

RESEARCH NOTE

The effect of drone strikes on civilian communication: evidence from Yemen

Fotini Christia¹ , Spyros I. Zoumpoulis² , Michael Freedman^{3,4} , Leon Yao¹ and Ali Jadbabaie^{1*}

¹Massachusetts Institute of Technology, Cambridge, Massachusetts, USA, ²INSEAD, Fontainebleau, France, ³University of Haifa, Haifa, Israel and ⁴Hebrew University of Jerusalem, Jerusalem, Israel

*Corresponding author. Email: jadbabaie@mit.edu

(Received 19 May 2020; revised 23 September 2020; accepted 3 November 2020)

Abstract

Although covert warfare does not readily lend itself to scientific inquiry, new technologies are increasingly providing scholars with tools that enable such research. In this note, we examine the effects of drone strikes on patterns of communication in Yemen using big data and anomaly detection methods. The combination of these analytic tools allows us to not only quantify some of the effects of drone strikes, but also to compare them to other shocks. We find that on average drone strikes leave a footprint in their aftermath, spurring significant but localized spikes in communication. This suggests that drone strikes are not a purely surgical intervention, but rather have a disruptive impact on the local population.

Keywords: Measurement

In this note, we propose new ways to study the effects of unmanned aerial vehicles that play an important role in America's wars. Drones, fitted with missiles to track and target individuals or groups often in remote areas, are a weapon increasingly employed in conflict zones around the world (Weidmann, 2015; Berman *et al.*, 2018). They can loiter above battlefields for 24 hours while pilots remain out of harm's way (Williams, 2013). People on the ground, including the targets, do not know of an impending attack until seconds before a missile makes impact. The US army and the CIA have launched drone strikes targeting suspected militants in Pakistan, Yemen, and Somalia.

Existing attempts to study the effects of drone strikes confront a paucity of information. Some scholars assail them as ineffective and even counterproductive (Boyle, 2013; Hazelton, 2017). Others contend the opposite: they inflict little harm on civilians and decimate terrorist organizations (Jordan, 2014; Mir, 2018; Mir and Moore, 2019). It has proven difficult to settle these debates as these new forms of stealth warfare are by their very nature hard to study using existing methods such as in-the-field interviews, survey experiments, or randomized controlled trials. Even when possible, these means of data collection are likely to be confronted with several sources of bias (Beath *et al.*, 2013; Blair *et al.*, 2013, 2014). Our research note highlights how tools from emerging technologies such as big data and improved computational methods could be effectively brought to the task.

Specifically, we overcome obstacles associated with data collection by examining how exogenous drone strikes impact levels of communication, with an original dataset of over 9-billion call detail records (CDRs). These CDRs consist of time- and antenna-stamped indicators of calls, offering high temporal and spatial resolution along with extensive coverage. Researchers have drawn on cellphone data generally (Gonzalez *et al.*, 2008; Eagle *et al.*, 2009; Blumenstock, 2012, 2016) and CDRs specifically, to examine the change in patterns of communication after

emergencies (Candia *et al.*, 2008; Bagrow *et al.*, 2011). But leveraging CDRs to study conflict is both novel and, we believe, a promising way to shed light on the impact of opaque phenomena, such as drone strikes, on civilians in data poor contexts (Lazer *et al.*, 2014; Bertolotti *et al.*, 2020).

We spatially combine call data with information on drone strikes from the New America Foundation and the Bureau of Investigative Journalism (SI Data Appendix). We focus our examination on the effects of drone strikes on nationwide cell phone usage in Yemen from 2010 to 2012, a critical time when al-Qaeda took control of swathes of territory and the United States escalated its campaign of drone strikes in response.

The large scale of our data lends itself to anomaly detection methods analysis, which enables us to examine the intensity and duration of *individual* strikes. Our anomaly detection methods achieve this by constructing a statistical model for “normal behavior” using a training dataset, and then calculate the likelihood that a test instance has been generated from the learnt model. If a test instance has sufficiently low probability of being generated, it is considered an anomaly. Anomaly detection analysis overcomes the limitations of traditional fixed effects methods (which only provide a reliable estimate of the *average* effect of drone strikes), while also giving us better contextual understanding of the effects as it allows for comparisons of drone strikes to other violent and non-violent events.

Our study suggests that the impact of drone strikes in Yemen is not purely surgical. Violence causes persistent disruptions to those living nearby—even when it is as “precise” as a drone strike. Rather than affecting only militants, drones appear to have a wider ripple effect on the civilian population in the broader strike area. As the United States increasingly moves away from deploying boots on the ground and turns to indirect means of warfare, these effects are worth bearing in mind. As well, we find that drone strikes have a higher impact than al-Qaeda attacks in Yemen, even though the latter get more media attention.

These findings suggest that CDRs can be leveraged for modeling and predicting the impact of conflict, including hard-to-measure phenomena such as drone strikes or militant attacks. Furthermore, our findings allow for the comparison of drone strikes to other violent and non-violent events such as conventional strikes and civilian targeted attacks, as well as religious holidays and popular sports events. Although we identify an increase in call volume, we are unable to assess *how* this increased communication facilitates the continuation or end of conflict, and how militant groups might use such events to recruit supporters in affected areas as we have no information on call content. These remain important questions for future study.

Our note highlights the need for a broader research agenda on the theories and mechanisms behind big data empirical research on covert warfare. With our discipline shifting toward big data empirics and machine learning tools, traditional in-the-field survey work and qualitative research will remain an essential complement for scientific inference.

1. Theory

Existing literature has examined the effects of drone technology on a variety of dependent variables. These include the organizational longevity or capacity of a warring group (Price, 2012; Jordan, 2014; Shah, 2018), the group’s ability to carry out terrorist attacks (Johnston *et al.*, 2016), and long-term stability of and relations with the target country and its population (Johnston, 2012; Boyle, 2013; Horowitz *et al.*, 2016). We extend this research by examining the broader impact of drone strikes on civilian daily life, as civilians have a significant impact on the dynamics of conflict, given their capacity to either aid insurgents or cooperate with the government (Berman *et al.*, 2018). We measure the impact of drone strikes on civilian lives by utilizing changes in real-time call volume during drone strikes. In the broader literature, call volume has been frequently leveraged as a proxy to measure the scale and duration of an emergency among the general population (Wang *et al.*, 2020). It has been used in diverse contexts ranging from natural disasters (Tomaszewski, 2014), to the spread of disease (Baldo and Closas, 2013;

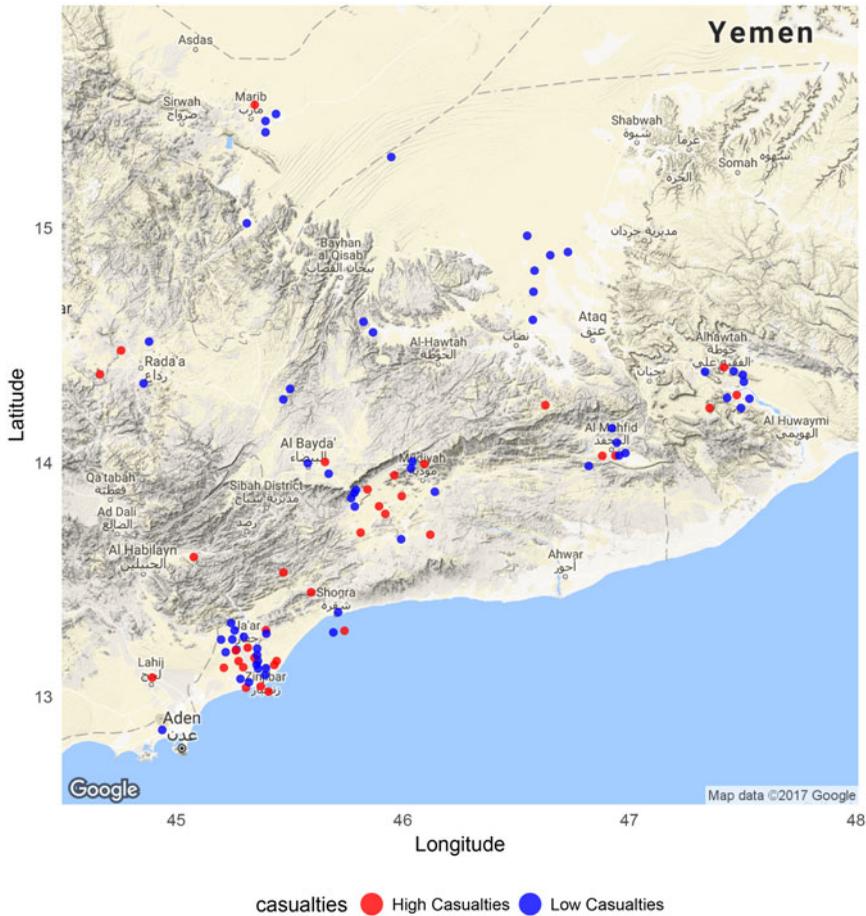


Figure 1. Drone Strikes in Yemen from 2010 to 2012. We label as high-casualty strikes with ten or more dead. See Table S1 for summary statistics.

Lima *et al.*, 2015; Tompkins and McCreesh, 2016; Mari *et al.*, 2017), and population displacement (Bozcaga *et al.*, 2019). Beyond emergencies, call volume has served as a proxy for other social phenomena such as poverty and socio-demographics (Blumenstock and Eagle, 2012; Blumenstock, 2016).

As noted by Bertolotti *et al.* (2019), changes in call volume are also associated with other broader negative outcomes such as civilian displacement. We argue that measuring changes in call volume can proxy to what extent people register drone strikes as physical threats and social disruptions. Such disruptions are also likely to impact civilian support for operations against militants (Boyle, 2013; Horowitz *et al.*, 2016).

2. Data

Drone strikes in Yemen have a relatively long history: indeed, the first American drone strike outside of a war zone occurred in Yemen in 2002, when the USA killed a member of al-Qaeda believed to be behind the attack on the USS Cole in 2000. According to the New America Foundation, there have been over 370 US drone strikes in Yemen that have killed over 1200 militants. Between January 2010 and October 2012, the United States launched 108 drone strikes and

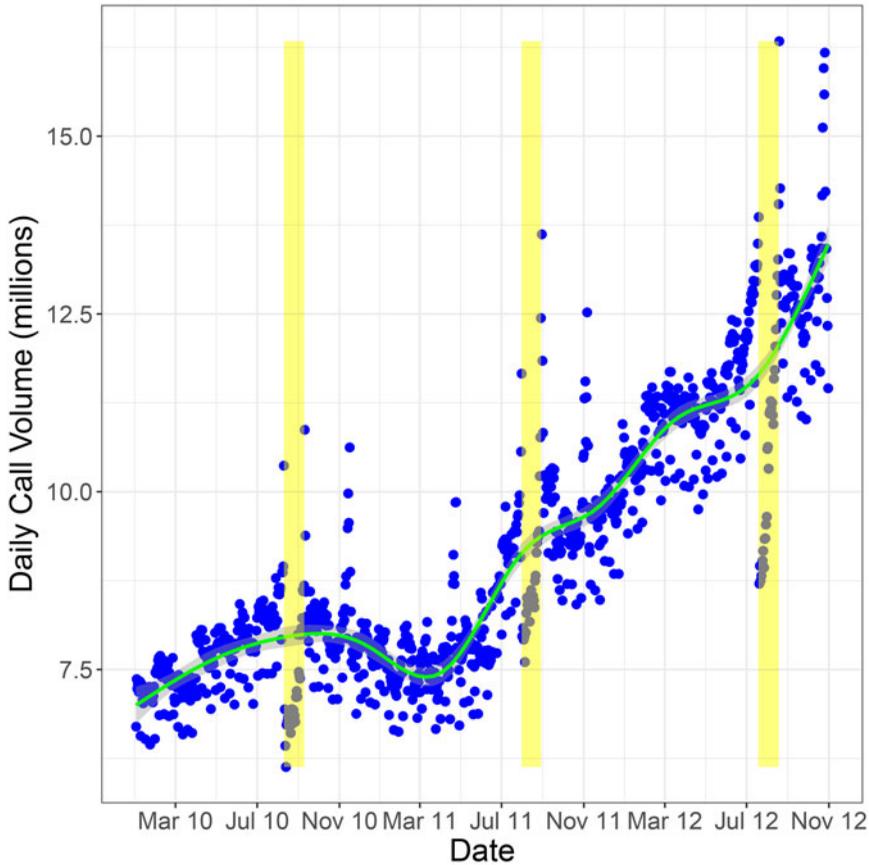


Figure 2. Daily call volume across Yemen including incoming and outgoing calls. Ramadan periods are highlighted in yellow.

other covert actions in Yemen. Drone strikes peaked in 2012 as part of a larger campaign to retake territory from Islamic movements in the aftermath of the 2011 Yemeni revolution. Each entry in the strike dataset includes the date, location, and estimates for militant and civilian casualties. For most strikes, we also know the estimated time of day of the strike, the type of target, and whether militant leaders were killed. [Figure 1](#) shows drone strike locations for the period under study. Many strikes occurred in the southwestern towns of Zinjibar and Jaar, where government forces battled Islamist groups for control. The majority of strikes caused fewer than ten casualties (Table S1).

With the cooperation of a major cellphone service provider in Yemen, we obtained nationwide CDRs for our three years of interest. This trove of data, encompasses more than 9 billion incoming and outgoing calls by 40 million distinct and fully anonymized phone numbers. For each call, we possess a unique anonymized identifier for who initiated the communication and for who received the call; the start and end time of the communication; and an identifier of the tower that serviced the communication on the side of the initiator and recipient. We also obtained information on the location of each cellular tower.

The data are broadly representative of communication patterns among Yemenis. In 2010, Yemen's population stood at 23.5 million, and although it had low Internet penetration and no mobile data network available at the time, a large proportion of Yemenis owned cell phones and predominantly drew on them during this period to make calls, rather than access the Internet

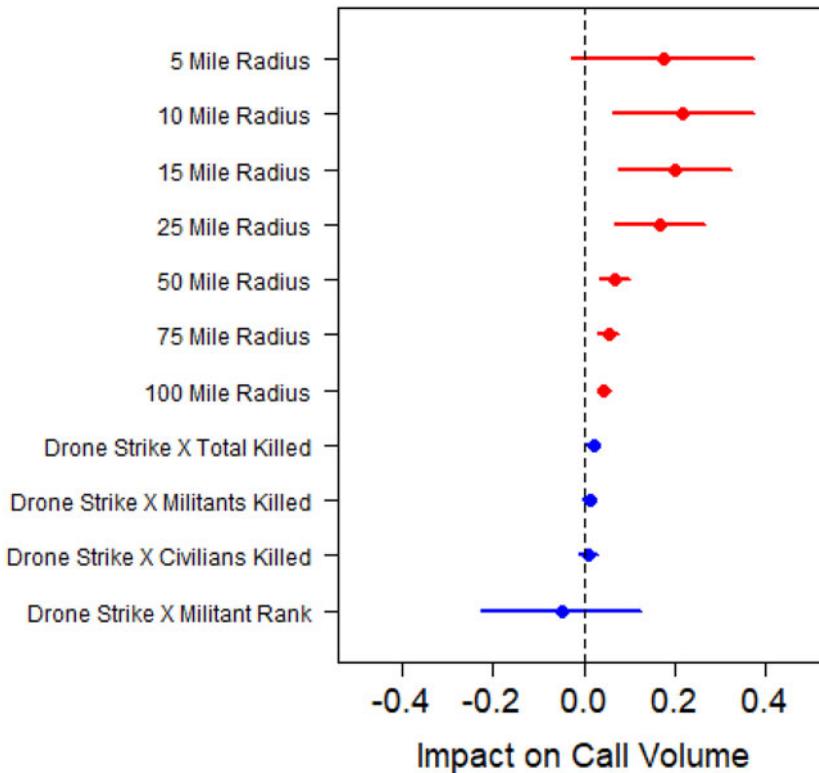


Figure 3. Impact of drone strikes on call volume. The plot shows the coefficients and 95 percent confidence intervals from separate regressions using our OLS panel two-way fixed effects regression. Our model includes fixed effects for the tower and month and a covariate for uncertainty of the time of the strike. Standard errors are clustered by tower.

or social media sites (Gelvanovska *et al.*, 2014). Figure 2 plots the total number of daily calls serviced by all towers across Yemen in our data. Daily call volume increased on average from around 7 million in early 2010 to over 13 million in late 2012.

3. Results

We present two sets of empirical results. First, we use a traditional panel setup with two-way fixed effects that exploits the temporal and spatial variation in drone strikes. Thus, our strategy is similar in spirit to a difference-in-differences approach that uses the variation of drone strikes over space and time to control for possible space- or time-specific effects. However, this design does not strictly allow for making causal inferences (Papadogeorgou *et al.*, 2020).

Our main dependent variable is call volume (incoming and outgoing), which captures levels of civilian communication in Yemen. To account for the fact that people's call patterns differ by time of day, we divide the day's calls into three tighter 8-hour intervals: morning, midday, and evening. Subsequently, we aggregate our spatial data by 8-hour intervals for each unique tower location. To account for overall call volume increases over time between 2010 and 2012, we normalize call volume. Our main treatment variable is the occurrence of a drone strike within a given proximity.

The results in Figure 3 indicate that the impact of drone strikes is strongest for towers within a short range of 5 to 25 miles. Drone strikes increase call volume by about one-fifth of a standard deviation on average, representing about 850 calls during an 8-hour span for each of the

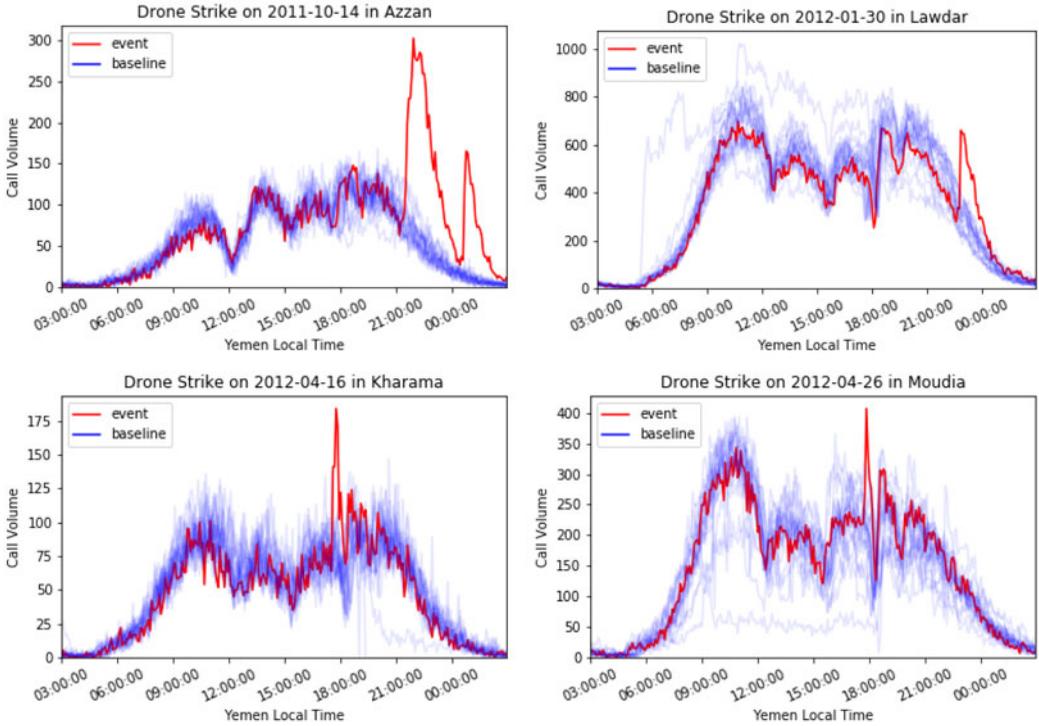


Figure 4. Spikes in the call volume due to strikes. Call volume over time on the day of the strike, in red, as compared to call volume on 20 baseline days (same day of the week, for the ten weeks preceding and the ten weeks following the attack), in blue, for four strikes that our anomaly detection methods detect.

surrounding towers. The impact remains significant on towers within a 100-mile range, although the effects are weaker (about one-tenth of a standard deviation).

Our results are robust to different model specifications (Tables S2 and S3) and varying measures of call volume (Tables S4 and S5). We also show that our results are not driven by tower shutdowns, drone strikes during conflict, the holy month of Ramadan, multiple drone strikes on the same day, or bots (Table S6). We also test whether call volume depends on the nature and number of targets. We rerun our main specification with a series of interaction models. We find that drone strikes have a larger impact on call volume when there are more casualties. Although militant casualties prove more influential than civilian ones, militant rank does not play a role (Figure 3).

Although the fixed effects methods provide a reliable estimate of the average effect of drone strikes, we also employ anomaly detection methods to learn about the impact of individual strikes, including the duration and intensity. Our anomaly detection methods apply a statistical test to compare the observed volume of calls during each five-minute interval against a baseline sample of “normal behavior,” and determine whether the realization is likely to be part of normal behavior, or rather is anomalous (Figure 4).

We test three prominent anomaly detection methods on the classification task of deciding between strikes and non-strikes, based only on the volume of calls, and without knowledge of whether a strike happened or not.¹

¹As noted in our Appendix on anomaly detection methods, the detection settings are selected so as to maximize the area under the ROC (Receiver Operating Characteristic) curve (AUC). For a given ROC curve, the detection threshold is selected so as to maximize the true positive rate of the classifier, subject to restricting the false positive rate below a threshold, thus

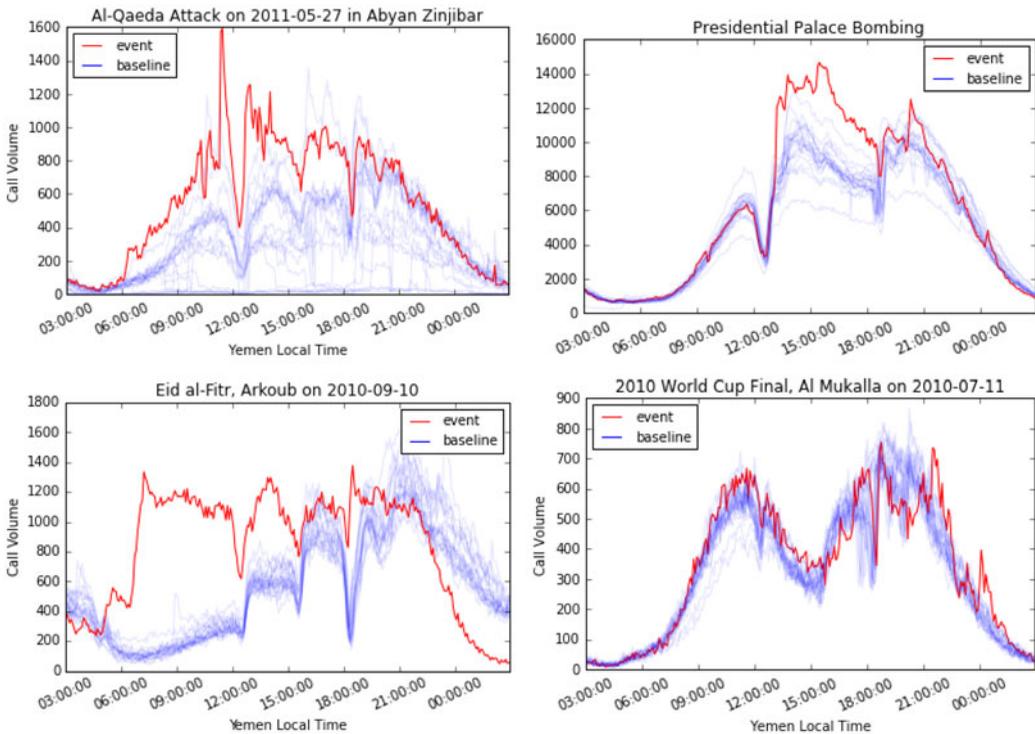


Figure 5. Detection of non-drone strike events. The call volume the day of the event, in red, is compared against the baseline call volume, in blue.

Using the selected anomaly detection settings, we detect up to 58.1 percent of all strikes with a tower within 15 miles in the dataset, indicating that the majority of strikes have a significant impact on communication patterns in Yemen. Across our selected detection settings, we find that the median duration of a call volume anomaly among the detected strikes is between 75 and 100 minutes (Figure S3). The median largest deviation in the volume of calls (z -value) during a five-minute interval is about four to five standard deviations above the mean volume (Figure S3). Overall, we find strong evidence that drone strikes have a notable impact on patterns of communication, and that our results are not driven by a few well-publicized strikes.

Drone strikes are just one type of shock detected by our anomaly detection methods. To place them in context, it is important to analyze other shocks as different event attributes (type of violence, localization, and duration) can contribute to how people react to an event. Thus, we compare the effects of drone strikes to other violent episodes, such as al-Qaeda militant attacks and the bombing of Yemen's Presidential Palace during the Arab Spring; the religious holiday marking the end of the Islamic holy month of Ramadan (Eid al-Fitr); and the big sports event of 2010 men's soccer FIFA World Cup final.

Our results suggest that instantaneous violent events, such as drone strikes and the Presidential Palace bombing during the Arab Spring, yield significant but localized effects on call volume. On the other hand, Al-Qaeda attacks, which are violent but protracted events in the Yemeni context as they include battlefield combat, register no such effect (Figure 5). As for nonviolent phenomena, consistent with expectation, we find they have a countrywide rather than a localized effect:

balancing sensitivity and specificity. All the proposed anomaly detection methods have an AUC higher than 0.70 (Method 1: 0.710, Method 2: 0.728, Method 3: 0.736), indicating a good classification performance (Figures S1 and Figure S2)

Yemenis across the country make many more calls on the religious celebration of Eid al-Fitr than on a typical weekday during Ramadan. The World Cup final, a popular event in soccer-loving Yemen, causes nationwide spikes in call volume corresponding to key junctures during the game (Figure 5).

4. Discussion

Three US presidents since 2001 have embraced drones as a preferred means for striking suspected militants. As demand for such actions continues, we find that drone strikes are disruptive, leaving a clear and measurable communications footprint. The methods and data presented here provide a framework for combining machine learning techniques with other analytic tools to capture the effects on cellphone communication brought about by exogenous violent shocks such as drone strikes. Although we hope this starts a broader research agenda on the theory and mechanisms behind this effect, we want to emphasize the added value of combining results from a traditional panel fixed effects model with anomaly detection methods. Beyond providing robust empirics, this combination allows us to quantify the effects of drone strikes and compare them to other shocks such as bombings, al-Qaeda attacks, or important religious and social events. Our findings suggest that drone strikes have a disruptive effect with a notable local increase in communications, a result consistent with other studies suggesting that drone strikes cause information cascades within networks, as well as increased displacement (Bertolotti *et al.*, 2019).

The nature of the data, however, divulges nothing about call content or how militants, religious leaders, or other influential figures may use them as rallying cries for increased violence (Hudson *et al.*, 2012; Dafoe and Lyall, 2015; Shapiro and Weidmann, 2015). In-the-field data collection such as interviews or survey work will remain an important complement to contextualizing such big data work.

Supplementary material. The supplementary material for this article can be found at <https://doi.org/10.1017/psrm.2021.22>.

Acknowledgments. Fotini Christia and Ali Jadbabaie recognize support from ARO MURI award No. W911NF-121-0509.

References

- Bagrow JP, Wang D and Barabási A-L** (2011) Collective response of human populations to large-scale emergencies. *PLoS ONE* **6**, e17680.
- Baldo N and Closas P** (2013) Disease outbreak detection by mobile network monitoring: a case study with the D4D datasets in Proceedings of third conference on the Analysis of Mobile Phone Datasets (NetMob 2013), 1-3 May 2013, MIT, Cambridge, MA (USA). *NetMob D4D Challenge* 1-4.
- Beath A, Christia F and Enikolopov R** (2013) Empowering women through development aid: evidence from a field experiment in Afghanistan. *American Political Science Review* **107**, 540-557.
- Berman E, Felner JH and Shapiro JN** (2018) *Small Wars, Big Data: The Information Revolution in Modern Conflict*. Princeton University Press. ISBN 9780691177076.
- Bertolotti P, Christia F and Jadbabaie A** (2019) The social network effects of drone strikes. *Working Paper*.
- Bertolotti P, Jadbabaie A and Christia F** (2020) Tests for network cascades via branching processes. *IEEE Transactions on Network Science and Engineering* **7**, 2693-2701.
- Blair G, Fair CC, Malhotra N and Shapiro JN** (2013) Poverty and support for militant politics: evidence from Pakistan. *American Journal of Political Science* **57**, 30-48.
- Blair G, Imai K and Lyall J** (2014) Comparing and combining list and endorsement experiments: evidence from Afghanistan. *American Journal of Political Science* **58**, 1043-1063.
- Blumenstock JE** (2012) Inferring patterns of internal migration from mobile phone call records: evidence from Rwanda. *Information Technology for Development* **18**, 107-125.
- Blumenstock JE** (2016) Fighting poverty with data. *Science* **353**, 753-754.
- Blumenstock JE and Eagle N** (2012) Divided we call: disparities in access and use of mobile phones in Rwanda. *Information Technologies and International Development* **8**, 1-16.
- Boyle MJ** (2013) The costs and consequences of drone warfare. *International Affairs* **89**, 1-29.

- Bozcaga T, Christia F, Daskalakis C, Harwood E and Papadimitriou C** (2019) Assessing Syrian refugee integration using call detail records from Turkey. In AA Salah, A Pentland, B Lepri and E Letouzé (eds). *Guide to Mobile Data Analytics in Refugee Scenarios*. Springer, pp. 223–249. ISBN 978-3-030-12554-7.
- Candia J, González MC, Wang P, Schoenharl T, Madey G and Barabási A-L** (2008) Uncovering individual and collective human dynamics from mobile phone records. *Journal of Physics A: Mathematical and Theoretical* **41**, 224015.
- Dafoe A and Lyall J** (2015) From cell phones to conflict? Reflections on the emerging ICT-political conflict research agenda. *Journal of Peace Research* **52**, 401–413.
- Eagle N, Pentland ASS and Lazer D** (2009) Inferring friendship network structure by using mobile phone data. *Proceedings of the National Academy of Sciences* **106**, 15274–15278.
- Gelvanovska N, Rogy M and Rossotto CM** (2014) *Broadband Networks in the Middle East and North Africa: Accelerating High-Speed Internet Access*. Directions in Development—Communication and Information Technologies, Washington, DC: The World Bank. © World Bank. <https://openknowledge.worldbank.org/handle/10986/16680>. License: CC BY 3.0 IGO.
- Gonzalez MC, Hidalgo CA and Barabasi A-L** (2008) Understanding individual human mobility patterns. *Nature* **453**, 779–782.
- Hazelton JL** (2017) Drone strikes and grand strategy: toward a political understanding of the uses of unmanned aerial vehicle attacks in US security policy. *Journal of Strategic Studies* **40**, 68–91.
- Horowitz MC, Kreps SE and Fuhrmann M** (2016) Separating fact from fiction in the debate over drone proliferation. *International Security* **41**, 7–42.
- Hudson L, Owens CS and Callen DJ** (2012) Drone warfare in Yemen: fostering emirates through counterterrorism?. *Middle East Policy* **19**, 142–156.
- Johnston PB** (2012) Does decapitation work? Assessing the effectiveness of leadership targeting in counterinsurgency campaigns. *International Security* **36**, 47–79.
- Johnston PB, Sarbahi AK, Dylan B-L, Gabriel K-D, Don R and Muhammad AU** (2016) The impact of US drone strikes on terrorism in Pakistan. *International Studies Quarterly* **60**, 203–219.
- Jordan J** (2014) The effectiveness of the drone campaign against Al Qaeda central: a case study. *Journal of Strategic Studies* **37**, 4–29.
- Lazer D, Kennedy R, King G and Vespignani A** (2014) The parable of Google flu: traps in big data analysis. *Science* **343**, 1203–1205.
- Lima A, De Domenico M, Pejovic V and Musolesi M** (2015) Disease containment strategies based on mobility and information dissemination. *Scientific Reports* **5**, 10650.
- Mari L, Gatto M, Ciddio M, Dia ED, Sokolow SH, De Leo GA and Casagrandi R** (2017) Big-data-driven modeling unveils country-wide drivers of endemic schistosomiasis. *Scientific Reports* **7**, 489.
- Mir A** (2018) What explains counterterrorism effectiveness? Evidence from the U.S. drone war in Pakistan. *International Security* **43**, 45–83.
- Mir A and Moore D** (2019) Drones, surveillance, and violence: theory and evidence from a US drone program. *International Studies Quarterly* **63**, 846–862.
- Papadogeorgou G, Imai K, Lyall J and Li F** (2020) Causal inference with spatio-temporal data: estimating the effects of airstrikes on insurgent violence in Iraq. *arXiv preprint arXiv:2003.13555*.
- Price BC** (2012) Targeting top terrorists: how leadership decapitation contributes to counterterrorism. *International Security* **36**, 9–46.
- Shah A** (2018) Do US drone strikes cause blowback? Evidence from Pakistan and beyond. *International Security* **42**, 47–84.
- Shapiro JN and Weidmann NB** (2015) Is the phone mightier than the sword? Cellphones and insurgent violence in Iraq. *International Organization* **69**, 247–274.
- Tomaszewski B** (2014) *Geographic information systems (GIS) for disaster management*. New York: Routledge.
- Tompkins AM and McCreesh N** (2016) Migration statistics relevant for malaria transmission in Senegal derived from mobile phone data and used in an agent-based migration model. *Geospatial Health* **11** ((Supp. 1), 408.
- Wang Y, Li J, Zhao X, Feng G and Luo XR** (2020) Using mobile phone data for emergency management: a systematic literature review. *Information Systems Frontiers*, 1–21. doi:10.1007/s10796-020-10057-w.
- Weidmann NB** (2015) Communication, technology, and political conflict. *Journal of Peace Research* **52**, 263–268.
- Williams BG** (2013) *Predators: The CIA's Drone War on al Qaeda*. Potomac Books, Inc.