Master Thesis: **International Politics**

Collective Mobilization, Armed Conflict Onset and the Liberating & Repressing Aspects of Technology

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Abstract

The introduction of cell phones and the Internet into society has change the means through which collective mobilization efforts are done, increasingly using online platforms or messaging services to do so. This paper brings forward the following research question: *What is the effect of ICT on the onset of armed conflict?* The discussion will be operationalized by a cross-national country analysis on seven ASEAN countries between 2001 and 2017. These economies have seen an exponential spread of individual-access to ICT since they have become widely available to the masses, while also being continuously affected by severe on-going armed conflict. To answer the research question, the theoretical link between ICT and conflict onset is empirically examined by testing three hypothesis quantitively, using a negative binomial regression model. Based on the existing literature on conflict onset, I expected a positive relationship: an increase of ICT would be associated with an increase in armed conflict onset. The findings confirm most of the expectations, while others ask for more nuanced research on cell phone and Internet availability and the relationship with armed conflict onset.

Introduction

Over the past decades, the world has moved into an unprecedented interconnectedness, and developments in information communication technology (hereafter; ICT) do not indicate that this trend is slowing down. The number of individuals using the Internet increased from 0.25% in 1993 up to 49% in 2019, corresponding to 3.6 billion users worldwide (World Bank, 2020a). Additionally, people who previously did not have the means to install fixed telephone lines, are now presented with an opportunity to catch up on globalization efforts through the introduction of modern cellphone technology (Kefela, 2011).

Increased connectivity through cell phones, as well as the Internet, have helped developing countries boost their economies, by eliminating geographical barriers that inhibit people from finding job opportunities and levelling out competition surrounding commodity prices (Aker & Mbiti, 2010). It has also enhanced financial inclusivity, by creating the possibility for individuals to get access to mobile payments and money transfers at low or zero transaction costs (Pelletier, et al. 2019).

Some of the most prominent and widely used new services are social media platforms and messaging apps, such as Facebook, Instagram or WhatsApp (Silver, et al, 2019). Sharing beliefs, ideas and information across geographical borders has never been so effortless. These developments surrounding worldly interconnectivity increasingly shape the way politics are lived and conducted. For example, the efforts of President Bashar al-Assad to deny and downplay the severity of the Syrian civil war, were powerless in the face of the mass live streaming of war crimes by affected civilians on YouTube and Facebook. (Nashashibi, 2016; MEE staff, 2016).

This increased connectivity through cell phones and the Internet also has its downsides. The lawlessness of the Internet and its easy accessibility as a communication platform means that anyone can connect through it – including insurgent, antigovernment and terrorist groups. (Shapiro & Siegel, 2015). One prominent example of this is the recruitment of European soldiers by the Islamic State, whom could either be deployed in their domestic countries to mobilize more masses and coordinate terrorist attacks or be summoned to the pro-claimed caliphate to combat against governments and the international coalition (Gates & Podder, 2015).

In this context, this paper proposes a theoretical framework which suggests that the increase in ICT can contribute towards the onset of armed conflict. The objective of this study is to determine whether access to ICT can increase the likelihood of conflict onset, by facilitating the process of armed collective mobilization. Additionally, it would be interesting to find out if conflict is more likely to occur when more alternative sources of communication are available to the public. Therefore, it brings forward the following research question: *What is the effect of ICT on the onset of armed conflict?* The discussion will be empirically analyzed by a cross-national analysis of several cases, in seven southeast Asian countries, namely Cambodia, Indonesia, Laos, Malaysia, Myanmar, the Philippines and Thailand between 2001 and 2017. The reasoning for this choice of countries, as well as the timeframe derive from the local exponential spread of individual-assess ICT since they have become more widely available to the masses, while also being continuously affected by severe on-going conflict.

Literature review

Whereas the presence of ICT, such as cell phones and internet, has piqued the curiosity of many scholars, the research that has so far been undertaken to determine whether ICT access has any effect on the probability of armed conflict onset has yielded ambiguous results so far.

The literature on the effect of ICT on conflict is divided along the notions of 'repression technology' and 'liberation technology', first theorized by Rød and Weidmann (2015). Technology as a means of repression, indicates that manipulation and censoring information on the Internet by governments aids in diminishing the potential for collective action in incumbent regimes (Gohdes, 2015). For instance, Camber (2015) states that "centralized 'mass' communication technologies – such as radios – foster vertical linkages between state and society [and] evidence demonstrates that the geographic reach of mass media penetration generates substantial pacifying effects". Scholars emphasizing this line of thought also point out that state-run telecommunications agencies are often the main providers of online access. This conveniently allows governments to track suppliers and consumers of information (Rød and Weidmann, 2015).

Additionally, it is through the presence of an adequate functioning mobile phone and internet infrastructure that pro-government civilians or militias can collaborate with security forces to suppress rebellions and increase opportunities for coordinated intelligence collection on potential dissidents (Shapiro & Siegel, 2015; Shapiro & Weidmann, 2015; Weidman, 2015). Thus, it can be argued that civic engagement with governments can be increased by technological availability (Weidmann, 2015; Boulianne, 2009; Bailard, 2015).

Contrarily, Bell et al. (2013) state that the widespread use of mobile phone and internet technology, in combination with citizens' rights to freedom of assembly and association, increases the occurrence of political violence. This view corresponds to the notion of 'liberation technology', an argument that is part of a larger discourse in the literature supporting the idea that 'the diffusion of ICTs can substantially alter the contours of collective violence in developing nations' (Camber, 2015). The most prominent work on the effect of communication technology on armed conflict comes from Pierskalla and Hollenbach (2013). Although the authors do not focus on the Internet per se, they find that 'the availability of cell phones as a communication technology allows political groups to overcome collective actions problems more easily and improve in-group cooperation, and coordination' and significantly increase the probability of violent conflict (2013). This claim is supported by, amongst others, Collier and Hoeffler (2004). The authors find that overcoming organizational problems, such as diminishing communication costs or making communication possible between two large areas, has more effect on the likelihood of armed mobilization to occur than grievance factors, such as high inequality or ethnic divisions.

More nuanced research on the effect of ICT on conflict has combined the two notions of liberation and repression. Weidmann (2019), combines the two concepts and finds that there is a threshold that needs to be taken into account: governments in authoritarian settings can repress the Internet, but there is a point at which dissenting civilians can overcome these ICT barriers and mobilize. After this point has been reached, governments lose the control, and the internet proves itself to have a liberating effect. In countries with less repression, this threshold is much lower.

The main argument put forth by the few scholars that have ventured into political ICT research revolves around the increase of dissenting communications and antigovernment actors to coordinate themselves into collective actions by increased ICT developments (Shapiro & Siegel, 2015). According to Camber (2015), it is especially due to the "'decentralized 'social' communication technologies – such as cell phones – that foster horizontal linkages between the members of a society". This increases the potential for collective violence, especially when a targeted government lacks robust mass media infrastructure to counterbalance these efforts.

Research up until now has taken place either on an aggregate cross-country level or focused substantially on volatile areas central to media coverage, such as the Arab Spring or Hong Kong protests. Few case studies exist that look at the effect of ICT on armed conflict, although those that do exist have determined patterns in internet mobilization efforts (Davies et al. 2016). However, it requires more in-depth cross-country research on multiple geographic areas to properly discern the interplay between government and civilians, to place these patterns into international context and grasp fully why and how conflict occurs.

Theory

The core argument of this paper is that ICT availability can increase the chances of violent conflict by facilitating armed collective mobilization. ICT is ‘an umbrella term for all the various media employed in communication information’ (Chandler & Munday, 2020). This encompasses numerous devices ranging from radios to video conferencing tools, and from computers to satellite systems. The area of ICT we are interested in is widely available to the masses and allows for peer-to-peer communication. This kind of technology includes cellphone networks and computers connected to the Internet and the most prominent resources that facilitate peer-to-peer communication are social media channels, e-mails and messaging services. As conflict is a population driven phenomenon that requires some levels of coordination and organization between people (often operating clandestinely and with little lead time), these resources are of particular interest in studying the how ICT is related to conflict.

Contrary to former means of mass communication, such as radio, printing press and television, the Internet is an open-access channel that can more easily be instrumentalized by anyone. The notion has emerged in academia that the Internet can be dissected along two separate, albeit interlinked, dimensions of liberation and repression technology (Rød & Weirdmann, 2015). It is especially because of this duality that studies have diverged in their outcomes on the effect of the internet on conflict.

On the one hand, following the liberating dimension, the use of cellphones and the Internet can open up channels of independent communication and mobilization for citizens, allowing them to access different sources of information and communicate at extremely low transaction costs. It has also allowed people to share opinions and norms, build online communities, and strengthen civil society (Diamond, 2010).

However, the Internet is not always solely used for peaceful purposes by citizens. For one, cyberterrorism has become an increasingly harmful danger worldwide. Another example would be the worldwide objective to take down the ‘darknet’, an online network of websites undetectable from regular search engines where the user’s privacy is safeguarded (Europol, 2020). These unregulated and hidden areas of the Internet have made it the perfect tool for insurgencies to mobilize fighters around the globe, most notably during the Syrian civil war. Numerous citizens from Southeast Asian nations were mobilized to fight in Syria and Iraq on behalf of the Islamic State and Al-Nusra and trained to organize violent attacks upon return to their home counties (Kibtiah, 2016).

Armed collective mobilization is facilitated through ICT accessibility on an organizational dimension. Over the past few decades, the rapid expansion of Internet and cellphone access around the world has brought forward the ability to send direct messages and eliminated the need for mail or in-person messengers to organize group action (SOURCE). These mediums are much cheaper and more widely available in comparison to other mass media outlets, such as broadband television and radio access (Pierskalla & Hollenbach, 2013). Therefore, against little to no cost, a larger audience can be reached with minimal effort. This has eliminated constraints relating to time, geography and transaction costs required to exchange beliefs and information over large distances, allowing groups to reproduce belief-systems at an unprecedented speed and ease (Bailard, 2015). In more extreme cases, it has also allowed both organizations and private persons to organize and recruit for armed collective action.

As previously mentioned, massive online mobilization took place and is argued to be the main catalysts of decapitalizing long-standing leaders in Egypt and Tunisia, and bringing mass civil unrest to Bahrain, Libya, Syria and Yemen during the Arab Spring (Aday et al. 2012). However, another dimension to this is that, simultaneously as the events were unfolding, the rest of the world served as a live audience to these insurgencies and uprisings, having access to documentations made by the individuals living through all types of political violence on Twitter, Facebook, and YouTube (Aday et al. 2012). In sum, the Internet decreased the transaction costs of collective action and allowed people to mobilize action across national borders at rapid speed. This example demonstrates how the Internet has enabled dispersed antigovernment groups to organize themselves in a more cost- and time-effective manner. Collier and Hoeffler's (2004) claim that the economic viability of mobilization increases the chances of conflict onset significantly. Therefore, I expect that:

H1: The availability of and access to ICT increases the likelihood of armed mobilization, which can in turn lead to conflict onset

The rapid development of ICT has made it hard for governments to keep up, with some acting more drastically than others, through means of general censorship and increased social media shutdowns (Lührmann et. al, 2020). The repressive dimension of the Internet involves government interference, that often negatively affects freedoms of speech and association. Following the repression technology theory, authoritarian regimes can benefit from technological innovations, as this helps them to censor and influence public opinions as well as track members of the opposition (Rød & Weirdmann, 2015). Some regimes justify their choice to limit or censor internet access with questions surrounding national security, whereas citizens in turn see these measures as diminishing their freedom of speech, assembly and the press.

However, the shift towards a more informally organized system of gathering information and news has also forced governments, especially authoritarian ones, to adapt. Governments can try to implement channels of communication to improve vertical linkages, through which civilians can issue complaints they may have. This may reduce conflict, as citizens have other means to peacefully resolve grievances (Weidmann, 2019). By contrast, governments can also choose to completely or partially block access to the Internet or censor its content (Weidmann, 2019).

Simultaneously, governments who engage in media censorship ensure news coverage is always in favor of their actions, while hiding their failures. In such cases, the media is often not free and independent, and journalists do not enjoy any protection for their freedom of speech. It is not uncommon that individuals speaking up against the government be silenced.

Constraints on information access inevitably limit ordinary civilians' access to accurate and objective news coverage, which keeps them from forming educated opinions on their leaders. More importantly, from a government's perspective, it inhibits violent antigovernment groups from organizing collective action or even coordinating terrorist attacks on state leaders.

The repression dimension of ICT sees curtailments of the Internet, most commonly to prevent online communication from turning into violent offline action. By controlling channels of communication and the content that citizens can share and discuss online, governments can block people from mobilizing armed collective action against each other or against the government. This leads to the second expectation.

H2: The less government control over the Internet; the more likely conflict is to occur

Governments may choose not to directly control the Internet as a medium of communication, but instead control the information that is available on it. The boundlessness of the Internet provides citizens with access to multiple alternative sources of information about anything that may be of concern to them. This is a drastic change to thirty years ago, when governments could more easily monopolize power over the media (TV, radio, print).

As mentioned before, sharing beliefs and opinions is becoming more effortless when the Internet and cell phones become more accessible. The conglomeration of like-minded people in one virtual room also allows for the online organization of collective mobilization and allows organizers to spread organizational in-group information, as well as coverage of events the government is silencing (Pierskalla & Hollenbach, 2013).

Additionally, as the Internet is not constrained by borders (with some exceptions, such as the Chinese Firewall), foreign information and ideas can spread more easily. Seeing ‘evidence’ online that citizens of other countries have it better can lead to relative grievances which in turn manifest themselves in collective action for domestic change, either peaceful or violent (Rød & Weidmann, 2015).

Another side-effect of increased online presence is the intensification of opinions and beliefs through the introduction of algorithms and so called “bubbles” of ideology (Just & Latzer, 2017; Spohr, 2017). Whereas traditional news sources allowed for large populations to read, hear or see the same news stories, sometimes portrayed from different angles, today digitalization has caused media offerings to be replaced with more diverse and personally based coverage. This individuality is enabled by algorithms, which decide which content a person might be interested in based on your search history, friends on social media platforms and location (Krafft, et. al, 2019).

Research suggests that these bubbles are ‘centrally culpable for the societal and ideological polarization experienced in many countries’ (Bruns, 2019). Existing views of societal matters and our already establishes interests or political preferences are therefore severely reinforced, leading to tunnel vision. Consequences of these bubbles are said to have been The United Kingdom’s decision to secede from the European Union and the victories of both US President Donald Trump, as well as Jair Bolonaro, President of Brazil (Bruns, 2019).

To recap, the chances for collective action can increase with the presence of more alternative sources of information. Whereas this may lead to positive outcomes, such as peaceful protest or the toppling of autocratic regimes, it can also lead to increasing political violence by insurgents (Shapiro & Weidmann, 2015). The objectives of such insurgencies can range from secessionist ambitions to religious fractionalization and can be intensified and spread through online ‘bubble’ interactions. This leads to the final expectation.

H3: The more alternative sources of information, the more likely conflict is to occur

Research Design

In order to test the hypothesis, I will look at the number of conflicts per year in 7 countries taking part in the Association of Southeast Asian Nations (ASEAN) specifically, as my unit of analysis[1].

[1] The association consists of ten nations: Cambodia, Indonesia, Malaysia, Myanmar, Laos, the Philippines, Thailand, Brunei, Singapore and Vietnam. Due to a lack of data on conflict occurrence, the latter three are not included in this study.

While the region studied varies differently, one generalization can be made: all countries saw improvements of standards since the 1980s and now all fall in the group of medium human development, or higher (Booth, 2019). The choice to focus on this region was not solely made upon this improvement, but also on the visible proliferation of communication technologies hand in hand with the context of political volatility overserved in the last two decades. The timeframe, 2001 to 2017, reflects a period during which cellphone usage and the Internet have become an unprecedented influence within the region.

Additionally, the rapid economic changes that this region has undergone, partly due to the opening of its economies for, and participation in, global trade and tourism, has resulted in more media coverage, which has also made domestic conflicts more prone to documentation. For instance, in the recent years, Myanmar has been scrutinized for its persecution of the Rohingya Muslim minority in the northern region of the Rankin state, increased clashes between the Myanmar state and non-state actors, increased tensions between the radical Buddhist nationalist groups as well as other armed groups operating throughout the country (ACLED, 2018a). Other examples that highlight domestic conflicts rigorously covered by international media include, but are not limited to, the ongoing Philippine drug war lead by President Rodrigo Duterte and the political turmoil and the multiple *coup d'états* in Thailand (ACLED, 2018b, ACLED, 2016).

Dependent variable

The dependent variable in this paper is the frequency of armed conflict observed per year per country studied. A collaboration between the Uppsala Conflict Data Program [UCDP] and the Peace Research Institute Oslo [PRIO] has produced the UCDP Georeferenced Event Dataset (GED) Global Version, 20.1 (hereafter; UCDP GED), representing a timeframe since 1946, which is updated consistently (Sundberg & Melander, 2013; Högbladh, 2020). The unit of analysis for the UCDP GED dataset is a conflict occurrence, defined as 'an incident where armed force was used by an organized actor against another organized actor, or against civilians, resulting in at least 1 death at a specific location and a specific date' (Högbladh, 2020). The two elements in the definition above that are of interest in this study are the use of armed force by an organized actor. Whereas the prior is operationalized by the UCDP GED codebook as 'the use of arms in order to promote the parties' general position in the conflict, resulting in deaths', the latter is explained as 'a government of an independent state, a formally organized group or an informally organized group' following several other criteria specified in the codebook (Högbladh, 2020).[2] The data is manually curated and collected from global newswire reporting; global monitoring and local news translations by the BBC and secondary sources, such as local media and reports by non-governmental and international organizations (Högbladh, 2020).

The variable is coded as a count ratio variable, whereby each case represents the number of conflicts present in a given country per year. As a comparison of seven countries over a span of seventeen years, we obtain an N of 119. Figure 1 provides an overview of the total observed conflicts in the studied ASEAN countries per year, while Figure 2 disaggregates conflict by country.

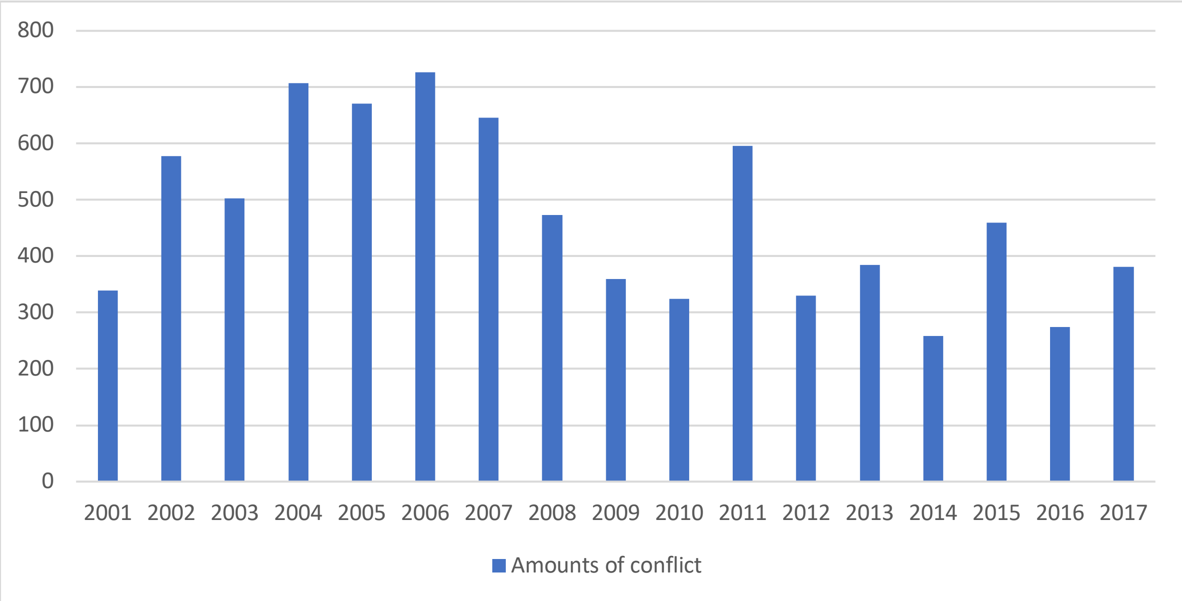

Figure 1: Total amount of conflicts per year

[2] Alternatively, the use of the Correlates of War (hereafter; COW) dataset was attempted for computing the dependent variable. However, holding a minimum threshold of at least 1.000 deaths per conflict per year, the conflicts included in this dataset mainly include intra- and inter-state wars (Sarkees & Wayman, 2010). On the other end of the extreme, the Armed Conflict Location & Event Data Project (hereafter; ACLED) can be found. This dataset does not include a minimum fatality criterion for events to be included in the dataset and also includes coverage on (peaceful) instances of conflict (ACLED, n.d.). As the dependent variable of this study is the amount of armed conflict, the usage of this dataset cannot be justified as it does not provide the data needed.

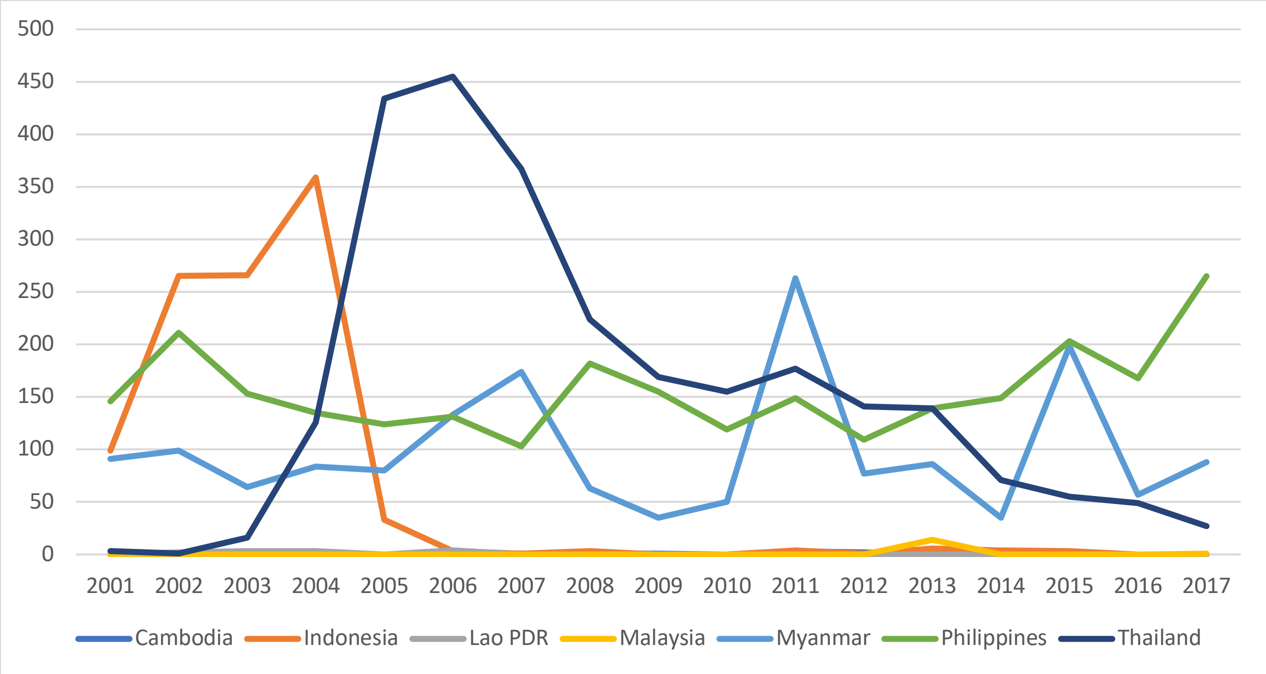

Figure 2: Conflicts per year per country

Independent variables

The three previously theorized hypotheses focus on different sets of indicators that are predicted to have a positive relationship with conflict onset. The World Bank provides the two main independent variables used to test H1 that operationalize the spread and use of ICT over time: the amount of mobile phone subscriptions per year per country (World Bank, 2020.b) and individuals using the internet expressed as a percentage of the population per year for each country (World Bank, 2020a).

Censorship is central to the H2. For opalization, a self-made censorship index is used, made up of three variables. The first two variables, that of Internet censorship effort and government Internet filtering in practice, are derived from the V-Dem dataset (V-Dem, 2020). While the prior focusses on whether the government attempts to censor textual, audio or visual information on the Internet, the latter revolves around government Internet filtering of political content especially (Coppedge, et. al. 2020). Censorship includes 'Internet filtering (blocking access to certain websites or browsers), denial-of-service attacks, and partial or total Internet shutdowns' (Coppedge, et. al. 2020). Censoring explicit content, such as child pornography, religious offensive content or intelligence secrets, are not included unless used as a meaning to deepen government opinions or political information (Coppedge, et. al. 2020).

To enlarge the scope of the self-made index, a third component is derived from the Freedom of the Press dataset, provided by the Freedom House (2020a). Although useful as a whole to determine government oppression of the media, the dataset as a whole is beyond the scope of this research. Therefore, especially the 'political environment' component of the Freedom of the Press dataset was extracted and used in this research. Under examination in this component are 'the editorial independence of both state-owned and privately owned outlets; access to information and sources; official censorship and self-censorship, the vibrancy of the media and the diversity of news available within each country or territory; the ability of both foreign and local reporters to cover the news in person without obstacles or harassment; and reprisals against journalists or bloggers by the state or other actors, including arbitrary detention, violent assaults, and other forms of intimidation' (Freedom House, 2020b). As can be detected, with the inclusion of this third variable, the scope of the censorship index is extremely enlarged and encompasses offline sources of media as well. The censorship index is scaled from 1 (large amounts of government censorship) to 5 (no government censorship) pear year for each country.

Whether there exist alternative sources of information in the studied countries is of interest for the last hypothesis. The Variety of Democracy (hereafter; V-Dem) dataset includes an alternative sources of information index, that measures the extent to which citizens have access to a plurality of information sources (V-Dem, 2020; Coppedge, et. al. 2020). The index is measured based upon three factors, namely: 'to what extend is the media (a) un-bias in their coverage or lack of coverage of the opposition, (b) allowed to be critical of the regime, and (c) representative of a wide array of political perspective?' (Coppedge, et. al. 2020). The scale of the index ranges from 0 (lack of alternative sources of information) to 1 (presence of a plurality of un-bias sources of information) per year for each country (Coppedge, et. al. 2020).

Control variables

An extensive amount of literature exists emphasizing on other factors that may lead to increased predictability of conflict. To control for other possible causes for conflict, seven control variables are included in some of the models. Firstly, I control for other possible pre-existing motivations for conflict and grievances. For example, conflict can arise through large inequalities, whereby a group may feel discriminated against and thus take to arms (Fearon & Laitin, 2003). Therefore, I control for 'Exclusion by social group' and 'Equal distribution of resources'. Both variables are taken from the V-Dem dataset (V-Dem, 2020). The index that is used to measure the equal distribution of resources is scaled from 0 (no equality) to 1 (high equality) and includes both tangible (food, water, housing) and intangible (education, healthcare and access to social services) (Sigman et al. 2015). This variable was chosen instead of merely an indicator of inequality, such as the GINI-coefficient, as it is through the inequal distribution of sources that the poorer population is not able to participate in any meaningful way to society. Therefore, social and economic inequality can ultimately lead to political inequality as well (Sigman et al. 2015). The variable for exclusion based on social group is also scaled from 0 (no exclusion) to 1 (high levels of systematic exclusion) (Sigman et al. 2015). Whereas an ethnoreligious or ethnolinguistic fractionalization index, such as the HIEF, would have been preferred measures for grievances in relation to ethnicity, no dataset was available for the timeframe of this study (Drazanova, 2019). Alternatively, the V-Dem dataset provided an exclusion index based upon social group, whereby a social group is defined as: ‘differentiated within a country by caste, ethnicity, language, race, region, religion, migration status, or some combination thereof. It does not include identities grounded in sexual orientation, gender, or socioeconomic status’ (Sigman et al. 2015). This variable largely focuses on political exclusion, however, in a similar but opposing manner as explained hereabove, this can ultimately also lead to economic and social exclusion. Therefore, the use of this variable is justified.

I will also control for the presence of mountainous, as this has proven to be influential on the likelihood of conflict onset (Fearon & Laitin, 2003; Collier & Hoeffler, 2004). Mountainous terrain is known to increase the likelihood of conflict, as it harbors and hides rebels from government forces (Fearon & Laitin, 2003). As it is not expected that the percentage of mountainous terrain changes throughout the years, a replication dataset is used for the variable to express the number of mountains as percentages of the total country land (Dorff, 2011).

A control for the presence of a large portion of revenue derived from natural resources is included. With higher natural resource rents, the likelihood of conflict increases as (a) primary commodities can easily be used to finance insurgency and (b) oil producing countries tend to have a weak state (Fearon & Laitin, 2003). The variable is computed based on World Bank data, expressing the amount of total natural resource rents as a percentage of the country’s total GDP (2020c).

Furthermore, following Collier & Hoeffler (2004), controls are added for GDP per capita and population density. The variable for GDP per capita is expressed in current US Dollars. Population density is expressed by the number of people per square kilometers of land area per country. Both variables are extracted from the World Bank (2020d; 2020e).

The seventh and last control variable is concerned with male unemployment. A high number of unemployment can make any form of opportunity to earn money interesting. By this logic, high unemployment rates can facilitate recruitment of rebels for armed conflict, and therefore increase the likelihood of conflict occurrence (Paasonen, 2020). The variable is derived from the World Bank and expressed in the male unemployment rate as a percentage of the male labor force as a total (World Bank, 2020f).

Please see Table 1 for an overview of all variables and their descriptive statistics.

Table 1: Descriptive statistics of variables

	N	Min.	Max.	Mean	Std. Dev.	Variance
Number of conflicts	119	0	445	66.7227	97.02445	9413.744
Mobile cellular subscriptions - total	119	22671	435193605	52915510.2	82429040	6.795E+15
Individuals using the Internet (% of population)	119	0	80.14	18.8952	20.75420	431.152
Alternative sources of information index	119	.02	.92	.4889	.33455	.112
Censorship index	119	1.04	4.31	3.0589	.78584	.618
GDP per capita (current $ USD)	119	137.17	11319.08	2785.6232	2743.36298	7526040.42
Population density (people per sq. km of land area)	119	23.44	352.73	120.0955	85.52235	7314.073
Male unemployment (% of male labour force)	119	.33	6.95	2.2360	1.73418	3.007
Estimated % of mountainous terrain	119	1	35.80	17.7571	12.88266	165.963
Total natural resource rents (% of GDP)	119	.52	17.99	6.3858	4.48069	20.077
Equal distribution of resources index	119	.12	.85	.4334	.21209	.045
Exclusion by social group index	119	.28	.88	.5751	.15168	.023

Methodology

As the dependent variable is a count variable that consists of only nonnegative integers. Table 1 shows that the variable depicting the amount of conflict is over dispersed with a variance of 9413.744 that is much higher than a mean of 66.723. Poisson regression model, which assumes an equal variance and mean, is not suitable. Therefore, I employ a Negative Binomial regression model which takes this into account.

One additional test was performed to check for the accuracy of the models performed above. Similar models were used as in the NB GLM above, but instead a different approach was taken as how to code the dependent variable. While in this study, the dependent variable, was a count variable representing the amounts of conflicts per country per year, in this additional test, it was computed as a dichotomous variable: 0 = absence of conflict per year per country; and 1 = presence of conflict per year per country. In this manner, the number of conflict occurrences per year per country do not influence the results. As a dichotomous variable is used as a dependent variable, a Binomial Logistic Regression model was employed. The syntax code and results table can be found in Appendices 1 and 2 representatively.

The decision not to use this model comes from my intention to preserve the meaning of the dependent variable as a count variable. By coding the number of conflicts per year as a dichotomous variable, this model does not grasp the enormous differences of the number of conflicts observed per year per country. It reduces the presence of conflict, no matter how little or much, to one and the same vector. Therefore, information can get lost in the statistical analysis. Additionally, the results in Appendix 2 show that none of the independent variable, nor almost none of the control variables, show any statistical significance. This might indicate that there the method employed is not a good fit.

Empirical Results & Discussion

8 negative binomial generalized lineal models (NB GLM) were used to determine the effect of each of the explanatory variables on the number of conflicts per year per country in the ASEAN region. The first 4 models were performed without control variables, as can be seen in Table 2. The first model includes only the two variables for total mobile cellular subscriptions and the percentage of individuals in one country using the Internet. Together, these two variables express the integration of ICT use in the studied societies. Model 2 includes one variable, that of alternative sources of information, which expresses governments allow civilians to access accurate and objective news coverage, without bias news coverage and impeding independent coverage on the regime, opposition and other political perspectives. The third and last explanatory variable included is a censorship index. This variable examines direct and indirect means of the government to censor information on media outlets. Finally, Model 4 combines the previously mentioned models and their explanatory variables. Table 2 further lists models 5-8, which examine the same effects as models 1-3, but with the added control variables discussed in the previous section.

Table 2: NB GLM for conflicts between 2001 – 2017, all models

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Mobile cellular subscriptions - total	9.065E-10			-1.869E-8***	-8.226E-9***			-1.423E-8***
	(4.1445E-9)			(1.9823-9)	(1.8627E-9)			(1.8250E-9)
Individuals using the Internet (% of population)	-.009			0.013	-.049***			-.026
	(.0096)			(0.0061)	(.0129)			(.0127)
Censorship index		-.165		-2.919***		-.118		-1.326***
		(.1054)		(.2418)		(.2033)		(.2942)
Alternative sources of information index			2.514***	10.234***			6.565***	9.338***
			(.2773)	(.7063)			(.8868)	(1.0255)
GDP per capita (current $ USD)					0.000	.000***	-.001***	.000
					(0.0001)	(7.5028E-5)	(6.7521E-5)	(.0001)
Population density (people per sq. km of land area)					0.49***	.029***	.042***	.024***
					(.0044)	(.0038)	(.0042)	(.0042)
Male unemployment (% of male labour force)					1.031***	.412*	1.022***	.058
					(.1250)	(.1348)	(.1227)	(.1517)
Estimated % of mountainous terrain					-012	.029	-.017	.058*
					(.0192)	(.0178)	(.0175)	(.0188)
Total natural resource rents (% of GDP)					-.315***	-.049	-.304***	-.042
					(.638)	(.0577)	(.0623)	(.0592)
Equal distribution of resources index					5.206***	4.317***	5.793***	2.054*
					(.5922)	(.5927)	(.6285)	(.06865)
Exclusion by social group index					31.692***	24.828***	30.696***	15.269
					(3.0573)	(2.4360)	(3.1058)	(3.0930)
Observations	119	119	119	119	119	119	119	119
LR Chi-Squared	2.033	1.531	73.823***	228.284***	290.393***	327.401***	264.284***	389.259***
AIC	1243.471	1241.973	1169.681	961.221	969.111	930.102	993.220	874.245
BIC	1215.809	1247.076	1175.240	975.116	996.902	955.114	1018.232	907.595
Log-likelihood	-618.736	-618.896	-582.841	-475.610	-474.556	-456.051	-487.610	-425.123

First, I analyse the results for H1 and interpret the results for the two explanatory variables total amount of cellular subscriptions and percentage of the population using the Internet. To begin, I look at mobile cellular subscriptions. Model 1shows a positive relationship between cell phone subscriptions and conflict onset. However, the variable in model 1 is not statistically significant by itself. Contrarily to the expectations of H1, when other explanatory variables, as well as the control variables are included in the models 4, 5 and 8, the relationship between cell phone subscriptions and conflict onset become a negative. This means that with an increase in subscriptions, a decrease in conflict onset is predicted. Models 4, 5 and 8 also show that cell phone subscriptions become statistically significant. However, as the B-coefficient is very small, the relationship is not very strong.

The second explanatory variable for hypothesis 1 is the percentage of individuals using the Internet. The results in Models 1, 5 and 8 show a negative relationship between this variable and the number of conflicts to be expected. This means that the probability of conflict occurrence decreases when the percentage of the population that is using the Internet increases. This is in direct juxtaposition with the expectations of H1. However, the variable for only becomes significant when the control variables have been included in the regression, as can be seen in Model 5. Contrarily to the other models but in line with what was previously expected, only model 4 shows a positive relation between the explanatory variable and the number of conflicts. However, this result does not prove to be statistically significant. Throughout all models, the B-coefficient is small, signifying that the relationship is not strong.

With a mostly negative relation between the two explanatory variables and conflict onset, the results are not strong enough to confirm the expectations of the first hypothesis: *the availability of and access to ICT increases the likelihood of armed mobilization, which can in turn lead to conflict onset.* The results should be interpreted with caution, as significance is only present for the cellular subscriptions variable and not for the number of individuals using the Internet.

Next, the results for H2 are analyzed. Here, it is expected that with an increase in government control over the Internet, the probability of conflict decreases. In line with this expectation, the relationship between the censorship index and conflict occurrence remains negative throughout all models. However, the B-coefficient, stating how large the effect of the explanatory variable is on the predictability of conflict is, is not very large, neither is it small. It is seen to be largest in Models 5 and 8. Additionally, the variable is only statistically significant in Models 4 and 8. This implies that H2, *the less government control over the* *internet; the more likely conflict is to occur,* is accepted. However, taking into account the B-coefficient and statistical insignificance in the two models, these observations could indicate that other factors may be more important indicators of conflict. Therefore, the results should be interpreted with caution.

Last, I analyse the results for the alternative sources of information index, the explanatory variable for H3. In line with the expectations in H3, Model 2, showing the isolated effect of the variable on the prediction of conflict occurrence, shows a strong positive relationship. This positive relationship remains present once the other explanatory and control variables are included in the regression, as seen in Models 4, 6 and 8. Moreover, throughout all models, the B-coefficient is relatively large. From this can be deducted that the relationship between the explanatory variable is strong on the probability of conflict occurrence. Therefore, the expectation that *the more alternative sources of information, the more likely conflict is to occur,* is confirmed.

After interpretations, four control variables used in this study support the literature on conflict onset. As was expected, an increase in population density, male unemployment, mountainous terrain and exclusion of social groups are all positively correlated with the predictability of conflict occurrence. A negative relationship between an increased likelihood of conflict frequency and the variables for GDP per capita and equal distribution of resources was expected. Contrarily, the relationship was seen to be positive instead. In a similar manner, it was also expected that an increase in natural resource rents would increase the likelihood of conflict occurrence. Surprisingly, the opposite was detected.

In sum, the results support the general assumption that higher ICT availability in the ASEAN countries studies is linked to increased collective mobilization, which in turn can lead to armed conflict. Although H1, which expected that the more cellphone subscriptions and people using the Internet would increase conflict levels, was rejected, one explanation for this could be that ICT access has exponentially grown over the past decades, but not all using these services aim to get involved in armed conflict.

Conclusion

This paper investigates the relationship between ICT and conflict onset. Previous studies on this topic have been widespread, but no largescale statistical analysis have been done focusing solely on the ASEAN region. Further building on the notions of liberation and repression technology, I argue that an increase in ICT leads to facilitated collective mobilization efforts, resulting in a higher probability of armed conflict onset.

An empirical cross-national analysis was undergone, using the number of conflicts in my sample of seven ASEAN countries over a timespan of 17 years, from 2001 to 2017. This resulted in 119 cases. Different casual mechanisms were tested to determine whether the predicted relationship between ICT access and armed conflict onset is accepted. Three hypotheses were tested. Contrary to my expectations, were the results of the first hypothesis, showing that an increase in cellphone subscriptions and individuals using the Internet as a percentage of the population, do not increase the likelihood of conflict occurrence. This could be justified by the fact that the widespread availability of these services has exponentially increased whereas it has not become an instrument only individuals aiming for conflict are using.

The influence of ICT availability and armed violent conflict still requires further research to fully grasp the political context. This study brings forward a better understanding of the relationship between the liberating and repressing nature of technology. It also provides insights for governments, activists and individuals seeking armed collective action on how to develop meaningful strategies for action or how to refrain groups from being able to undertake them. Moreover, the results suggest that people in highly repressive countries living under high media censorship, are statistically speaking less likely to mobilize themselves and take on violent armed conflict because the information presented to them domestically shows only positive information on their governments. A demand for change is thus relatively hard to demand. However, there is still hope. With the boundlessness of the Internet, it is becoming increasingly harder to shield people away from beliefs, habits and news coverage from abroad (except from the great Chinese Firewall of course).

With the hope of increased alternative sources of information for citizens under repressive governments, which will hopefully become available through ICT access, it is predicted that the number of armed conflicts will increase. When this occurs, the demand for domestic change will be made and hopefully, this will aid in toppling repressive government and increasing human rights conditions worldwide.

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Appendix 1: Syntax coding Negative Binomial Regression Models

```
**Descriptive Statistics

DESCRIPTIVES VARIABLES=Amount_Conflicts
  /STATISTICS=MEAN STDDEV VARIANCE MIN MAX.


** Transforming values for Index

RECODE v2smgovfilprc_ord (0=1)
    (1=2) (2=3) (3=4) (4=5) (SYSMIS=SYSMIS) (ELSE=SYSMIS).
EXECUTE.

COMPUTE int_censorship_effort=((v2mecenefi_ord - 1) / 3) * 5.
EXECUTE.

COMPUTE freedomhouse_media=((freedom_media - 0) / 40) * 5.
EXECUTE.


**Creating Composite Index

COMPUTE
censorship_index=MEAN(int_censorship_effort,freedomhouse_media,v2smgovfilprc_ord).
EXECUTE.

FREQUENCIES VARIABLES=censorship_index
  /ORDER=ANALYSIS.


**Model 1 - Cellphone + Internet

* Generalized Linear Models.
GENLIN Amount_Conflicts WITH Mobile_cellular_subscriptions
    Individuals_using_the_Internet____of_the_population_
  /MODEL Mobile_cellular_subscriptions
Individuals_using_the_Internet____of_the_population_
    INTERCEPT=YES
 DISTRIBUTION=NEGBIN(1) LINK=LOG
  /CRITERIA METHOD=FISHER(1) SCALE=1 COVB=MODEL MAXITERATIONS=100
MAXSTEPHALVING=5
    PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-012
ANALYSISTYPE=3(WALD) CILEVEL=95 CITYPE=WALD
    LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION.
```

**Model 2 - Alternative Sources of Information Index

```
* Generalized Linear Models.
GENLIN Amount_Conflicts WITH v2xme_altinf
  /MODEL v2xme_altinf INTERCEPT=YES
 DISTRIBUTION=NEGBIN(1) LINK=LOG
  /CRITERIA METHOD=FISHER(1) SCALE=1 COVB=MODEL MAXITERATIONS=100
MAXSTEPHALVING=5
    PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-012
ANALYSISTYPE=3(WALD) CILEVEL=95 CITYPE=WALD
    LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION.
```

**Model 3 - Index of Censorship

```
* Generalized Linear Models.
GENLIN Amount_Conflicts WITH censorship_index
  /MODEL censorship_index INTERCEPT=YES
 DISTRIBUTION=NEGBIN(1) LINK=LOG
  /CRITERIA METHOD=FISHER(1) SCALE=1 COVB=MODEL MAXITERATIONS=100
MAXSTEPHALVING=5
    PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-012
ANALYSISTYPE=3(WALD) CILEVEL=95 CITYPE=WALD
    LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION.
```

** Model 4 - All of the above

```
* Generalized Linear Models.
GENLIN Amount_Conflicts WITH censorship_index Mobile_cellular_subscriptions
    Individuals_using_the_Internet____of_the_population_ v2xme_altinf
  /MODEL censorship_index Mobile_cellular_subscriptions
    Individuals_using_the_Internet____of_the_population_ v2xme_altinf INTERCEPT=YES
 DISTRIBUTION=NEGBIN(1) LINK=LOG
  /CRITERIA METHOD=FISHER(1) SCALE=1 COVB=MODEL MAXITERATIONS=100
MAXSTEPHALVING=5
    PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-012
ANALYSISTYPE=3(WALD) CILEVEL=95 CITYPE=WALD
    LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION.
```

**Model 5 - Cellphone + Internet + Control Variables

```
* Generalized Linear Models.
GENLIN Amount_Conflicts WITH Mobile_cellular_subscriptions
   Individuals_using_the_Internet____of_the_population_ male_unemployment GDP_capita
pop_density
   nat_resources e_v2xeg_eqdr_3C mntest v2xpe_exlsocgr
  /MODEL Mobile_cellular_subscriptions
Individuals_using_the_Internet____of_the_population_
   male_unemployment GDP_capita pop_density nat_resources e_v2xeg_eqdr_3C mntest
v2xpe_exlsocgr
   INTERCEPT=YES
 DISTRIBUTION=NEGBIN(1) LINK=LOG
  /CRITERIA METHOD=FISHER(1) SCALE=1 COVB=MODEL MAXITERATIONS=100
MAXSTEPHALVING=5
   PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-012
ANALYSISTYPE=3(WALD) CILEVEL=95 CITYPE=WALD
   LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION.
```

**Model 6 - Alternative Sources of Information Index + Control Variables

```
* Generalized Linear Models.
GENLIN Amount_Conflicts WITH male_unemployment GDP_capita pop_density
nat_resources e_v2xeg_eqdr_3C
   mntest v2xpe_exlsocgr v2xme_altinf
  /MODEL male_unemployment GDP_capita pop_density nat_resources e_v2xeg_eqdr_3C
mntest
   v2xpe_exlsocgr v2xme_altinf INTERCEPT=YES
 DISTRIBUTION=NEGBIN(1) LINK=LOG
  /CRITERIA METHOD=FISHER(1) SCALE=1 COVB=MODEL MAXITERATIONS=100
MAXSTEPHALVING=5
   PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-012
ANALYSISTYPE=3(WALD) CILEVEL=95 CITYPE=WALD
   LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION.
```

**Model 7 - Index of Censorship + Control Variables

```
* Generalized Linear Models.
GENLIN Amount_Conflicts WITH male_unemployment GDP_capita pop_density
nat_resources e_v2xeg_eqdr_3C
   mntest v2xpe_exlsocgr censorship_index
  /MODEL male_unemployment GDP_capita pop_density nat_resources e_v2xeg_eqdr_3C
mntest
   v2xpe_exlsocgr censorship_index INTERCEPT=YES
 DISTRIBUTION=NEGBIN(1) LINK=LOG
  /CRITERIA METHOD=FISHER(1) SCALE=1 COVB=MODEL MAXITERATIONS=100
MAXSTEPHALVING=5
   PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-012
ANALYSISTYPE=3(WALD) CILEVEL=95 CITYPE=WALD
   LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION.
```

** Model 8 - All + Control Variables

```
* Generalized Linear Models.
GENLIN Amount_Conflicts WITH male_unemployment GDP_capita pop_density
nat_resources e_v2xeg_eqdr_3C
   mntest v2xpe_exlsocgr censorship_index Mobile_cellular_subscriptions
   Individuals_using_the_Internet____of_the_population_ v2xme_altinf
  /MODEL male_unemployment GDP_capita pop_density nat_resources e_v2xeg_eqdr_3C
mntest
   v2xpe_exlsocgr censorship_index Mobile_cellular_subscriptions
   Individuals_using_the_Internet____of_the_population_ v2xme_altinf INTERCEPT=YES
 DISTRIBUTION=NEGBIN(1) LINK=LOG
  /CRITERIA METHOD=FISHER(1) SCALE=1 COVB=MODEL MAXITERATIONS=100
MAXSTEPHALVING=5
   PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-012
ANALYSISTYPE=3(WALD) CILEVEL=95 CITYPE=WALD
   LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION.
```

Appendix 2: Syntax Binomial Logistic Regression

** Additional Test 1: Dependent variable as Dummy Variable using a Binomial Logistic Regression

**Recoding DV to dummy variable

```
RECODE Amount_Conflicts (0=0) (SYSMIS=SYSMIS) (MISSING=SYSMIS) (ELSE=1)
INTO Conflict_Dummy.
EXECUTE.
```

**Model 1

```
LOGISTIC REGRESSION VARIABLES Conflict_Dummy
  /METHOD=ENTER Mobile_cellular_subscriptions
Individuals_using_the_Internet____of_the_population_
    v2xme_altinf censorship_index
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT SUMMARY
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).
```

**Model 2

```
LOGISTIC REGRESSION VARIABLES Conflict_Dummy
  /METHOD=ENTER v2xme_altinf
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT SUMMARY
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).
```

**Model 3

```
LOGISTIC REGRESSION VARIABLES Conflict_Dummy
  /METHOD=ENTER censorship_index
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT SUMMARY
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).
```

**Model 4

```
LOGISTIC REGRESSION VARIABLES Conflict_Dummy
  /METHOD=ENTER Mobile_cellular_subscriptions
Individuals_using_the_Internet____of_the_population_
    v2xme_altinf censorship_index
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT SUMMARY
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).
```

** Model 5

```
LOGISTIC REGRESSION VARIABLES Conflict_Dummy
  /METHOD=ENTER Mobile_cellular_subscriptions
Individuals_using_the_Internet____of_the_population_
    GDP_capita pop_density male_unemployment mntest nat_resources v2xeg_eqdr
v2xpe_exlsocgr
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT SUMMARY
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).
```

**Model 6

```
LOGISTIC REGRESSION VARIABLES Conflict_Dummy
  /METHOD=ENTER GDP_capita pop_density male_unemployment mntest nat_resources
v2xeg_eqdr
    v2xpe_exlsocgr v2xme_altinf
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT SUMMARY
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).
```

**Model 7

```
LOGISTIC REGRESSION VARIABLES Conflict_Dummy
  /METHOD=ENTER GDP_capita pop_density male_unemployment mntest nat_resources
v2xeg_eqdr
    v2xpe_exlsocgr censorship_index
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT SUMMARY
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).
```

**Model 8

```
LOGISTIC REGRESSION VARIABLES Conflict_Dummy
  /METHOD=ENTER GDP_capita pop_density male_unemployment mntest nat_resources
v2xeg_eqdr
    v2xpe_exlsocgr censorship_index Mobile_cellular_subscriptions
    Individuals_using_the_Internet____of_the_population_ v2xme_altinf
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT SUMMARY
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).
```

Appendix 3: Table for BLR for conflicts between 2001 – 2017

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Mobile cellular subscriptions - total	.000 (.000)			.000** (0.000)	.000 (.000)			.000 (.000)
Individuals using the Internet (% of population)	-.029* (.010)			-.012 (.014)	-.175 (.070)			-.128 (.086)
Alternative sources of information index		3.736*** (.738)		9.404*** (1.755)		9.951 (3.965)		13.092 (15.086)
Censorship index			.276 (.250)	- 2.103*** (1.158)			.522 (.719)	2.020 (1.532)
GDP per capita (current $ USD)					.001 (.000)	0.000 (.000)	.000 (.000)	.000 (.001)
Population density (people per sq. km of land area)					.163* (0.56)	.034 (0.19)	.086*** (.022)	.198 (.115)
Male unemployment (% of male labour force)					-.198 (.670)	-.216 (.415)	-.041 (.337)	-1.219 (.929)
Estimated % of mountainous terrain					.223 (.091)	.106 .046	.103 (.053)	.455 (.172)
Total natural resource rents (% of GDP)					-.233 (.138)	-.107 (.114)	-.113 (.112)	-.276 (.144)
Equal distribution of resources index					1.842 (5.665)	5.309 (3.947)	3.691 (3.243)	10.331 (8.910)
Exclusion by social group index					26.348 (19.179)	30.207 (12.687)	19.623 (11.216)	43.052 (24.508)
Constant	.870** (.288)	-1.054** (.360)	-.197 (.715)	3.247** (1.158)	-29.170 (14.104)	- 27.111* (.004)	-21.394 (9.037)	-56.183 (21.893)

Note: Standard errors produced by the negative binomial models are in brackets. * Significant at 90%; ** significant at 95%; *** significant at 99%.