



European
University
Institute



ECO 2021/01
Department of Economics

When Facebook Is the Internet: The Role of Social Media in Ethnic Conflict

Tuuli Tähtinen

European University Institute
Department of Economics

**When Facebook Is the Internet: The Role of Social Media in
Ethnic Conflict**

Tuuli Tähtinen

EUI Working Paper **ECO** 2021/01

Terms of access and reuse for this work are governed by the Creative Commons Attribution 4.0 (CC-BY 4.0) International license. If cited or quoted, reference should be made to the full name of the author(s), editor(s), the title, the working paper series and number, the year and the publisher.

ISSN 1725-6704

© Tuuli Tähtinen, 2021

This work is licensed under a Creative Commons Attribution 4.0 (CC-BY 4.0) International license.
<https://creativecommons.org/licenses/by/4.0/>

Published in October 2020 by the European University Institute.
Badia Fiesolana, via dei Roccettini 9
I – 50014 San Domenico di Fiesole (FI)
Italy

Views expressed in this publication reflect the opinion of individual author(s) and not those of the European University Institute.

This publication is available in Open Access in Cadmus, the EUI Research Repository:
<https://cadmus.eui.eu>



With the support of the
Erasmus+ Programme
of the European Union

The European Commission supports the EUI through the European Union budget. This publication reflects the views only of the author(s), and the Commission cannot be held responsible for any use which may be made of the information contained therein.

When Facebook Is the Internet: The Role of Social Media in Ethnic Conflict

Tuuli Tähtinen*

February, 2021

Abstract

This paper investigates whether social media affects the intensity of ethnic conflict. To distinguish the potential effects of social media from those of the broader internet, I focus on the ongoing Myanmar conflict because in such context internet is mainly accessed via Facebook. To identify the causal effect of social media on conflict, I take advantage of a shock in Facebook availability and use local variation in cell phone coverage as an exogenous determinant of social media use. Results indicate that on average social media availability reduced the occurrence of conflict. The analysis, however, reveals important regional differences suggesting that inflammatory content on social media may escalate conflict in areas where ethnic tensions are particularly high.

JEL codes: D74, O33

Keywords: internet, social media, conflict, propaganda, Myanmar, Rohingya

*Department of Economics, European University Institute. E-mail: tuuli.tahtinen@eui.eu

1. Introduction

Social media provides a platform for sharing content with an unprecedented freedom and ease. They help individuals to find friends and job opportunities and firms to advertise and build business networks. The other side of the coin, however, is that social media can facilitate sharing of simplistic, false and inflammatory messages, and increasing anecdotal evidence suggests that online outrage may lead to violence offline. For example, in 2016, Human Rights Watch (2016) warned Facebook that the platform could be used for propaganda, censorship and surveillance. A UN investigation in Myanmar found that Facebook had been instrumental in spreading anti-Muslim hate speech (Human Rights Council 2018), and a number of NGO's active in Myanmar also criticized Facebook for not preventing the spread of hate speech on the platform (Mozur 2018). As a result, the CEO of Facebook was called to testify before the U.S. Congress about Facebook's role in ethnic violence in Myanmar, as well as about data privacy and misinformation campaigns during the U.S. Presidential election (The Washington Post 2018).

This paper investigates whether social media affected the intensity of ethnic conflict. Due to the endogenous nature of social media use, causal estimates of its effects are still scarce.¹ Furthermore, it is not obvious how to distinguishing the potential effects of social media from those of the broader internet. To this end, I focus on the ongoing Myanmar conflict since in such context internet is mainly accessed via Facebook. Indeed, an important driver of increased internet penetration in many developing countries has been the emergence of zero rated apps. Zero rating means that a mobile network provider agrees to waive data charges associated with a particular app. As the cost of internet remains prohibitive for many people, zero rated content may often be the only justifiable way to access internet (Eisenach 2015). The rapid spread of Facebook in the developing world has led to situations in which Facebook effectively is the internet. A number of reports describe Facebook being so popular that it is considered synonymous to the wider internet. Anecdotal evidence suggests that many users do not know how to access other websites, or do not know they are accessing internet (see e.g. PRI 2017; Regan 2019).

This paper focuses on Facebook's zero rating campaign which was offered in Myanmar between June, 2016 and September, 2017. As the service could only be accessed with a SIM card from one provider, Myanma Post and Telecom (MPT), my empirical strategy is to use mobile phone coverage by MPT as an exogenous determinant of social media use. With information on the locations of cell phone towers, I use a model of electromagnetic signal propagation to calculate the predicted cell phone coverage (Olken 2009). The signal strength in a given location is primarily determined by distance to a cell tower and the terrain between a location and a cell tower. Cell phone coverage provided by other

1. Few recent exceptions I will discuss in Section 2 are Enikolopov et al. (2020), Bursztyn et al. (2019), Campante, Durante, and Sobbrío (2018), Falck, Gold, and Heblich (2014), and Czernich (2012).

companies can be used to control for the general effect of cell phone coverage. Information on cell phone towers is obtained from OpenCellID, which is a crowdsourced project to collect cell phone tower locations.

To measure the outcome, ethnic violence, I use a georeferenced data on conflict events. I take advantage of two datasets. The first data source is the GDELT Project (2019), which uses an automated system to extract information on conflict events from news media, by using natural language and data mining algorithms. It is the most comprehensive database on conflict events. In order to examine the reliability of this data, I conduct a comparative analysis with the Armed Conflict Location & Event Data (ACLED 2019). It is a widely used manually compiled data source, which makes it considerably narrower, but means there is less misreporting.

I conduct both cross-sectional and a difference-in-differences analysis in order to explore different sources of variation. I use the cross-sectional analysis to compare conflict outcomes in areas that are similar in terms of socio-economic and geographical characteristics, but that have different cell phone coverage due to terrain between the location and cell towers. The results show that on average, higher Facebook availability had a decreasing effect on conflict occurrence. Previous literature has shown that disseminating propaganda tends to influence beliefs and behaviour in the intended way (e.g. Yanagizawa-Drott 2014; Adena et al. 2015; Peisakhin and Rozenas 2018), whereas enhancing the ability to communicate may either mitigate or exacerbate conflict (Pierskalla and Hollenbach 2013; Shapiro and Weidmann 2015). Therefore, this result suggest that inflammatory content on social media might play less of a role than the ability to communicate.

When I focus on Rakhine State, a region which is central in the military's crackdown on the Rohingya people (a predominantly Muslim ethnic minority), the results suggest that availability of Facebook led to a small increase in probability of conflict. The result indicates that the role of social media varies in different regional contexts, and that the anti-Muslim hate speech and other inflammatory content may have escalated conflict in deeply fractured and particularly volatile areas.

To further study the impact of social media on conflict, I also use time variation in the Facebook campaign in a difference-in-differences set-up. In this setting, the information on population and spatial characteristics stays constant and I only examine whether there is systematic time variation in conflict depending on the cell phone coverage. This analysis indicates that there is no systematic variation in conflict within locations. However, the panel approach exacerbates attenuation bias due to measurement error in cell phone coverage.

The remainder of the paper is organized as follows. Section 2 briefly presents the related literature. Section 3 describes the conflict situation in Myanmar and the details of the Facebook campaign. Section 4 provides a description of the data. Section 5

describes the empirical strategy, and section 6 presents the results. Section 7 concludes.

2. Literature

This article is closely related to the literature on media bias and persuasion. In particular, it contributes to the empirical literature on the effects of social media by providing new causal estimates. This article also contributes to the literature on the impact of communication technology on political outcomes.² The literature distinguishes roughly two broad channels of how internet influences political outcomes. First, providing information may persuade receivers to change their behavior or beliefs. Second, it can enhance communication and coordination between agents.

Studies on democratic regimes have focused on how access to internet affects voter participation. The effect varies depending on the relative importance of information and entertainment content (cf. DellaVigna and Gentzkow 2010; Strömberg 2015). The role of internet as a low cost channel of information may be especially important in an environment where traditional media is under state control. Miner (2015) shows that in Malaysia, where the government held strict control over mass media, expanding uncensored internet penetration led to a decrease in the ruling party's support. Similarly, Enikolopov, Petrova, and Zhuravskaya (2011) find that in Russia availability of an independent TV channel decreased vote for the government party and increased vote for the opposition. Guriev, Melnikov, and Zhuravskaya (2019) suggest that wider access to internet may reduce government approval, particularly when traditional media is censored, by exposing corruption. However, if internet is also censored, increased access does not affect opinion on the government.

Mass media may be captured by an authoritarian regime and used to spread propaganda. Studying cross-border media, DellaVigna et al. (2014) find that exposure to nationalistic Serbian radio in Croatia increased ethnic animosity towards Serbs and increased vote for Croatian nationalist parties, whereas Peisakhin and Rozenas (2018) find that access to Russian state owned TV in Ukraine increased support for the pro-Russian candidates in 2014. Adena et al. (2015) examine the effect of radio before and after Hitler became the chancellor in Germany. During the democratic period pro-government radio had a mitigating influence on Nazi support, but After Hitler's rise to power the radio content also shifted to reflect the views of the regime, which increased Nazi popularity. Yanagizawa-Drott (2014) shows that radio propaganda had an important role in inflaming the Rwandan genocide, and significantly increased killings and participation in violence. In an opposite setting in Uganda, Armand, Atwell, and Gomes (2020) show that defection messaging was effective in mitigating conflict.

Research on enhanced communication in conflict situations exhibits mixed results.

2. For a more thorough literature review, see Zhuravskaya, Petrova, and Enikolopov (2020).

For example, access to cell phones may either increase (Pierskalla and Hollenbach 2013), or decrease incidence of violent events (Pierskalla and Hollenbach 2013; Shapiro and Weidmann 2015). Internet and social media also facilitate communication, and there are several examples of governments shutting down cell phone networks or administering internet blackouts in an attempt to contain protests (Manacorda and Tesei 2020). However, disentangling the effect of social media from other technology and information sources is a difficult challenge in empirical research. Enikolopov et al. (2020) use information on the early users of a Russian social media platform VK as an instrument for geographic variation in the penetration of the platform years later. The authors show that during a protests wave in 2011, higher social media use had a significant positive effect on probability of protest and protest participation.

Bursztyn et al. (2019) investigate whether social media use is related to hate crimes and xenophobic attitudes. Exploiting the identification strategy from Enikolopov et al. (2020), they show that social media does not have an average effect, but in areas where the pre-existing level of nationalism is high, the impact of social media is also more adverse. The effects are also found to be more pronounced in the initial years of social media diffusion. Based on a survey experiment, Bursztyn et al. (2019) suggest that social media facilitates finding other intolerant people and thereby increases the number of people with xenophobic beliefs. Using information on internet outages, Müller and Schwarz (2020) show that anti-refugee sentiment on social media is linked to higher level of hate crimes against refugees, and similarly suggest that social media enables spreading extremist views. The importance of pre-existing prejudices is also evident in the literature on propaganda in traditional media (e.g. Adena et al. 2015).

3. Background

3.1. Ethnic Conflict in Myanmar

Myanmar has a severely divided society, and the country has been engrossed with ethnic conflict since its independence in 1948. The state has supported the domination of the Bamar-Buddhist majority, and many of the country’s numerous ethnic groups have been subjected to discrimination and exclusion. According to the Human Rights Council (2018), the state’s systematic marginalization of many ethnic groups has served a deliberate purpose in motivating the military’s powerful position in politics.

One source of ethnic conflict is the citizenship law from 1982, which granted citizenship only to the so called “national races”. “National race” has since become a key component in identity politics, defining who belongs to Myanmar and who doesn’t. A number of minority groups, including the Rohingya, are not a national race, but are instead seen as

immigrants.³ As a consequence, most have not been granted citizenship, and have been rendered de facto stateless (Human Rights Council 2018).

During the past decade, Buddhist nationalism, anti-Muslim rhetoric and violence between Buddhists and Muslims has intensified. According to the Human Rights Council (2018), the violence is related to an anti-Muslim and anti-Rohingya campaign led by radical Buddhist organizations and the military officials. The campaign has sought to spread fear and hate, calling Muslims and Rohingya illegal immigrants and terrorists. The Rohingya crisis is mostly taking place in the Rakhine state, which is home to most of the Rohingya minority. The violence in Rakhine flared up in 2012 and the conflict has been ongoing since then. Violent conflicts continue between the military and ethnic armed groups also in several other regions of Myanmar, including Chin, Kachin and Shan states.

The UN Human Rights Council has accused the government of human rights violations and war crimes due to its unlawful and disproportionate security operations against ethnic and religious minorities. A case against Myanmar has been brought to the International Court of Justice, accusing the government of genocide against the Rohingya. According to a UN Human Rights Council report (Human Rights Council 2018), the security operations have been characterized by attacks against civilians and indiscriminate attacks, arbitrary arrests, torture, sexual violence, looting and destruction of property. One of the motivations for the operations seems to be dissuading civilians from getting involved in the ethnic armed organizations.

3.2. Zero Rated Facebook and Social Media Use

I focus on the role of Facebook, which is the dominant social media platform in Myanmar. According to StatCounter, during 2011–2018, Facebook constituted on average almost 95% of all social media use in Myanmar.⁴ I focus on the zero rated bundle of websites and apps called “Free Basics”, a recent Facebook campaign to gain users in the developing world.⁵ Free Basics users are required to sign up for Facebook, and they can then browse the websites and apps included in the platform without data charges. The campaign was launched in Myanmar in June 2016, but discontinued in September 2017 (Singh 2018). Although Free Basics gives access to a stripped down versions of a number of sites, Facebook is the main attraction (see e.g. Solon 2017). The number of Facebook users is estimated to have skyrocketed from 2 million in 2014 to 30 million in 2017 (Singh 2018).

The prevalence of Facebook was also noted by the UN investigation on Myanmar

3. For example, the government refers to the Rohingya as “Bengali”, claiming that they are immigrants from Bangladesh.

4. StatCounter’s statistics are based on tracking page visits to particular sites.

5. The platform was originally called Internet.org, and rebranded as Free Basics by Facebook in 2015.

(Human Rights Council 2018), which concluded that social media and Facebook had been used to spread hate speech. The chairman of the Mission stated that social media has “substantively contributed to the level of acrimony and dissension and conflict . . . As far as the Myanmar situation is concerned, social media is Facebook, and Facebook is social media” (Miles 2018). A Freedom House (2018) report also observed that anti-Muslim hate speech and discrimination had been amplified by social media, as well as some state institutions and mainstream news websites. A Reuters investigation found “more than 1,000 examples of posts, comments and pornographic images attacking the Rohingya and other Muslims on Facebook” (Stecklow 2018).

Free Basics is provided in participation with local mobile network providers, who agree to waive the data charges associated with the platform. It can only be accessed in the given countries and with a SIM card from one of the participating mobile network providers. The providers offering Free Basics are not paid by Facebook (Eisenach 2015). In Myanmar Free Basics was only available through a single provider—Myanma Posts and Telecommunications (MPT). Because I don’t have information on individuals’ cell phone or internet use, I will use cell phone coverage by MPT as a proxy for availability of zero rated Facebook.

In a country where access to broadband internet is limited, cost of mobile data is high, but mobile phones are common, availability to zero rated content represents a significant availability shock on internet access. According to GSM Association (2018), in Myanmar the cost of medium basket (mobile plan with 1 GB of data) was almost 20% of income for lowest 40% of earners, and 8% of average income. In 2018, 79% of all internet traffic in Myanmar was consumed by mobile phones (We Are Social, n.d.). During the past decade, internet use has increased rapidly: from an estimated 1% of population in 2010, to 8% in 2013, and 31% in 2017 (ITU, n.d.).

4. Description of Data

4.1. GDELT Data

I consider two different dependent variables: a binary measure of incidence of conflict in a township, and the number of conflict events in a township, weighted by population. My main source of conflict data is the GDELT Event Database (GDELT Project 2019). GDELT is a project that uses language and data mining algorithms to monitor print, broadcast, and web news media from across every country in the world. The algorithms are used to find geographic reference of the actors and the action. Due to the automated collection, the GDELT database contains significantly more events than other georeferenced conflict data.

I consider conflict events in the CAMEO event categories *coerce*, *assault*, *fight*, and

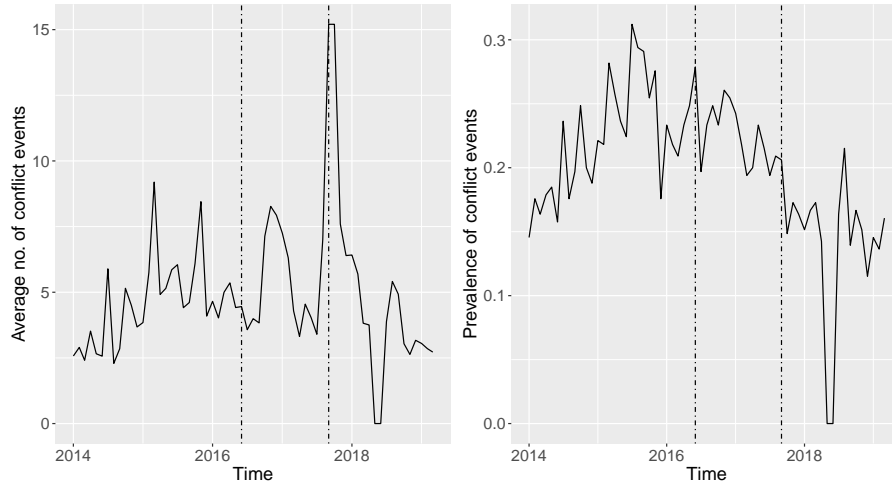


Figure 1: Distribution of events during the sample period The vertical dashed lines show the beginning and end of the Facebook campaign. Data source: GDELT

use conventional mass violence. Most of the events fall into the categories coerce and fight. Coercion includes, for example, arrests, detentions, seizing and damaging property, and imposing restrictions on rights of civilians. Fight consists of all uses of military force, fighting and killings, which usually take place between organized groups. Assault includes the less organized forms of violence, such as physical assaults, abductions, assassinations, and use of explosive devices.⁶ The number of events in the main categories is shown in the Appendix figure B.1.

The dataset contains 101,891 events of violent conflict during January 1, 2014–March 31, 2019. Figure 1 shows the distribution of conflict events over the time period. The left panel shows the average monthly number of conflict events across townships. The increased activity in late 2017 marks the timing of the military’s anti-Rohingya “clearance operation” in Rakhine State (Human Rights Council 2018). The right panel of Figure 1 presents the monthly share of townships with conflict events. Every month on average 20% of townships experienced at least one conflict event. The figure shows that the share of townships experiencing conflict has decreased since 2016. Although the number of conflict events spiked at the end of 2017, the events were geographically very concentrated. Appendix Figure B.2 plots the frequency of different types of violent events.

4.2. ACLED Data

To assess the robustness of GDELT data I also conduct analysis with the Armed Conflict Location & Event Data Project (ACLED 2019; Raleigh et al. 2010). Because the data is collected by researchers, it contains considerably less events than GDELT (5,416 conflict events in the time period January 1, 2014–March 31, 2019). However, because the data is reviewed and checked, there is also less incorrect reporting. ACLED collects data

6. For a more detailed description of the event types, see Event Data Project (2012).

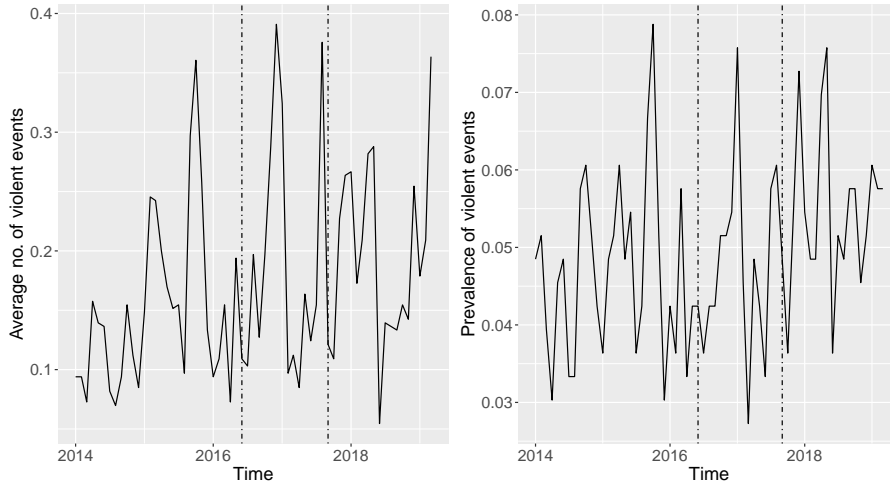


Figure 2: Violent events during the sample period. The vertical dashed lines show the beginning and end of the Facebook campaign. Data source: ACLED

on political violence and protest (defined as having a political purpose or motivation). Because ACLED uses a different categorisation of events, it allows me to further explore heterogeneity in conflict types.

The events in ACLED are categorized violent events, demonstrations, and non-violent actions. My main focus is on violent events, which are further classified as *battles*, *explosions/remote violence*, and *violence against civilians*. Most frequent event type is battles, and more specifically armed clashes. Most frequent actor types are state forces and political militias. Figure 2 plots the time series of violent events in ACLED data. The left panel shows the monthly number of violent events in Myanmar, and the right panel shows the monthly share of townships with conflict events. During the sample period, every month on average 5% of townships experienced at least one violent event. Unlike GDELT, ACLED data exhibits a slightly increasing trend in conflict occurrence. Appendix Figure B.3 shows the frequency of different types of violent events.

Figure 3 shows the geographic distribution of conflict events in the two sources. Both panels map the population weighted number of conflict events between June, 2016 and end of August, 2017. The figures show that conflict events are more pronounced in the peripheral areas, and particularly in Rakhine state (in Western Myanmar) which is home to majority of the Rohingya, and in the Shan (North-Eastern Myanmar) and Kachin states (Northern Myanmar). ACLED contains much less conflict events than GDELT, and the events are more geographically concentrated on the northern and eastern parts of the country. In a related study, Manacorda and Tesei (2020) compare GDELT with ACLED and Social Conflict Analysis Database (another manually compiled dataset). The authors show that, assuming that the probability that an event is correctly reported is larger than the probability of incorrect reporting, true reporting is more likely in GDELT data than in the manually compiled datasets.

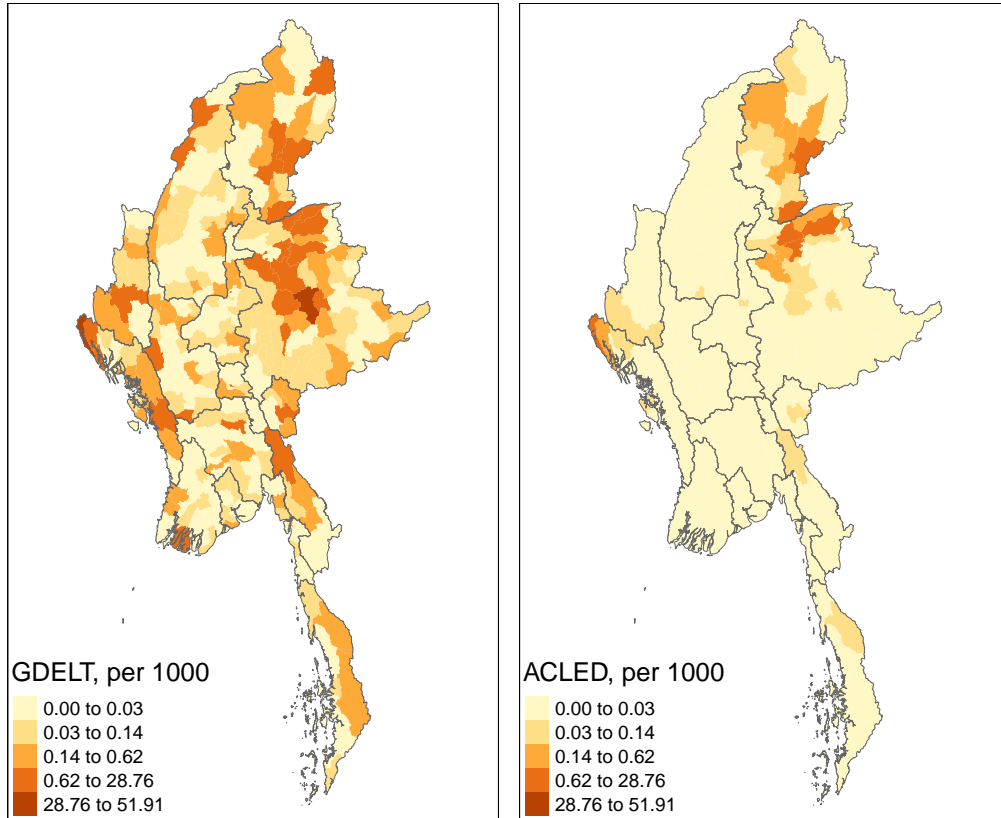


Figure 3: Locations of conflict events during June, 2016–August, 2017. The breaks coincide with the 50th, 75th, 90th, 99th, and 100th percentiles from GDELT.

4.3. Cell phone coverage

Information on the locations of cell phone towers is obtained from OpenCellID. The OpenCellID project was created to serve as a data source for GSM localization. The data is mostly generated by crowdsourcing, i.e. by individual smartphone users who use apps that collect data for the OpenCellID. The measurements of cell phone tower locations are collected by devices that utilize the wireless network provided by those cell towers. Cell ID data is also obtained from other sources, including GSM network providers and databases of other apps. Globally, the OpenCellID database contains 157.89 million cells (as of April, 2019).

In addition to cell tower locations, the data includes an identifier for the operator, the network technology (GMS, LTE, etc.), and date when the location measure was created. The database contains 33,137 cell tower locations in Myanmar. 14,350 of these belong to the Myanma Post and Telecommunications (MPT), and 18,787 to other mobile network providers. Appendix Figure B.4 shows the locations of MPT’s cell towers and the expansion of the network during 2015–2017. Most of the network is located in the populous Irrawaddy river valley, stretching between the three biggest cities, Yangon, the capital Nay Pyi Taw, and Mandalay. Appendix Figure B.5 shows the number of cell

tower by provider and when they were added in OpenCellID.

Because the data does not have information on when the cell towers were built, the measure date is used as a proxy. Most of the cell towers were reported to the dataset in 2015 and 2016. Although some of the cell towers are probably older, the increase likely reflects the actual development in the telecom sector. The Burmese telecom market only opened up for foreign competition in 2014, and before that the state-owned MPT was a monopoly. As new firms entered the market in 2014, also MPT had to start expanding its network to remain competitive. When constructing the predicted cell phone coverage, I use all cell phone towers that were included in the dataset before September 2017.

The strength of cell phone signal in a given location is primarily determined by distance to the cell tower and whether the receiver (i.e. mobile phone) is in line of sight of the cell tower. Obstructions, such as hills, buildings, or dense foliage, reduce the signal. I use a radio propagation model to predict where the signal is strong enough for cell phone reception. I apply the irregular terrain model (ITM), as introduced by Olken (2009), to calculate the predicted network coverage area. The model calculates predicted signal loss due to topography and distance between a transmitter and receiver. A number of validation studies have found that the ITM yields highly accurate predictions, and the model has been widely used in professional radio planning (Crabtree and Kern 2018).

The surface area of Myanmar is first divided into $200\text{m} \times 200\text{m}$ cells, and then for each cell, the ITM predicts whether the signal is strong enough for reception (See Appendix A for a more detailed description of the coverage prediction). I aggregate these predictions to obtain share of each township with cell phone reception. I do this separately for MPT and for the combination of all other mobile network providers. The share of township with coverage from MPT is the main independent variable. Figure 4 maps the geographic variation in the predicted MPT cell phone coverage. The predicted coverage is very unevenly distributed, with fairly comprehensive coverage in the central parts of the country, and large peripheral areas with very poor cell phone coverage.

Because I use crowdsourced data, it is likely that not all cell towers are included in the data, and there might be some error in the exact locations of the towers. I also need to approximate a number of technical parameters when conducting the coverage prediction. Measurement error in the independent variable may therefore bias the estimates towards zero.

Measures of terrain elevation are obtained from NASA's Shuttle Radar Topography Mission (SRTM), which has generated publicly available high resolution topographic data of the world (Jarvis et al. 2008). I use the one arc second resolution (approximately 30 meters at the equator) in the cell phone coverage calculation. In addition to elevation, the signal propagation model also takes into account how land use—e.g. water, forest, cropland—affects propagation. The land cover classification is obtained from the University of Maryland.

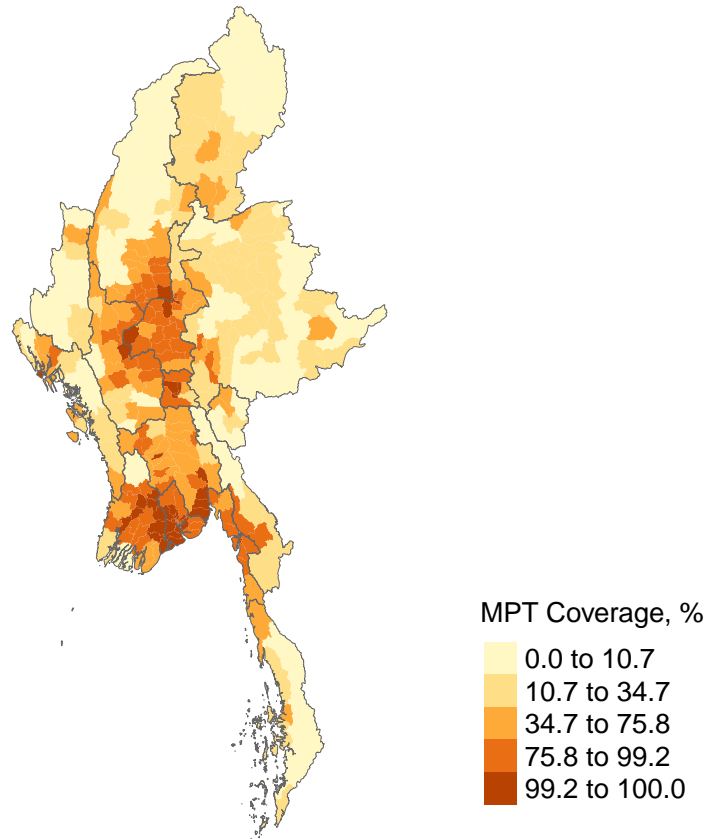


Figure 4: Predicted MPT cellphone coverage at township level

4.4. Local level characteristics

Information on population characteristics comes from the Myanmar 2014 Census. The main analysis is conducted at the township level.⁷ Summary statistics for the townships are presented in the Appendix Table C.1. Because I do not have information on the ethnic composition of the population at a disaggregated level, I use information on identity cards as a proxy. Specifically, not having an identity card is used to proxy share of discriminated minorities. According to the Census, more than a quarter of the population does not have any identity card.

As the Census data is only available for township level, I obtain additional information on population from the Gridded Population of the World collection for 2015 (CIESIN 2016). This dataset takes the Myanmar 2014 census data as input and uses uniform areal-weighting to disaggregate the population to approximately 1 km² grid cells. I aggregate the cells to obtain estimates of village tract population.⁸ Moreover, I use geospatial data provided by the Myanmar Information Management Unit to obtain administrative

7. Myanmar consists of states and regions, which are broken into districts, that are divided into townships, and finally village tracts.

8. See Appendix Figure B.7 for the geographic distribution of population.

boundaries, locations of towns, and railway and road networks. I measure distances from the township centroid to the nearest major city (capital, state/region capital or district town), railway, major road, cell phone tower by MPT, and cell phone tower by another mobile network provider. I use the SRTM elevation data to complement the data with topographic characteristics.

5. Empirical Strategy

My empirical strategy is to use mobile phone coverage by a mobile network provider offering the zero-rated plan as an exogenous determinant of social media use. The aim is to compare otherwise similar locations that were differently exposed to Facebook access. To identify the causal effect of mobile phone coverage on probability of conflict, variation in mobile phone coverage must be uncorrelated with all other determinants of the outcome.

The endogeneity concern is that cell towers are located strategically in areas that are more prone to conflict. I exploit plausibly exogenous local variation in cell phone signal strength, which is due to topographic variation between cell phone towers and receiver locations. First, I use the Irregular Terrain Model to predict where cell phone signal is strong enough for reception. I then compute the share of each township with reception, and use that as the main independent variable. I conduct both cross-sectional and panel data analysis.

5.1. Linear Probability Model

In the cross-sectional analysis I estimate the following linear probability model

$$Y_i = \beta CoverageFB_i + \delta Coverage_i + X_i'\gamma + \lambda_d + \varepsilon_i \quad (1)$$

where Y_i is the outcome in township i , $CoverageFB_i$ is the predicted cell phone coverage by MPT and β is the key parameter of interest. To distinguish the effect of Facebook access from cell phone coverage in general, I control for cell phone coverage from other providers, denoted by $Coverage_i$. X_i is a set of township level controls, λ_d is a district fixed effect, and ε_i is the error term.

The source of exogenous variation that I exploit comes only from terrain differences between locations and cell towers. I control for the factors that might be correlated both with incidence of conflict and having cell phone coverage. Because it is likely that the cell phone towers are located so as to maximize covered population, to control for the demand factors, I include controls for log population, log population density, dummy for below median urban rate, share of 15-64-year-olds, share of population with no ID, share of households with electricity, mobile phone, landline phone, and internet at home. As geographic and topographic characteristics of a town can influence the cost of providing

cell phone coverage, as well as propensity of conflict, I include second order polynomials of distance to major town, distance to major road and distance to railway, town mean elevation, slope, aspect of the slope, and variance of elevation and slope. I also include distance to nearest cell phone tower from MPT and from another provider. District fixed effects are included to control for broader geographical trends.⁹ I cluster standard errors at the district level (one level above township) to account for possible contemporaneous correlation between neighboring areas.

The identification relies on the assumption that predicted cell phone coverage is an exogenous determinant of social media use. In other words, after controlling for local population and geographic characteristics, and distances to transmitters, differences in cell phone coverage are due to the terrain between the location and nearby transmitters. Then, cell phone coverage by MPT affects conflict only through increased Facebook access. As long as *CoverageFB* is exogenous, β is equal to the causal effect of *CoverageFB*.

As I do not observe individuals' cell phone subscriptions or internet use, but only have a measure of availability (i.e. cell phone reception), the empirical approach is an encouragement design: I estimate the effect of availability of zero rated Facebook, instead of Facebook use per se (Duflo, Glennerster, and Kremer 2007). The intuition of the empirical strategy is the following. Offering zero rated content constitutes a negative price shock on internet use. Zero rated content is only available to consumers that have a SIM card from MPT, and cell phone reception from that provider is a prerequisite for accessing zero rated content. Moreover, better coverage from a mobile network provider in a given area is likely to be associated with higher probability that consumers obtain a mobile plan from that provider. Furthermore, having access to the zero rated content is expected to increase Facebook use (i.e. that the individual is exposed to the treatment).

It is likely that both the outcome and the independent variable are measured with some error. First, the conflict data is based on monitoring the news, so there might be some reporting bias. For instance, particular types of events, or events occurring in particular areas, might be more likely to be reported. Second, because the data collection in GDELT is automated, there may be some duplicate reporting. Measurement error can bias the results if it is correlated with the treatment, i.e. cell phone coverage from MPT (conditional on observables). The direction of the bias would depend on the nature of the error. Better cell phone coverage could naturally lead to higher reporting of violence, which could drive up the estimates. However, if access to cell phone coverage lead to higher reporting of conflict incidents, both *CovergaFB* and *Coverage* should have a positive effect on probability of conflict. Alternatively, intensified violence could also lead to lower reporting mechanically. For example, if a township is subject to mass

9. The topographic variables are calculated from the SRTM data. Distances are calculated from township centroids using data from Myanmar Information Management Unit. Calculations are done using GIS software.

deportations or burning down villages, subsequent conflict events may become unlikely.

Second, because I use crowdsourced data on cell phone towers, it is likely that not all towers are included in the data. There may also be some error in the exact locations of the towers, and many of the technical parameters need to be approximated in the coverage prediction. Measurement error in the independent variable will bias the estimates towards zero. Furthermore, if some areas lost cell phone coverage as a result of increased conflict, it would cause the treatment effect to be underestimated.

5.2. Difference-in-differences

In order to take advantage of the time variation in Facebook availability, I also conduct a difference-in-differences analysis. Because the information on population and spatial characteristics is constant over time, the analysis uses only within township variation to identify the effect of Facebook availability on conflict. I estimate the following model:

$$Y_{it} = \beta_1 CoverageFB_i \cdot Treat_t + \beta_2 CoverageFB_i \cdot Post_t + \tau_t + \lambda_i + Treat_t + Post_t + \varepsilon_{it} \quad (2)$$

where Y_{it} is indicator for conflict in township i in time t . The unit of observation is township-month. $CoverageFB$ represents the treatment intensity. The time variables $Treat_t$ and $Post_t$ indicate the treatment period (June, 2016–August, 2017), and post-treatment period (September, 2017–March, 2019). The time effect τ_t captures time specific effects that are common to all townships, and the township fixed effect λ_i captures all township specific time invariant characteristics.

The coefficient β_1 represent the effect of Facebook availability during the Free Basics campaign (the treatment period), and β_2 is the post-treatment effect. I use three time periods to allow for possible time variation or persistence in the treatment effect. As the treatment period is relatively long and conflict events are observed both before, during and after the treatment, I am able to study whether the impact of Facebook availability is different during and after the treatment period. Social media use may take some time to influence users' beliefs and behavior, and these effects may depend on the share of population using social media. The availability treatment may have taken time to affect Facebook use. It is likely that Facebook gained popularity during the Free Basics campaign, which lead to growth in its user base also after the campaign.

The difference-in-differences approach allows estimating the causal effect of treatment even if the treatment itself is not randomly assigned, but instead determined by the unobservable characteristics captured by λ_i . Unfortunately, the fixed effects approach exacerbates measurement error in the regressor, which increases attenuation bias.

Table 1: Cross-sectional results for probability of conflict

	Conflict dummy, GDELT			Conflict dummy, ACLED		
	(1)	(2)	(3)	(4)	(5)	(6)
CoverageFB	-0.142*	-0.258**	-0.134*	0.029	-0.054	-0.028
	(0.080)	(0.101)	(0.079)	(0.040)	(0.048)	(0.053)
Coverage	0.104	0.201**	0.185**	-0.024	0.013	0.024
	(0.084)	(0.098)	(0.075)	(0.042)	(0.058)	(0.058)
Observations	330	330	330	330	330	330
District dummies	✓	✓	✓	✓	✓	✓
Spatial controls		✓	✓		✓	✓
Population controls			✓			✓

*p<0.1; **p<0.05; ***p<0.01. Robust standard errors clustered at district level are reported in parentheses. The dependent variable is an indicator for conflict in a township between June 2016 until end of August 2017. Population controls: log population, log population density, dummy for below median urban rate, age (15–64 y.o.), population with no ID, population with electricity, mobile phone, landline phone, and internet at home. Spatial controls: 2nd order polynomials of distance to major town, distance to major road, distance to railway, distance to MPT transmitter, distance to other transmitter, mean elevation, slope and aspect of the slope, variance of elevation and slope. The predictors are standardized.

6. Results

6.1. Cross-sectional estimates

Table 1 presents the OLS estimates of model (1). The dependent variable is an indicator for experiencing conflict in the treatment period, i.e. when Free Basics was available (from June, 2016 until end of August, 2017). The dependent variable in columns (1)–(3) is an indicator for an event of violent conflict from the GDELT, and in columns (4)–(6) an indicator for a violent event from the ACLED data.

The estimates suggest that cell phone coverage provided by MPT, i.e. free access to Facebook, is associated with lower probability of conflict. The coefficient of *CoverageFB* in column (1) indicates that, after filtering out the district fixed effects and controlling for cell phone coverage from other providers, one standard deviation increase in MPT cell phone coverage is on average associated with 14.2 percentage point decrease in the probability of conflict. The positive coefficient on *Coverage* suggests that better cell phone coverage per se is correlated with higher probability of conflict.

A placebo test (Table C.2 in the Appendix) shows that *CoverageFB* had no effect in the pre-treatment period, but the effects only appears in the treatment and post-treatment periods. The two sources of conflict data exhibit different patters—in GDELT, the estimate is marginally significant in the treatment period, and relative large although imprecise in the post.treatment period, whereas based on ACLED the effect appears only after the Facebook campaign has ended.

Table 2: Cross-sectional results for number of conflict events

	No. conflict events, GDELT			No. conflict events, ACLED		
	(1)	(2)	(3)	(4)	(5)	(6)
CoverageFB	0.524 (0.500)	-0.330 (0.710)	-0.152 (0.946)	0.029 (0.030)	0.027 (0.023)	0.020 (0.023)
Coverage	-0.537 (0.495)	0.563 (0.779)	0.802 (0.952)	-0.038 (0.029)	-0.028 (0.025)	-0.024 (0.022)
Observations	330	330	330	330	330	330
District dummies	✓	✓	✓	✓	✓	✓
Spatial controls		✓	✓		✓	✓
Population controls			✓			✓

*p<0.1; **p<0.05; ***p<0.01. Robust standard errors clustered at district level are reported in parentheses. The dependent variable is number of conflict events per 1,000 population. Population controls: log population, log population density, dummy for below median urban rate, age (15–64 y.o.), population with no ID, population with electricity, mobile phone, landline phone, and internet at home. Spatial controls: 2nd order polynomials of distance to major town, distance to major road, distance to railway, distance to MPT transmitter, distance to other company’s transmitter, mean elevation, slope and aspect of the slope, variance of elevation and slope. The predictors are standardized.

The results are consistent with the interpretation that incendiary content on social media may have played a smaller part than enhanced communication and coordination. Whereas the previous literature shows that propaganda and mass media tend to work in the intended direction, the literature on the role of communication technology in conflict situations presents mixed results.¹⁰ As availability of social media increases, occurrence of conflict becomes less likely. In a related study, Shapiro and Weidmann (2015) find that the expansion of cell phone infrastructure in Iraq decreased insurgent violence. The authors suggests that access to cell phones benefited counter-insurgents, for instance by making it easier to covertly inform security forces of militia activity.

Table 2 presents results for number of conflict events per 1,000 people. The results suggest that Facebook availability has no effect on the intensive margin. The point estimates in columns (1)–(3) are also much more sensitive to controls than in the linear probability model. The point estimates in (4)–(6) very small, which reflects the low number of conflict events in the ACLED data.

Next, Table 3 examines whether the treatment effect varies by conflict type. The outcome variables are indicators for different types of conflict events. The results show that social media availability and cell phone coverage influence different conflict types with varying intensity. Columns (1)–(4) show that, in GDELT data, the negative effect of Facebook on conflict is mostly due to its effect on assaults and fighting. Events categorized as assaults include abductions, physical assaults, and use of explosive devices.

10. See e.g. Pierskalla and Hollenbach (2013), Shapiro and Weidmann (2015), and Manacorda and Tesei (2020).

Table 3: Cross-sectional results for probability of conflict: by type of conflict

	Coerce (1)	Assault (2)	Fight (3)	Mass violence (4)	Battle (5)	Civilians (6)	Explosion (7)
CoverageFB	-0.034 (0.111)	-0.277** (0.127)	-0.253** (0.099)	-0.054 (0.059)	-0.120** (0.060)	0.001 (0.051)	-0.005 (0.031)
Coverage	0.167 (0.116)	0.325*** (0.108)	0.214* (0.112)	0.033 (0.046)	0.036 (0.051)	0.026 (0.040)	-0.036 (0.035)
Data	GDELT	GDELT	GDELT	GDELT	ACLED	ACLED	ACLED
Mean(Y)	0.51	0.31	0.52	0.07	0.14	0.08	0.09
District FE	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓

*p<0.1; **p<0.05; ***p<0.01. Robust standard errors clustered at district level are reported in parentheses. The dependent variable is an indicator for conflict of particular type in a township between June 2016 until end of August 2017. All regressions include population controls and spatial controls. Population controls: log population, log population density, dummy for below median urban rate, age (15–64 y.o.), population with no ID, population with electricity, mobile phone, landline phone, and internet at home. Spatial controls: 2nd order polynomials of distance to major town, distance to major road, distance to railway, distance to MPT transmitter, distance to other company’s transmitter, mean elevation, slope and aspect of the slope, variance of elevation and slope. The predictors are standardized. There are 330 observations.

Fight includes most forms of conventional military force. Based on ACLED, the negative effect on conflict is driven by a decrease in battles. ACLED (2019) defines a battle as “violent interaction between two politically organized armed groups at a particular time and location.” Although the event classifications are somewhat different between GDELT and ACLED, the pattern is quite similar.

6.2. Panel Estimates

I now turn to the difference-in-differences model. The dependent variable in columns (1)–(2) of Table 4 is an indicator for conflict events, and in columns (3)–(4) the number of conflict events per 1,000 population. All specifications include township fixed effects and month-year fixed effects. The coefficients on the interaction terms correspond to a one standard deviation change in *CoverageFB*. *Treat* and *Post* are indicators for the treatment period and post-treatment period, respectively. Because the measure of cell phone coverage is time invariant, it is captured by the township fixed effects.

The coefficients on the interaction terms show that on average, during or after the treatment period, higher MPT cell phone coverage is not associated with any change in probability of conflict or number of conflict events per capita. These results show no systematic change in conflict occurrence over time that is associated with the Facebook campaign, although occurrence of conflict is on average more likely during the treatment period.

Table 5 examines the effect of Facebook availability on different conflict types. The outcomes are dummy variables that take value one if there was at least one conflict event of that type in the township in a particular month. The estimates show that there is some variation between conflict types, although the coefficients are imprecise. The point

Table 4: Difference-in-differences estimates

	Conflict dummy		No. conflict events	
	(1)	(2)	(3)	(4)
CoverageFB·Treat	−0.004 (0.008)	−0.002 (0.004)	−0.001 (0.008)	0.0004 (0.001)
CoverageFB·Post	0.004 (0.008)	−0.005 (0.005)	0.004 (0.008)	−0.003 (0.002)
Treat	0.184*** (0.018)	0.026*** (0.009)	0.034* (0.021)	0.004 (0.005)
Post	0.136*** (0.016)	0.023 (0.015)	−0.017 (0.012)	0.001 (0.002)
Data source	GDELT	ACLED	GDELT	ACLED
Township FE	✓	✓	✓	✓
Month-Year FE	✓	✓	✓	✓

*p<0.1; **p<0.05; ***p<0.01. Robust standard errors clustered at district level are reported in parentheses. The dependent variable in columns (1)–(2) is an indicator for conflict in a township, and in columns (3)–(4) number of conflict events per 1,000 population. The predictors are standardized. There are 20,790 township-month observations.

estimates on violence against civilians (column (6)) and remote violence (column (7)) are marginally statistically significant, and the coefficient on coercion is also relatively large. The average time trend documented in 4 is driven mostly by increases in coercion and fights, and to a lesser degree by assaults and violence against civilians.

6.3. Effect on the Rohingya Crisis

The analysis so far has looked at average effects across all regions of Myanmar. Because there are several ongoing conflicts in different parts of the country, it is possible that the estimates are confounded by different regional effects. The previous literature has shown that the effect of mass media and access to communication technology on conflict may be very context specific (see e.g. Adena et al. 2015). There is a lot of anecdotal evidence that in Myanmar Facebook has been used to spread anti-Muslim and anti-Rohingya propaganda, and therefore it could have had a different impact in the Rohingya conflict. As many of the ethnic conflicts in Myanmar are regional, I now focus on the Rakhine state—home for most of the Rohingya population in Myanmar—to gauge the effect of social media on Rohingya-related conflict.

I conduct the analysis at village level, to retain enough units of observation, and only consider conflict measured from GDELT. The share of Rakhine villages that experienced at least one conflict event during the treatment period is slightly higher, and the number of conflict events is significantly higher, than on average in Myanmar. Table 6 presents cross-sectional estimates. In contrast to the previous results, in Rakhine villages Face-

Table 5: Difference-in-differences estimates on different conflict types

	Coerce (1)	Assault (2)	Fight (3)	Mass violence (4)	Battle (5)	Civilians (6)	Explosion (7)
CoverageFB·Treat	−0.008 (0.007)	−0.002 (0.004)	−0.003 (0.006)	−0.001 (0.002)	−0.002 (0.004)	0.001 (0.002)	−0.006 (0.004)
CoverageFB·Post	−0.012 (0.007)	0.0003 (0.004)	0.005 (0.007)	−0.003 (0.005)	−0.001 (0.005)	−0.004* (0.002)	−0.007** (0.003)
Treat	0.091*** (0.016)	0.031*** (0.008)	0.077*** (0.016)	0.009** (0.004)	0.012 (0.010)	0.023** (0.009)	0.006 (0.007)
Post	0.052*** (0.012)	0.015* (0.009)	0.041** (0.016)	−0.003 (0.006)	0.003 (0.012)	0.032** (0.013)	0.006 (0.009)
Observations	20790	20790	20790	20790	20790	20790	20790
Data	GDELT	GDELT	GDELT	GDELT	ACLED	ACLED	ACLED
Township FE	✓	✓	✓	✓	✓	✓	✓
Month-Year FE	✓	✓	✓	✓	✓	✓	✓

*p<0.1; **p<0.05; ***p<0.01. Robust standard errors clustered at district level are reported in parentheses. All regressions include township and month-year fixed effects. The predictors are standardized. There are 20,790 township-month observations.

book availability is associated with a small increase in probability of conflict. Although the estimates are small and only marginally significant, they demonstrate that there is important regional heterogeneity. Moreover, the estimates are likely biased down as they do not account for the large number of Rohingya fleeing from Myanmar during the conflict. There are reports of completely burned down Rohingya villages, and an influx of people filling into refugee camps in Bangladesh, which could mechanically reduce subsequent violence.¹¹ The estimated effects on number of conflict events are very imprecise, but suggest a negative effect on the intensive margin. Examining different conflict types reveals that increasing probability of conflict is driven particularly by increased fighting (see Table C.3 in the Appendix).

Although the Rohingya have been subjected to discrimination for decades, the anti-Muslim hate campaign and Buddhist nationalism has intensified during the past decade. Violence in the Rakhine state flared up in 2012 and since then there have been increasing reports of attacks, particularly against the Rohingya (Human Rights Council 2018). Therefore, these results are consistent with Adena et al. (2015) who show that the effectiveness of propaganda varies with the receivers' predisposition towards the message. Similarly, Bursztyn et al. (2019) suggest that social media use may aggravate xenophobic attitudes and lead to more hate crimes when intolerant views are already prevalent. The results presented in this section support the view that pre-existing ethnic tensions and animosity may be an important determinant for the impact of social media in conflict.

11. For information on the refugee crisis, see <https://www.unocha.org/rohingya-refugee-crisis>.

Table 6: Cross-sectional results for conflict in Rakhine State

	Conflict dummy			No. conflict events		
	(1)	(2)	(3)	(4)	(5)	(6)
CoverageFB	-0.008 (0.009)	0.027* (0.015)	0.027* (0.015)	25.142 (25.587)	-22.878 (16.556)	-33.832 (23.837)
Coverage	-0.001 (0.009)	-0.019 (0.015)	-0.017 (0.015)	-30.099 (21.805)	-51.634 (42.714)	-44.133 (34.805)
Observations	1059	1059	1059	1059	1059	1059
District dummies	✓	✓	✓	✓	✓	✓
Spatial controls		✓	✓		✓	✓
Population controls			✓			✓

*p<0.1; **p<0.05; ***p<0.01. Robust standard errors are reported in parentheses. The dependent variable is an indicator for conflict of particular type in a township between June 2016 until end of August 2017. Conflict data is from GDELT. Population controls: log population, log population density, dummy for below median urban rate, age (15–64 y.o.), population with no ID, population with electricity, mobile phone, landline phone, and internet at home. Spatial controls: 2nd order polynomials of distance to major town, distance to major road, distance to railway, distance to MPT transmitter, distance to other company’s transmitter, mean elevation, slope and aspect of the slope, variance of elevation and slope. The predictors are standardized.

7. Conclusions

This paper has studied the effect of availability of Facebook on conflict. I exploit geographic variation in cell phone coverage together with time variation in an availability shock of Facebook to estimate whether social media affects probability or intensity of conflict.

The results suggest that availability of social media may have had an average negative effect on conflict incidence. The cross-sectional analysis that exploits exogenous variation in cell phone coverage suggests that social media availability had a mitigating effect on conflict. However, this effect cannot be identified in the panel analysis. Furthermore, there is evidence that social media may have led to a slightly higher incidence of Rohingya-related conflict. Therefore, it seems that influence of social media depends greatly on the environment in which it is introduced.

Without access to Facebook content at the time, or more detailed information about internet or cell phone use, it is difficult to further disentangle these effects. There is a need for further research on the impacts of social media use in different circumstances.

References

- ACLED. 2019. *Armed Conflict Location & Event Data Project (ACLED)*. <https://acleddata.com/%5C#/dashboard>.
- Adena, Maja, Ruben Enikolopov, Maria Petrova, Veronica Santarosa, and Ekaterina Zhuravskaya. 2015. "Radio and the Rise of the Nazis in Prewar Germany." *The Quarterly Journal of Economics* 130 (4): 1885–1939.
- Armand, Alex, Paul Atwell, and Joseph F Gomes. 2020. "The Reach of Radio: Ending Civil Conflict Through Rebel Demobilization." *American Economic Review* 110 (5): 1395–1429.
- Bursztyn, Leonardo, Georgy Egorov, Ruben Enikolopov, and Maria Petrova. 2019. *Social Media and Xenophobia: Evidence from Russia*. National Bureau of Economic Research.
- Campante, Filipe, Ruben Durante, and Francesco Sobbrío. 2018. "Politics 2.0: The Multifaceted Effect of Broadband Internet on Political Participation." *Journal of the European Economic Association* 16 (4): 1094–1136.
- CIESIN. 2016. *Gridded Population of the World, Version 4 (GPWv4): Basic Demographic Characteristics, Revision 11*. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC): Center for International Earth Science Information Network - CIESIN - Columbia University.
- Crabtree, Charles, and Holger L Kern. 2018. "Using Electromagnetic Signal Propagation Models for Radio and Television Broadcasts: An Introduction." *Political Analysis* 26 (3): 348–355.
- Czernich, Nina. 2012. "Broadband Internet and Political Participation: Evidence for Germany." *Kyklos* 65 (1): 31–52.
- DellaVigna, Stefano, Ruben Enikolopov, Vera Mironova, Maria Petrova, and Ekaterina Zhuravskaya. 2014. "Cross-Border Media and Nationalism: Evidence from Serbian Radio in Croatia." *American Economic Journal: Applied Economics* 6 (3): 103–32.
- DellaVigna, Stefano, and Matthew Gentzkow. 2010. "Persuasion: Empirical Evidence." *Annu. Rev. Econ.* 2 (1): 643–669.
- Duflo, Esther, Rachel Glennerster, and Michael Kremer. 2007. "Using Randomization in Development Economics Research: A Toolkit." *Handbook of development economics* 4:3895–3962.
- Eisenach, Jeffrey A. 2015. "The Economics of Zero Rating." *NERA Economic Consulting, March*.

- Enikolopov, Ruben, Alexey Makarin, Maria Petrova, and Leonid Polishchuk. 2020. “Social Image, Networks, and Protest Participation.” *Networks, and Protest Participation* (April 26, 2020).
- Enikolopov, Ruben, Maria Petrova, and Ekaterina Zhuravskaya. 2011. “Media and Political Persuasion: Evidence from Russia.” *American Economic Review* 101 (7): 3253–85.
- Event Data Project. 2012. *CAMEO Conflict and Mediation Event Observations Event and Actor Codebook*. <https://www.gdeltproject.org/>.
- Falck, Oliver, Robert Gold, and Stephan Heblich. 2014. “E-lelections: Voting Behavior and the Internet.” *American Economic Review* 104 (7): 2238–65.
- Freedom House. 2018. “Freedom in the World 2018: The Rise of Digital Authoritarianism.” <https://freedomhouse.org/report/freedom-world/2018/myanmar>.
- GDELT Project. 2019. *Global Database of Events, Language, and Tone (GDELT)*. <https://www.gdeltproject.org/>.
- GSM Association. 2018. “Taxing Mobile Connectivity in Asia Pacific: A Review of Mobile Sector Taxation and its Impact on Digital Inclusion.”
- Guriev, Sergei, Nikita Melnikov, and Ekaterina Zhuravskaya. 2019. “3G Internet and Confidence in Government.” *Available at SSRN 3456747*.
- Human Rights Council. 2018. “Report of the Independent International Fact-Finding Mission on Myanmar.” A/HRC/39/64. https://www.ohchr.org/Documents/HRBodies/HRCouncil/FFM-Myanmar/A_HRC_39_64.pdf.
- Human Rights Watch. 2016. “Human Rights Watch Letter to Facebook.” July 18, 2016. <https://www.hrw.org/news/2016/07/18/human-rights-watch-letter-facebook>.
- ITU. n.d. *Percentage of Individuals Using the Internet*. International Telecommunication Union. <https://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx>.
- Jarvis, Andy, Hannes Isaak Reuter, Andrew Nelson, Edward Guevara, et al. 2008. *Hole-filled SRTM for the Globe Version 4*. Available from the CGIAR-CSI SRTM 90m Database (<http://srtm.csi.cgiar.org>).
- Manacorda, Marco, and Andrea Tesei. 2020. “Liberation Technology: Mobile Phones and Political Mobilization in Africa.” *Econometrica* 88 (2): 533–567.
- Miles, Tom. 2018. “U.N. Investigators Cite Facebook Role in Myanmar Crisis.” March 12, 2018, *Reuters*. <https://www.reuters.com/article/us-myanmar-rohingya-facebook/un-investigators-cite-facebook-role-in-myanmar-crisis-idUSKCN1GO2PN>.
- Miner, Luke. 2015. “The Unintended Consequences of Internet Diffusion: Evidence from Malaysia.” *Journal of Public Economics* 132:66–78.

- Mozur, Paul. 2018. "Groups in Myanmar Fire Back at Zuckerberg." April 5, 2018, *The New York Times*. <https://www.nytimes.com/2018/04/05/technology/zuckerberg-facebook-myanmar.html?module=inline>.
- Müller, Karsten, and Carlo Schwarz. 2020. "Fanning the Flames of Hate: Social Media and Hate Crime." *Available at SSRN 3082972*.
- Olken, Benjamin A. 2009. "Do Television and Radio Destroy Social Capital? Evidence from Indonesian Villages." *American Economic Journal: Applied Economics* 1 (4): 1–33.
- Parsons, John David. 2000. *The Mobile Radio Propagation Channel*. Wiley Online Library.
- Peisakhin, Leonid, and Arturas Rozenas. 2018. "Electoral Effects of Biased Media: Russian Television in Ukraine." *American Journal of Political Science* 62 (3): 535–550.
- Pierskalla, Jan H, and Florian M Hollenbach. 2013. "Technology and Collective Action: The Effect of Cell Phone Coverage on Political Violence in Africa." *American Political Science Review* 107 (2): 207–224.
- PRI. 2017. "In Myanmar, Fake News Spread on Facebook Stokes Ethnic Violence." November 1, 2017, *PRI's The World*. <https://www.pri.org/stories/2017-11-01/myanmar-fake-news-spread-facebook-stokes-ethnic-violence>.
- Raleigh, Clionadh, Andrew Linke, Håvard Hegre, and Joakim Karlsen. 2010. "Introducing ACLED-Armed Conflict Location and Event Data." *Journal of Peace Research* 47 (5): 651–660.
- Regan, Helen. 2019. "Facebook Wades into World's Longest Civil War, but Does It Know What It's Doing?" February 9, 2019, *CNN*. <https://edition.cnn.com/2019/02/08/asia/facebook-bans-myanmar-ethnic-groups-intl/index.html>.
- Shapiro, Jacob N, and Nils B Weidmann. 2015. "Is the Phone Mightier than the Sword? Cellphones and Insurgent Violence in Iraq." *International Organization* 69 (2): 247–274.
- Singh, Manish. 2018. "After Harsh Criticism, Facebook Quietly Pulls Services from Developing Countries." May 1st, 2018, *The Outline*. <https://theoutline.com/post/4383/facebook-quietly-ended-free-basics-in-myanmar-and-other-countries?zd=1&%20zi=buaj62ap>.
- Solon, Olivia. 2017. "'It's Digital Colonialism': How Facebook's Free Internet Service Has Failed Its Users." July 27th, 2017, *The Guardian*. <https://www.theguardian.com/technology/2017/jul/27/facebook-free-basics-developing-markets>.

- Stecklow, Steve. 2018. “Why Facebook is losing the war on hate speech in Myanmar.” August 15, 2018, *Reuters*. <https://www.reuters.com/investigates/special-report/myanmar-facebook-hate/>.
- Strömberg, David. 2015. “Media and Politics.” *Annu. Rev. Econ.* 7 (1): 173–205.
- The Washington Post. 2018. “Transcript of Mark Zuckerberg’s Senate Hearing.” April 10, 2018, *The Washington Post*. https://www.washingtonpost.com/news/the-switch/wp/2018/04/10/transcript-of-mark-zuckerbergs-senate-hearing/?utm_term=.b5a32ee4ec81.
- We Are Social. n.d. *Distribution of Internet Traffic in Myanmar as of January 2018, by Device*. In Statista - The Statistics Portal. <https://www-statista-com.ezproxy.eui.eu/statistics/804014/share-of-internet-traffic-by-device-myanmar/>.
- Yanagizawa-Drott, David. 2014. “Propaganda and Conflict: Evidence from the Rwandan Genocide.” *The Quarterly Journal of Economics* 129 (4): 1947–1994.
- Zhuravskaya, Ekaterina, Maria Petrova, and Ruben Enikolopov. 2020. “Political Effects of the Internet and Social Media.” *Annual Review of Economics* 12.

Appendices

A. Estimation of cell phone coverage

Cell phone signals are ultra high frequency radio signals. Radio propagation follows the laws of physics so it is possible to use an electromagnetic signal propagation model to calculate predicted coverage. Cell phone signals' primary propagation mode is direct wave, and the signal strength decreases proportionally with the inverse of squared distance. The signal strength can also be greatly reduced by objects, such as hills, buildings, or dense foliage, lying on the line of sight. Even if an object does not block the line of sight but lies in the Fresnel zone, it can reduce the signal (Parsons 2000). Therefore, for a given cell tower height and transmission strength, the signal strength in a given location is primarily determined by distance to the tower and whether the receiver (i.e. mobile phone) is in line of sight of the tower.

Because I do not have access to the technical details of the cell phone towers, I approximate the parameters needed for the calculation. The end result can therefore be considered as an augmented line of sight analysis, where the ITM is used to define a potential coverage area, as determined by the cell tower locations and plausible parameter values. Intuitively, I take into account if a given point is within the maximum range to receive a signal, and whether there exists a line of sight between that point and a cell tower.

I apply the irregular terrain model (ITM), also known as Longley-Rice model, to calculate the predicted coverage area. To apply the ITM, I use a freely available software for RF propagation simulation, called Radio Mobile.¹² I start by defining the maximum allowed path loss. Maximum allowed path loss is defined as: Transmitter power (dBm) – Transmitter attenuation (dB) + Antenna gains (dBi) – Receiver line loss (dB) – Receiver sensitivity (dB). If the free space path loss—i.e. path loss due to distance—and the propagation loss due to topography are less than the maximum allowed path loss, the signal is sufficiently strong for reception. The surface area of Myanmar is divided into 200*200 m grids, and the prediction is calculated for each grid cell.

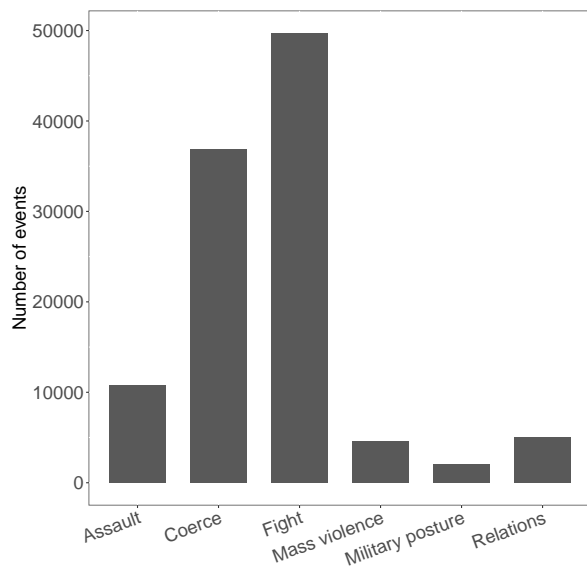
I approximate the cell phone tower parameters so as to mimic transmission in a rural area. Antenna height is assumed to be 35 meters, and antennas are assumed to be omnidirectional. In reality antennas are usually directional, and there are a couple of antennas in a cell tower that cover different segments around the tower. Cell phone tower heights vary a lot, and 30–40 meter towers can be considered high. I limit the maximum range of the signal to 25 km. Due to timing advance, the theoretical maximum range for a standard GSM equipment is 35 kilometers. Because of limitations of network architecture and poor performance of cell phone antennas, in practice the maximum range will be much

12. Radio Mobile is copyright of Roger Coudé VE2DBE.

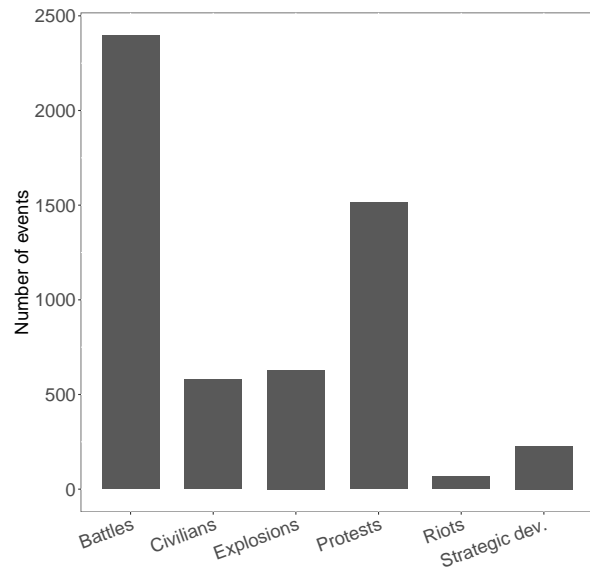
lower. A typical macro cell in a rural area might offer a range of 15 km.

Both the free space loss and loss due to obstacles also depend on the signal frequency. I infer frequency from the network type. For example, GSM signal is delivered in 900 or 1800 MHz frequency bands in most parts of the world. Typically the spectrum is divided into bands that are allocated for different service providers by a national regulator. To approximate the frequency, I use the frequency bands that the mobile network providers have reported in the Mobile World Live website, together with information on how the frequency bands are divided between operators. In this procedure, I use the same parameter values for all cell towers. In reality, all the parameters are likely to vary substantially depending on the propagation environment (e.g. urban vs rural) and operator (Parsons 2000).

B. Figures



(a) Data: GDELT



(b) Data: ACLED

Figure B.1: Number of different conflict events in the two datasets.

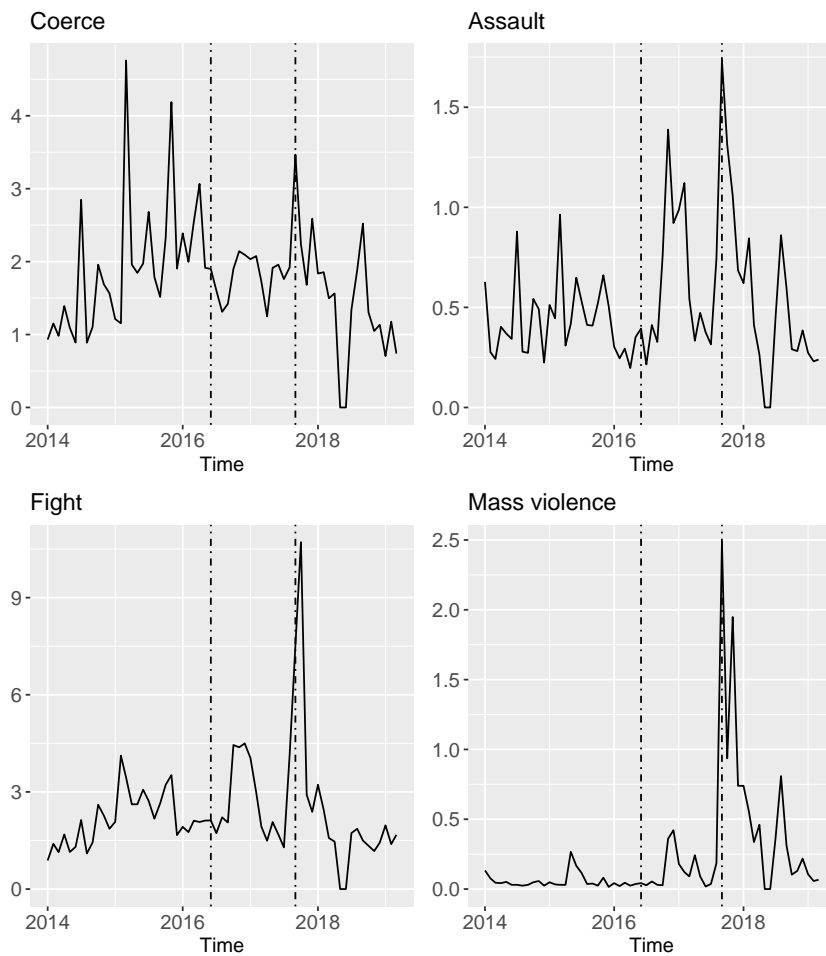


Figure B.2: Number of the main types of violent events over time. The vertical dashed lines show the beginning and end of the Facebook campaign. Data source: GDELT

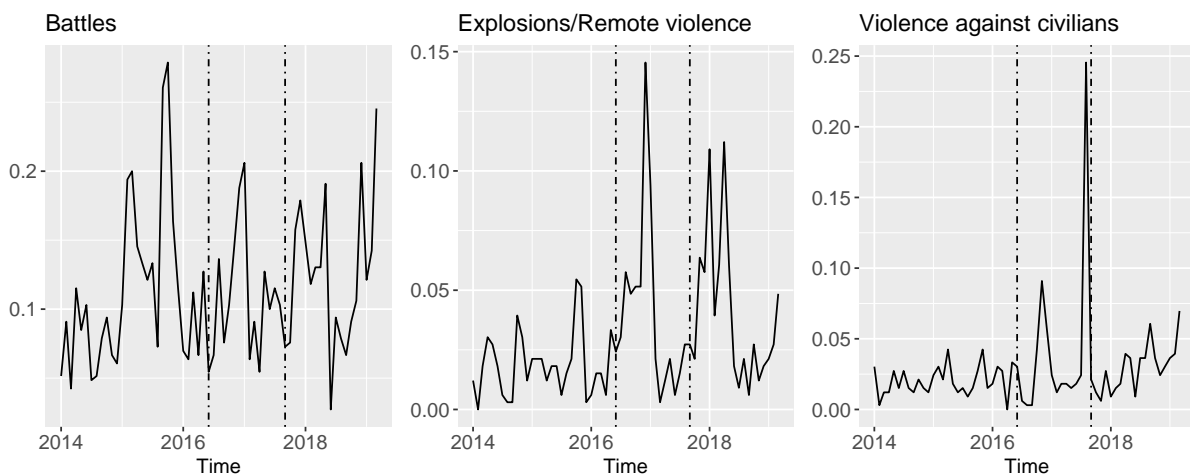


Figure B.3: Types of violent events. The vertical dashed lines show the beginning and end of the Facebook campaign. Data source: ACLED

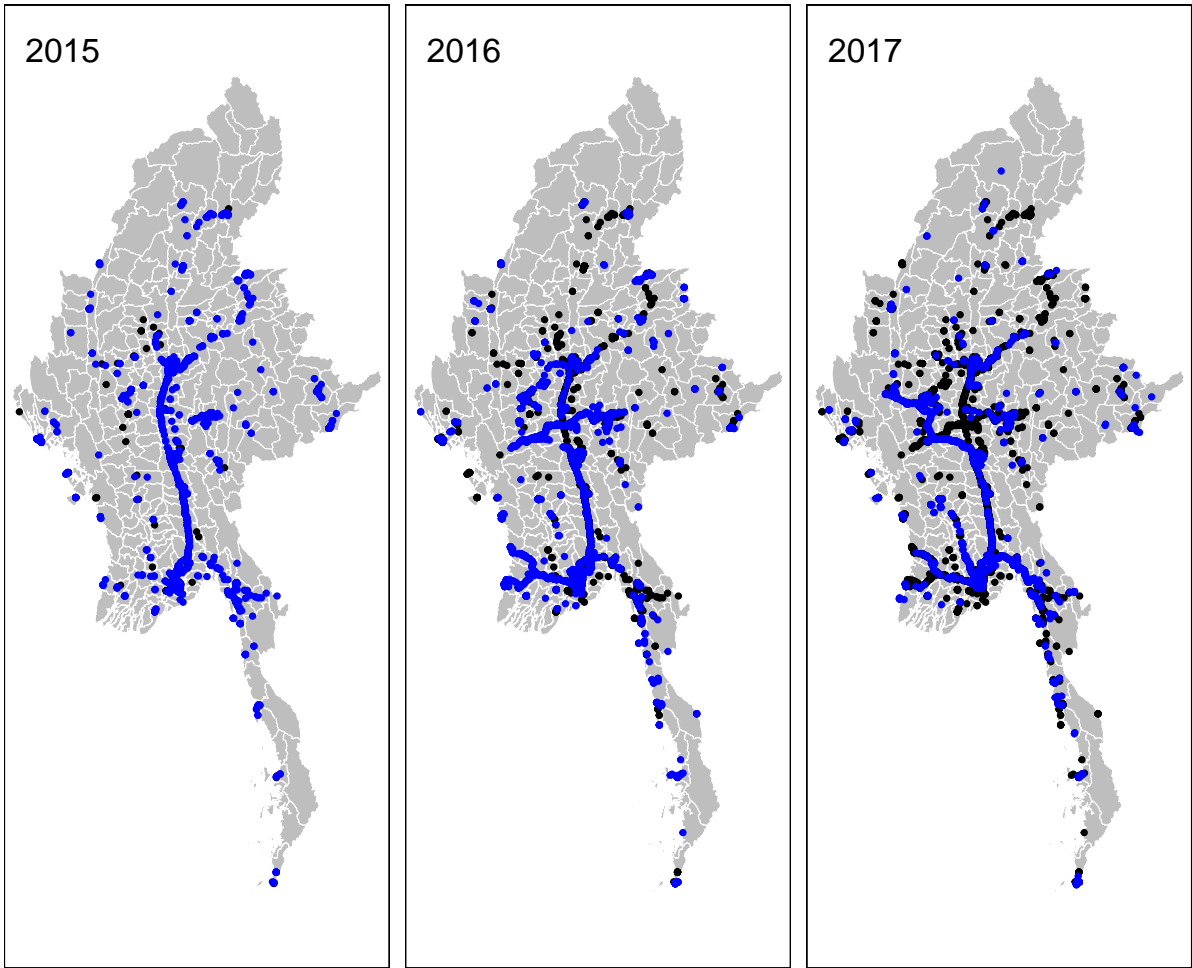
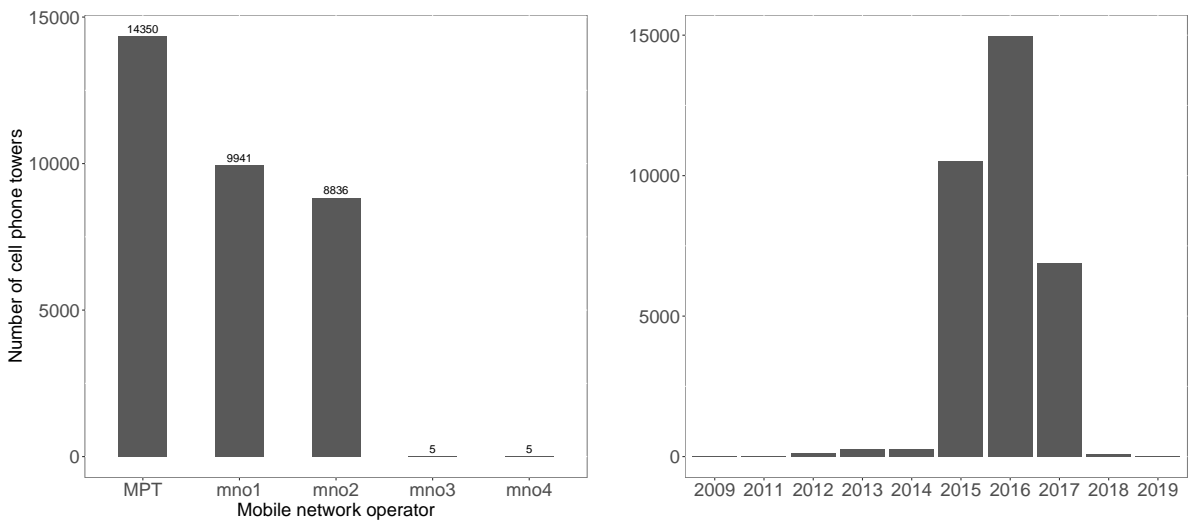


Figure B.4: Expansion of the cell tower network of MPT. The blue dots show locations of cell phone towers that are added to the data each year, and the black dots show locations of the pre-existing cell phone towers.



(a) Number of cell towers by provider

(b) Creation of cell towers over time

Figure B.5: Panel (a) presents the total number of cell phone towers by mobile network operator. Panel (b) shows when cell towers were reported in the OpenCellID data.

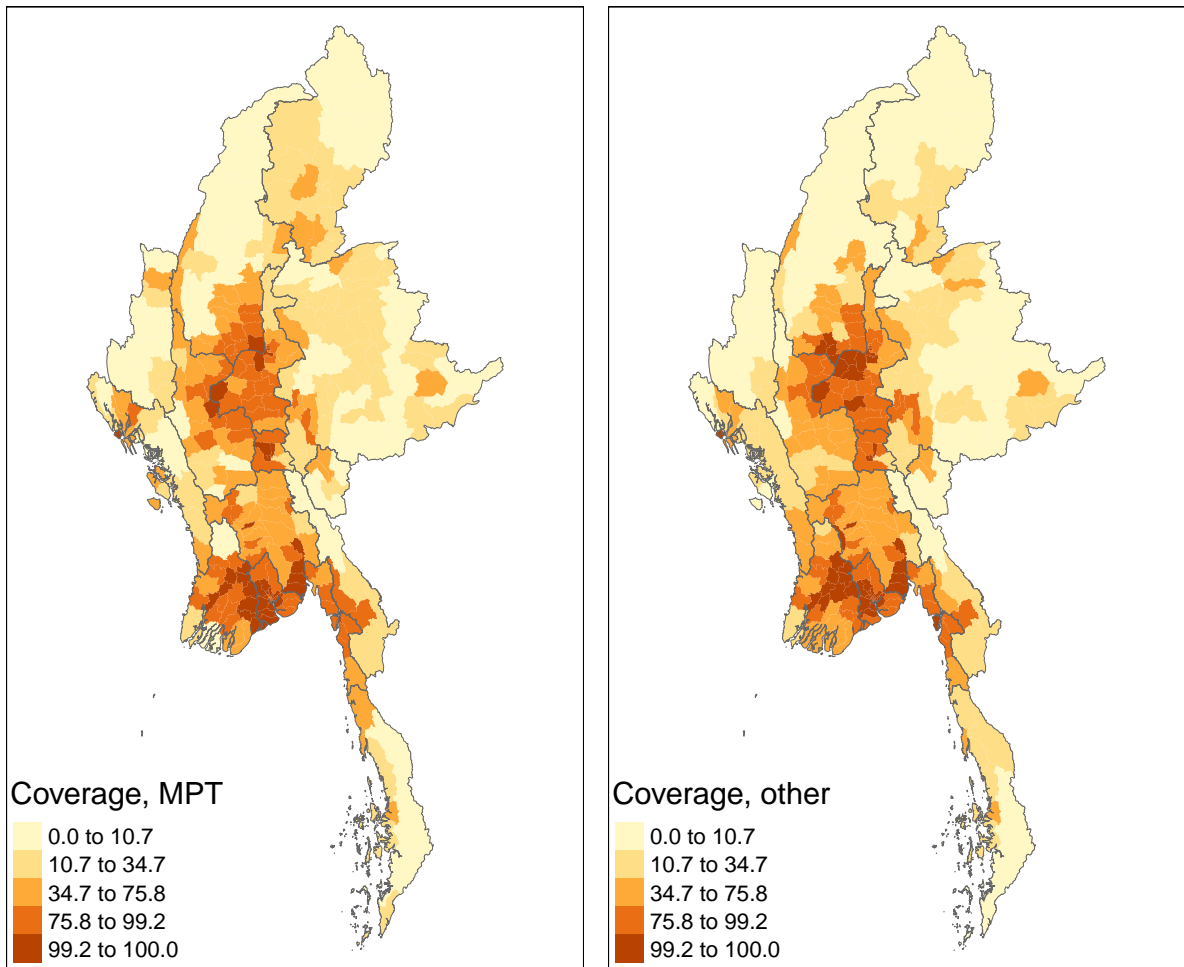


Figure B.6: Predicted cellphone coverage by MPT (left) and by other providers (right) at township level.

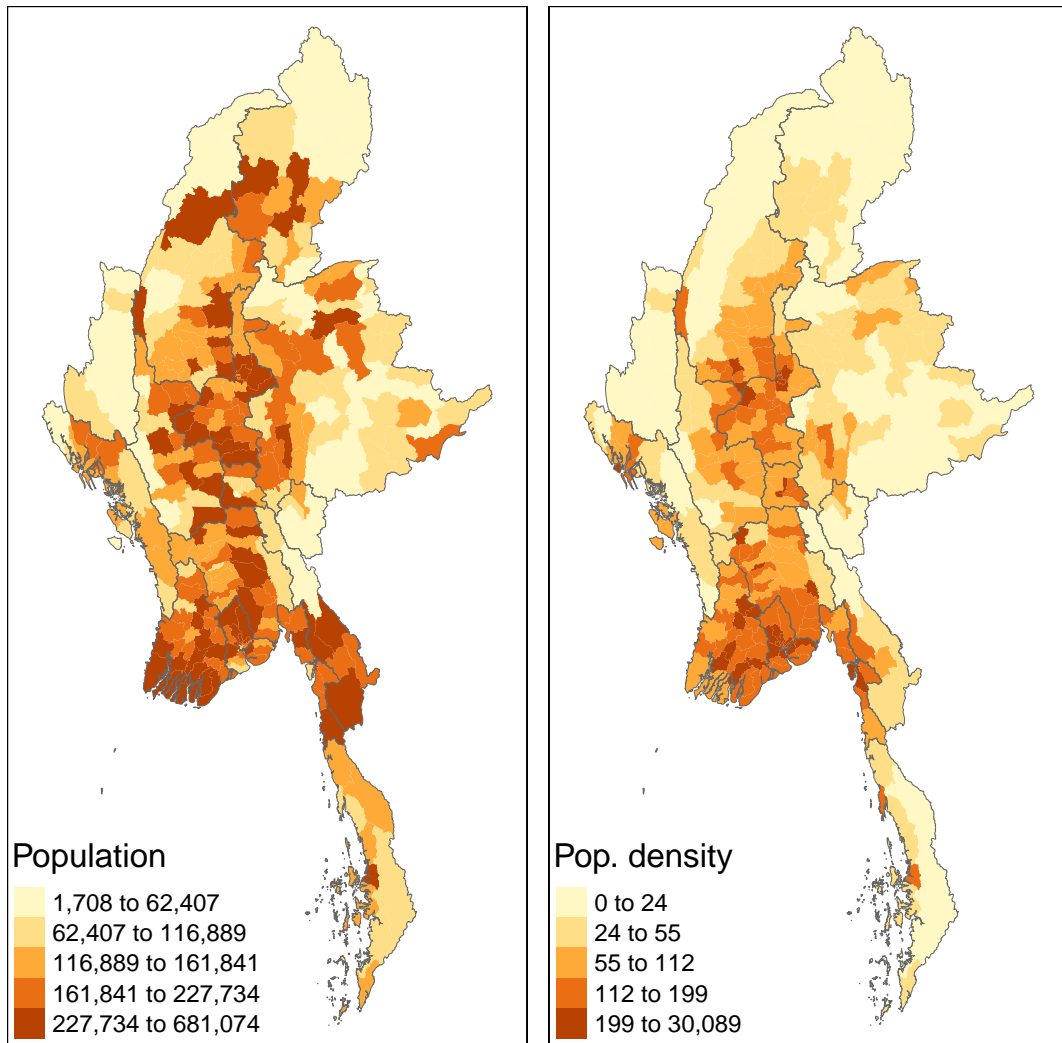


Figure B.7: Township population (left) and population density (right). Calculated from the CIESIN data for 2015.

C. Tables

Table C.1: Summary statistics at township level

	Mean	St.dev
Dependent variables		
Conflict dummy, GDELT	0.65	0.48
Conflict dummy, ACLED	0.17	0.37
Conflict events, per 1000, GDELT	0.76	4.85
Conflict events, per 1000, ACLED	0.03	0.18
Independent variables		
Cell phone coverage, MPT, %	53.61	38.71
Cell phone coverage, other, %	52.90	40.32
Cell tower density, per 1000, MPT	0.35	1.07
Cell tower density, per 1000, other providers	0.43	1.22
Population	150,360	93,860
Population density	2,077	7,129
Female, %	51.46	2.58
Urban, %	28.09	29.03
Age 0-14, %	29.35	5.91
Age 15-64, %	64.99	5.14
Citizenship Scrutiny Card, %	69.43	13.72
Other type of ID, %	3.28	4.25
No ID, %	27.29	12.85
Electricity, %	31.31	27.49
Landline phone, %	5.47	6.90
Mobile phone, %	31.62	22.87
Internet at home, %	6.31	10.58
Distance to major road, km	12.52	16.88
Distance to railway, km	51.25	66.46
Distance to nearest city, km	37.96	27.83
Distance to nearest cell tower, MPT, km	21.39	29.47
Distance to nearest cell tower, other, km	27.23	41.11
Mean elevation, m	389.58	461.06
Mean slope, degrees	88.68	5.09
Mean aspect, degrees	179.11	10.53

The conflict dummies take value one if a conflict event was recorded in the township during 01.01.2014–08.31.2017. Number of conflict events refers to the same time period. Cell phone coverage is the share of township area with sufficient cell phone signal. Other types of ID include Associate Scrutiny Card, Naturalized Scrutiny Card, National Registration Card, Religious Card, Temporary Registration Card, Foreign Registration Card or Foreign Passport. Electricity refers to main source of lightning. Distances are measured from township centroid. City refers to capital, state/region capital or district town (usually district capital). There are 330 townships.

Table C.2: Results for probability of conflict: by treatment period

	Pre		Treat		Post	
	(1)	(2)	(3)	(4)	(5)	(6)
CoverageFB	0.074 (0.083)	-0.067 (0.059)	-0.134* (0.079)	-0.028 (0.053)	-0.102 (0.118)	-0.164** (0.076)
Coverage	0.168* (0.090)	0.051 (0.062)	0.185** (0.075)	0.024 (0.058)	0.305*** (0.103)	0.119* (0.070)
Observations	330	330	330	330	330	330
Data	GDELT	ACLED	GDELT	ACLED	GDELT	ACLED
Mean(Y)	0.761	0.245	0.648	0.167	0.624	0.258
District dummies	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓

*p<0.1; **p<0.05; ***p<0.01. Robust standard errors clustered at district level are reported in parentheses. The dependent variable in columns (1)–(2) is an indicator for conflict in a township between January 1, 2014 and May 31, 2016; in columns (3)–(4) between June 1, 2016 and August 31, 2017; and in columns (5)–(6) between September 1, 2017 and March 31, 2019. Population controls: log population, log population density, dummy for below median urban rate, age (15–64 y.o.), population with no ID, population with electricity, mobile phone, landline phone, and internet at home. Spatial controls: 2nd order polynomials of distance to major town, distance to major road, distance to railway, distance to MPT transmitter, distance to other transmitter, mean elevation, slope and aspect of the slope, variance of elevation and slope. The predictors are standardized.

Table C.3: Cross-sectional results for conflict in Rakhine State: by conflict type

	Coerce (1)	Assault (2)	Fight (3)	Mass violence (4)
CoverageFB	0.012 (0.013)	0.001 (0.012)	0.026* (0.015)	-0.005 (0.006)
Coverage	-0.018 (0.011)	-0.013 (0.008)	-0.017 (0.014)	-0.008 (0.007)
Observations	1059	1059	1059	1059
Mean(Y)	0.021	0.016	0.029	0.007
District dummies	✓	✓	✓	✓
Controls	✓	✓	✓	✓

*p<0.1; **p<0.05; ***p<0.01. Robust standard errors are reported in parentheses. The dependent variable is an indicator for different conflict types. Conflict measures are based on data from GDELT. Population controls: log population, log population density, dummy for below median urban rate, age (15–64 y.o.), population with no ID, population with electricity, mobile phone, landline phone, and internet at home. Spatial controls: 2nd order polynomials of distance to major town, distance to major road, distance to railway, distance to MPT transmitter, distance to other company’s transmitter, mean elevation, slope and aspect of the slope, variance of elevation and slope. The predictors are standardized.