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

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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 mobile phones and the Facebook app in particular. 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. However, the analysis 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

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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 can affect the occurrence and 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. In this setting availability of social media constitutes a significant shock to communication and access to information. 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 waives 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

1. Few recent exceptions are Enikolopov et al. (2020), Bursztyn et al. (2019), Campante, Durante, and Sobbrio (2018), Falck, Gold, and Heblich (2014), and Czernich (2012).

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 indeed 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 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. The cross-sectional analysis compares conflict outcomes in areas that are similar in terms of socio-economic and geographical characteristics, but have different cell phone coverage due to terrain between the location and cell towers. The results show that social media availability did not on average increase conflict occurrence. On the contrary, the results suggest that conflict decreased, although the estimates are imprecise. Examining different types of conflict reveals that specifically violence between organized armed groups, which involves higher levels of organization and conventional weaponry decreases. Furthermore, examining different types of actors reveals that probability of events involving rebel groups decreases. The panel analysis exploits within township variation around the time of the Facebook campaign. Population and spatial characteristics are constant and I only examine whether there is systematic time variation in conflict depending on the cell phone coverage. I do not find any average effect on conflict within townships. However, the panel approach may exacerbate attenuation bias due to measurement error in cell phone coverage.

The results also demonstrate important regional variation. 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. Previous literature has shown that disseminating propaganda tends to influence beliefs and behavior (e.g. Yanagizawa-Drott 2014; Adena et al. 2015; Peisakhin and Rozenas 2018). Instead, enhancing the ability to communicate may either mitigate or exacerbate conflict depending on whether it benefits more the organization of violence (Pierskalla and Hollenbach 2013) or its prevention (Shapiro and Weidmann 2015). The results indicate that the role of social media varies in different regional contexts. The anti-Muslim hate speech and other inflammatory content may have escalated conflict in deeply fractured and particularly volatile areas. On average, the misinformation seems to have played a smaller role than enhanced communication and coordination, which have benefited the prevention of conflict.

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. It contributes to the empirical literature on how communication technology—and social media in particular—influences 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.

Different forms of media may also be used by authoritarian regimes 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 pro-Russian candidates. 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.

2. For a more thorough literature review, see Zhuravskaya, Petrova, and Enikolopov (2020) and Weidmann and Rød (2019).

In an opposite setting in Uganda, defection messaging was effective in mitigating conflict (Armand, Atwell, and Gomes 2020).

Research on enhanced communication in conflict situations provides mixed results. 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 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 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 (2021) 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; Voigtländer and Voth 2015).

3. Background

3.1. Ethnic Conflict in Myanmar

Myanmar has been under military rule for most of its independence. The state has supported the domination of the Buddhist Bamar majority, while many of the country's numerous ethnic groups have been subjected to discrimination. 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. The citizenship law from 1982 is an important source of ethnic conflict. It granted citizenship only to the so called "national races", and at the same time defined who belongs to Myanmar and who doesn't. A number of minority groups, including the Rohingya, don't have a national race status, 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. Violence in Rakhine State—home to most of the Rohingya minority—flared up in 2012 and the Rohingya crisis has remained ongoing since then. Violent conflicts between the military and ethnic armed groups continue 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.

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

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 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. The campaign was launched in Myanmar in June, 2016, and discontinued in September, 2017 (Singh 2018).

After signing up for Facebook, Free Basics users can browse the websites and apps included in the platform without data charges. 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; Global Voices 2017). A report that tested Free Basics in several countries found that many of the apps and sites included are not available in local languages, and services like news sites are mostly from US and UK and not related to local issues

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.

(Global Voices 2017).[6] The number of Facebook users is estimated to have increased substantially—with estimates as large as from 2 million users in 2014 to 30 million in 2017 (Singh 2018). 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.).

Numerous reports attest to Facebook being a widely used as a source of news. It is used by the government and military officials for public communication, and as a consequence has also been used to spread false information.[7] The prevalence of Facebook was also noted by the UN investigation on Myanmar (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).

6. Common services include for instance AccuWeather, BabyCenter, BBC News, and bing. The services may have very limited free content, for instance when a search engine is included the results are usually behind data charges.(Global Voices 2017).

7. See e.g., Beech (2017), PRI (2017), and Regan (2019).

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 *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.[8] The number of events in the main categories is shown in the Appendix figure C.1.

The dataset contains 85,261 events of violent conflict during January 1, 2015–December 31, 2018. 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 experiencing 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

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

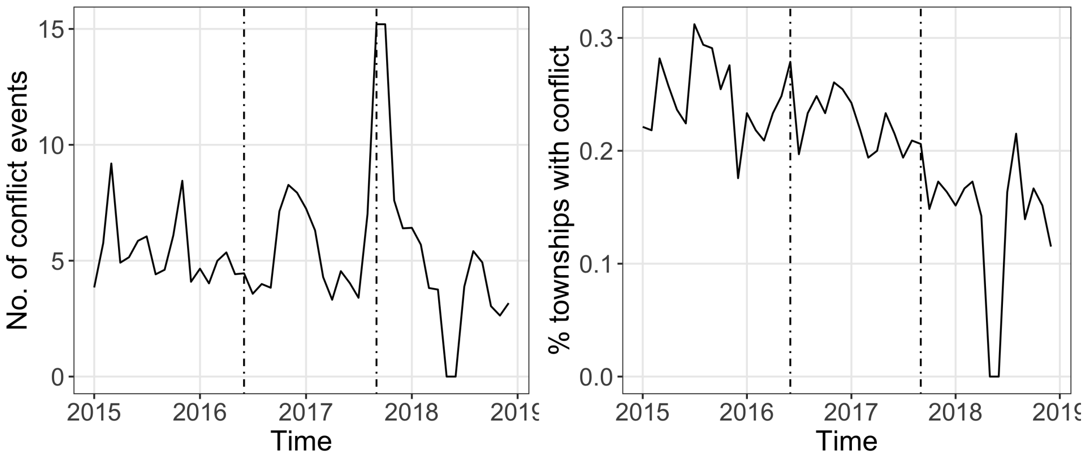

Figure 1: Average monthly number of events during the sample period The vertical dashed lines show the beginning and end of the Facebook campaign. Data source: GDELT

very concentrated. Appendix Figure C.2 plots the frequency of different types of violent events.

4.2. ACLED Data

Because the automated collection of GDELT data raises concerns about misreporting and duplicated data (Wang et al. 2016), I also conduct analysis with the Armed Conflict Location & Event Data Project (ACLED 2019; Raleigh et al. 2010). The data is collected by researchers, and it contains considerably less events than GDELT (4,143 conflict events in total between January 1, 2015–December 31, 2018). However, because the data is reviewed and checked, there is less incorrect reporting. ACLED collects data 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 as 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 average monthly number of violent events across townships,

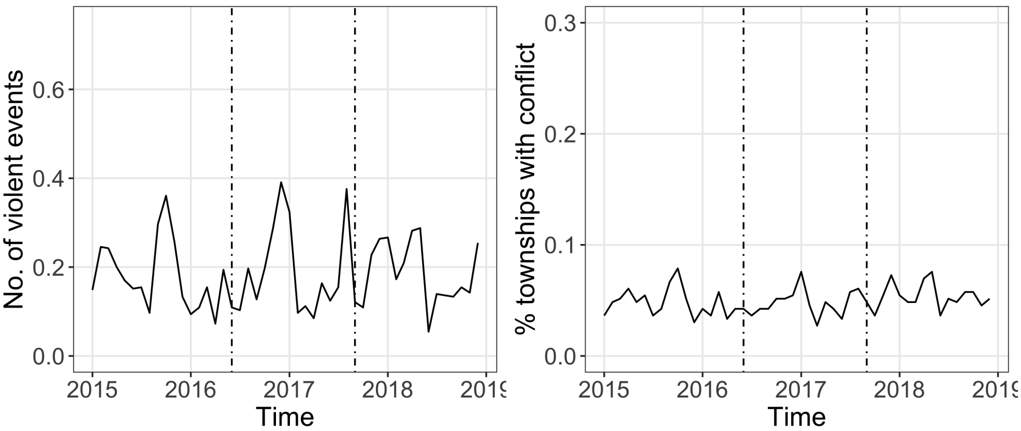

Figure 2: Average monthly number of violent events during the sample period. The vertical dashed lines show the beginning and end of the Facebook campaign. Data source: ACLED

and the right panel shows the monthly share of townships experiencing conflict events. During the sample period, every month on average 5% of townships experienced at least one violent event. Unlike GDELT, ACLED data does not exhibit a decreasing trend in conflict occurrence. Appendix Figure C.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.

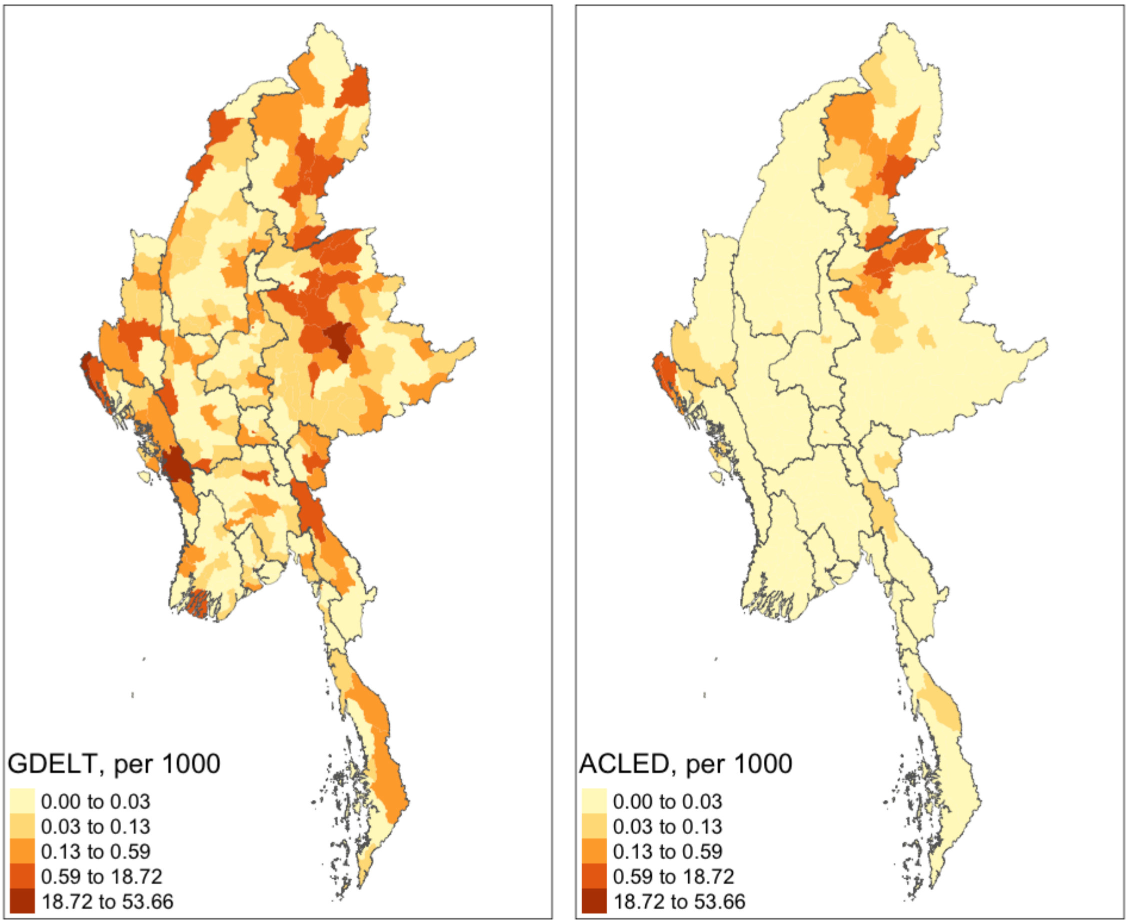

Figure 3: Locations of conflict events during June, 2016–August, 2017.
The breaks coincide with the 50th, 75th, 90th, 99th, and 100th percentiles from GDELT.

4.3. Cell phone coverage

Information on the locations of cell phone towers is obtained from OpenCellID, which is the largest open database of cell towers in the world. 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, as well as from databases of other apps and contributions from GSM network providers.

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. Several mobile network operators can have antennas in the same cellphone tower. Myanma Post and

Telecommunications (MPT) has 14,350 cell phone tower locations, and other operators have 18,787 tower locations. Appendix Figure C.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 C.5 shows the number of cell tower by provider and when they were added in OpenCellID.

Most of the cell towers were reported to the dataset in 2015 and 2016. Although the date when a cell tower was reported in the database might not be the same as when it was built, 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. Appendix Figure C.5 shows that MPT's network expansion has closely followed that of other providers. When constructing the predicted cell phone coverage, I only use cell phone towers that were included in the dataset before September 2017. The time information is not used further so as not to introduce bias from confounding factors.

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).

Because I don't have all the technical details of the cell towers, the estimated coverage can be thought of as using a fixed radius around a cell tower while taking into account topographic features. The prediction is calculated for 200m resolution grid cells.[9] These

9. See Appendix A for a more detailed description of the coverage prediction.

predictions are aggregated to obtain share of each township with cell phone reception. I do this separately for MPT and for the set 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, based on cell towers reported before September 2017. The predicted coverage is 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. Nevertheless, I use this data instead of, for instance, the commonly used GSM coverage maps from Collins Bartholomew, because with the latter it is not possible to differentiate coverage by mobile network provider (MNO), which is important for the empirical strategy. Moreover, when data is not available directly from MNOs, the GSM maps are also based on data from OpenCellID.

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. 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.

4.4. Local level characteristics

Information on population characteristics comes from the Myanmar 2014 Census. The main analysis is conducted at the township level.[10] Summary statistics for the townships are presented in the Appendix Table D.1. Because I do not have information on the ethnic composition of the population at a disaggregated level, I use information on identity

10. Myanmar consists of 18 states and regions, which are broken into 76 districts, that are divided into 330 townships, and finally 13,800 village tracts.

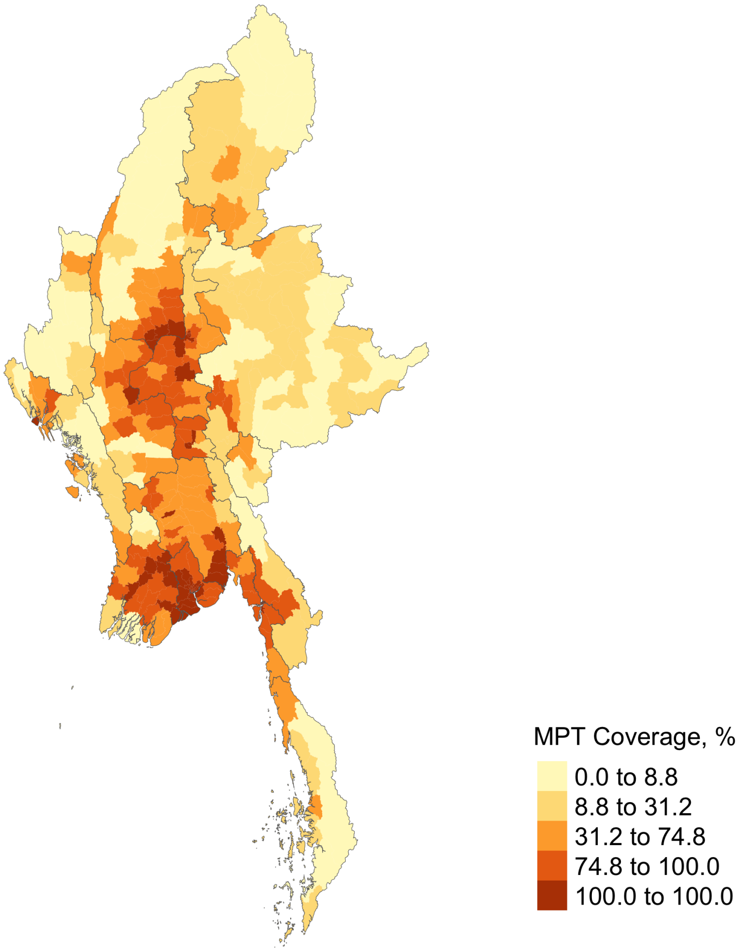

Figure 4: Predicted MPT cellphone coverage at township level

cards as a proxy.[11] 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.

Because the census data is only available for township level and only for one year, I obtain additional information on population from WorldPop. I use the 100m resolution population counts that have been adjusted to match the corresponding official United Nations population estimates. I aggregate the cells to obtain estimates of village tract population as well as time series information.[12] I use geospatial data provided by the Myanmar Information Management Unit (2019) to obtain administrative boundaries,

11. Moreover, the available information may be misleading. According to the Census Observation Mission, most of the observed respondents who self-identified as Rohingya were either not enumerated in the census or their ethnicity information was skipped.

12. See Appendix Figure C.7 for the geographic distribution of population.

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 with 30 arc second resolution 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 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. Cross-sectional analysis

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

$$Y_i = \beta CoverageFB_i + \delta Coverage_i + X_i'\gamma + \lambda_d + \varepsilon_i \tag{1}$$

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. My main outcome of interest is probability of conflict. Focusing on the external margin alleviates potential issues with duplicate events. 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 cell phone coverage. Because cell phone towers are likely 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, mean 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.[13] District is one administrative level higher than township, and there are 76 districts. I cluster standard errors at the district level 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

13. 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.

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. Better coverage from a mobile network provider in a given area is 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, because the data collection in GDELT is automated, there may be duplicate reporting. Using a dummy variable as the outcome alleviates this concern. Second, because the conflict data is based on monitoring the news, 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. 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. If access to cell phone coverage lead to higher reporting, both *CovergaFB* and *Coverage* should have a positive effect on conflict. Alternatively, more violence could mechanically lead to lower reporting. For example, if a township is subject to mass deportations or burning down villages, subsequent conflict events may become unlikely.

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 dataset starts in the beginning of 2014. The time effect τ_t captures time specific effects that are common to all townships, and the township fixed effect λ_i captures 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 examine 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.

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 in the GDELT, and in columns (4)–(6) an indicator for a violent event in the ACLED data.

Table 1: Cross-sectional estimates on probability of conflict

	Conflict dummy, GDELT			Conflict dummy, ACLED		
	(1)	(2)	(3)	(4)	(5)	(6)
CoverageFB	−0.132	−0.267*	−0.122	0.048	−0.020	−0.003
	(0.117)	(0.142)	(0.131)	(0.039)	(0.040)	(0.046)
Coverage	0.090	0.212	0.169	−0.051	−0.034	−0.015
	(0.119)	(0.145)	(0.132)	(0.041)	(0.059)	(0.064)
Observations	330	330	330	330	330	330
R^2	0.259	0.321	0.440	0.599	0.640	0.651
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 1, 2016 and August 31, 2017. Population controls: log population, log population density, dummy for below median urban rate, share of working age (15–64 y.o.) population, share of population with no ID, share of 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.

The estimates in Table 1 are imprecise, but the point estimates suggest that cell phone coverage provided by MPT, i.e. free access to Facebook, is associated with lower probability of conflict. In Columns (1)-(3), the point estimates are relatively large but imprecise. 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 associated with 16.2 percentage point decrease in probability of conflict. The estimate is statistically significant only in Column (2) which adds spatial controls, but once population characteristics are included in Column (3) the estimate is again nonsignificant.

A placebo test (Table D.2 in the Appendix) shows that *CoverageFB* had no effect in the pre-treatment period. The point estimates indicate that possible effects took place in the treatment or post-treatment periods. The two sources of conflict data exhibit slightly different patterns—in GDELT, the estimate is large but imprecise in the treatment period, whereas in ACLED the effect appears only in the post-treatment period, after the Facebook campaign has ended.

Table 2: Cross-sectional estimates on number of conflict events

	log(no. conflict events), GDELT			log(no. conflict events), ACLED		
	(1)	(2)	(3)	(4)	(5)	(6)
CoverageFB	−0.396	−0.690	−0.222	0.100	−0.177	−0.139
	(0.369)	(0.471)	(0.450)	(0.082)	(0.126)	(0.115)
Coverage	0.541	0.503	0.394	−0.141	−0.139	−0.131
	(0.413)	(0.538)	(0.493)	(0.092)	(0.147)	(0.119)
Observations	330	330	330	330	330	330
R^2	0.283	0.357	0.466	0.733	0.786	0.798
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 logged number of conflict events+1 between June 1, 2016 and August 31, 2017. Population controls: log population, log population density, dummy for below median urban rate, share of working age (15–64 y.o.) population, share of population with no ID, share of 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.

Table 2 presents results for logged number of conflict events.[14] The results show no significant effect on intensity of conflict. The point estimates again suggest a negative affect on conflict. Based on GDELT, there are on average more conflict events in areas with better cell phone coverage, whereas ACLED data (Columns (4)–(6)) does not exhibit this pattern. The estimates for coverage with Facebook access in Columns (1)–(3) are also quite sensitive to controls. This could be due to duplicates and misreporting in the GDELT data, which are likely to be correlated with cell phone coverage.

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 fighting. The point estimate on assaults is quite large in magnitude, but the effect seems to be less systematic. Events categorized as assaults include abductions, different types of physical assaults, and use of explosive devices. Fight includes most forms of conventional military force. Based on

14. One event is added to all observations because the logarithm is not defined at zero.

Table 3: Cross-sectional estimates on probability of conflict: by type of conflict

	Coerce (1)	Assault (2)	Fight (3)	Mass violence (4)	Battle (5)	Civilians (6)	Explosion (7)
CoverageFB	−0.022	−0.201	−0.224*	−0.057	−0.112**	0.025	0.004
	(0.152)	(0.158)	(0.120)	(0.057)	(0.052)	(0.059)	(0.028)
Coverage	0.139	0.186	0.184	0.026	0.035	−0.008	−0.058
	(0.158)	(0.156)	(0.132)	(0.058)	(0.062)	(0.056)	(0.041)
Observations	330	330	330	330	330	330	330
R^2	0.377	0.372	0.482	0.387	0.708	0.552	0.737
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 1, 2016 and August 31, 2017. All regressions include population controls and spatial controls. Population controls: log population, log population density, dummy for below median urban rate, share of working age (15–64 y.o.) population, share of population with no ID, share of 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.

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." Majority of the events classified as battles involve both state forces and rebel groups. Although the event classifications are somewhat different between GDELT and ACLED, the pattern is quite similar—violence conducted by or between organized armed groups decreases. The results suggest that on the whole, the communication and coordination channel have been important for prevention of organized violence, whereas misinformation and hate speech do not seem to have increased conflict.

To further explore the possible mechanism, I next examine conflict by actor type. Actors can be both perpetrators or victims or violent events. Table 4 presents estimates from regressions where the outcome variable is a dummy that takes value one if a specific type of actor was involved in the conflict event. Columns (1)-(4) present estimates from GDELT. In column (1), the outcome takes value one if one of the actors involved is part of state forces, i.e., police forces, government, or military. In the data, state forces are most often involved in fighting and coercion. Insurgents includes insurgents (all rebels who attempt to overthrow their national government) and separatist rebel. Rebels

Table 4: Cross-sectional estimates on probability of conflict: by type of actor

	State (1)	Insurgents (2)	Rebels (3)	Civilians (4)	State (5)	Militias (6)	Rebels (7)
CoverageFB	−0.062	−0.043	−0.182**	−0.193	−0.020	−0.033	−0.075
	(0.157)	(0.055)	(0.071)	(0.141)	(0.040)	(0.059)	(0.047)
Coverage	0.214	0.039	0.091	0.125	0.011	−0.010	0.023
	(0.165)	(0.065)	(0.061)	(0.145)	(0.055)	(0.050)	(0.050)
Observations	330	330	330	330	330	330	330
R^2	0.433	0.478	0.524	0.402	0.723	0.554	0.712
Data	GDELT	GDELT	GDELT	GDELT	ACLED	ACLED	ACLED
Mean(Y)	0.51	0.06	0.1	0.39	0.14	0.1	0.13
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 1, 2016 and August 31, 2017. All regressions include population controls and spatial controls. Population controls: log population, log population density, dummy for below median urban rate, share of working age (15–64 y.o.) population, share of population with no ID, share of 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.

includes armed and violent opposition groups and individuals. Insurgents and rebels are mostly involved in fighting. Columns (5)-(8) present estimates from ACLED. Militia includes both political militias and identity militias. In both data the negative effect is most pronounced for violence involving rebels. In ACLED, rebel groups are defined as "political organizations whose goal is to counter an established national governing regime by violent acts" (ACLED 2019).

The results are consistent with the interpretation that incendiary content on social media may have played a smaller part than enhanced communication and coordination. The previous literature shows that propaganda and mass media tend to shift individuals' beliefs in the intended direction. For example, Yanagizawa-Drott (2014) shows that during the Rwandan genocide anti-Tutsi propaganda significantly increased violence by persuading people to participate in the violent acts. Instead, the literature on the role of communication technology in conflict finds mixed results, depending on whether the technology benefits more organization or prevention of conflict.[15] As the results indi-

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

cate that availability of social media leads to conflict becoming less likely, it seems that the anti-Rohingya and other inflammatory content on Facebook were less important in the current context than the communication channel. 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. A similar mechanism may be at work in the Burmese context. As Table 3 demonstrates, the decrease in violence is driven by decreased fighting between organized armed groups, whereas other types of violence are not similarly affected. For instance coercion, which is defined as repression and violence against civilians (e.g., detentions, destruction of property, restrictions on political freedoms), is not significantly affected by social media availability.

Because the GDELT may contain considerable amount of duplicate reporting, in addition to comparing results to ACLED, I also check the results using only the so called root events, indicating particularly important events. About half of the conflict events in the data are also root events. The results for probability of conflict and number of conflict events are presented in Table D.3 in the Appendix. The estimates portray similar patterns as the main results. Examining different conflict types, the estimated effect on Fight is smaller and nonsignificant when we only focus on root events, but the other estimates are relatively unaffected.

As a further robustness check, I also estimate the effect of population weighted cell phone coverage on conflict. Tables D.4 in the Appendix present results for the dummy outcome and number of conflict events. The estimates on dummy outcomes and number of conflict events in GDELT are close to zero, while the estimate on number of events in ACLED is close to that of Table 2. Appendix Table D.5 presents results for different conflict types. The estimates are somewhat smaller but similar estimates in Table 3.

Table 5: Difference-in-differences estimates

	Conflict dummy		log(no. conflict events)	
	(1)	(2)	(3)	(4)
CoverageFB·Treat	−0.0002	−0.001	−0.023	−0.003
	(0.007)	(0.004)	(0.016)	(0.005)
CoverageFB·Post	0.011	−0.005	0.001	−0.009
	(0.009)	(0.005)	(0.019)	(0.008)
Treat	0.002	0.004	0.027	0.015*
	(0.011)	(0.005)	(0.024)	(0.008)
Post	−0.039**	0.008	−0.012	0.021
	(0.016)	(0.007)	(0.034)	(0.013)
Observations	15840	15840	15840	15840
R^2	0.398	0.413	0.665	0.424
Data source	GDELT	ACLED	GDELT	ACLED
Township FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

*p<0.1; **p<0.05; ***p<0.01. Robust standard errors clustered at township level are reported in parentheses. Unit of observation is township-month. The dependent variable in columns (1)–(2) is an indicator for conflict in a township, and in columns (3)–(4) logged number of conflict events+1. All regressions control for log population and log population density. The predictors are standardized.

6.2. Panel Estimates

I now turn to the difference-in-differences model. The dependent variable in columns (1)–(2) of Table 5 is an indicator for conflict events, and in columns (3)–(4) the logged number of conflict events. All specifications include township fixed effects and 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 periods, respectively. Because the measure of other cell phone coverage is time invariant, it is captured by the township fixed effects.

The results show no systematic change in conflict occurrence over time that is associated with the Facebook campaign. Using population weighted cell phone coverage in the panel specifications yields very similar estimates (see Appendix Table D.6). Since most of the covariates are only available for the cross-section, it is possible that there are some important factors that vary between townships and over time that are omitted and can

Table 6: 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	−0.006	0.001	0.003	−0.002	−0.001	0.002	−0.005**
	(0.006)	(0.005)	(0.006)	(0.002)	(0.003)	(0.002)	(0.002)
CoverageFB·Post	−0.006	0.003	0.011	−0.006	−0.001	−0.002	−0.007***
	(0.008)	(0.005)	(0.007)	(0.005)	(0.004)	(0.002)	(0.003)
Treat	−0.009	0.016**	0.018*	0.008**	0.004	−0.004	0.010***
	(0.010)	(0.007)	(0.009)	(0.004)	(0.004)	(0.003)	(0.004)
Post	−0.050***	0.018*	−0.009	0.033***	0.006	−0.006	0.018***
	(0.014)	(0.009)	(0.013)	(0.009)	(0.006)	(0.005)	(0.006)
Observations	15840	15840	15840	15840	15840	15840	15840
R^2	0.394	0.399	0.385	0.501	0.389	0.160	0.233
Data	GDELT	GDELT	GDELT	GDELT	ACLED	ACLED	ACLED
Township FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓

*p<0.1; **p<0.05; ***p<0.01. Robust standard errors clustered at township level are reported in parentheses. Unit of observation is township-month. All regressions include township and month-year fixed effects. All regressions control for log population and log population density. The predictors are standardized.

bias the estimates.

Table 6 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 again reveal variation between conflict types. However, the pattern is somewhat different from the cross-sectional results. Remote violence is the only conflict type that clearly decreases. Fighting increases after the treatment period, however the same pattern is not evident in the ACLED data.

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

Table 7: Cross-sectional estimates on conflict in Rakhine State

	Conflict dummy			log(no. conflict events)		
	(1)	(2)	(3)	(4)	(5)	(6)
CoverageFB	−0.005	0.025*	0.021	0.003	0.010	0.0003
	(0.008)	(0.014)	(0.013)	(0.018)	(0.048)	(0.049)
	[0.655]	[0.12]	[0.173]	[0.966]	[0.742]	[0.995]
Coverage	−0.003	−0.011	−0.003	−0.012	−0.049	−0.032
	(0.008)	(0.012)	(0.012)	(0.021)	(0.033)	(0.028)
	[0.735]	[0.492]	[0.844]	[0.672]	[0.229]	[0.333]
Observations	1059	1059	1059	1059	1059	1059
R^2	0.011	0.055	0.077	0.008	0.028	0.062
District dummies	✓	✓	✓	✓	✓	✓
Spatial controls		✓	✓		✓	✓
Population controls			✓			✓

*p<0.1; **p<0.05; ***p<0.01. Robust standard errors clustered at village level are reported in parentheses. The p-values for wild cluster bootstrap standard errors at the township level are reported in square brackets. The dependent variable in Columns (1)-(3) is an indicator for conflict of particular type in a township between June 1, 2016 and August 31, 2017, and in (4)-(6) logged number of conflict events. Conflict data is from GDELT. Population controls: log population, log population density, dummy for below median urban rate, share of working age (15–64 y.o.) population, share of population with no ID, share of 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.

state—home for most of the Rohingya population in Myanmar—to gauge the effect of social media on Rohingya-related conflict.

Because Rakhine consists of only 17 townships, I conduct the analysis at village level to retain enough units of observation. The population controls, apart from population counts and density that are derived from WorldPop, correspond to the township level measures. I only consider conflict measured from GDELT as the ACLED data is too sparse. 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 7 presents cross-sectional estimates. In contrast to the previous results, in Rakhine villages Facebook availability is associated with a small increase in probability of conflict.Although the estimates in Columns (1)-(3) are somewhat imprecise, they suggest that there is important regional heterogeneity. Because of the small number of townships, I report robust standard errors, as well as p-values for wild cluster bootstrap standard errors at the township level (Cameron, Gelbach, and Miller 2008). 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 into refugee camps in Bangladesh, which could mechanically reduce subsequent violence.[16] The estimated effects on number of conflict events are imprecise and small. Examining different conflict types reveals that increasing probability of conflict is driven particularly by increased fighting (see Table D.8 in the Appendix). Finally, Appendix Table D.9 presents estimates of population weighted cell phone coverage, which are very close to the estimates above.

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.

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 of Facebook to estimate whether social media affects probability and intensity of conflict.

The results suggest that availability of social media may have had an average negative effect on conflict occurrence. The cross-sectional analysis that exploits exogenous

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

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 local context in which it is introduced. In an already volatile situation, it may exacerbate the existing prejudices.

Without access to Facebook content, 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.

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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.[17] 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 prediction is then calculated for 200m resolution grid cells.

17. Radio Mobile is copyright of Roger Coudé VE2DBE.

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, but because of limitations of network architecture and poor performance of cell phone antennas, in practice the range can be much lower.

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. 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. Robustness

B.1. Count model

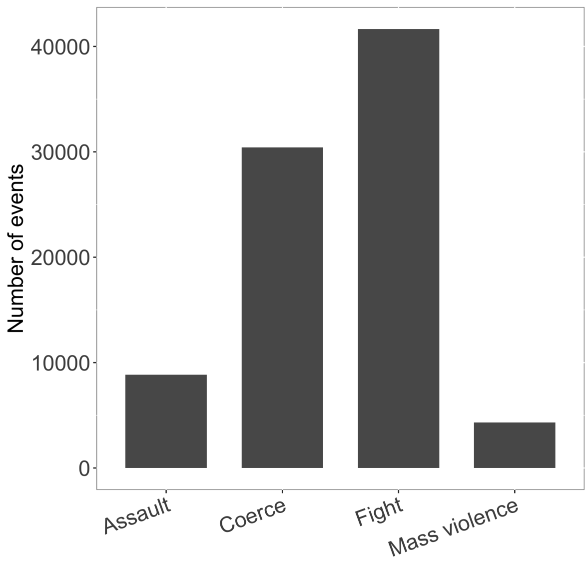
Although log transforming the data already smotths the distribution of number of conflict events, the data still has a positive skew. Therefore, I also estimate a negative binomial model. The estimates are presented in Table B.1. The estimated coefficients are somewhat larger than in the OLS model (Table 2) but they are also quite imprecise. It is likely that the the OLS estimates are attenuated because of the large number of zeros.

Table B.1: Estimates from negative binomial model

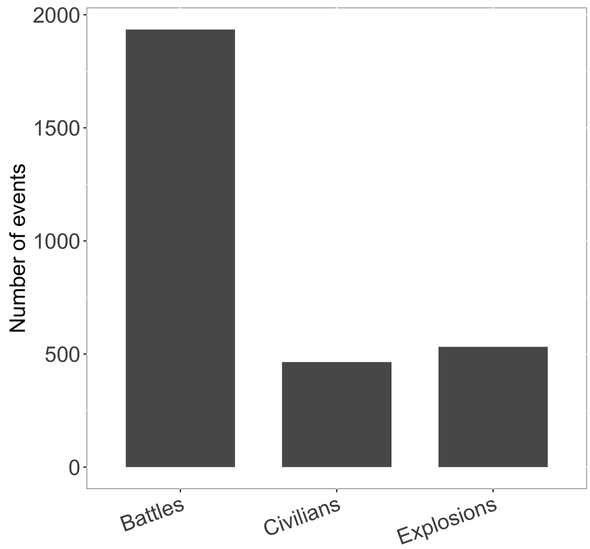
	Conflict events, GDELT			Conflict events, ACLED		
	(1)	(2)	(3)	(4)	(5)	(6)
CoverageFB	-0.377	-0.975^{**}	-0.465	0.487	-0.306	-0.520
	(0.306)	(0.414)	(0.534)	(0.412)	(0.686)	(0.986)
Coverage	0.498	0.719	0.256	-0.629	-0.606	-0.651
	(0.339)	(0.483)	(0.570)	(0.440)	(0.616)	(0.784)
Observations	330	330	330	330	330	330
District dummies	✓	✓	✓	✓	✓	✓
Spatial controls		✓	✓		✓	✓
population controls			✓			✓

*p<0.1; **p<0.05; ***p<0.01. Robust standard errors clustered at village level are reported in parentheses. Unit of observation is village tract. The dependent variable is number of conflict events between June 1, 2016 and August 31, 2017. The number of events is capped at the 95th percentile (164 events in GDELT and 11 in ACLED) to facilitate convergence. Population controls: log population, log population density, dummy for below median urban rate, share of working age (15–64 y.o.) population, share of population with no ID, share of 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.

C. Figures



(a) Data: GDELT



(b) Data: ACLED

Figure C.1: Number of different conflict events in the GDELT and ACLED during January 1, 2015 – December 31, 2018.

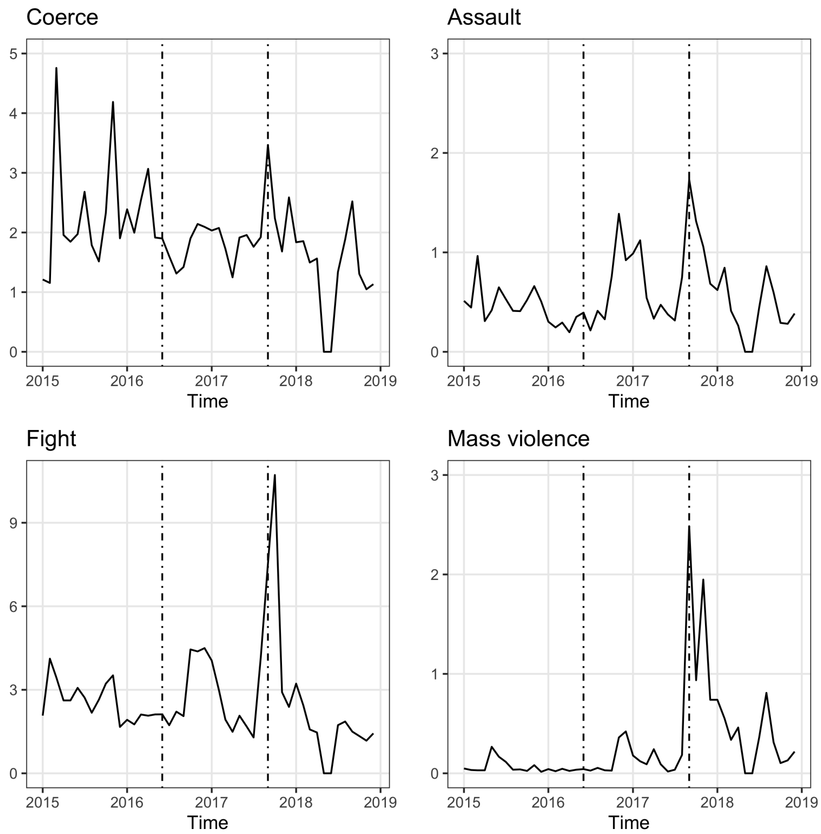


Figure C.2: Monthly number of the main types of violent events over time. The vertical dashed lines show the beginning and end of the Facebook campaign. Data source: GDELT

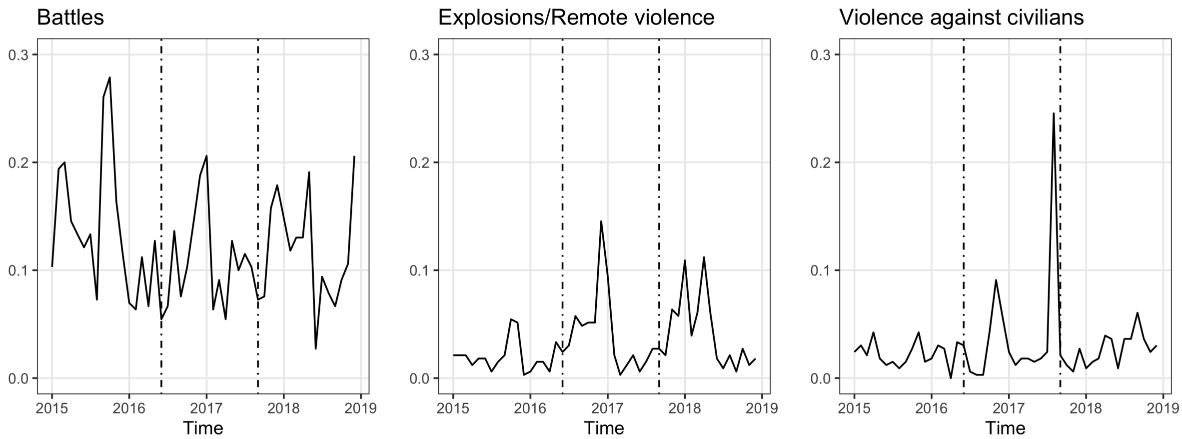


Figure C.3: Monthly number of different types of violent events. The vertical dashed lines show the beginning and end of the Facebook campaign. Data source: ACLED

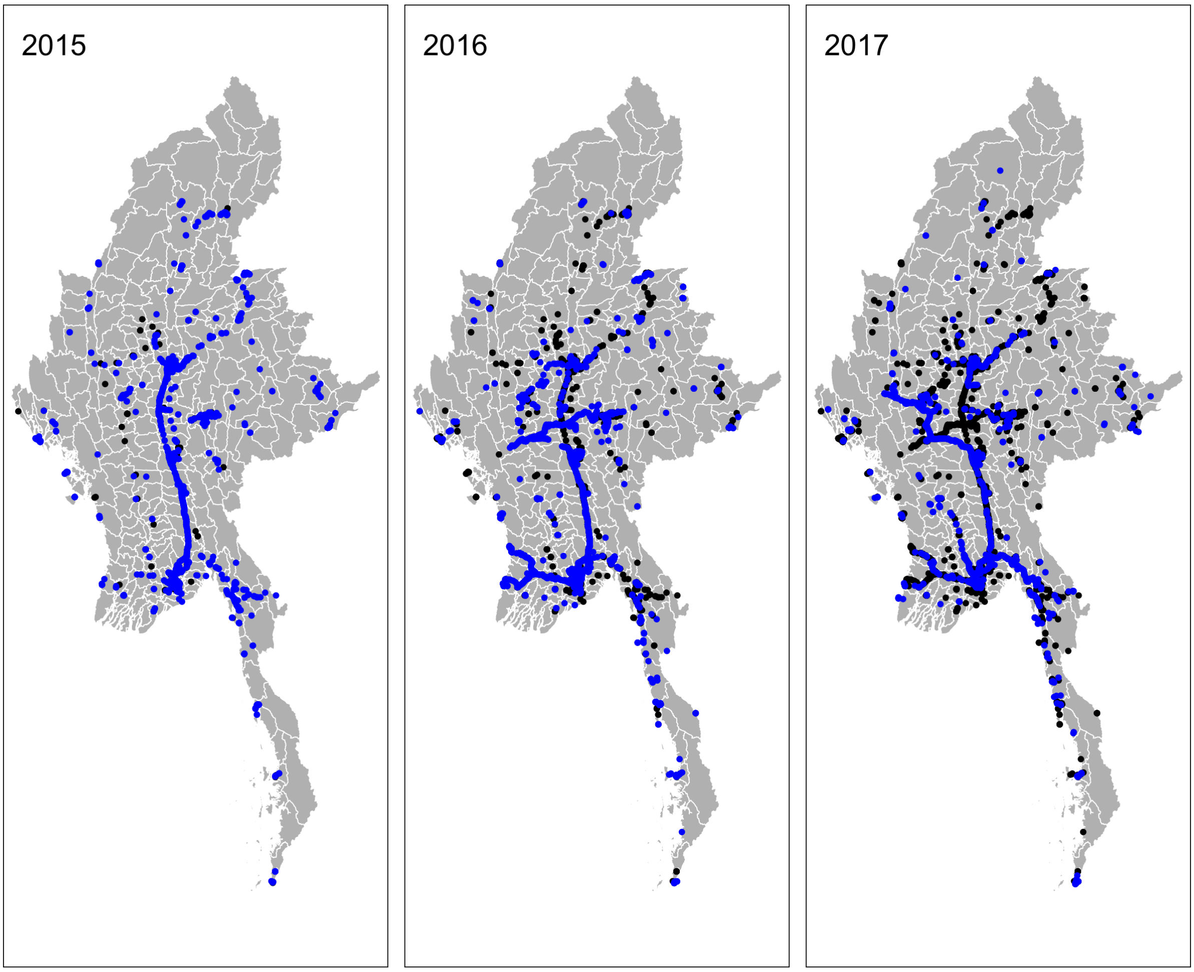
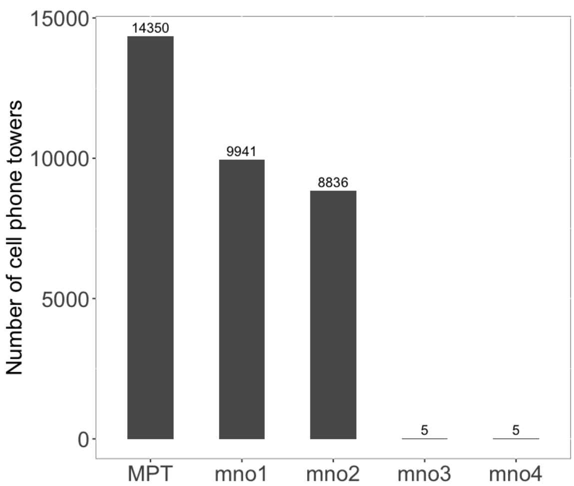
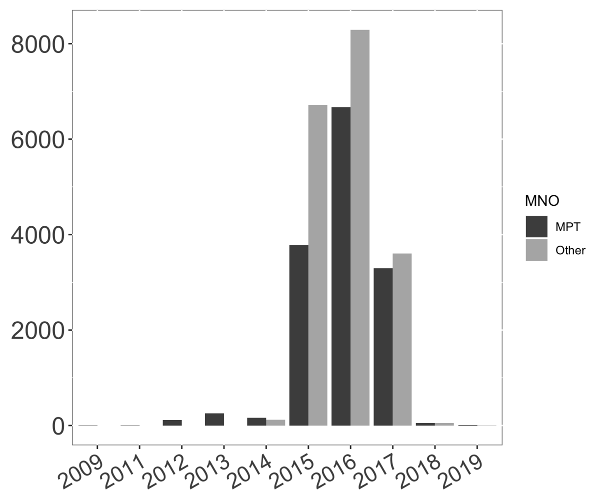


Figure C.4: Expansion of the cell tower network of MPT. The blue dots show locations of cell phone towers that are added to the data each year, and the black dots show locations of the pre-existing cell phone towers.



(a) Number of cell towers by provider



(b) Creation of cell towers over time

Figure C.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.

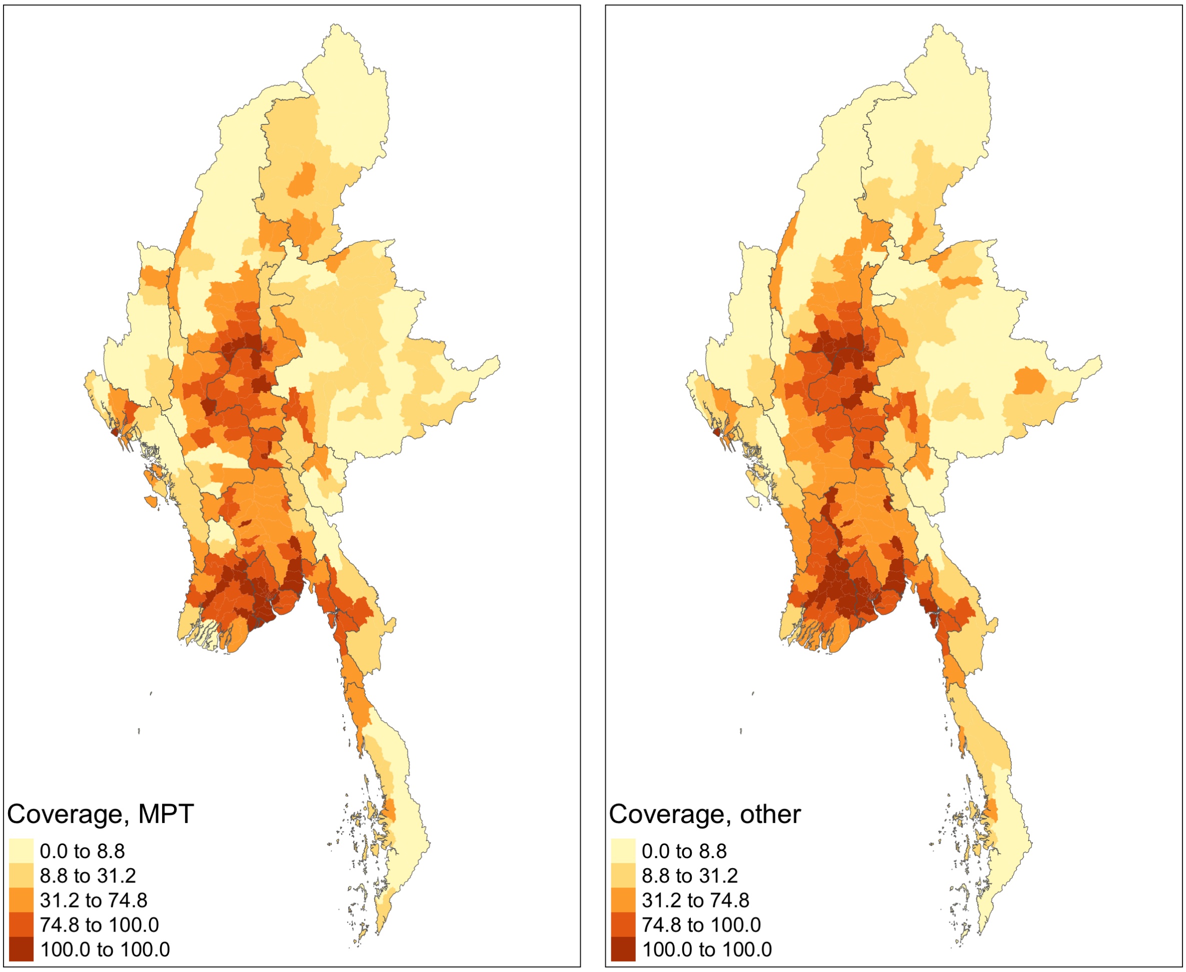


Figure C.6: Predicted cellphone coverage by MPT (left) and by other mobile network operators (right) at township level.

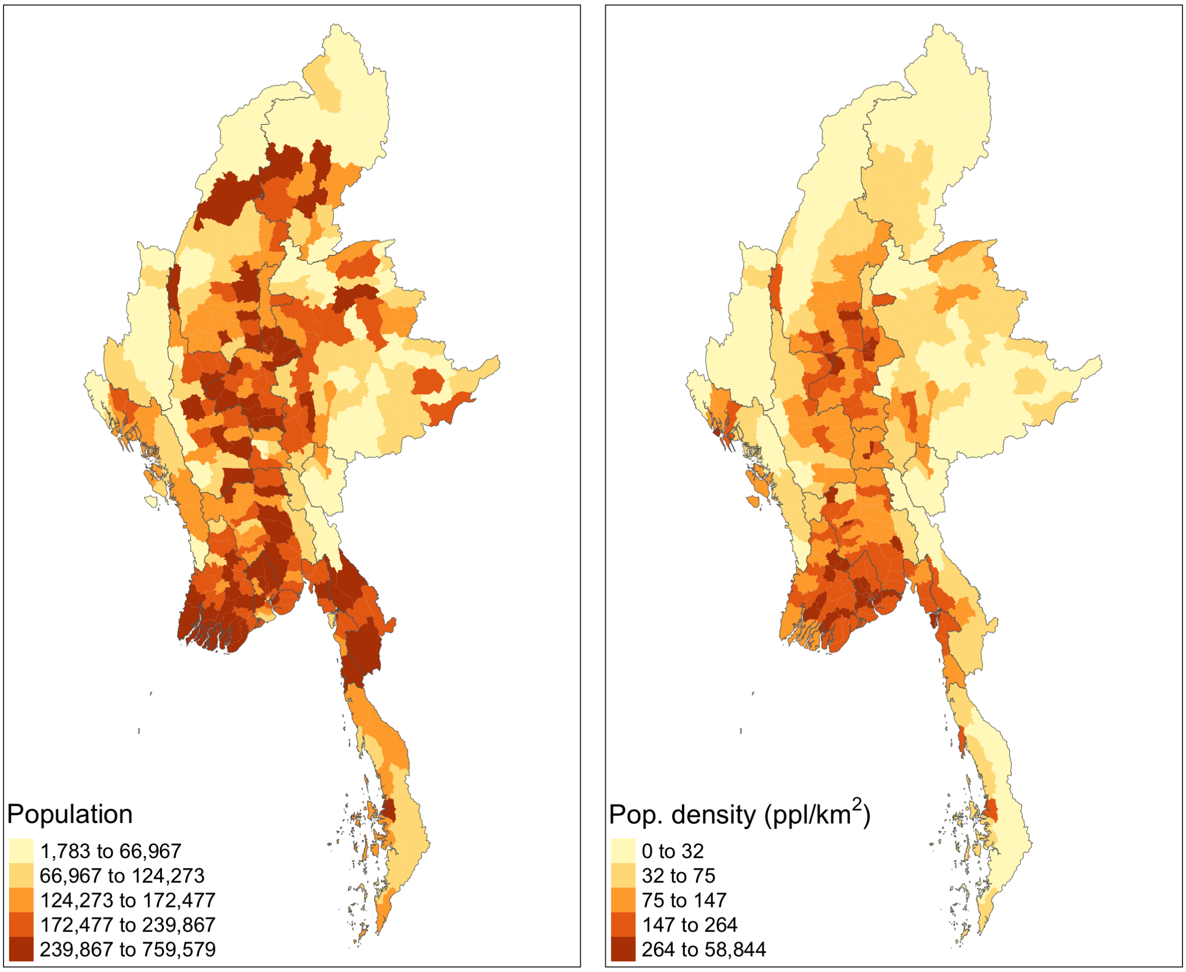


Figure C.7: Township population (left) and population density (right). Calculated from WorldPop data for 2016.

D. Tables

Table D.1: Summary statistics at township level

	N	Mean	Std.Dev.
Cell phone coverage, MPT, %	330	52.59	39.19
Cell phone coverage, other, %	330	54.21	40.54
Cell tower density, per 1000, MPT	330	0.35	1.07
Cell tower density, per 1000, other providers	330	0.43	1.22
Citizenship Scrutiny Card, %	330	69.43	13.72
Conflict dummy, ACLED	330	0.17	0.37
Conflict dummy, GDELT	330	0.65	0.48
Conflict events, per 1000, ACLED	330	0.03	0.18
Conflict events, per 1000, GDELT	330	0.76	4.85
Distance to major road (km)	330	12.52	16.88
Distance to nearest cell tower, MPT (km)	330	21.39	29.47
Distance to nearest cell tower, other (km)	330	27.23	41.11
Distance to nearest city (km)	330	37.96	27.83
Distance to railway (km)	330	51.25	66.46
electricity, %	330	31.31	27.49
Internet at home, %	330	6.31	10.58
Landline phone, %	330	5.47	6.90
Mean aspect, degrees	330	179.11	10.53
Mean elevation, m	330	389.58	461.06
Mean slope, degrees	330	88.68	5.09
Mobile phone, %	330	31.62	22.87
No ID, %	330	27.29	12.85
Other type of ID, %	330	3.34	4.30
Population	330	152363.33	95347.49
Population aged 0-14, %	330	29.35	5.91
Population aged 15-64, %	330	64.99	5.14
Population density	330	2079.82	7140.20
Population, urban, %	330	28.10	29.03
Population, women, %	330	51.46	2.58

The conflict dummies take value one if a conflict event was recorded in the township during June 1, 2016–August 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 D.2: Cross-sectional estimates on probability of conflict: by treatment period

	Pre		Treat		Post	
	(1)	(2)	(3)	(4)	(5)	(6)
CoverageFB	0.134	−0.058	−0.122	−0.003	0.023	-0.203^{***}
	(0.126)	(0.052)	(0.131)	(0.046)	(0.154)	(0.075)
Coverage	0.027	0.019	0.169	−0.015	0.127	0.103
	(0.149)	(0.053)	(0.132)	(0.064)	(0.154)	(0.077)
Observations	330	330	330	330	330	330
R^2	0.365	0.709	0.440	0.651	0.448	0.647
Data	GDELT	ACLED	GDELT	ACLED	GDELT	ACLED
Mean(Y)	0.703	0.197	0.645	0.167	0.594	0.233
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, 2015 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 December 31, 2018. Population controls: log population, log population density, dummy for below median urban rate, share of working age (15–64 y.o.) population, share of population with no ID, share of 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 D.3: Cross-sectional estimates on root events

	Event dummy	log(no. events)	Coerce	Assault	Fight	Mass violence
	(1)	(2)	(3)	(4)	(5)	(6)
CoverageFB	−0.022	−0.087	0.051	−0.193	−0.059	0.043
	(0.133)	(0.387)	(0.144)	(0.133)	(0.124)	(0.033)
Coverage	0.023	0.212	0.055	0.137	0.093	−0.033
	(0.156)	(0.440)	(0.174)	(0.149)	(0.150)	(0.048)
Observations	328	328	328	328	328	328
R^2	0.398	0.445	0.351	0.352	0.470	0.434
Mean(Y)	0.56	40.43	0.44	0.25	0.44	0.05
District FE	✓	✓	✓	✓	✓	✓
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 in (1) is an indicator for conflict root event in a township between June 2016 until end of August 2017; in (2) logged number of conflict root events; and in (3)-(6) an indicator for conflict of particular type between June 1, 2016 and August 31, 2017. Population controls: log population, log population density, dummy for below median urban rate, share of working age (15–64 y.o.) population, share of population with no ID, share of 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 D.4: Cross-sectional estimates of population weighted cell phone coverage

	Conflict dummy		log(no. conflict events)	
	(1)	(2)	(3)	(4)
CoverageFB_popw	0.010	0.019	0.013	−0.107
	(0.094)	(0.050)	(0.325)	(0.127)
Coverage_popw	−0.032	−0.075	−0.016	−0.196
	(0.131)	(0.058)	(0.436)	(0.125)
Observations	328	328	328	328
R^2	0.398	0.662	0.464	0.802
Data	GDELT	ACLED	GDELT	ACLED
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 in Columns (1)-(2) is an indicator for conflict in a township between June 1, 2016 and August 31, 2017. The dependent variable in Columns (3)-(4) is logged number of conflict events+1. The coverage variables are population weighted averages. Population controls: log population, log population density, dummy for below median urban rate, share of working age (15–64 y.o.) population, share of population with no ID, share of 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.

Table D.5: Cross-sectional estimates of population weighted cell phone coverage: by type of conflict

	Coerce (1)	Assault (2)	Fight (3)	Mass violence (4)	Battle (5)	Civilians (6)	Explosion (7)
CoverageFB_popw	−0.018	−0.035	−0.035	−0.057*	−0.043	−0.036	0.002
	(0.101)	(0.114)	(0.114)	(0.034)	(0.053)	(0.054)	(0.024)
Coverage_popw	0.101	−0.053	−0.053	−0.042	−0.065	0.047	−0.062*
	(0.140)	(0.121)	(0.121)	(0.050)	(0.047)	(0.052)	(0.036)
Observations	328	328	328	328	328	328	328
R^2	0.371	0.363	0.363	0.395	0.721	0.556	0.738
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 specifications are estimated on village level data, and the number of observations refers to villages in Rakhine State. The dependent variable is an indicator for conflict of particular type in a township between June 1, 2016 and August 31, 2017. The coverage variables are population weighted averages. All regressions include population controls and spatial controls. Population controls: log population, log population density, dummy for below median urban rate, share of working age (15–64 y.o.) population, share of population with no ID, share of 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.

Table D.6: Difference-in-differences estimates with population weighted cell phone coverage

	Conflict dummy		log(no. conflict events)	
	(1)	(2)	(3)	(4)
CoverageFB_popw·Treat	−0.005	−0.001	−0.030*	−0.0001
	(0.008)	(0.004)	(0.017)	(0.005)
CoverageFB_popw·Post	−0.001	−0.008*	−0.030	−0.013*
	(0.010)	(0.005)	(0.021)	(0.007)
Treat	0.001	0.004	0.027	0.015*
	(0.011)	(0.005)	(0.024)	(0.008)
Post	−0.040**	0.008	−0.013	0.021
	(0.016)	(0.007)	(0.034)	(0.013)
Observations	15840	15840	15840	15840
R^2	0.397	0.413	0.665	0.424
Data source	GDELT	ACLED	GDELT	ACLED
Township FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

*p<0.1; **p<0.05; ***p<0.01. Robust standard errors clustered at township level are reported in parentheses. Unit of observation is township-month. The dependent variable in columns (1)–(2) is an indicator for conflict in a township, and in columns (3)–(4) logged number of conflict events+1. All regressions control for log population and log population density. The predictors are standardized.

Table D.7: Difference-in-differences estimates on different conflict types with population weighted cell phone coverage

	Coerce (1)	Assault (2)	Fight (3)	Mass violence (4)	Battle (5)	Civilians (6)	Explosion (7)
CoverageFB_popw·Treat	−0.009	−0.002	−0.001	−0.002	0.001	0.001	−0.003
	(0.006)	(0.006)	(0.007)	(0.002)	(0.003)	(0.002)	(0.002)
CoverageFB_popw·Post	−0.017**	−0.001	0.003	−0.005	−0.005	−0.002	−0.006**
	(0.008)	(0.005)	(0.007)	(0.005)	(0.004)	(0.002)	(0.002)
Treat	−0.009	0.015**	0.018*	0.008**	0.004	−0.004	0.010***
	(0.010)	(0.007)	(0.009)	(0.004)	(0.004)	(0.003)	(0.004)
Post	−0.050***	0.017*	−0.010	0.033***	0.006	−0.006	0.018***
	(0.014)	(0.009)	(0.013)	(0.008)	(0.006)	(0.005)	(0.006)
Observations	15840	15840	15840	15840	15840	15840	15840
R^2	0.393	0.399	0.384	0.501	0.389	0.160	0.233
Data	GDELT	GDELT	GDELT	GDELT	ACLED	ACLED	ACLED
Township FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓

*p<0.1; **p<0.05; ***p<0.01. Robust standard errors clustered at township level are reported in parentheses. Unit of observation is township-month. All regressions include township and month-year fixed effects. All regressions control for log population and log population density. The predictors are standardized.

Table D.8: Cross-sectional estimates on conflict in Rakhine State: by conflict type

	Coerce (1)	Assault (2)	Fight (3)	Mass violence (4)
CoverageFB	0.008	−0.003	0.021	−0.004
	(0.011)	(0.011)	(0.013)	(0.006)
Coverage	−0.009	−0.001	−0.008	−0.003
	(0.007)	(0.007)	(0.011)	(0.003)
Observations	1059	1059	1059	1059
R^2	0.051	0.039	0.066	0.054
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 clustered at village level are reported in parentheses. Unit of observation is village tract. 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.

Table D.9: Cross-sectional estimates of population weighted cell phone coverage in Rakhine State

	Conflict dummy (1)	log(events) (2)	Coerce (3)	Assault (4)	Fight (5)	Mass violence (6)
CoverageFB_popw	0.023*	0.005	0.007	−0.002	0.022*	−0.005
	(0.013)	(0.045)	(0.011)	(0.011)	(0.012)	(0.006)
Coverage_popw	−0.009	−0.048*	−0.008	−0.002	−0.014	−0.003
	(0.012)	(0.026)	(0.007)	(0.007)	(0.010)	(0.003)
Observations	1059	1059	1059	1059	1059	1059
R^2	0.078	0.063	0.051	0.039	0.067	0.055
District dummies	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓

*p<0.1; **p<0.05; ***p<0.01. Robust standard errors clustered at village level are reported in parentheses. The dependent variable in Column (1) is an indicator for conflict event, in Column (2) logged number of conflict events, and in Columns (3)-(6) an indicator for a particular type of conflict event. Conflict measures are based on data from GDELT. The coverage variables are population weighted averages. All regressions include population controls and spatial controls. Population controls: log population, log population density, dummy for below median urban rate, share of working age (15–64 y.o.) population, share of population with no ID, share of 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.