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

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November, 2023

Abstract

This paper investigates whether social media access is associated with increased probability or intensity of ethnic conflict in Myanmar. In this context most people use mobile phones, and particularly the Facebook app, to access the internet. To distinguish the effects of social media from those of the broader internet, I exploit geographic variation in mobile phone coverage as a proxy for Facebook availability. Despite compelling evidence of a hate-campaign utilizing Facebook to reach wide audiences, I do not find that social media is related to conflict. The only exception to the null result is variation related to the Rohingya crisis: in this regional setting suggestive evidence points to Facebook availability being associated with higher probability of conflict.

JEL codes: D74, O33

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

*I am grateful to the anonymous referees for their insightful comments and suggestions. I also thank Michèle Belot, Enrico Cantoni, Thomas Crossley, Andrea Ichino, Andrea Mattozzi, Niklas Potrafke, Arthur Schram, Alessandro Spiganti, Nicole Stoelinga, Roope Uusitalo, and seminar participants at the EUI and UNU-WIDER for useful comments. I am grateful for the hospitality of Aalto University School of Business and Helsinki Graduate School of Economics.

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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 facilitates sharing of simplistic, false, and inflammatory messages, and increasing anecdotal evidence suggests that online outrage may lead to violence offline. This paper investigates how access to social media relates to conflict. This question has accompanied the world wide rise of social media, especially with respect to Facebook. I examine this question in the context of Myanmar in 2016–2017.

Myanmar is an important setting for several reasons. The military regime in Myanmar has remained among the longest uninterrupted dictatorships, which faces strong democratizing pressure from inside as well as outside, and for which violent conflicts are almost a pivotal pillar of its existence. Hence conflicts are common across different parts of Myanmar. Myanmar is also a setting to examine whether economic and technological development could deliver political rights, or at least reduce violence and repression. It is important as a case that may well shed light on other non-democratic regimes across the world.

The case of Facebook in Myanmar combines several aspects that are helpful to disentangle the effects of social media from those of the broader internet. First, most people use mobile phones to access internet. In 2018, 79 % of all internet traffic in Myanmar was consumed by mobile phones (We Are Social, n.d.). Second, Facebook introduced a package for mobile phone users that bundled a limited internet access with Facebook access for free over a significant period of time. Third, Facebook's package is tied to the main mobile network operator, MPT. Other service providers are not associated primarily with Facebook and their coverage can be used as a control for mobile phone access.

An important driver of increased internet penetration in many developing countries has been the emergence of such "zero-rated" apps. Zero rating means that a mobile network operator waives data charges associated with a particular app. As the cost of internet remains prohibitive for many people, zero-rated content may be the only

justifiable way to access internet (Eisenach, 2015). The rapid spread of Facebook in the developing world has strengthened its dominant positions and led to situations in which internet is primarily accessed via Facebook, making Facebook effectively the internet. Several reports describe Facebook as being so prominent that it is considered synonymous to the wider internet (see e.g., PRI, 2017; Regan, 2019).

My empirical strategy is to use mobile phone coverage by MPT as a determinant of social media availability. I use a model of electromagnetic signal propagation to estimate topography-corrected coverage (following Olken, 2009). As mobile phone signal strength is primarily determined by distance to a cell tower and the terrain between a location and a cell tower and also reduced by objects such as hills or dense foliage, the aim is to compare townships that are similar in terms of socio-economic and geographical characteristics but have different mobile phone coverage due to terrain differences between the location and nearest cell towers.

Information on cell phone towers is obtained from OpenCelliD, a crowdsourced project to collect cell phone tower locations. To measure the outcome, I use comprehensive georeferenced data on conflict events, which comes from GDELT Project (2019), which uses natural language and data mining algorithms to extract information on conflict events from different language news media.

The results do not show that access to Facebook, as proxied by mobile phone coverage, is associated with probability of conflict. Examining different types of conflict and different types of actors involved does not reveal any significant relationship. This null result is robust to different model specifications, estimation strategies, heterogeneous local characteristics, and using a different, manually compiled conflict data on conflict, Armed Conflict Location & Event Data (ACLED, 2019a).

The only exception to the null result is regional variation related to the Rohingya crisis. 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 is associated with a small increase in probability of conflict. Previous literature shows that propaganda can be highly effective at influencing beliefs

and behavior, particularly when there are pre-existing prejudices (e.g., Adena et al., 2015; Voigtländer & Voth, 2015; Yanagizawa-Drott, 2014). Since the Rohingya have been a particular target of hate speech, it is possible that in this context Facebook access may have amplified conflict.

This paper contributes to the empirical literature on how the media and communication technologies influence conflict.[1] Related studies portray the nuanced relationship between mass media, misinformation, and conflict escalation across the world. Much of the literature has studied the impact of traditional mass media as a tool for inciting violence. For example, radio has been used to disseminate propaganda, which has been an effective tool of persuasion in varying context, such as escalation of killings during the Rwandan genocide (Yanagizawa-Drott, 2014), fostering anti-Semitic beliefs in Nazi Germany (Adena et al., 2015; Voigtländer & Voth, 2015). The effects are particularly pronounced in areas with pre-existing prejudices. The emerging literature focusing especially on social media yields similar findings. Social media has been shown to increase ethnic hate crimes, especially in regions characterized by a pre-existing high levels of nationalism (Bursztyn et al., 2019; Müller & Schwarz, 2021, 2023).

There is also evidence indicating the effectiveness of information-based interventions. For instance, during the democratic period in pre-war Germany, pro-government political news had a moderating influence on support for the Nazi party (Adena et al., 2015). In another historical context, during the Lord's Resistance Army insurgency in Uganda, the government attempted to mitigate the conflict by broadcasting messages encouraging defection. This policy significantly decreased the number of attacks and fatalities and increased the number of returnees (Armand et al., 2020). I add to this literature by examining how social media availability is related to ethnic conflict in a context where traditional media is state controlled and social media is used to spread anti-Muslim content.

This paper is also related to the literature examining the role of communication technologies in conflict settings. On the one hand, the new technologies—mobile phones,

[1] For a thorough review of the literature, see Weidmann and Rød (2019) and Zhuravskaya et al. (2020).

internet, social media—are expected to promote political mobilization by facilitating uncensored communication (see e.g., Diamond, 2010). Related research underscores the influence of mobile phones (Guriev et al., 2021; Manacorda & Tesei, 2020) and social media (Enikolopov et al., 2020; Fergusson & Molina, 2021) in amplifying protest movements. On the other hand, authoritarian regimes can use these tools for propaganda and repression (Frantz et al., 2020; Rød & Weidmann, 2015). Qin et al. (2017), for example, demonstrate the power of social media monitoring as an effective instrument for detecting protests and monitoring citizens. The empirical findings relating to violent conflict are also mixed: improved ability to communicate and coordinate can improve rebel groups' ability to organize attacks (Gagliarducci et al., 2020; Pierskalla & Hollenbach, 2013), but enhanced communication technology can also benefit counter-insurgents, for example by making it easier to covertly inform security forces of local militia activity, by decreasing rebels' ability to punish informants (Shapiro & Siegel, 2015; Shapiro & Weidmann, 2015), and by improving government's surveillance capability (Shapiro & Weidmann, 2015). I add to this literature by investigating how social media access is related to different forms of violence in a non-democratic regime with frequent conflicts.

The remainder of the paper is organized as follows. Section 2 describes the context, Section 3 provides a description of the data, Section 4 describes the empirical strategy, and Section 5 presents the results. Section 6 concludes.

2 Context

2.1 Ethnic Conflict in Myanmar

Myanmar has been under military rule for most of its independence since 1948. The state has supported the domination of the Buddhist 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 does not. Several minority groups, including the Rohingya, do not have a national race status, but are instead seen as immigrants.[2] 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, criminals, and terrorists. A database on online influence operations similarly identifies a coordinated campaign by the state which produced news websites, Facebook pages, and other online content to promote propaganda and disinformation, designed to incite violence against the Rohingya (Martin et al., 2022). Violence in Rakhine State—home region of the Rohingya minority—flared up in 2012 and the Rohingya crisis has since remained ongoing, with significant peaks in violence during the "clearance operations" against the Rohingya in 2016 and 2017. 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. 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.

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

2.2 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.[3] 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.[4] Free Basics is provided in participation with local mobile network operators, who agree to waive the data charges associated with use of the platform. It can only be accessed in the given countries and with a SIM card from one of the participating mobile network operators. The operators offering Free Basics are not paid by Facebook (Eisenach, 2015). In the study period, Free Basics was available in Myanmar only through the state-owned Myanma Posts and Telecommunications (MPT). Because I do not have information on individuals' mobile phone or internet use, I use mobile 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).

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 extremely limited, cost of mobile data is high, but mobile phones are ubiquitous, 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.).

Facebook is used widely as a source of news, it is used by the government and military officials for public communication, but also for coordinated propaganda and disinformation campaigns seeking to stoke fear and violence against ethnic minorities, especially the Rohingya, and attack posts that are critical of the military (Martin et al., 2022;

[3]StatCounter's statistics are based on tracking page visits to particular sites.

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

PRI, 2017; Regan, 2019). For example, there is evidence of a state-orchestrated disinformation campaign, which involved the creation of fabricated Buddhist Facebook pages that falsely warned of impending "jihad attacks" by Rohingya Muslims (Martin et al., 2022). Reuters' investigative reporting also found "more than 1,000 examples of posts, comments and pornographic images attacking the Rohingya and other Muslims on Facebook" (Stecklow, 2018).

The prevalence of Facebook was also noted by the UN investigation on Myanmar (Human Rights Council, 2018), which stated that social media and Facebook had been instrumental in spreading anti-Muslim hate speech. The chairman of the Mission said that social media had "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). The CEO of Facebook was called to testify before the U.S. Congress about Facebook's role in ethnic violence in Myanmar (The Washington Post, 2018), and the platform has faced a lot of criticism about not preventing the spread of hate speech on the platform (Mozur, 2018).

3 Description of Data

3.1 Conflict Data

I use two dependent variables: a binary measure of conflict in a township, and the number of conflict events in a township. I use the GDELT 2.0 Event Database (GDELT Project, 2019), which is based on a project that uses language and data mining algorithms to monitor print, broadcast, and web news media in several languages across every country in the world. The algorithms are used to find detailed descriptions of events, including time, location, and actors involved. Due to the automated data collection, the GDELT database contains significantly more events than other georeferenced conflict data. I conduct robustness tests with the Armed Conflict Location & Event Data (ACLED, 2019a).

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

Figure 1: Average number of mentions (left) and average tone (right) of events. The vertical dotted lines show the beginning (June 2016) and end (September 2017) of the Facebook campaign. Data source: GDELT

conventional mass violence. 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 less organized forms of violence, such as physical assaults, abductions, assassinations, and use of explosive devices. Mass violence includes for instance mass expulsions, mass killings, and ethnic cleansing.[5]

Figure 1 plots the distribution of conflict events in 2015–2018. There are 62,874 events of violent conflict between January 1, 2015, and December 31, 2018.[6] The left panel shows the average monthly number of conflict events across townships. The increased activity in late 2017 marks the timing first attacks by the Arakan Rohingya Salvation Army (ARSA) on military posts in northern Rakhine, and the military's following anti-Rohingya "clearance operation" in Rakhine state (Human Rights Council, 2018). The right panel shows the monthly share of townships experiencing conflict. On average 19 % of townships experience conflict each month, although there is a decreasing trend. Although the number of conflict events spiked in late 2017, the events were geographically very concentrated.

[5]For a more details on the event types, see Event Data Project (2012).

[6]Since GDELT 2.0 has full coverage of conflict records only from mid February, those records from GDELT 1.0 from January-February 2015 which are not included in GDELT 2.0 are added to the data. I limit the data to events that that are geolocated at city or landmark level.

Figure 2: Number of conflict events scaled by population (in 1000) by township between June 2016 and August 2017. Gray lines depict state borders. Data source: GDELT.

Appendix Figure E.1 plots the frequency of different types of violent events. Figure 2 maps the population weighted number of conflict events during the Facebook campaign between June 2016 and August 2017. Conflict events are more frequent in the peripheral areas, and particularly in Rakhine state (Western Myanmar), and in the Shan (North-Eastern Myanmar) and Kachin state (Northern Myanmar).

3.2 Mobile Phone Coverage

Information on the locations of cell phone towers comes from OpenCelliD, 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. Cell phone tower IDs and 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 operators.

In addition to cell tower locations, the data includes an identifier for the mobile network operator (MNO), the network technology (GSM, LTE, etc.), and the date when the location was first recorded. By the end of 2018, 33,125 cell tower locations were included in the data set for Myanmar. MPT is associated with 14,342 cell phone tower locations, and other MNOs combined with 18,783 tower locations. Appendix Figure E.3 shows the number of cell towers by MNO and recording date. One tower can be fitted with several antennas. Appendix Figure E.2 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 area in central Myanmar, stretching between the three largest cities, Yangon, Nay Pyi Taw, and Mandalay.

Most of the cell towers were recorded to the database in 2015 and 2016, which marks the period of rapid expansion of the telecommunication sector. The telecommunications market was opened for foreign competition in 2014, prior to which 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 E.3 shows that the network expansion of MPT and other service providers has been closely aligned. When constructing the predicted mobile phone coverage, I only use cell phone towers that were recorded in the database before September 2017. Since the date when a cell tower location was recorded in the database may be later than when the tower started operating, the time information is not used further so as not to introduce bias from confounding factors.

I use a radio propagation model to predict where the signal is strong enough for mobile phone reception. The signal strength in a 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 the irregular terrain model (ITM) to calculate the predicted network coverage area. The model calculates predicted signal loss due to topography and distance between a transmitter and receiver. Validation studies have found that the ITM yields

highly accurate predictions, and the model has been widely used in professional radio planning (Crabtree & Kern, 2018). It was also used in the seminal paper by Olken (2009) to study the impact of television on social capital, and has since been used in a number of papers studying the impacts of radio and television (see e.g., Adena et al., 2015; Bursztyn & Cantoni, 2016; DellaVigna et al., 2014; Enikolopov et al., 2011; Peisakhin & Rozenas, 2018; Yanagizawa-Drott, 2014).

Due to the lack of comprehensive technical details on the cell towers, the coverage estimation can be viewed as using a fixed radius around a cell tower and correcting it by topographic features that influence radio propagation. Predictions are calculated for grid cells with a 200m resolution.[7] These predictions are aggregated using population weights to obtain township-level mobile phone coverage. The calculations are done separately for MPT and for the combined coverage area of all other service providers. The population-weighted share of township with coverage from MPT is the main independent variable. Figure 3 maps the predicted MPT mobile phone coverage, based on cell tower locations recorded by the end of August 2017. The predicted coverage is uneven: while central regions have fairly comprehensive coverage, large peripheral areas experience notably weak mobile phone reception.

Because the data is crowdsourced, it is likely that not all cell towers are included in the data. I also need to approximate several technical parameters when conducting the coverage prediction. Measurement error in the independent variable may therefore bias the estimates towards zero. In any event, I use the OpenCelliD data instead of the more commonly used GSM coverage maps from Collins Bartholomew, because with the Collins Bartholomew data it is not possible to differentiate coverage by service provider, which is crucial for the empirical strategy. In fact, when Collins Bartholomew does not have data directly from service providers, 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

[7] See Appendix B for a more detailed description of the coverage calculation.

Figure 3: Share of township with MPT mobile phone reception, weighted by population

meters at the equator) in the mobile phone coverage calculation. The signal propagation model also takes into account how land use—e.g., water, forest, cropland—affects propagation.

3.3 Local Level Characteristics

Information on population characteristics comes from the Myanmar 2014 Census. The main analysis is conducted at the township level.[8] Summary statistics for the townships are presented in the Appendix Table A.1. Because information on the ethnic composition of the population is not available at a disaggregated level, I use information on identity cards as a proxy for presence of discriminated minorities.[9] According to the Census, more

[8]Myanmar consists of 18 states and regions, which are broken into 76 districts, that are divided into 330 townships, and 14,165 wards or village tracts.

[9]Ethnicity information is only available at state level and may be misleading. According to the Census Observation Mission, most of the observed respondents who self-identified as Rohingya were either not

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 (2018). I use the population counts at 100 m spatial resolution that have been adjusted to match the corresponding United Nations population estimates. I aggregate the cells to village tract and township level to obtain estimates of village tract population as well as time series information.[10]

I also use georeferenced data from several sources to control for local characteristics. These include nighttime luminosity (Elvidge et al., 2021), to proxy for local economic development (Henderson et al., 2011; Weidmann & Schutte, 2017), locations of diamond and gemstone deposits (Gilmore et al., 2005; Lujala, 2009), as well as oil and gas fields (Lujala et al., 2007) to control for natural resources, land cover classifications (ESA, 2017), and weather conditions, particularly droughts (Vicente-Serrano, Beguería, & López-Moreno, 2010).

I use geospatial data provided by the Myanmar Information Management Unit (2019) to obtain administrative boundaries, locations of towns, 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 any other MNO. Finally, I use the SRTM elevation data (Jarvis et al., 2008) to complement the data with topographic characteristics, including elevation, slope, and terrain ruggedness. Descriptions of the data are provided in Table A.2, and summary statistics are presented in Table A.1.

4 Empirical Strategy

The main specification that I estimate is the following cross-sectional model:

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

enumerated in the census or their ethnicity information was skipped.

[10] Appendix Figure E.5 maps the geographic distribution of population.

where Y_i is the conflict outcome in township i, $CoverageFB_i$ is the predicted mobile phone coverage by MPT, weighted by population, and β is the key parameter of interest. To distinguish Facebook access from mobile phone coverage, I control for mobile phone coverage from other wireless service providers, denoted by $Coverage_i$. It is constructed based on the combined coverage area of all providers other than MPT. X_i is a set of township level controls, λ_d is a district fixed effect, and ε_i is the error term.

I use mobile phone coverage by the mobile network operator MPT offering the zero-rated plan as a proxy for social media access. This approach is essentially an encouragement design (Duflo et al., 2007): with no information on individuals' social media usage, I instead take advantage of the fact that if there is mobile phone coverage, it is possible to use mobile internet, and if there is coverage from MPT, it is possible to use Facebook without data charges. Intuitively, better coverage from a wireless service provider is associated with more mobile phone usage and subscriptions to the provider. Availability of zero-rated Facebook constitutes a negative price shock and is expected to increase Facebook use. Figure 4 demonstrates the correlation between the predicted mobile phone coverage by MPT, *CoverageFB*, and number of mobile phone users by state or region in 2016. The right panel demonstrates that during the Facebook campaign, there was also a sharp increase in Google searches for "MPT".

The aim is to compare otherwise similar locations that had differences in mobile phone coverage by MPT and hence different Facebook access. The source of plausibly exogenous variation comes from terrain differences between locations and cell towers. Because the topography-corrected mobile phone coverage is quite coarsely estimated, to minimize potential endogeneity bias, I include many controls for confounding factors that may influence both conflict and mobile phone coverage.

First, because cell phone towers are likely located so as to maximize the covered population, I control for demand factors by nighttime luminosity as a proxy for income, area covered by agriculture land, area covered by urban settlements, log population, log population density, a dummy for below median urban rate, share of working age population, share of population with no ID, share of households with electricity as their

Figure 4: Number of mobile phone users per 100 people in 2016 against MPT mobile phone coverage (left) and relative volume of Google searches for "MPT" in Myanmar. Grey dots in left panel plot share of households with a mobile phone according to the 2014 census, ρ is the correlation coefficient. Data on mobile phone users in 2016 comes from Myanmar Statistical Information Service, and data on Google searches comes from Google Trends.

main source of lightning, mobile phone, landline phone, and internet at home. I control for weather conditions, particularly droughts, as they are correlated with topographic features and also influence agricultural outputs and thus the opportunity cost of fighting (Miguel et al., 2004). I also control for the presence of gemstone deposits and oil and gas fields, as they have been associated with more severe conflict (Christensen et al., 2019; Lujala, 2009), and may also lead to better mobile phone coverage to accommodate mining companies.

Second, as terrain features and distance to road and rail network can influence armed groups' ability to operate as well as the cost of providing mobile phone coverage, I include second order polynomials of distance to major road, distance to railway, and distance to major town. I also include the area of the administrative unit and length of roads to further control for remoteness. Additional controls for terrain features include second order polynomials of elevation, slope, and terrain ruggedness. I include district fixed effects to control for broader geographical trends, and I cluster standard errors at the district level to account for possible contemporaneous correlation between neighboring areas.[11]

[11] District is one administrative level higher than township, and there are 76 districts.

Both the outcome and the independent variable may be measured with some error. First, because the data collection in GDELT is automated, there may be duplicate reporting. Therefore, in majority of the analysis, I use a dummy variable as the dependent variable. The incidence of conflict events in an area is much less affected by duplicated reporting, or reporting bias, than event counts. When examining event counts, I use the logged form as it is less sensitive to duplication.

Second, reporting bias may be present because the conflict data is based on monitoring the news. Measurement error can bias the results if it is correlated with the treatment, i.e., mobile phone coverage from MPT (conditional on observables). The main concern is that better mobile phone coverage and Facebook access may lead to higher reporting of conflict events. In that case, the coefficient of *CoverageFB* could be overestimated. To address this concern, I conduct a sensitivity analysis to investigate the extent to which the association between Facebook availability and conflict depends on potential reporting bias. The analysis is presented in Appendix D. In short, I do not find any clear dependence between the effect of Facebook availability on conflict and conflict reporting.

5 Results

5.1 Cross-Sectional Estimates

Table 1 presents the OLS estimates of model (1). The dependent variable in columns (1)–(3) is an indicator for any conflict events in the township in the treatment period, i.e. when Free Basics was available (from June 2016 until end of August 2017), and in columns (4)–(6) the logged number of conflict events.[12] Overall, the parameter estimates of Facebook availability lack statistical significance.

If expansion of mobile phone coverage was affected by conflict, the estimates could be confounded by reverse causality. To test the exogeneity of the topography-corrected MPT mobile phone coverage, I conduct a placebo test, in which I estimate the same cross-sectional model using conflict data only from the pre-treatment period (January 1,

[12] One event is added to all observations because the logarithm is not defined at zero.

Table 1: Facebook availability and probability and intensity of conflict

	Conflict dummy			log(Conflict events)		
	(1)	(2)	(3)	(4)	(5)	(6)
CoverageFB	-0.047	-0.123	-0.119	-0.078	0.085	0.098
	(0.085)	(0.111)	(0.105)	(0.308)	(0.406)	(0.408)
N	330	330	329	330	330	329
R^2	0.250	0.365	0.443	0.275	0.357	0.448
District dummies	✓	✓	✓	✓	✓	✓
Spatial controls		✓	✓		✓	✓
Additional 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)–(3) is an indicator for conflict in a township between June 1, 2016, and August 31, 2017, and in columns (4)–(6) log number of conflict events+1. *CoverageFB* is standardized. 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, mean slope, mean ruggedness, length of roads, and township area. Additional controls: share of agriculture land, share of forests, share of urban settlements, nighttime luminosity, presence of gemstones, share of oil fields, drought, log population, log population density, dummy for below median urban rate, share of working age population, share of population with no ID, share of households with electricity, mobile phone, landline phone, and internet at home.

2015–May 30, 2016). If past conflict had driven lower mobile phone coverage, *CoverageFB* should be associated with less conflict in the pre-treatment period. The placebo test shows that *CoverageFB* is not associated with conflict before the treatment period (Table C.1).[13] As a further robustness test, I estimate a negative binomial model for the count outcome. The estimates are similar to the OLS model (see Appendix Table C.3).

Since availability of social media could be differently related to different forms of conflict, I explore heterogeneity in types of conflict and actors involved in the conflict events (Table 2). The dependent variables in columns (1)–(4) are indicators for different types of conflict events, and in columns (5)–(8) for different types of actors.[14] Despite numerous reports that Facebook was used by the government and extremist Buddhist organizations to spread anti-Muslim propaganda, the estimates do not suggest that Facebook availability was related to organized violence such as fighting between organized groups. Nor is

[13]Table C.1 also presents estimates on post-treatment outcomes, i.e., using conflict data from after the Free Basics campaign (September 1, 2017–December 31, 2018), which similarly suggest no association.

[14]Actors can be either perpetrators or victims or violent events. *State* refers to state forces, i.e., police forces, government, or military. *Insurgents* includes insurgents (rebels who attempt to overthrow their national government) and separatist rebels, whereas *Rebels* refers to armed and violent opposition groups and individuals (Event Data Project, 2012).

Table 2: Facebook availability and probability of conflict: by conflict and actor type

	Conflict types				Actor types			
	Coerce (1)	Assault (2)	Fight (3)	Mass violence (4)	State (5)	Insurgents (6)	Rebels (7)	Civilians (8)
CoverageFB	-0.025	0.032	-0.158	-0.063	-0.014	-0.056	-0.098	-0.073
	(0.134)	(0.135)	(0.111)	(0.051)	(0.133)	(0.057)	(0.061)	(0.145)
N	329	329	329	329	329	329	329	329
R^2	0.394	0.436	0.477	0.401	0.441	0.453	0.479	0.381
Mean(Y)	0.509	0.321	0.533	0.061	0.515	0.058	0.1	0.388
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 column (1) is an indicator for conflict of particular type in a township between June 1, 2016, and August 31, 2017, and in column (2) log number of conflict events+1. *CoverageFB* is standardized. All regressions include the full set of controls: district dummies, 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, mean slope, mean ruggedness, length of roads, and township area, share of agriculture land, share of forests, share of urban settlements, presence of gemstones, nighttime luminosity, share of oil fields, drought, 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 households with electricity, mobile phone, landline phone, and internet at home.

Facebook availability related to non-organized violence or individuals' participation in violence: it is not related to probability on conflict events involving civilians, coercion, which includes repression and violence against civilians or their rights or properties, or assaults, which include abductions, different types of physical assaults, and use of explosive devices.

Previous studies have also documented that expansion of new communication technologies can reduce conflict (Shapiro & Weidmann, 2015). The Myanmar government has used several methods to monitor its citizens online, for instance, Freedom House (2017) reports that the military appears to use interceptions for domestic surveillance. Similarly, OpenNet Initiative OpenNet Initiative (2012) reports that the regime has engaged in pervasive internet filtering, internet shutdowns, surveillance, as well as cyberattacks on opposition groups. Despite this, the estimates do not suggest that Facebook availability was associated with organized groups' ability to carry out attacks.

5.2 Difference-in-Differences

In order to address potential non-random assignment of mobile phone coverage, and to take advantage of the time variation in Facebook availability, I conduct a difference-

in-differences analysis. The analysis uses only within township variation to determine how Facebook availability is related to conflict. Table 3 presents the estimates from the following model:

$$Y_{it} = \beta(CoverageFB_i \cdot Treat_t) + \tau_t + \lambda_i + Treat_t + X'_{it}\gamma + \varepsilon_{it} \tag{2}$$

The dependent variable in column (1) is an indicator for conflict in township i in time t, and in column (2) logged number of conflict events. The unit of observation is township-month. The variable *CoverageFB* represents the treatment intensity. It is time invariant and based on cell phone towers recorded in the data before September 2017. $Treat_t$ takes value one after the Facebook campaign started in June 2016. The coefficient β represents the difference in within-township differences between the townships with better or worse coverage during the Facebook campaign. The controls include lagged log population, lagged nighttime luminosity, and drought, and interactions between a linear time trend and time invariant controls.

The estimates in Table 3 are in line with the cross-sectional results: point estimates have a negative sign but do not suggest Facebook availability is related to conflict. Unlike in the cross-sectional regressions that limit the analysis to the treatment period, now the whole period after the Facebook campaign is considered as treated to detect potential association between Facebook availability and conflict that would take longer to appear. Examining different conflict types and actors similarly suggests Facebook access has no systematic effect on conflict (Table F.1).

I estimate placebo regressions to assess the parallel trends assumption. These regressions use placebo treatment dates and limit data only to the pre-treatment period (January 2015–May 2016). All placebo treatment effects are zero, indicating that there are no differential changes in conflict trends associated with different levels of mobile phone coverage before the actual treatment period (Table C.2).

Table 3: Difference-in-differences estimates

	Conflict dummy (1)	log(no. conflict events) (2)
CoverageFB·Treat	-0.029	-0.076
	(0.021)	(0.057)
N	15792	15792
R^2	0.398	0.641
Controls	✓	✓
Township FE	✓	✓
Quarter 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 column (1) is an indicator for conflict in a township, and in column (2) logged number of conflict events+1. In columns (3)–(10) the dependent variable is an indicator for conflict of particular type. *CoverageFB* is standardized. All regressions include time varying controls lagged log population, lagged nighttime luminosity, and drought, and an interaction between a linear time trend and time invariant 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, mean slope, mean ruggedness, length of roads, and township area, share of agriculture land, share of forests, share of urban settlements, presence of gemstones, share of oil fields, dummy for below median urban rate, share of working age population, share of population with no ID, share of households with electricity, mobile phone, landline phone, and internet at home.

5.3 The Rohingya Crisis

The analysis so far has examined average effects across Myanmar. Given that conflicts occur in different parts of the country, often involving different ethnic groups, the estimates may be confounded by different regional dynamics. Previous literature has demonstrated that the effects of media and communication technologies on conflict are context specific.

Many ethnic groups in Myanmar have long been marginalized and subject to racism and discrimination, but the Rohingya have been subject to particular hostility and an intense anti-Muslim campaign. They are frequently referred to for instance as "illegal immigrants", "fleas", "savages", "bullies an rapists" (Selth, 2018). Nationalist Buddhist monks, who are revered in Myanmar, have been key figures in the anti-Muslim campaign, actively spreading conspiracy theories about Muslims being terrorists backed by international Islamist groups and planning to turn Myanmar into an Islamist state (Fisher, 2013; Hodal, 2013). Numerous accounts show that Facebook has been used to dissemi-

nate these messages (Fink, 2018; Martin et al., 2022). Facebook availability could have therefore uniquely affected the Rohingya conflict.

To that end, I focus on the Rakhine state, home for most of the Rohingya in Myanmar. Drawing on the previous literature on propaganda (e.g., Adena et al., 2015; Müller & Schwarz, 2023; Yanagizawa-Drott, 2014), the hypothesis is that anti-Muslim content on social media could persuade individuals to believe that the Rohingya are dangerous terrorist who do not belong to Myanmar. Stoking fear and dehumanizing the victims could increase acceptance of violence and push some people to assaults, destruction of property, or to take part in attacks. Historical grievances between the two largest ethnic groups in Rakhine state, the Rakhine Buddhists and the Rohingya (Human Rights Council, 2018), could make users predisposed to anti-Rohingya messaging.

Because Rakhine consists of only 17 townships, I conduct the analysis at village level to retain enough observations. The population characteristics, apart from population counts and density that are derived from WorldPop, correspond to the township level measures. I report robust standard errors and p-values for wild cluster bootstrap standard errors at the township level (Cameron et al., 2008). Table 4 presents the estimates. In contrast to the previous results, in Rakhine villages Facebook availability is associated with a small increase in conflict. Although the estimates are imprecise, they are in stark contrast with the estimates for the whole country and are suggestive of important regional heterogeneity.

I complement the event data with satellite-detected fires and destroyed villages in northern Rakhine.[15] Although the data has a very limited geographic scope, the benefit is that it is not subject to potential reporting bias. The point estimates are positive but imprecise, providing suggestive evidence in support of the interpretation that mobile phone coverage, through increased Facebook access, may have contributed to increased violence in the Rakhine state (see Table F.4 in the Appendix).

[15]The fire detection was conducted from August, 25 to November, 25 2017, and detection of destroyed or damaged settlements from August 2017 to March 2018.

Table 4: Facebook availability and conflict in Rakhine State

	Conflict dummy (1)	log(events) (2)	Coerce (3)	Assault (4)	Fight (5)	Mass violence (6)
CoverageFB	0.022*	0.035	0.013	0.005	0.023*	0.001
	(0.013)	(0.038)	(0.011)	(0.009)	(0.012)	(0.007)
N	1058	1058	1058	1058	1058	1058
R^2	0.091	0.081	0.066	0.043	0.082	0.061
Mean(Y)	0.655	1.728	0.509	0.321	0.533	0.061
Bootstrap p-values	0.1	0.19	0.116	0.481	0.079	0.465
Controls	✓	✓	✓	✓	✓	✓

*p<0.1; **p<0.05; ***p<0.01. Robust standard errors are reported in parentheses. The table also reports p-values for wild cluster bootstrap standard errors. The dependent variable in column (1) is an indicator for conflict event, in column (2) logged number of conflict events+1, and in columns (3)-(6) a dummy for particular type of conflict event. *CoverageFB* is standardized. All regressions include the full set of controls: district dummies, 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, mean slope, mean ruggedness, length of roads, and township area, share of agriculture land, share of forests, share of urban settlements, presence of gemstones, lagged nighttime luminosity, share of oil fields, drought, lagged log population, lagged log population density, dummy for below median urban rate, share of working age population, share of population with no ID, share of households with electricity, mobile phone, landline phone, and internet at home.

5.4 Heterogeneity Tests

To further explore whether the association between Facebook availability and conflict is masked by regional differences, I explore heterogeneity to local characteristics. First, I explore heterogeneity to presence of minorities, proxied by share of paperless. Second, I examine proxies for number of potential social media users: share of households with mobile phone and households with electricity as their main source of lighting.[16] Third, I explore heterogeneity in terms of remoteness: distance from major cities, distance from the road network, and share of households with landline phone. Fourth, I examine factors that affect the opportunity cost of fighting: economic development, proxied by nighttime luminosity in 2015, and drought, as it impacts agricultural output. I estimate a model in which *CoverageFB* is interacted with a dummy for above median value of the characteristic of interest. The estimates do not suggest any significant heterogeneity along these dimensions (Table F.2). Finally, a potential confounding factor is the influence of mobile phone coverage and social media access on economic development, leading to higher opportunity cost of conflict. I estimate the effect of coverage on subsequent local development, proxied by nighttime luminosity and population. The estimates do not

[16]These variables are based on the 2014 census and reflect the pre-treatment levels.

suggest that mobile phone coverage is related to income or population growth (see Table F.3).

6 Conclusions

This paper has studied how availability of Facebook is related to conflict. I exploit geographic variation in mobile phone coverage together with time variation in Facebook availability to estimate whether Facebook access is associated with changes in probability or intensity of conflict. Despite compelling evidence of a hate-campaign against Muslims in general and the Rohingya in particular, which utilized Facebook to reach wide audiences, I find no systematic evidence that Facebook access was associated with higher probability of conflict. The null result is robust to different model specifications and estimators, and heterogeneity in terms of conflict types and local characteristics.

The only exception to a robust null is the analysis of the specific regional context of Rakhine state. I find suggestive evidence that Facebook availability is associated with higher probability of conflict. In this setting, tensions between the majority ethnic groups and the Rohingya are high, and the Rohingya have been a particular target of hate speech.

It is important to stress that the results should be interpreted with caution. What this paper shows is that there is no significant association between better mobile phone coverage—which arguably provided better access to Facebook—and probability of conflict. The results indicate that a large and significant average effect caused by differential mobile phone coverage is unlikely. Due to the data limitations the analysis relies on many approximations and assumptions, and therefore a more subtle influence of social media cannot be ruled out.

For one, other media sources, such as state-run newspapers, were also utilized to disseminate anti-Rohingya sentiment. Anti-Rohingya propaganda is not a new phenomenon in Myanmar brought by social media, although it may have amplified its fervor and reach. It is possible that the intense prejudice against the Rohingya was already so wide spread in the population, that differential exposure to the particular content on Facebook, fa-

cilitated by mobile phone coverage, played a more nuanced role, not picked up by the research design. Importantly, this paper exclusively examines the availability of Facebook, not Facebook usage. Therefore, it is not correct to conclude that social media had no impact on ethnic conflict in Myanmar. Future research both on Myanmar, and on the impacts of social media in different circumstances is needed.

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A Data Sources and Summary Statistics

Table A.1: Township summary statistics

	N	Mean	Std.Dev.
Conflict dummy, GDELT	330	0.65	0.48
Conflict events, per 1000, GDELT	330	0.61	4.60
Conflict events, GDELT	330	56.89	382.74
Cell phone coverage, MPT, %	330	63.04	37.82
Cell phone coverage, other, %	330	63.25	40.35
Cell tower density, per 1000 pop, MPT	330	0.35	1.07
Cell tower density, per 1000 pop, other providers	330	0.43	1.22
Population in 2014	330	152363.33	95347.49
Population density, 2014	330	2079.82	7140.20
Population, urban, %	330	28.10	29.03
Population aged 15-64, %	330	64.99	5.14
Population with no ID, %	330	27.29	12.85
Electricity, %	330	31.31	27.49
Landline phone, %	330	5.47	6.90
Mobile phone, %	330	31.62	22.87
Internet at home, %	330	6.31	10.58
Distance to major road, km	330	12.52	16.88
Distance to railway, km	330	51.25	66.46
Distance to nearest city, km	330	37.96	27.83
Distance to nearest cell tower, MPT, km	330	21.39	29.47
Distance to nearest cell tower, other, km	330	27.23	41.11
Area, sqkm	330	2025.95	1864.31
Roads, km	330	115.27	104.35
Mean elevation, m	330	389.58	461.06
Slope, degrees	330	88.49	5.17
Ruggedness	330	32.43	29.31
Agriculture coverage, %	330	47.01	34.31
Forest coverage, %	330	31.78	30.15
Urban coverage, %	330	9.06	26.26
Diamonds, dummy	330	0.11	0.31
Oil fields, %	330	12.37	27.49
Drought, %, 2016	329	2.71	4.02
Nightlight, 2015	330	2.47	7.84

The conflict dummy take value one if a conflict event was recorded in the township during June 1, 2016, and August 31, 2017. Number of conflict events refers to the same time period. Mobile phone coverage is the population weighted township area with sufficient signal for mobile phone reception. Distances are measured from township centroid. City refers to capital, state/region capital or district town (usually district capital). There are 330 townships.

Table A.2: Description of variables and data sources

Variable	Source	Description
Conflict events	GDELT, ACLED	Number of violent events, obtained from GDELT 2.0 (GDELT Project, 2019) and Armed Conflict Location & Event Data Project (ACLED, 2019a). From GDELT, events in the CAMEO event categories coerce, assault, fight, and use conventional mass violence, are used. From ACLED, events categorized as violent events are used.
Cell phone towers	OpenCelliD	Data on cell phone towers is obtained from OpenCelliD, available from https://www.opencellid.org. The data includes cell tower coordinates, network type, mobile network code, timestamp for when the measure was added to the database.
Population	Myanmar census 2014, WorldPop	Cross-sectional specifications use population data from the Myanmar census. The panel specifications use gridded population data from WorldPop (2018). I use the unconstrained individual countries UN adjusted 100m resolution population counts for Myanmar in 2015-2018. From the census, I calculate a dummy for below median share of urban population, share of working age (15-64) population, share of population (10 years and over) with no identity card, share of households with electricity as their source of lighting, and share of households with a mobile phone, with a landline phone, and with internet at home.
Topography	NASA	Measures of terrain elevation are obtained from NASA's Shuttle Radar Topography Mission (SRTM). I use the 1 arc second resolution data provided by CGIAR-CSI GeoPortal (Jarvis et al., 2008). Mean elevation, slope, and ruggedness for each township or village tract are computed with GQIS.
Distances	Myanmar Information Management Unit	Myanmar town points, road network, railway network as geospatial data (Myanmar Information Management Unit, 2019). I calculate the distance from township (or village tract) centroid to the nearest point of the feature. I also calculate road length in each administrative unit.
Drought	SPEI	Drought is measured with the Standardized Precipitation-Evapotranspiration Index (SPEI) (Vicente-Serrano, Beguería, & López-Moreno, 2010; Vicente-Serrano, Beguería, López-Moreno, et al., 2010). I use the SPEIbase v2.7, available from https://spei.csic.es/database.html. The data is available at 0.5 degree resolution. For each area I calculate share of year it experiences drought (SPEI≤ -1.5), and I use mean for 2016 in the cross-sectional models.
Nightlight	EOG	Average annual night light intensity from the Visible and Infrared Imaging Suite (VIIRS) Day Night Band (DNB). Data is downloaded from Earth Observation Group (EOG) as Annual VNL v2.1 (Elvidge et al., 2021), and it is available at 15 arc second resolution.
Land use	ESA CCI-LC	Global land cover maps at 300 m resolution for 2015, produced by the European Space Agency (ESA) Climate Change Initiative (CCI) (ESA, 2017). I follow the IPCC classes and aggregate to the categories "forests" (classes 50,60,70,80,90,100,160,170), "agriculture" (classes 10, 20, 30, 40), and "urban" (class 190). The values indicate the percentage of the area covered by the land cover category.
Gemstones	DIADATA, GEMDATA	Dummy for diamond or gemstone site. The variable is constructed by combining data sets on gemstone (Lujala, 2009) and diamond deposits (Gilmore et al., 2005).
Oil	PETRODATA	Share of the administrative unit covered by oil or gas fields, data set version 1.2. I use information on onshore oil and gas deposits (Lujala et al., 2007).
Destroyed settlements	UNITAR - UNOSAT	Satellite-detected fires and destroyed or otherwise damaged settlements in Buthidaung, Maungdaw, and Rathedaung Townships in Northern Rakhine State in Myanmar, provided by UNITAR - UNOSAT & United Nations Institute for Training and Research - Operational Satellite Applications Program (Garcia, 2018).

B Estimation of Mobile Phone Coverage

As mobile phone signals are ultra-high frequency radio signals, it is possible to use an electromagnetic signal propagation model to calculate predicted coverage. Mobile 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 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 consider whether 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.

I approximate the cell phone tower parameters to mimic transmission in a rural area. Antenna height is assumed to be 35 meters, and antennas are assumed to be omnidirec-

[17] Radio Mobile is copyright of Roger Coudé VE2DBE.

tional. In reality, antennas are usually directional, with several antennas in a cell tower covering different segments around the tower. The tower heights vary a lot, and 30–40 meter towers can be considered high. I limit the maximum free space 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 mobile phone antennas, in practice the range is much lower.

Both the free space loss and loss due to obstacles also depend on the signal frequency, with higher frequencies more affected by obstacles. 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 operators have reported in the Mobile World Live website. UMTS technology, which was used for 3G signals in Myanmar, uses 900 and 2100 frequency bands. I use the same parameter values for all cell towers. In reality, the parameters are likely to vary depending on the propagation environment (e.g., urban vs rural) and the MNO (Parsons, 2000).

C Robustness Checks

C.1 Placebo Test

Table C.1 present results from a placebo regression, in which the cross-sectional model is estimated using data before the treatment period, from January 2015 to May 2016. The table also shows the baseline estimate for comparison (columns (3) and (4)), as well as estimates using data after the treatment (columns (5) and (6)). Table C.2 presents results difference-in-differences estimates from placebo treatments. In this analysis the data is limited to the time before the actual treatment (January 2015 – May 2016).

Table C.1: Cross-sectional estimates on probability of conflict: by time period

	Pre-treatment		Treatment period		Post-treatment	
	dummy (1)	count (2)	dummy (3)	count (4)	dummy (5)	count (6)
CoverageFB	0.052	0.182	-0.119	0.098	0.004	-0.065
	(0.098)	(0.314)	(0.105)	(0.408)	(0.139)	(0.345)
N	329	329	329	329	329	329
R^2	0.427	0.475	0.443	0.448	0.418	0.476
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 in January 2015–May 2016; in columns (3)–(4) in June 2016–August 2017; and in columns (5)–(6) in September 2017–December 2018. *CoverageFB* is standardized. All regressions include the full set of controls: district dummies, 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, mean slope, mean ruggedness, length of roads, and township area, share of agriculture land, share of forests, share of urban settlements, presence of gemstones, lagged nighttime luminosity, share of oil fields, drought, lagged log population, lagged log population density, dummy for below median urban rate, share of working age population, share of population with no ID, share of households with electricity, mobile phone, landline phone, and internet at home.

Table C.2: Difference-in-differences estimates – placebo treatments

	Dummy (1)	log(count) (2)	Dummy (3)	log(count) (4)	Dummy (5)	log(count) (6)	Dummy (7)	log(count) (8)	Dummy (9)	log(count) (10)
CoverageFB·Treat$_{2015Q2}$	0.039	0.016								
	(0.037)	(0.065)								
CoverageFB·Treat$_{2015Q3}$			0.008	-0.032						
			(0.033)	(0.061)						
CoverageFB·Treat$_{2015Q4}$					0.030	-0.028				
					(0.033)	(0.064)				
CoverageFB·Treat$_{2016Q1}$							0.027	0.013		
							(0.036)	(0.059)		
CoverageFB·Treat$_{2016Q2}$									0.032	0.039
									(0.050)	(0.082)
N	5593	5593	5593	5593	5593	5593	5593	5593	5593	5593
R^2	0.453	0.654	0.452	0.654	0.453	0.654	0.453	0.654	0.453	0.654
Township FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Quarter 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. Time period is limited to January 2015–May 2016. Each row present estimates from a model where the placebo treatment starts in the quarter indicated by the $Treat$ subscript. *CoverageFB* is standardized. All regressions include time varying controls lagged log population, lagged nighttime luminosity, and drought, and an interaction between a linear time trend and time invariant 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, mean slope, mean ruggedness, length of roads, and township area, share of agriculture land, share of forests, share of urban settlements, presence of gemstones, share of oil fields, dummy for below median urban rate, share of working age population, share of population with no ID, share of households with electricity, mobile phone, landline phone, and internet at home.

C.2 Count Model

Although log transforming the data already smooths 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 C.3. The estimated coefficients are similar to the OLS model in Table 1.

Table C.3: Estimates from negative binomial model

	(1)	(2)	(3)
CoverageFB	0.021	-0.030	-0.101
	(0.216)	(0.359)	(0.430)
N	330	330	329
District dummies	✓	✓	✓
Spatial controls		✓	✓
Additional 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 between June 1, 2016, and August 31, 2017. The number of events is capped at the 97th percentile to facilitate convergence. *CoverageFB* is standardized. 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, mean slope, mean ruggedness, length of roads, and township area. Additional controls: share of agriculture land, share of forests, share of urban settlements, nighttime luminosity, presence of gemstones, share of oil fields, drought, log population, log population density, dummy for below median urban rate, share of working age population, share of population with no ID, share of households with electricity, mobile phone, landline phone, and internet at home.

C.3 Alternative conflict data

Because the automated collection of GDELT data raises concerns about misreporting and duplicated data (Hammond & Weidmann, 2014; Wang et al., 2016), I conduct robustness tests with the Armed Conflict Location & Event Data Project (ACLED, 2019a; Raleigh et al., 2010).[18] The data is collected by researchers, and it contains considerably less events than GDELT: 0.03 violent events per 1000 population during the Facebook campaign,

[18] Armed Conflict Location & Event Data Project (ACLED); https://acleddata.com

Figure C.1: Average monthly number of violent events. The vertical dotted lines indicate the beginning (June 2016) and end (September 2017) of the Facebook campaign. Data source: ACLED

compared to 0.54 based on GDELT. Figure E.6 maps the geographic distribution of conflict events in ACLED. The events are much more geographically concentrated on the northern and eastern parts of the country than events in GDELT.

Table C.4 presents cross-sectional results with ACLED data. The event and actor classifications are somewhat different than in GDELT, but similarly to the main results, the estimates do not suggest that Facebook availability was related to conflict.

Table C.5 presents the difference-in-differences estimates with ACLED data. Again, the estimates do not suggest that social media availability was related to conflict. The violent events in ACLED are categorized slightly differently as *battles*, *explosions/remote violence*, and *violence against civilians*. Most similar categories are fighting in GDELT and battles in ACLED, which both involve higher levels of organization and use of conventional military force. ACLED defines battles as exclusively taking place between organized armed groups, including state and non-state actors, whereas the GDELT definition also includes attacks against civilians. In ACLED, actor only refers to the perpetrator, and civilians are always victims of violent acts (ACLED, 2019b).

Table C.4: Cross-sectional estimates using ACLED data

	ACLED dummy (1)	log(events) (2)	Battle (3)	Civilians (4)	Explosion (5)	State (6)	Militias (7)	Rebels (8)
CoverageFB	0.030	-0.084	-0.015	-0.029	-0.006	0.027	-0.008	-0.003
	(0.055)	(0.150)	(0.054)	(0.065)	(0.022)	(0.052)	(0.056)	(0.054)
N	329	329	329	329	329	329	329	329
R^2	0.668	0.804	0.736	0.594	0.751	0.738	0.574	0.745
Mean(Y)	0.17	0.329	0.139	0.085	0.094	0.139	0.097	0.133
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 column (1) is an indicator for conflict, in column (2) logged number of conflict events+1, and in columns (3)–(8) an indicator for conflict of particular type of conflict in a township in June 2016–August 2017. *CoverageFB* is standardized. All regressions include the full set of controls: district dummies, 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, mean slope, mean ruggedness, length of roads, and township area, share of agriculture land, share of forests, share of urban settlements, presence of gemstones, nighttime luminosity, share of oil fields, drought, 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 households with electricity, mobile phone, landline phone, and internet at home.

Table C.5: Difference-in-differences estimates using ACLED data

	ACLED dummy (1)	log(events) (2)	Battle (3)	Civilians (4)	Explosion (5)	State (6)	Militias (7)	Rebels (8)
CoverageFB·Treat	0.016	0.012	0.008	0.002	0.006	0.016	0.007	0.013
	(0.017)	(0.026)	(0.013)	(0.008)	(0.009)	(0.017)	(0.009)	(0.012)
N	15792	15792	15792	15792	15792	15792	15792	15792
R^2	0.442	0.469	0.423	0.199	0.276	0.422	0.159	0.438
Township FE	✓	✓	✓	✓	✓	✓	✓	✓
Quarter 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 column (1) is an indicator for conflict, in column (2) logged number of conflict events+1, and in columns (3)–(8) an indicator for particular type of conflict in a township. *CoverageFB* is standardized. All regressions include time varying controls lagged log population, lagged nighttime luminosity, and drought, and an interaction between a linear time trend and time invariant 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, mean slope, mean ruggedness, length of roads, and township area, share of agriculture land, share of forests, share of urban settlements, presence of gemstones, share of oil fields, dummy for below median urban rate, share of working age population, share of population with no ID, share of households with electricity, mobile phone, landline phone, and internet at home.

D Measurement Error in Conflict Data

Because the information on conflict events is largely based on news reporting, it may be subject to reporting bias. Weidmann (2016) distinguishes different forms of selective reporting. First, reporting bias in which some conflict events that happened are failed to be reported leads to classical measurement error. If it is uncorrelated with the independent variable, it does not bias the results, but decreases precision of the estimates.

Second, reporting of conflict events could be correlated with the independent variable, which would bias the estimates. Weidmann (2016) demonstrates that in that case both the proportion of reported violence and how strongly reporting depends on mobile phone coverage affect the resulting bias. Mobile phone coverage is likely associated with whether conflict events are reported in the media or not. An alleviating factor is that I estimate the effect of coverage from one provider, MPT, while controlling for coverage from other providers. However, it is still possible that by providing Facebook access, coverage from MPT could influence conflict reporting, conditional on other coverage.

To get a sense of how dependent the effect of MPT mobile phone coverage is on possible reporting bias, I conduct a sensitivity analysis following Weidmann (2016) and Dafoe and Lyall (2015). The idea is that more severe conflict events, for example those involving more casualties, are more likely to be reported in the media regardless of how good local mobile phone coverage is. Therefore, the dependence of conflict reporting on mobile phone coverage should be stronger with *less severe* events. Without mobile phone coverage, less severe events are more likely not reported. The estimated effect of mobile phone coverage on conflict should therefore be more positive (or less negative) for less severe events.

Since the GDELT does not have information on casualties, I use another measure of severity. The GDELT reports the average tone of all documents mentioning the event, which can be used to assess the importance of the event (GDELT Project, 2019). Average tone ranges between -100 (extremely negative) and $+100$ (extremely positive), with common values between -10 and $+10$. Negative tone is measured as the percentage of all words in an article that have a negative emotional connotation, and vice versa

Figure D.1: Sliding window analysis for GDELT events.

The top graph shows estimated coefficients of *CoverageFB* from the cross-sectional model with full set of controls and 95 % confidence intervals. The dashed vertical line indicates the full sample estimate. The bars in the bottom graph represent the average tone of events in each window. Each window contains 6,274 events, and the window is moved in steps of 100 events.

for positive tone. Events with more negative tone should be more likely to be reported regardless of mobile phone coverage, which means that if reporting bias affected the results, there should be a more positive effect on events with more negative tone. I order the events by average tone, and again estimate the effect of MPT mobile phone coverage on a conflict dummy in a sliding window.

Figure D.1 presents the sensitivity analysis. In the sensitivity analysis, the data is first organized based on average tone. I then take a subsample of about one third of the events ($N = 6,274$) which have the least negative tone and estimate the cross-sectional model on that subsample. For the next subsample, the "window" is moved by 100 events such that the average tone in the subsample slightly decreases. The sliding window analysis

Figure D.2: Sliding window analysis for ACLED events.

Note: The top graph shows estimated coefficients of *CoverageFB* from the cross-sectional model with full set of controls and 95 % confidence intervals. The dashed vertical line indicates the full sample estimate. The bars in the bottom graph represent the average number of casualties in each window. Each window contains 310 events, and the window is moved in steps of 15 events.

continues in this manner in steps of 100 events, so that the average tone in each window becomes more negative. The estimates do not exhibit any clear dependence on severity.

Figure D.2 presents the same sensitivity analysis for ACLED data. I use data on the events that take place in the treatment period, I order them by number of fatalities, and I estimate the effect of MPT mobile phone coverage on a conflict dummy in a subsample, or sliding window, containing about one third of the violent events ($N = 310$). The window is moved in steps of 15 events so that the average number of casualties in each subsample is slowly increasing. Note that most of the events are not associated with any fatalities. The estimates do not exhibit any clear dependence on severity.

E Additional Figures

Figure E.1: Monthly number of the main types of violent events over time. The vertical dotted lines show the beginning and end of the Facebook campaign. Data source: GDELT

Figure E.2: Expansion of the cell tower network of MPT. The blue dots indicate locations of cell phone towers that are added to the data each year, and the black dots indicate locations of pre-existing cell phone towers.

Figure E.3: Total number of cell phone towers by mobile network operator (left) and number of cell towers recorded in the OpenCelliD data by year and MNO (right).

Figure E.4: Share of township with mobile phone reception from MPT (left) and by other mobile network operators (right), weighted by population.

Figure E.5: Township population (left) and population density (right). Calculated from WorldPop data for 2016.

Figure E.6: Number of conflict events scaled by population (in 1000) by township between June 1, 2016, and August 31, 2017. Data source: ACLED.

F Additional Tables

Table F.1: Difference-in-differences estimates on different conflict and actor types

	Conflict types				Actor types			
	Coerce (1)	Assault (2)	Fight (3)	Mass violence (4)	State (5)	Insurgents (6)	Rebels (7)	Civilians (8)
CoverageFB·Treat	-0.028	-0.028	-0.017	-0.010	-0.018	-0.002	0.005	-0.009
	(0.019)	(0.017)	(0.020)	(0.016)	(0.021)	(0.003)	(0.013)	(0.014)
N	15792	15792	15792	15792	15792	15792	15792	15792
R^2	0.384	0.375	0.385	0.474	0.391	0.297	0.432	0.366
Township FE	✓	✓	✓	✓	✓	✓	✓	✓
Quarter 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. *CoverageFB* is standardized. All regressions include time varying controls lagged log population, lagged nighttime luminosity, and drought, and an interaction between a linear time trend and time invariant 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, mean slope, mean ruggedness, length of roads, and township area, share of agriculture land, share of forests, share of urban settlements, presence of gemstones, share of oil fields, dummy for below median urban rate, share of working age population, share of population with no ID, share of households with electricity, mobile phone, landline phone, and internet at home.

Table F.2: Heterogeneous effects of Facebook availability

	Electricity (1)	Cellphone (2)	Paperless (3)	Landline (4)	City (5)	Road (6)	Nightlight (7)	Drought (8)
CoverageFB	-0.153	-0.140	-0.200*	-0.134	-0.035	-0.051	-0.113	-0.078
	(0.111)	(0.107)	(0.115)	(0.111)	(0.133)	(0.110)	(0.108)	(0.096)
CoverageFB·Electricity	0.117							
	(0.080)							
CoverageFB·Cellphone		0.096						
		(0.081)						
CoverageFB·Paperless			0.140					
			(0.087)					
CoverageFB·Landline				0.023				
				(0.068)				
CoverageFB·City dist					-0.116			
					(0.085)			
CoverageFB·Road dist						-0.098		
						(0.083)		
CoverageFB·Nightlight							-0.010	
							(0.099)	
CoverageFB·Drought								-0.070
								(0.107)
N	329	329	329	329	329	329	329	329
R^2	0.450	0.448	0.451	0.445	0.449	0.457	0.444	0.447
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 event in a township in June 2016–August 2017. *CoverageFB* is standardized. The second variable in the interaction term is an indicator for above median value of that variable, except for Drought, which indicates strictly positive values. All regressions include the full set of controls: district dummies, 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, mean slope, mean ruggedness, length of roads, and township area, share of agriculture land, share of forests, share of urban settlements, presence of gemstones, lagged nighttime luminosity, share of oil fields, drought, lagged log population, lagged log population density, dummy for below median urban rate, share of working age population, share of population with no ID, share of households with electricity, mobile phone, landline phone, and internet at home.

Table F.3: Effect of mobile phone coverage on local development

	ΔNightlight (1)	ΔPopulation (2)	Nightlight 2018 (3)	Population 2018 (4)	Nightlight 2017 (5)	Population 2017 (6)
CoverageFB	0.002	0.000	-0.174	0.020		
	(0.013)	(0.000)	(0.233)	(0.017)		
Coverage	0.008	0.000	0.537	-0.011		
	(0.018)	(0.000)	(0.359)	(0.018)		
CoverageFB_{2016}					0.032	-0.009
					(0.065)	(0.007)
Coverage_{2016}					0.228	0.000
					(0.167)	(0.014)
N	329	329	329	329	329	329
R^2	0.801	0.999	0.960	0.997	0.975	0.997
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 column (1) is change in nighttime luminosity between 2018 and 2017, in column (2) change in population between 2018 and 2017, in column (3) is average nighttime luminosity in 2018, in column (4) population in 2018, in column (5) average nighttime luminosity in 2017, and in column (6) population in 2017. $CoverageFB_{2016}$ and $Coverage_{2016}$ are share of township with mobile phone coverage from MPT and other service providers, respectively, calculated using only cell phone towers recorded in the OpenCelliD data before June 2016. The measures of cell phone coverage are standardized. All regressions include the full set of controls: district dummies, 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, mean slope, mean ruggedness, length of roads, and township area, share of agriculture land, share of forests, share of urban settlements, presence of gemstones, nighttime luminosity, share of oil fields, drought, 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 households with electricity, mobile phone, landline phone, and internet at home.

Table F.4: Effect on destroyed villages in Rakhine State

	Affected villages (1)	Damaged settlements (2)	Fires detected (3)
CoverageFB	0.002	0.068	0.025
	(0.014)	(0.153)	(0.110)
N	266	266	266
R^2	0.616	0.469	0.214
Mean(Y)	0.511	1.474	0.165
Controls	✓	✓	✓

*p<0.1; **p<0.05; ***p<0.01. Bootstrap standard errors clustered at township level are reported in parentheses. The unit of observation is village tract. The sample is restricted to the Buthidaung, Maungdaw and Rathedaung townships that were included in the satellite-image analysis. The dependent variable in column (1) is a dummy for any damaged settlements or fires detected in the village tract, in column (2) number of damaged settlements, and in column (3) number of fires detected in the village tract. *CoverageFB* is standardized. All regressions include the following 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, mean slope, mean ruggedness, length of roads, and township area, share of agriculture land, share of forests, share of urban settlements, lagged nighttime luminosity, lagged log population, lagged log population density, dummy for below median urban rate, and share of working age population.