

² Lara Jakes, "Who's Part of the Islamic State? Depends on Who You Ask," *Foreign Policy*, (2015), available at: <http://foreignpolicy.com/2015/05/21/whos-part-of-the-islamic-state-depends-whom-you-ask/>; Charlie Winter, "The Virtual 'Caliphate': Understanding Islamic State's Propaganda Strategy," *Quilliam Foundation* (2015), available at: <http://www.quilliamfoundation.org/wp/wp-content/uploads/publications/free/the-virtual-caliphate-understanding-islamic-states-propaganda-strategy.pdf>; Aaron Zelin, "New Video Message from the Islamic State: 'Victory from God and An Imminent Conquest—Wilayat al-Khayr,'" *Jihadology* (2015), available at: <http://jihadology.net/2015/05/11/new-video-message-from-the-islamic-state-victory-from-god-and-an-imminent-conquest-wilayat-al-khayr/>.

³ The Soufan Group. "Foreign Fighters: An Updated Assessment of the Flow of Foreign Fighters into Syria and Iraq," (2015), available at: http://soufangroup.com/wp-content/uploads/2015/12/TSG_ForeignFightersUpdate3.pdf.

technical sense of a re-sounding, and it serves as a measure of effectiveness by quantifying the geographic degree and intensity of propaganda spread and uptake by the populace. Resonance analysis works by identifying the distinct language in a group's propaganda, and quantifying the uptake of that language in general population social media use. It answers the question, are the people talking more or less like an extremist group?

Resonance analysis is an innovative application of existing corpus linguistics methods to a national security problem, to create an inexpensive, scalable population analysis tool. The analysis suggests three outcomes. First, Daesh's propaganda is measurable and distinct from other Salafi groups, such as the Egyptian Muslim Brotherhood. Second, while Daesh's propaganda generally does not resonate with Egyptians, its uptake increased in Upper Egypt and the Sinai regions during 2014. Finally, linguistic fingerprints can be used to measure the spread of violent extremists' propaganda to local populations over time, using off-the-shelf technology and cheap/accessible social media data.

Egyptians as a Sample Population to Test the Method

To conduct this analysis, we collected 6,210,354 tweets from four sub-regions within Egypt between January and December 2014. The four sub-regions were the Sinai Peninsula, Alexandria and the coastal provinces, the greater Cairo and Nile Delta region, and Upper Egypt. We chose Egypt in 2014 for three reasons. First, Daesh made significant gains in this country during this period; hence, it is an opportunity to observe the social media environment surrounding Daesh success. First, the Egyptian terror group Ansar Beit al-Maqdis pledged allegiance to Daesh in November 2014 and was accepted into the Caliphate by Daesh leaders.⁴ Within a year, fighters from Ansar Beit al-Maqdis, now known as the Islamic State in Sinai, placed an improvised explosive device on a Russian aircraft departing the Sinai.⁵ Second, the Egyptian population is one of the most connected to social media in the region, and thereby, one of the most vulnerable to an extremist group

⁴ David Kirkpatrick, "Militant Group in Egypt Vows Loyalty to ISIS," *The New York Times*, November 10, 2014, available at: http://www.nytimes.com/2014/11/11/world/middleeast/egyptian-militant-group-pledges-loyalty-to-isis.html?_r=1.

⁵ Andrew Roth, "Russia Confirms Sinai Plane Crash was the Work of Terrorists," *The Washington Post*, November 17, 2015, available at: https://www.washingtonpost.com/world/russia-confirms-sinai-crash-was-the-work-of-terrorists/2015/11/17/496286f4-8d05-11e5-ae1f-af46b7df8483_story.html.

infamous for its social media prowess.⁶ Third, Egyptian political space is highly contested terrain, with secular, moderate Islamic and extremist ideologies all competing for the hearts and minds of the population.

This article proceeds in five sections. The first section summarizes the use of social media, particularly the Twitter data, to study hard to reach populations and, more specifically, violent extremists. The second section provides a brief discussion of Daesh and its use of social media in support of its campaign in Iraq, Syria, and beyond. We discuss the data and methods we used to measure Daesh's appeal to Egyptians in the third section. In the fourth section, we present the results from our analysis. The fifth section concludes with a discussion of the implications for United States policy and future research on the resonance of violent extremists' messaging.

Using Social Media to Analyze Hard-to-Reach Populations

Social media, and specifically Twitter data, has been gaining acceptance within the academic community as a new avenue for examining local populations, especially hard-to-reach populations. Computers and mobile devices enable people anywhere in the world to interact with each other. In a previous era, states funded and operated global broadcast networks such as the Voice of America to engage in messaging; today, extremist non-state actors such as Daesh operate sophisticated propaganda, recruiting, and funding operations on social media for marginal costs.

There is thus an important need for effective social media analytic methods that address national security problems. In addition, while social media users are not a representative sample of the population at large, using Twitter data has proved to be useful for analysis in four areas: User networks, user sentiments, user demographics, and the flow of information. This section provides a brief overview of how researchers can use Twitter data to address these four analytical areas and its application to studies on terrorism and political violence.

In terms of social networks, users engage with each other through mentions and re-tweets, forming virtual global networks. Past research found that, much like off-line social connections, Twitter users tend to mention and

⁶ Racha Mourtada and Fadi Salem, "Citizen Engagement and Public Services in the Arab World: The Potential of Social Media," *Arab Social Media Report Series* (2014): 1-54 Available at: [10.2139/ssrn.2578993](https://ssrn.com/abstract=2578993).

follow others who hold similar views.⁷ Thus, Twitter data can be used to build and analyze networks of persons with similar views, such as those who might support certain political candidates.⁸ Along these lines, in recent years, researchers have begun to use social media data to describe the structure of a violent extremist group and its online presence.⁹ In 2015, Jytte Klausen applied a snowball sampling method to study networks of jihadists in Syria and Iraq on Twitter.¹⁰

Twitter data also have proven to be useful in analyses of users' sentiment towards a pre-designated subject. One of the earliest applications of this method involved market studies of how positive (or negative) Twitter users felt about specific brands and products.¹¹ Other research on users' sentiment has attempted to gauge how well a population's mood corresponds to daily variation in stock market indices or even regional variation in support for certain political issues.¹² This type of research has proven to be particularly

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- 7 Miller McPherson, Lynn Smith-Lovin, and James M. Cook, "Birds of a Feather: Homophily in Social Networks," *Annual Review of Sociology* 27:1 (2001): 415, available at: [10.1146/annurev.soc.27.1.415](http://annurev.soc.27.1.415); Warren Pearce, Kim Holmberg, Iina Hellsten, and Brigitte Nerlich, "Climate Change on Twitter: Topics, Communities and Conversations about the 2013 IPCC Working Group 1 Report," *PLoS One* 9:4 (2014), available at: <http://journals.plos.org/plosone/article?id=10.1371/journal.pone.0094785>; Elanor Colleoni, Alessandro Rozza, and Adam Arvidsson, "Echo Chamber or Public Sphere? Predicting Political Orientation and Measuring Political Homophily in Twitter Using Big Data," *Journal of Communication* 64:2 (2014), 317, available at: doi: 10.1111/jcom.12084.
- 8 Mitchell S. McKinney, J. Brian Houston, and Joshua Hawthorne, "Social Watching a 2012 Republican Presidential Primary Debate," *American Behavioral Scientist* 58:4(2013): 556, available at: <http://abs.sagepub.com/content/early/2013/10/17/0002764213506211> or doi:10.1177/0002764213506211.
- 9 Sarita Azad and Arvind Gupta, "A Quantitative Assessment on 26/11 Mumbai Attack using Social Network Analysis," *Journal of Terrorism Research* 2:2 (2011): 4, available at: <http://jtr.st-andrews.ac.uk/articles/10.15664/jtr.187/>.
- 10 Jytte Klausen, "Tweeting the Jihad: Social Media Networks of Western Foreign Fighters in Syria and Iraq," *Studies in Conflict & Terrorism* 38:1 (2015): 1, available at: doi:10.1080/1057610X.2014.974948.
- 11 Bernard J. Jansen, Mimi Zhang, Kate Sobel, and Abdur Chowdury, "Twitter Power: Tweets as Electronic Word of Mouth," *Journal of the American Society for Information Science and Technology* 60:11 (2009): 2169, available at: doi:10.1002/asi.21149; Marco Pennacchiotti and Ana-Maria Popescu, "A Machine Learning Approach to Twitter User Classification," (paper presented at the Fifth International AAAI Conference on Weblogs and Social Media, Sunnyvale, CA, 2011), available at: <http://www.aaai.org/ocs/index.php/ICWSM/ICWSM11/paper/view/2886>.
- 12 Johan Bollen, Huina Mao, and Xiaojun Zeng, "Twitter Mood Predicts the Stock Market," *Journal of Computational Science* 2:1 (2011): 1-8.; James W. Pennebaker, Matthias R. Mehl, and Kate G. Niederhoffer, "Psychological Aspects of Natural Language Use: Our Words, Ourselves," *Annual Review of Psychology* 54 (2003): 547-577, available at: doi:10.1146/annurev.psych.54.101601.145041; Garrett Glasgow, Matt Golder, and Sona N. Golder, "Who 'Wins'?" Determining the Party of the Prime Minister," *American Journal of Political Science* 55:4 (2011): 937.doi:10.1111/j.1540-5907.2011.00524.x.

valuable as it can track user sentiment over time and within pre-defined geographic spaces, while other researchers use social media to improve understanding of user sentiments towards certain violent extremists.¹³

Finally, using the text of Tweets, researchers also have derived insight from both the demographics of Twitter users. Researchers have explored how gender, ethnicity, political orientation, and age may correspond to specific features of Tweets, such as topic, number of tweets, vocabulary choices, and syntax.¹⁴ Findings from this research parallel the conclusions from similar “off-line research,” which has found that correspondence exists between language use and personal characteristics.¹⁵ Extending this research into the security realm, some researchers have attempted to identify emerging terrorist actors, based on social media data and machine learning techniques.¹⁶

In terms of the flow of information, researchers have tracked the flow of specific ideas through Twitter data, and identified quantitative features of Twitter networks that may make some ideas more likely to spread than others.¹⁷ Researchers also have charted the relative influence of different information sources on public knowledge.¹⁸

13 Gabriel Weimann, “Terror on Facebook, Twitter, and YouTube,” *Brown Journal of World Affairs* 16:2 (Spring/Summer 2010): 45, available at: <https://www.brown.edu/initiatives/journal-world-affairs/162/terror-facebook-twitter-and-youtube>.

14 Patricia Cavazos-Rehg, Melissa Krauss, Richard Grucza, and Laura Bierut, “Characterizing The Followers And Tweets Of A Marijuana-Focused Twitter Handle,” *Journal of Medical Internet Research* 16:6 (2014): 157, available at: doi:10.2196/jmir.3247; and Sen Pei, Lev Muchnik, José S. Andrade, Zhiming Zheng, and Hernán A. Makse, “Searching For Superspreaders of Information in Real-World Social Media,” *Scientific Reports* 4 (2014), available at: doi:10.1038/srep05547.

15 J.W. Pennebaker, M.R. Mehl, and K.G. Niederhoffer, “Psychological Aspects of Natural Language Use: Our Words, Ourselves” *Annual Review of Psychology* 54:1 (2003):547, available at doi:10.1146/annurev.psych.54.101601.145041; E. Hoff, “Interpreting the Early Language Trajectories of Children from Low-Ses and Language Minority Homes: Implications for Closing Achievement Gaps,” *Developmental Psychology* 49:1 (2013): 4, available at: doi:10.1037/a0027238.

16 Katie Cohen, Fredrik Johansson, Lisa Kaati, and Jonas C. Mork, “Detecting Linguistic Markers for Radical Violence in Social Media,” *Terrorism and Political Violence* 26:1 (2013): 246, available at: doi:10.1080/09546553.2014.849948.

17 Pei et al., “Searching for Superspreaders.”

18 Cinthya Chew and Gunther Eysenbach, “Pandemics in the Age of Twitter: Content Analysis of Tweets during the 2009 H1N1 Outbreak,” *PLoS One* 5:1 (2010), available at: doi:10.1371/journal.pone.0014118; Alessio Signorini, Alberto Maria Segre, and Phillip M. Polgreen, “The Use of Twitter to Track Levels of Disease Activity and Public Concern in the U.S. During the Influenza H1N1 Pandemic,” *PLoS One* 6:5 (2011): e19467, available at: doi: 10.1371/journal.pone.0019467.

In summary, social media analysis holds potential for the study of terrorism and political violence. Still social media analyses in this area remain rare. Most of the existing research focuses on user networks and sentiment analysis. For this study, we attempt to go one-step further and measure the extent to which Daesh's worldview, not specific ideas, resonates among local populations outside Iraq and Syria. In doing so, the intent is twofold: first, assist US policymakers as they attempt to halt Daesh's recruitment and expansion; and, second, demonstrate new uses for social media data in studies of political violence.

Daesh's Use of Social Media

Daesh relies on a multi-layered set of media centers to produce the content of its official propaganda. For example, *al-Furqan Media*, *al-Hayat Media*, *Ajnad Media*, and *al-I'tisam Media* all produce what could be considered as top-level messaging. This includes sermons issued by Daesh leader, Abu Bakr al-Baghdadi, audio addresses from spokesperson Abu Muhammad al-Adnani, and issues of the English-language magazine *Dabiq*.¹⁹ In addition to these top-level messages, Daesh has provincial media offices that produce local situation reports, such as the "Victory From God and An Imminent Conquest" video series from al-Khayr Province Media Office, or "To the Defiant Tribes of the Sinai," a statement from the Sinai Province Media Office.²⁰ Aaron Zelin's analysis of the 123 media releases from Daesh in a single week in April 2015 found that top-level outlets represented twenty-two percent of the media releases, while the other seventy-eight percent came from province-level media centers.²¹

Daesh targets its messages to a variety of audiences: active opponents, international publics, active members, potential recruits, disseminators, proselytizers, and enlisters.²² While Arabic language dominates, news outlets often translate or publish media releases in other languages.²³ Daesh's propaganda content is also sophisticated, varying along with its target

19 Zelin, "New Video Message."

20 Ibid; Aaron Zelin, "Picture or it Didn't Happen: A Snapshot of the Islamic State's Official Media Output," *Perspectives on Terrorism* 9:4 (2015): 85, available at: <http://www.washingtoninstitute.org/policy-analysis/view/picture-or-it-didnt-happen-a-snapshot-of-the-islamic-states-official-media>.

21 Zelin, "New Video Message."

22 Winter, "The Virtual Caliphate."

23 Berger and Morgan, "The ISIS Twitter Census."

audiences, covering a wide variety of themes, e.g. from brutality to mercy,²⁴ or governance to *his* (enforcement of adherence to Islamic principles).²⁵

In summary, Daesh and supporters run a sophisticated social media campaign, but questions remain on the impact of this campaign. Preliminary research on this topic, albeit limited, suggests that Daesh's swarmcast dissemination approach, and its content, are partly responsible for attracting foreign fighters to Syria and Iraq, now numbering 30,000.²⁶ Daesh's social media also appears to have some impact on the decisions by other jihadists to declare themselves as provinces of the Islamic State. Equally important, some evidence suggests that Daesh's approach has contributed to attacks by lone wolves in the United State and elsewhere, including the attack by Tashfeen Malik and Syed Rizwan Farook in San Bernardino, California in late 2015.²⁷ However, researchers know little about where and to what degree Daesh's messages resonate.

Theory & Rationale

We took a grounded approach to linguistic and rhetorical theory that treats language and worldview as inextricably linked: real world language use informs our social and political world, and our social and political realities influence our language.²⁸ In addition to communicating information, words also reflect/shape how we understand the world. Speakers have choices in the words they use and choose language to represent not only the world, as they understand it, but also in how they wish to construct it.²⁹

24 Winter, "The Virtual Caliphate..." 2015.

25 Zelin, "Picture or it Didn't Happen."

26 Doina Chiacu, "FBI Chief Warns of Islamic State Recruits, Lone wolf attacks," FBI Chief Warns of Islamic State Recruits, March 12, 2015, available at:

<http://www.reuters.com/article/us-usa-fbi-idUSKBN0M81TI20150312>; Patricia Zengerle, "U.S. fails to stop flow of foreign fighters to Islamic State: Study," *Reuters*, September 29, 2015, available at: <http://www.reuters.com/article/us-mideast-crisis-congress-fighters-idUSKCN0RT1VZ20150929>.

27 Declan Walsh, "Tashfeen Malik Was a 'Saudi Girl' Who Stood Out at a Pakistani University," *The New York Times*, December 6, 2015, available at:

http://www.nytimes.com/2015/12/07/world/asia/in-conservative-pakistani-city-a-saudi-girl-who-stood-out.html?_r=0; Rukmini Callimachi, "Islamic State Says 'Soldiers of Caliphate' Attacked in San Bernardino," *The New York Times*, December 5, 2015, available at: <http://www.nytimes.com/2015/12/06/world/middleeast/islamic-state-san-bernardino-massacre.html>.

28 Barbara Johnstone, *Discourse Analysis* (Malden, MA: Blackwell, 2008), p. 36.

29 David Kaufer and Amal Al-Malki, "A First for Women in The Kingdom: Arab/West Representations of Female Trendsetters in Saudi Arabia," *Journal of Arab & Muslim Media Research* 2:1-2 (2009): 113, available at: doi:10.1386/jammr.2.1and2.113/1; Jeffrey Collins, "Variations in Written English," (PhD diss., Carnegie Mellon University, 2003), available at: <http://www.dtic.mil/get-tr-doc/pdf?AD=ADA416543>; William M.

This link between linguistic behavior and worldview has important implications for our study. Controlling the terms of discussion—shaping *discourse*—is critical in persuasion and influence.³⁰ This has particular stakes in conflict, where constructing the discourse around the conflict confers political advantage. For example, if one side in a conflict can successfully frame the other as terrorists committing atrocities and massacres, the accuser now has a powerful social and political advantage for action.³¹ Shaping discourse has multiple dimensions, and in addition to specific word choice such as terrorist versus freedom fighter, volume and repetition can powerfully structure discourse.³²

Because of this link between language and worldview, and its role in public conflict, we can treat Daesh as an abstraction of advocacy: a *public*. Publics are "*that portion of the populace engaged in evolving shared opinion on a particular issue, with the intent of influencing its resolution*. They are not fixed and they are not idealized constructs, they are **emergences** (italics and formatting original)."³³ Publics are fluid and emerge from social practice, and so change over time dynamically. In this sense, publics, which are detectable by their linguistic structure, are like language itself: temporal, emergent, and contested.³⁴ Publics are important from an intelligence and information operations perspective because they offer a useful unit of analysis, and thus a way to make a weak signal detectable, in the form of the distinctive language that is characteristic of publics and help them achieve advocacy goals.³⁵

Using methods borrowed from corpus linguistics, we can treat Daesh' public talk as a linguistic corpus, and identify what is characteristic about it. With a

Marcellino, "Talk Like a Marine: USMC Linguistic Acculturation and Civil–Military Argument," *Discourse Studies* 16:3 (2014): 385, available at: doi:10.1177/1461445613508895.

30 Van Dijk, Teun A., *Discourse and Power* (New York: Palgrave Macmillan, 2008).

31 DeepaReddy, "Capturing Hindutva: Rhetorics and Strategies," *Religion Compass* 5:8 (2011): 427, p. 432, available at: doi:10.1111/j.1749-8171.2011.00289.x.

32 Katherine Clegg Smith and Melanie Wakefield, "Textual Analysis of Tobacco Editorials: How are Key Media Gatekeepers Framing the Issues?" *American Journal of Health Promotion* 19:5 (2005): 361, available at: doi:10.4278/0890-1171-19.5.361.

33 Hauser, Gerald A, *Introduction to Rhetorical Theory* (2nd ed.) (Longrove, IL: Waveland Press, 2002), 85. Formatting in the original.

34 Paul Hopper, "Emergent grammar" (Paper presented at Berkeley Linguistics Society: Proceedings of the Thirteenth Annual Meeting February 14-16, 1987), available at: doi:10.4324/9780203809068.ch21.

35 Hauser, Gerald A. *Vernacular Voices: The Rhetoric of Publics and Public Spheres* (Columbia, SC: University of South Carolina Press, 1999), 1-341.; David S. Kaufer and Brian B. Butler *Rhetoric and the Arts of Design* (New York: Routledge, 2010), 1-341, available at: http://site.ebrary.com/lib/alltitles/docDetail.action?docID=10814064_

large enough sample of word, it is possible to use statistical tests to identify the set of distinct words that distinguish one public from another. We can think of this as linguistic model for such groups: which words are statistically more likely to be used, and how much more likely—even when those word choices seem innocuous. We can then search for this linguistic model in social media traffic from the general population, to quantify and locate where the public's talk is resonant. This concept is distinct from an attempt to track or evaluate a meme or particular message; it is arguably a deeper, more holistic approach to evaluating to what extent a population has adopted a particular group's discourse, and thus representation of the world. In summary, we are measuring a national populace's uptake and reuse of propaganda over time, at a regional level of granularity.

Data

The results in this article draw on two categories of data sources: reference corpora and general population social media datasets. The first data category includes sets of public text from which to extract a linguistic model. For this study, we created five different corpora: A primary one of Daesh propaganda, a comparison of Muslim Brotherhood language, and three event-based corpora to test our model.

The first of these corpora consists of selected examples of language used by Daesh in their official propaganda.³⁶ The collection includes twenty-four documents released between January 2014 and March 2015, totaling 21,787 words. These publications incorporate speech transcripts from Daesh leaders, announcements of martyrdoms, daily news round-ups, and other official statements released through Daesh media outlets. The majority of the texts originated from JustPasteIt, a site popular among Daesh members and supporters.³⁷

36 Sheryl Prentice, Paul J. Taylor, Paul Rayson and Ellen Giebels, "Differentiating Act from Ideology: Evidence from Messages For and Against Violent Extremism," *Negotiation and Conflict Management Research* 5:3 (2012): 289, available at: doi:10.1111/j.1750-4716.2012.00103.x; Sheryl Prentice, Paul Rayson and Paul J. Taylor, "The Language of Islamic Extremism: Towards an Automated Identification of Beliefs, Motivations and Justifications," *International Journal of Corpus Linguistics* 17:2 (2012): 259, available at: doi: 10.1075/ijcl.17.2.05pre.

37 Carmen Fishwick, "How a Polish Student's Website Became an Isis Propaganda Tool" *The Guardian*, August 15, 2014, available at: <https://www.theguardian.com/world/2014/aug/15/-sp-polish-man-website-isis-propaganda-tool>.

Our second corpus consisted of language from the Muslim Brotherhood and enabled us to compare our findings against another extremist group's language.³⁸ This corpus contains 31,576 words, and is composed of statements from the official Muslim Brotherhood website (2012-2014), videos on the Muslim Brotherhood YouTube channel (2102-2014), and status updates on the official Muslim Brotherhood Facebook page (2014).

Finally, we created three event-based reference corpora to test the ability of our method to detect the spread of talk on real world events we knew had happened. These include text relating to a car bombing in the Sinai on 24 October 2014, the bombing of a bus full of Korean tourists on 16 February 2014, and a severe influenza outbreak in Egypt in the same year.

Our second major category of data, a target corpus of general population social media, consisted of a sample of data from the social media platform Twitter for several sub-regions in Egypt. Purchased from DataSift consisted of a thirty percent sample³⁹ of all tweets sent by Egyptian users in 2014. This dataset consisted of 6,210,354 tweets distributed among four regions: the Sinai Peninsula, Cairo/Nile Delta, Alexandria/Coast, and Upper Egypt. The range among regions was large (3 million Tweets in Cairo to 130,000 in the Sinai), but all regions contained enough data for valid corpus linguistics analysis.

Gathering tweets from the users of a specific country is a non-trivial task, and various researchers and organizations have used many methods. The standard way to filter tweets by location is by geo-tag, which matches Tweets containing geographic coordinates with a specific geographic area. While this method is highly accurate, few Twitter users report geo-coordinates when they tweet⁴⁰ and relying solely on geo-tagged Tweets can expose the researcher to considerable selection bias. Therefore, we expanded our data collection to include Tweets by non-geo-tagged users and instead leveraged other geographically specific meta-data to identify each user's location. This method is commonly referred to as geo-inferencing.

38 As part of our preliminary research, we also compared the Daesh reference corpus to others developed for al-Qaeda in the Arabian Peninsula, al-Qaeda senior leaders, and al-Nusrah Front. We were able to successfully distinguish *Daesh talk* from al-Qaeda. However, for this article, we focused on the Muslim Brotherhood as the main competitor and counterpoint for Daesh rhetoric in Egypt.

39 We gathered tweets from four random weeks per quarter in 2014 for a total of 16 weeks of data.

40 Estimates range from 0.5 percent to 2 percent of users.

To hone our geo-inferencing technique, we performed several dozen tests on different factors to evaluate the discriminatory power of each in filtering users by national-level location.⁴¹ Ultimately, we elected to use both city and province names in the user location field as our geoinferencing filter, resulting in an estimated confidence of at least eighty percent.⁴²

Methods: Corpus Linguistics and Statistical Analysis

Similar to the data sources, analysis methods for this article fall into two categories: Extracting a linguistic model for Daesh measuring resonance of Daesh's language among Egyptians, and aggregating Twitter data. More specifically,

1. We built a linguistic model for Daesh's talk by extracting statistically over-present words and word pairs. This lexical approach pulls out distinctive features from the building blocks of speech, as opposed to a thematic approach at the level of whole messages.
2. We then quantified the match between the Daesh model and Twitter accounts across Egypt questioning if a given Twitter account had a greater than random chance match with Daesh's distinctive language, and how many times the language was a greater than random chance match? These matches were aggregated by region, over the course of a year, to measure the resonance of Daesh's propaganda across Egypt as visible on social media.

Our linguistic model for Daesh uses software-based corpus analysis methods to find patterns in datasets too large for human analysis.⁴³ Our initial model

⁴¹ We used an evaluative approach similar to that used in a number of previous studies. See Eva Cheng, S. J. Davis, I. Burnett, and Christian Ritz, "The Role of Experts in Social Media—Are the Tertiary Educated Engaged?" (Paper presented at Proceedings of the 2010 IEEE International Symposium on Technology and Society: Social Implications of Emerging Technologies, New South Wales, Australia, June 7-9, 2010), available at: <http://ro.uow.edu.au/cgi/viewcontent.cgi?article=10764&context=infopapers>; Bo Han, Paul Cook and Timothy Baldwin, "Text-Based Twitter User Geolocation Prediction," *Journal of Artificial Intelligence Research* 49 (2014): 451, available at: <https://www.jair.org/media/4200/live-4200-7781-jair.pdf>.

⁴² Confidence bounds for geo-inferencing techniques are generally a lower bound of accuracy for that filter, as bounds rely on geo-tagged users as a *ground truth* dataset with which to compare. Given the bias inherent in geo-tagged data, the effect is similar to that of measurement error in our comparison dataset and biases our confidence bound toward zero.

⁴³ The specific software used for this study was RAND-Lex, a RAND developed suite of text analysis tools with modules implementing lexicogrammatical and topic-modeling methods.

was developed through keyness testing, using a log-likelihood approach. Keyness testing identifies conspicuously over present words by comparing how often words appear in a target collection of text, relative to how often we would expect them to appear in a representative sample of language.⁴⁴ In this case, we compared the aforementioned reference corpus for Daesh to a standard representative collection of Modern Standard Arabic.⁴⁵ Keywords identify distinctive features of a text collection and, because they are weighted, the resulting linguistic model is somewhat analogous to a fingerprint analysis. Our initial keyness tests yielded ninety-seven distinct words in Daesh propaganda. To add greater resolution to our model, we also calculated *collocates* for Daesh.⁴⁶

Unlike keywords, collocates are statistically conspicuous because of their (co)location near each other.⁴⁷ While there is always a random possibility of words being near each other in a text, some words appear near each other/in sequence because they have a semantic association: for example, turns of phrase ("You know," "I guess," etc.), or prosodic associations, such as "habitual" with negative words ("offender," "liar," etc.). However, collocates often refer to abstractions, e.g. proper names ("President Obama,") places ("New York City"), or concepts ("mass shootings"). This more refined approach yielded *fifty-one* two-word collocates and nine three-word collocates for Daesh. By adding these to the results of our keyness testing, we were able to detect much smaller variations of resonance among the sub-regions of Egypt.

Equation 1, summarizes how we measured word “keyness.” We used words and collocates that surpassed a keyness threshold of 10.83 log-likelihood ratio and a minimum frequency of twenty, which corresponds to 99.9 percent

44 M. Scott, “Mapping key words to problem and solution,” in Scott M & Thompson G (eds.) *Patterns of Text: in Honour of Michael Hoey* (Amsterdam: Benjamins, 2008), 109-128, p. 110.

45 Motaz K. Saad and Wesam Ashour, “OSAC: Open Source Arabic Corpora,” (paper presented at the 6th International Conference on Electrical and Computer System, European University of Lefke, Lefke, North Cyprus, November 25-26, 2010), available at: doi:10.13140/2.1.4664.9288.

46 In our first efforts, we found that using keywords alone meant only detecting strong resonance; adding collocates increased the granularity of our analysis.

47 Paul Baker, Costas Gabrielatos, Majid Khosravinik, Michal Krzyżanowski, Tony McEnery and Ruth Wodak, “A Useful Methodological Synergy? Combining Critical Discourse Analysis and Corpus Linguistics to Examine Discourses of Refugees and Asylum Seekers in the UK Press,” *Discourse & Society* 19:3 (2008): 273, available at: doi:10.1177/0957926508088962.

confidence that the word(s) distinguish our corpora of interest from more general language use.⁴⁸

Equation 1: Measuring Word “keyness” Through Log Likelihood-Based Frequency Analysis

$$K = 2 \cdot \left(\frac{f_p \cdot \ln \left(\frac{f_p}{f_r} \right) + (N_p - f_p) \cdot \ln \left(\frac{N_p - f_p}{N_p - f_r} \right)}{N_p} + \frac{f_r \cdot \ln \left(\frac{f_r}{N_r} \right) + (N_r - f_r) \cdot \ln \left(\frac{N_r - f_r}{N_t - f_r} \right)}{N_r} \right)$$

Where as:

- f_p Denotes how often the word appeared in specific reference corpus
- f_r Denotes how often the word appears in the general corpus
- N_p Counts the total number of words examined in specific reference corpus
- N_r Counts the total number of words examined in the general corpus
- N_t Counts the total number of words examined in both reference and general corpora

Using this formula, we performed keyness testing on each of the reference corpora mentioned previously.⁴⁹ Table 1, below, is an illustrative sample of keywords from the Daesh and Egyptian Muslim Brotherhood collections, meant to highlight how this method identified distinct language for both groups.

⁴⁸ Donald E. Hardy, *The Body in Flannery O'Connor's Fiction: Computational Technique and Linguistic Voice* (Columbia, SC: University of South Carolina Press, 2007), 98; Dorothy Kenny, *Lexis and Creativity in Translation: A Corpus-based Study* (Abingdon, Oxon: Routledge, 2014), 94.

⁴⁹ Paul Rayson and Roger Garside, “Comparing Corpora Using Frequency Profiling,” (paper presented at Workshop on Comparing Corpora '00 Proceedings of the Workshop on Comparing corpora—Volume 9, Hong Kong, October 7, 2000), available at: doi: 10.3115/1117729.1117730.

Table 1. Sample Keywords (KW) and Log-likelihood score (LL) from Daesh and Muslim Brotherhood Reference Corpora

Islamic States			Muslim Brotherhood		
KW	LL	Translation	KW	LL	Translation
الصفوي	2163	The Safavid	الاخوان	2882	The Brotherhood
الدولة_الاسلامية	643	#The_Islamic_State	الانقلاب	1631	The Coup
الخلافة	640	the caliphate	الشعب	914	The People
الفلوجة	427	Fallujah	الجماعة	434	The Association
البيشمركة	360	The Peshmerga	المصري	395	The Egyptian
الرافضي	271	The Rafidhi	مصر	332	Egypt
الدولة	259	The State	الرئيس	329	the president
الاسلامية	585	The Islamic	الثوار	319	The Revolutionaries
القاعدة	123	Al-Qaeda	جماعة	266	The group
العراق	78	Iraq	الانقلابيين	265	The coup-supporters
الشام	62	Sham	الارهاب	257	The terrorism

We wish to point out here that machine-based corpus analysis and human expert analysis will identify different features distinctive about a group's language. Whereas human analysis is very well suited to identifying macro-level themes and concepts in Daesh's public talk, machine-based approaches are well suited to detecting the weak signal of micro-level word frequencies. Think of a human expert that can visually identify architectural styles at the level of buildings, and a machine that can detect architectural styles at the level of bricks and mortar—both are looking at the same thing, but using different levels of features.⁵⁰

Given this linguistic model based on distinctive words, we were then able to quantify accurately the degree of match between Daesh and every Egyptian Twitter user. To do this, we first summed the likelihood scores of all keywords and collocates that appear in each user's Tweets. Second, we calculated the sum given the total number of words that appeared in the user's Tweets, and the frequency/average score of keywords and collocate among all Tweets. Equation 2, illustrates this approach.

⁵⁰ Sarah Allison, Ryan Heuser, Matthew Jockers, Franco Moretti and Michael Witmore, "Quantitative Formalism: An Experiment," *Machine Politics* 13 (2012) Available at: <https://nplusonemag.com/issue-13/essays/quantitative-formalism-an-experiment/>.

Equation 2: Egyptian Twitter User's Resonance Score

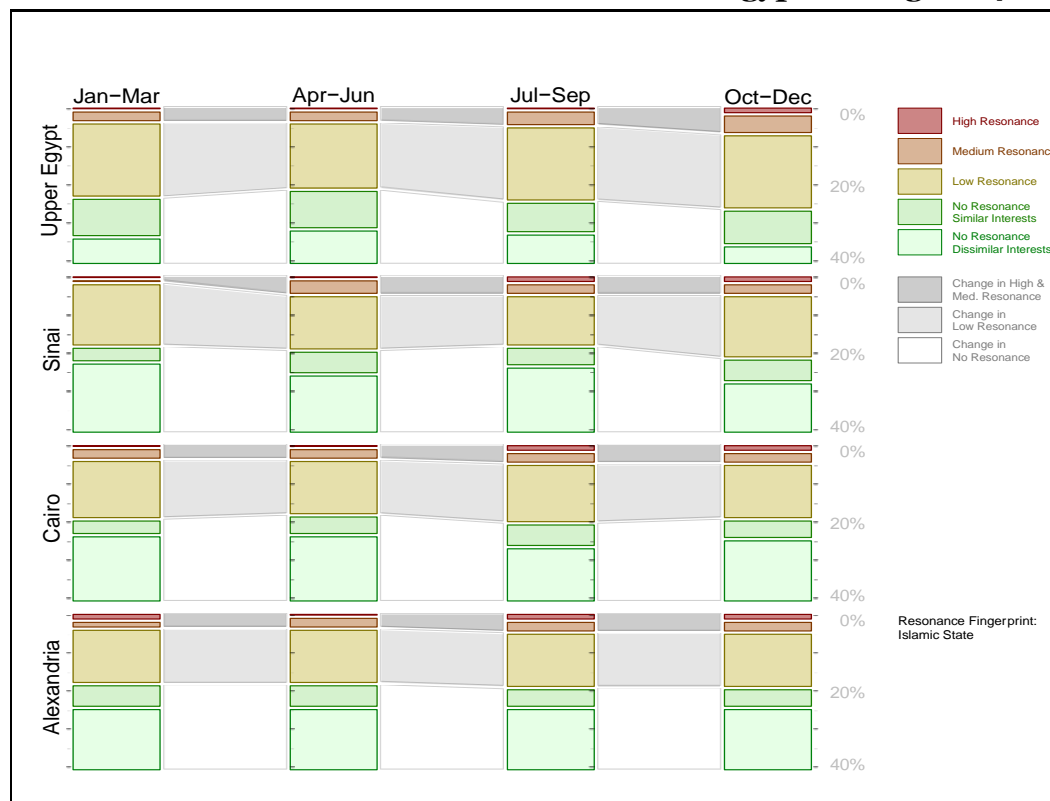
$$\frac{\sum_i (f_{ik} L)}{N_i \cdot \{\sum (f_k L) N^{-1}\}}$$

Whereas:

- N_i Counts the number of words appearing in User i's tweets
- N Counts the number of words appearing in the tweets of all sampled users
- f_{ik} Denotes the frequency with which a set of keywords and collocates appears in user i's tweets
- f_k Denotes the frequency with which a set of keywords and collocates appears in the tweets of all users
- L Scores each keyword according to how much more likely it is to appear in accounts promoting a certain worldview, compared to a reference corpus.

Results

Table 2 reports the findings from our analysis. It illustrates the extent to which Daesh's worldview resonated with residents of the four sub-regions of Egypt – the Sinai Peninsula, Cairo/Nile Delta, Alexandria/Coast and Upper Egypt—in 2014, as indicated through their Twitter use.

Table 2. Resonance of Daesh's Worldview in Egypt during 2014

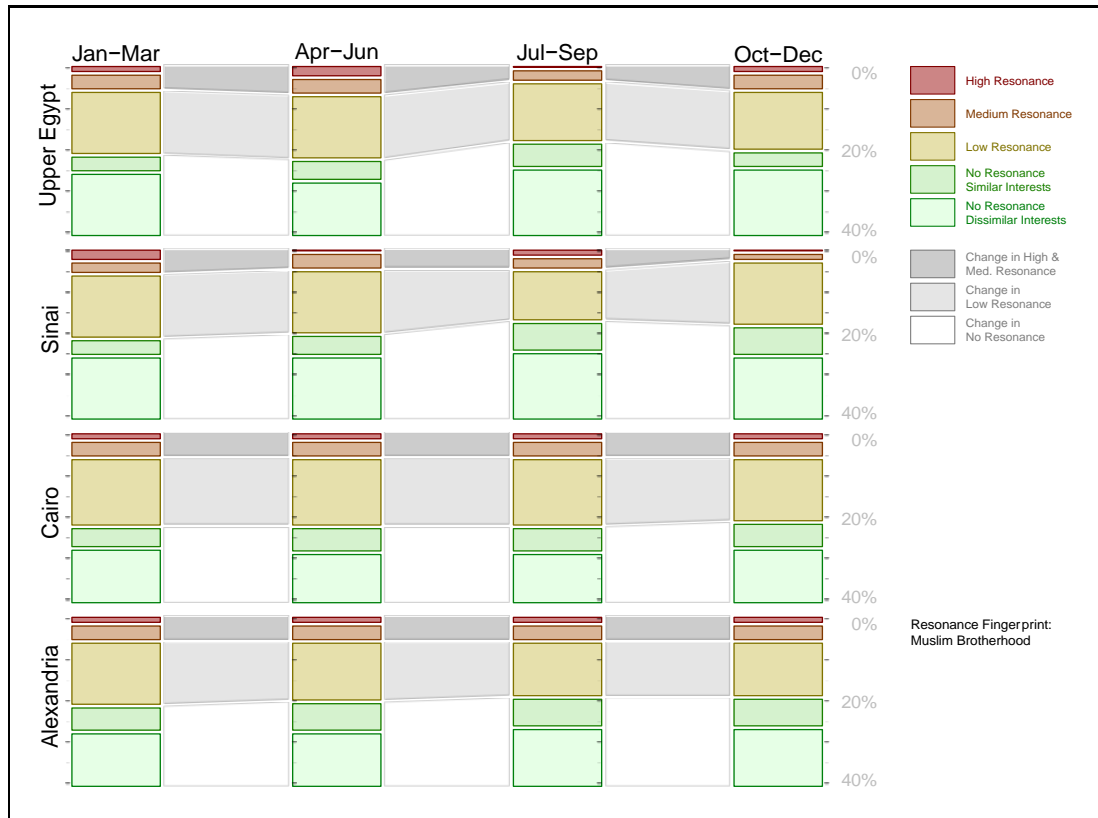
For each region, four stacked bar graphs go from left to right, corresponding to the four quarters of the 2014 calendar year. Each bar graph measures the proportion of Twitter users, in the defined region and time-period, whose tweets echo the worldview articulated by Daesh.⁵¹ The bar graphs are color coded in a “stoplight style:” red indicates that an account used 500 percent more Daesh language than we would expect by random chance alone, orange indicates 300 percent, yellow indicates 150 percent, and green users with no more Daesh language than we would expect by random chance alone.. The gray shaded segments between each bar graph highlight changes from one quarter to the next within each region and segment of resonance.

We chose to divide the results at 500 percent, 300 percent, and 150 percent based on their correspondence to P values across our test cases. The precise correspondence varies with the number of keywords, the average keyness score of keywords, and the total number each user’s words available for examination. However, 300 percent was consistently sufficient to identify

⁵¹ Given that each region as at least 40 percent of population scoring at “No Resonance,” the axis is truncated there to make the table more viewable

resonant users with just 1,000 words of user text at P values < 0.05 , and 500 percent was consistently sufficient to achieve P values < 0.05 with just 500 words of user text. One hundred fifty percent is generally statistically significant with a 5,000 sample of user words, but we report here to measure the number of users who might potentially be vulnerable to future radicalization. That said, we caveat that these cutoffs are statistically sensible, but not substantively meaningful—we do not know what level of resonance corresponds to a high likelihood of providing aid to or signing up to fight with Daesh. Future research is necessary to establish better the link between social medial outputs, and motivation to take real world action.

The data in Table 2 suggests that only one to two percent of Twitter users pass the threshold for high resonance with Daesh. Even lumping high and medium resonance, the total never exceeds – and tends to fall well short of – five percent of Twitter users within each region. Daesh’s way of talking and conceptualizing the world is highly salient to just a small sliver of the population in Egypt. However, resonance among this minority is intensely strong. On average, Twitter users who fell above the 300 percent threshold were 920 percent more likely to use words matching the Daesh linguistic fingerprint, compared to the word use we would expect by random chance along. Daesh’s fervent supporters may be relatively few in number, but they are firmly ensconced in the worldview. Moreover, their numbers grew throughout 2014. In the first quarter, two to four percent of Twitter users in each region meet the 300 percent threshold. By the last quarter, five to seven percent of users in each region passed threshold. The strongest gains occurred in the Sinai and Upper Egypt.

Table 3. Resonance of the Muslim Brotherhood's Worldview in Egypt during 2014

We also examined our data from the linguistic “fingerprint” of the Muslim Brotherhood -- an organization with similar Salafist ideological roots, but without Daesh’s violent extremism. In keeping with their similar ideological roots, there is strong overlap between those passing the 150 percent threshold for one group—showing some potential to become more firmly committed to the ideology in the future—and those passing it for the other. In fact, users who score as weakly resonant with one group are sixty percent more likely to score as weakly resonant with the other, compared to what we would expect by random chance alone.

Daesh and the Muslim Brotherhood’s populations deviate, however, in the higher thresholds of resonance. The Muslim Brotherhood had a larger, more stable cadre of high to medium resonant users for most of the year—consistently hovering around six percent in most areas throughout the year—and users almost never stop being Muslim Brotherhood resonant to start

being Islamic State resonant. In fact, there are only thirteen cases of resonance switching out of a sample containing over 30,000 user accounts.⁵²

In most areas, the Muslim Brotherhood platform appears to have kept pace with Daesh, but not in the Sinai. In that region alone, the number of twitter accounts passing the 300 percent threshold for the Muslim Brotherhood dropped by half, while those passing threshold for the Islamic State rose by a commiserate amount.

Validating the Method

Since our methodology approach involves novel features, we carried out a series of additional tests to assess the validity of our procedure. This section presents the results of those tests. Each test involved an “event” that we assumed would have high salience for a large segment of the Egyptian populations, and therefore, would produce a noticeable spike in social media activity. Each event is either salient during a specific timeframe or in a specific region. This allowed us to compare our social media measurements against known conditions on the ground.⁵³ Table 4, lists the events.

Table 5: Timing by Regionality Matrix

	<i>Not Year Round</i>	<i>Year Round</i>
<i>Affected One Region</i>	Bombing of Bus Carrying Korean Tourists in the Sinai	Car Bombings of Military Installations in the Sinai
<i>Affected All Regions</i>	Influenza Outbreaks (Lull During the Summer)	MB / IS Activities and Ideology

With respect to regions, two of our four test-events took place in the Sinai. We chose these events because the Sinai represented the lowest population of Twitter users across the four sub-regions, and thereby tends not to trend on Twitter unless something newsworthy has taken place. In both of the event-tests, the Sinai region registered the largest number of Twitter users “resonating” with the news event. This suggests that our methodology is able to accurately detect geographic differences in resonance.

⁵² Nine cases of Muslim Brotherhood resonators became Islamic State resonant, and four cases of Islamic State resonators became Muslim Brotherhood resonant.

⁵³ Methodological differences exist between detecting talk about an event and adopting language from a group.

We also tested based on timing. Two of our four tests involved predictable variation in timing over the course of 2014. The bombing of a bus carrying Korean tourists happened on an exact day, while influenza activity (unusually high in 2014) typically experiences a pronounced lull during the summer. Both tests cautioned that the relationship between twitter activity and event timing is more complex than its relationship with geographic proximity. In the case of the bus bombing, the Cairo and Alexandria regions show the expected pattern—resonance was highest in the first quarter, and declined thereafter. However, in Sinai, where the bombing took place, resonance continued to grow in the second quarter. In the case of influenza, resonance declined in all four regions during the summer, as expected, but the decline in percentage of resonant users was smaller than we initially expected. Thus, while both tests suggest that Twitter resonance does reflect the timing of events, they also suggest a certain degree of inertia—the social media conversation can fuel itself, even as the inciting event becomes more distant.

Conclusion

This article used an innovative combination of corpus linguistics and statistical methods to gain insight into one of the most salient threats to US national security today: Daesh and its appeal to local populations outside Iraq and Syria. To do this, we measured the uptake of Daesh propaganda in four sub-regions of Egypt for 2014. The findings suggest that only a limited proportion of Twitter users echo the discourse of Daesh's worldview, but where there is support is intense. Further, Daesh's discourse gained ground during the course of 2014 in the Sinai and (to a lesser extent) Upper Egypt, especially in comparison to the Muslim Brotherhood.

In terms of the methodology, our findings suggest that resonance analysis can serve as a measure of effectiveness of messaging efforts, by detecting and quantifying the uptake of a particular discourse (and implicit framing of the world) among a populace over time. If applied correctly, United States policymakers and their partners overseas can use these methods to triage counter-messaging efforts against extremist group's recruitment and expansion. We point out this approach also can be used to assess the effectiveness of countering violent extremism (CVE) programs: we can turn this lens on our own efforts.

While we acknowledge serious limitations with this method (social media data is not representative, and measuring uptake tells us nothing about the *why's* of any change), in comparison to many other approaches to population

observation, this methodology is highly cost effective to apply as mass scale. It uses off-the-shelf technology, lightweight computational strategies to enable analysis of large data with relatively few computational resources, and relies on social media data, which is affordable, available in real time, and of proven relevance in CVE efforts.

Beyond these applications, we believe resonance analysis helps evaluate the potential second- and third-order effects of counter-terrorism efforts on local populations. For example, one can assess whether resonance with Daesh increases because of airstrikes against senior leaders or operatives, use it as an indicator of recruitment effects, or as an indicator of shifts in support in response to specified counterterrorism measures. Finally, resonance is a methodology that allows policymakers to capture quickly and less expensively socio-cultural dynamics essential in mitigating the threats posed by violent extremists.