Internal Instability and Technology:
Do Text Messages and Social Media Increase Levels of Internal Conflict?

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Abstract

Political instability and internal conflict impact the lives of thousands every single day. Understanding when and why these conflicts occur has been the focus of governments, non-governmental organizations, and scholars for years. Predicting internal conflict was originally qualitative in nature, based on the advice and predictions of regional and country experts. More recently, as computational technology has become more widely used and effective, the efforts at predicting internal conflict have become more quantitative. This paper builds off the work of prior scholars to explore the impact of technology on internal instability. A logit model is used to test the effect of particular independent variables – specifically cell phone and internet users – on internal instability during the Arab Spring. The results show that political factors and technology are significant in explaining internal instability during the Arab Spring, while economic factors had little statistical significance or impact on the predictive probability of the model. Access to, and the use of technology will only continue to grow. As it does, it is vital that governments, NGOs, and scholars acknowledge its growing role in driving social and political movements and its impact on internal instability.

Key words/phrases: Internal Instability, Arab Spring, Technology, Logit

Political Instability and Internal Conflict

Political instability and internal conflict have plagued nation-states throughout history. Whether based on ethnic or tribal ties, political or ideological divisions, coups or attempts to gain personal power, internal conflicts have caused destruction and despair on an unprecedented level. Societal ties, economic centers, and political institutions are destroyed, taking years to rebuild and at times, never recovering. However, if governments, NGOs, and the international community are better able to predict when and where potential internal conflict would occur, not only could these events potentially be prevented but the world would be prepared to handle the short and long-term impacts. Whether it is the overflow of the violence into other nation-states, an outflow of refugees or a major impact on the international economy, understanding when and where internal conflicts occur would greatly improve the ability of the world to prevent, address, and react to these conflicts.

Governments, NGOs, and academics alike have tried to construct quantitative and qualitative estimates of the likelihood of internal conflict. Most of the early attempts at predicting internal conflict were qualitative in nature, based on the knowledge of country or regional experts. Models based on their expertise will ultimately rely on their *opinions* – which are potentially subjective – about where and when an internal conflict might occur. Such subjectivity leaves much to be desired in terms of the accuracy and consistency of these predictions.

As computational technology has become increasingly sophisticated, modeling internal conflict has become much more quantitative in nature. Using numerous data points (such as GDP, population, regime type, education levels, and previous episodes of conflict) governments, NGOs, and academics have attempted to model the likelihood, probability, and intensity of internal conflicts. However, these attempts have not led to consensus due to serious disagreement among the researchers about which models and variables are best suited to model internal conflict.

The aim of this study is to further the study of internal conflict, by developing and testing a variant of previous modeling attempts. To do so, this paper uses a logit regression model (with the binary dependent variable, internal instability) to demonstrate that certain variables – GDP per capita, unemployment, population, internet access, cell phone use, and several political indicators – exert a significant impact on internal instability and conflict. The key contribution of

this paper is the finding – untested in the previous research – that information technology is a significant predictor of internal conflict. Notably, as technology advances and people gain greater access to the internet, their ability to communicate about, and participate in protests, uprisings, and civil wars will increase.

The organization of this paper is as follows: after background and context are provided, previous scholarship and models are reviewed, which serve as the basis for the model in this paper. Next, a model is constructed that explores the predictive probability of several economic and political variables, and also captures the potential impact of technology on internal conflict. The model is then tested using data from the Arab Spring and surrounding years to test the impact of these factors. This paper establishes that *Mobile Cellular Subscriptions (per 100 people)*, *Political Stability and the Absence of Violence and Terrorism*, *Voice and Accountability*, and *Internet Users (per 100 people)* are statistically significant and impact the predictive probability of modeling regime collapse.[1] A discussion of these findings follows a general description of the results. The limitations and implications are then outlined.

The Arab Spring

The Arab Spring saw major uprisings in many nations throughout the Middle East and Africa (Boucekkine, et al., 2014). After years of oppression, lack of opportunity, and censorship, hundreds of thousands of people rose up against authoritarian rulers to demand change. These uprisings aimed to fundamentally restructure the political, social, and economic structures of the state. As Samuel Huntington noted in his seminal work *Political Order in Changing Societies*, revolutions are a "rapid, fundamental, and violent domestic change in the dominant values and myths of a society, in its political institutions, social structure, leadership, and government activity and policies" (Huntington, 1968, 264). However, not all intrastate conflicts are revolutions. Some are internal conflicts driven by ethnic, racial, tribal, economic, or ideological divides rather than a fundamental desire to dismantle and reform the institutions of power. How and why regime collapse and internal conflict occur has been the focus of extensive research in the social sciences and the study of comparative politics in particular.

[1] GDP per capita (% annual growth), Unemployment (% total labor force), Mobile Cellular Subscriptions (per 100 people), Internet Users (per 100 people), Population, Political Stability and the Absence of Violence and Terrorism, Rule of Law, and Voice and Accountability are all independent variables included in this study. A description of these variables and why they are included is explained further on in this paper under the *Model* section.

This study focuses specifically on the Arab Spring for several main reasons. First, the Arab Spring was the first major case of uprisings following the proliferation of technology. Many scholars, government advisors, and commentators discussed the potentially significant impact of technology on the internal instability of the Arab Spring. However, the impact of technology and social media on internal instability has not been quantitatively tested, as it is a recent phenomenon and the case studies are largely limited to the Arab Spring. Second, by focusing on a general region and time period (North Africa and the Middle East from 2007-2014), this study is better able to control for some of the variation that would arise with using different regions and time periods: the importance of and access to technology, the type of regime (largely authoritarian/monarchies).

Qualitative vs. Quantitative Analysis

Many scholars have theorized about the causes and timing of intrastate social and political conflicts using qualitative and expert analysis (Silverman, et al., 2008). Prior to the impressive technological advances since the 1990s, policy and decision makers relied heavily on the opinions of regional or country experts (O'Brien, 2010). A good example of this reliance on expert opinion is the United States State Department, which has Political Officers who analyze the "political climate" in the host country and "decipher events as they relate to U.S. interests, negotiations, and policies."[2] Leaders of many countries have a national security team made up of experts who provide advice and opinions as to what type and where conflict might occur. Prior to the more recent advances in modeling techniques, many governments and non-governmental organizations relied heavily on these expert opinion of officials on the ground and academics who were regional or country experts. However, these qualitative estimates were prone to human error with inconsistent and at times, wholly inaccurate predictions. More recently, governments and NGOs have become more reliant on the use of data and quantitative methods of prediction.

Since the 1990s, the type and quality of modeling techniques have improved and expanded. Furthermore, the increase in the availability of technology has allowed researchers to test theoretical models with empirical tests. This is perhaps the most significant development in the field of crisis modeling, as it allowed governments, NGOs, and private companies to rely more heavily of quantitative rather than qualitative data. The implications of creating an

[2] http://careers.state.gov/work/foreign-service/officer/career-tracks#po

objective, data-driven model of internal instability are tremendous. From preventative to reactionary foreign policy, foreign aid, and diplomacy, a model capable of predicting potential intrastate conflict and regime collapse would be of great assistance to those in government trying to shape foreign and domestic policy. But this model would also be of importance to business leaders and companies, as understanding the risks and potential occurrence of intrastate conflict and regime collapse would greatly impact decisions to invest or not invest in certain industries, markets, countries, and regions.

Yet, despite the consensus that developing a model capable of predicting intrastate conflict would provide invaluable assistance to governments, nongovernmental organizations, businesses, and militaries, opinions on which techniques and variables should be used and the validity of conclusions that are drawn differ greatly. Game theoretical, agent-based, geo-spatial, and logit models are all used to predict intrastate conflict. But there are also those who argue that it is the models that are not being used that have the most potential (Schrodt, 2013, 295). Furthermore, those that do use the same models cannot seem to agree on which variables to use, and – in the case of logit models – whether statistical significance (Fearon and Laitin, 2003, and Collier and Hoeffler, 2004) or predictive probability (O'Brien, 2010, Ward et al., 2010) of the independent variables are better evaluators of a model's strength. Due to discrepancies in the type of model and variables, and the inconsistencies in the conclusions drawn from them, modeling internal conflicts warrants further research.

Prior Scholarship

Some of the foundational work on modeling intrastate conflict focuses on a game theory approach. Using game theory modeling and a choice theoretic perspective Ginkel and Smith (1999), Pierskalla (2010), and Boucekkine et al. (2014) developed numerous explanations for the decision making process of a regime and regime opponents. In particular, game theoretical models focus on the cost benefit analysis and timing of regime opponents revolting and the response of the regime (Ginkel and Smith, 1999, Moore, 2000, Acemoglu and Robinson, 2001, Pierskalla, 2010, and Boucekkine, et al., 2012). These studies focus on the ability of a regime to suppress internal conflict, both in terms of the initial decision to revolt and the ability of the regime to put down the revolt if it begins. The studies found that the greater the ability of the regime to suppress dissent (either perceived by the opposition, or actual), the less likely internal

conflict begins and the more likely the regime is able to remain in power (Boucekkin, et al., 2012). Other studies have found that it is dangerous for a regime to offer concession as it encourages further demands. Additionally, major revolts, when they occur, are more likely in highly repressive regimes, as there is a greater level of trust between the masses and their leadership; and regimes collapse suddenly (Ginkel and Smith, 1999). Lastly, some prior work found that high rates of inequality are a driving force behind regime change in democracies and non-democracies alike, indicating the importance of economic factors on internal stability or instability (Acemoglu and Robinson, 2001). However, there is limited consensus regarding the ability of a regime to repress, the decision making process to revolt and repress, or when and where interstate conflict will occur. But as Pierskalla (2010) notes, there are two main areas of consensus: (1) that there is a negative correlation between the strength of democratic institutions and the use of repression and (2) the fact that governments, when faced with challenges to their power, will use repression to maintain control. Beyond these two findings, game theoretical modeling has provided limited understanding or agreement regarding the decision making process to revolt, how the government will react, or what tactics will be used. Furthermore, it does little to model when and if an intrastate conflict will occur. Rather, game theoretical modeling focuses on the decision making process rather than the factors (independent variables) that predict intrastate conflict (dependent variable). Pierskalla notes that prior research and analysis "is insufficient for capturing the strategic nature of protest and repression" as it relied heavily on qualitative analysis and would benefit greatly by including quantitative analysis (2010, pg. 1).

Recently, governments, non-governmental organizations (NGOs), and private institutions have moved towards a more data driven approach to predict conflict and crises. Leading the way for over fifty years is the Defense Advanced Research Projects Agency (DARPA). Its Integrated Crisis Early Warning System (ICEWS) uses heterogeneous statistical and agent-based models to analyze and predict crises throughout the world and provide US military Combatant Commanders (COCOMs) with real-time updates on potential instability and conflict (Lockheed Martin Corporation 2015). What is most impressive about the ICEWS is its use of several different sub-model techniques to predict instability and conflict. Unlike many prior Conflict Early Warning Systems (CEWs) that used single form models, ICEWS approaches instability and conflict prediction with an integrated and comprehensive modeling system.

Conflict early warning systems have relied extensively on three main modeling techniques (O'Brien 2010, 93). First, many scholars, government contractors, and private sector researchers use Agent-Based Models (ABMs) that focus on variables associated with individual leaders and the society to evaluate potential future outcomes. Second, designers of CEWs also use Geo-Spatial Network Models (disaster/crisis informatics) to predict crisis and conflict using "structural factors, event counts, and various types of spatial networks" (O'Brien 2010, 93). Third, logistic - "logit" - regression models use domestic and international political, economic, and societal data to forecast potential hotspots and conflict zones. Lastly, some have used Bayesian techniques to aggregate the three prior models. Basically, the Bayesian technique combines predictions from all three models with probability estimates for each crisis and conflict. These three models are outlined in the following paragraphs.

Agent-Based Models take on several forms and, according to O'Brien, the ICEWS uses both Silverman et al.'s *Factionism* and Lustick et al.'s *Political Science-Identity* (PS-I) models to provide further insight into the role of individuals and institutions on internal instability (2010, 93). Silverman et al. (2008) used the analysis of Subject Matter Experts (SMEs) to create comprehensive profiles of governmental and societal leaders (both in the regime, and those fighting against it) as well as the followers of both to understand domestic relations and potential conflict (122-123). While this is a game theory model, it is a behavioral game theory that explores and analyses the actions of different factions and the impact of individual leaders – fighting for and against the regime (124-125). Silverman et al. found that the more repressive or extreme a regime leader is, the more likely it was that supporters of the regime leaders would stop supporting them. In addition to losing support, a more repressive or extreme regime leader would also push the opposition towards for extreme positions, including violence against the regime and its leader (153). Like Silverman et al.'s *Factionism* AGM, Lustick's PS-I model also analyses "agents" of the state. However, the PS-I AGM uses agents that represent ethnic and political identities that are geographically located and represent not only the different groups in society but also the different regions within a state (Lustick, Miodownik, and Eidelson 2004). Lustick, Miodownik, and Eidelson find that government can spend relatively few resources and dramatically decrease ethnic and regional conflicts by increasing representation as compared to the amount of resources necessary to suppress these conflict using force (2004, 224). Both of these models rely heavily on SMEs and their "expert" knowledge based upon years of study and

research about particular groups and regions. While these experts do know an extensive amount about different states and their associated political, societal, and economic structures, these AGMs still rely heavily on soft qualitative data and the *opinions* and *estimates* of these experts, not on hard quantitative data. In order to address this concern, the ICEWS also aggregated several other models including geo-spatial network models and logistic regression.

Geo-spatial network models focus extensively on the interstate relationships of states. Using proxies for political, economic, and societal interconnection, geo-spatial network models aim to measure the importance of interstate relationships on stability and the potential for conflict (Gleditsch and Ward 2002, Hoff and Ward 2004). Geo-spatial models help to better understand the macro-level indicators of conflict, in particular inter-state relations and potential conflict zones and areas of instability. While macro-level interstate variables are important, geo-spatial models do not capture the same level of specificity on the local level that other models – specifically logistic regression models – are able to.

Logistic regression models are also used in the ICEWS to capture "macro-structural and event data factors" that focus on a particular country and include data points such as regime type, poverty level, education level, health of the society, to name a few potential intrastate indicators (O'Brien 2010, pg. 93). Logistic regression models model both the likelihood of an Event of Interest (EOIs) occurring and the statistical significance and predictive probability of individual independent variables.

The use of logistic models to predict intrastate conflict[3] is a more recent phenomena (Fearon and Laitin 2003, Collier and Hoeffler 2004, Shellman 2008, Shellman et al. 2010, Ward et al. 2010, Bell et al. 2013). While independent and dependent variables vary from study to study, all focus on the impact of independent variables on the likelihood of a given intra-state conflict occurring. The independent variables in all studies focused on political, social and economic dimensions of a country such as: regime type and state strength, religious and ethnic diversity, population, education levels, and GDP per capita and dependence on natural resources (in particular, oil). Fearon and Laitin (2003) found that the end of the Cold War, ethnic and religious diversity, and the location of broad ethnic or political grievances does not explain when or where civil wars will break out (pg. 75). Collier and Hoeffler found that high dependence on

[3] While these scholars look at many different specific types of conflict - ethnic, religious, state-nonstate, nonstate-nonstate, etc. – all focus on intrastate conflict. Therefore, this paper uses the term intrastate conflict to describe general internal conflict.

primary commodity exports and a highly dispersed population greatly increase the likelihood of internal conflict (580). Furthermore, they found that male secondary education enrollment, per capita income, higher GDP growth rate, a highly dispersed population and the overall population size are all statistically significant in their logit model (588). Specifically, they found that there was a positive correlation between these variables and the likelihood that a conflict would break out. However, in recent years, there has been a shift in how independent variables are valued in these civil war logit models. In the past, scholars focused on the statistical significance of independent variables in the model (Fearon and Laitin 2003, Collier and Hoeffler 2004). More recently the focus has been on the predictive probability of the model (O'Brien 2010, Ward et al. 2010).

Ward et al. (2010) explore the models of Fearon and Laitin (2003) and Collier and Hoeffler (2004) with a specific focus on impact of variables on the predictive probability of the model rather than the statistical significance of the individual model. In doing so, Ward et al. find that many of the independent variables that were found to be statistically significant (ethnic and religious fractionalization, commodity dependence, GDP growth) in both studies have a very limited impact on the predictive probability of the models (2010, 368-371). Furthermore, when Ward et al. apply the Fearon and Laitin, and Collier and Hoeffler models to an out-of-sample data set, they find that certain variables (GDP and population in the Fearon and Laitin model, and Population, Peace, and Male Secondary School in the Collier and Hoeffler model) have a very significant impact on the predictive probability of the model while other factors (religious and ethnic fractionalization in both models) have almost no impact on the predictive probability of the model despite a wide variation in the statistical significance of these variables in the original model. The work of Ward et al. (2010) tells us two important things: (1) predictive probability is of greater importance than statistical significance and, (2) which variables in the Fearon and Laitin (2003) and Collier and Hoeffler (2004) models have a significant impact on the predictive probability of intrastate conflict (GDP per capita, population, and male secondary education). While these three modeling techniques are widely used, there are scholars (Schrodt, 2013) that argue against using these models and advocate for the use of yet different models.

Schrodt makes a strong argument against using the typical models – such as those explained above – as other models "provide alternative structures for determining regularities in data" (2013, 295). Schrodt notes two examples, correspondence analysis and support vector

machines as being particularly robust and highly available – and yet not widely used (2013, pg. 295). While some of these models have potential to provide new evidence and a new way of thinking about modeling internal conflicts and crises, they are beyond both the knowledge, ability, and time of this author. Schrodt's argument is important to keep in mind as we continue to investigate possible ways of modeling conflict and crises. However, this research and paper focus on the more common models, and uses a logistic regression model to predict the probability of internal conflict and crises.

This paper aims to further the discussion of Fearon and Laitin (2003), Collier and Hoeffler (2004), Ward et al. (2010), and O'Brien (2010) to better understand which independent variables are statistically significant, and have an impact on the predictive probability of the logit model. Furthermore, this study specifically focuses on the impact of technology on the Arab Spring.

Model:

As previously stated, a logit regression model is used to explore the possibility of internal instability or regime change using a data set of nineteen countries over eight years (2007-2014). A logit regression model is used for two main reasons (1) the dependent variable is binary – either internal instability occurs, or it does not, and (2) like a OLS regression, a logit regression model allows exploration of the impact of specific variables (outlined below) on the likelihood of internal instability.

There are 19 countries in the data set, not all of which experienced internal instability during the selected time period (2007-2014).[4] Not all the countries faced serious challenges, but not all those that had major episodes of internal instability also experienced regime change. There were in fact only five nations that underwent partial regime collapse (Syria and Yemen) or complete regime change (Egypt, Libya, Tunisia). Other nations experienced some form of protest or attempts to remove a certain leader or regime from power. This paper aims to explore the importance of particular variables – notably technology – on internal instability during the Arab Spring.

[4] Those countries are: Algeria, Bahrain, Djibouti, Egypt, Iran, Iraq, Jordan, Kuwait, Lebanon, Libya, Mauritania, Morocco, Oman, Qatar, Saudi Arabia, Syria, Tunisia, United Arab Emirates and Yemen.

Model: Variables

This study focuses on internal instability during the Arab Spring between the years 2007-2014.

Dependent Variable

In this study, the dependent variable is whether or not there was internal instability between the years 2007-2014[5]. It is measured on a binary scale with 0 equivalent to no/minor internal instability and 1 representative of major internal instability or regime collapse. As noted, the study includes the years 2007-2014 which captures the Arab Spring (2010-2011). Again, there were only five nations that experienced partial or total regime change: Egypt, Libya, Syria, Tunisia, and Yemen. Because there were only five nations that experienced regime change, this study also includes major internal instability to broaden our understanding of what causes internal instability and the ultimate manifestation of this instability – regime change. This study relies on the analysis of Dr. Marshall, Director of the Center for Systemic Peace. Dr. Marshall compiled data on internal conflict in an impressive database titled "Major Episodes of Political Violence 1946-2014 (2014). As Dr. Marshall notes, "'Major Episodes of Political Violence' involve at least 500 'directly-related' fatalities and reach a level of intensity in which political violence is both systematic and sustained" (Marshall, 2014). The binary dependent variable used in this study is based largely upon the data and analysis of Dr. Marshall and the Center for Systemic Peace.

Independent Variables

GDP per capita (PPP – USD)

As previously outlined, prior research has shown that economic indicators that capture opportunities and inequality play a role in causing internal conflict. This study uses GDP per capita (PPP-USD) to capture some of these economic factors. It is a measurement of purchasing power parity in US dollars of a nations GDP per capita. (The World Bank, 2014). The PPP-USD of GDP per capita is used for two primary reasons. First, it is used because it is a measure of the health and strength of the economy and captures the economic opportunities within a nation.

[5] To clarify the paper, regime change and/or partial collapse will be referred to as regime collapse from this point forward in the paper.

Second, it was one of the most complete data sets in terms of a measure of economic health of a nation. While it would have been useful to measure the inequality in these countries, the data was very limited and did not provide a complete overview of the economic situation. The GDP per capita information used in this particular study is taken from The World Bank database, *World Development Indicators*.

Unemployment, male (% of male labor force) (modeled ILO Estimate)

Another important measure of the economic health of a nation is the level of unemployment. In this study, the unemployment data focuses on male unemployment, and while it is taken from the *World Bank* the data are based off of an estimate by the International Labor Organization. Unemployment levels are of particular interest, as the greater the number of unemployed, the weaker the economy and the fewer the opportunities. If individuals (particularly males) have fewer opportunities and they feel underserved by their government or the greater community, there is potentially a higher likelihood that they will join rebel or extremists groups (Collier and Hoeffler, 2004). However, while the level of unemployment could potentially provide insight into why internal instability occurs, the data are limited, and in this particular study, two separate regressions were run – one with *unemployment* as an independent variable and one without. This is due to the fact that there were numerous years and numerous countries that lacked unemployment data, which limited the number of observations. Nonetheless, it is possible that the level of male unemployment could shed some important light on the impact of the lack of opportunities and inequality on internal conflict.

Population

Another independent variable that has been found to be statistically significant and impact the predictive probability in pervious studies is the total population of a nation. As noted by O'Brien (2010) and Ward et al. (2010), the total population of a nation also impacts the predictive probability of internal conflict, while also being statistically significant as noted by Fearon and Laitin (2003) and Collier and Hoeffler (2004). These scholars argue that the larger the population, the harder it is for a government to control its population, and the more likely this population is able to organize and fight against the regime. It is also possible that the larger the population is, the less homogenous it is, and the more likely certain groups are to fight against one another – directly increasing the likelihood and severity of internal conflict. Therefore, this

study includes the commonly accepted conclusion that population does impact the likelihood of internal conflict, so the variable is included. The data comes from The World Bank *World Development Indicators* database.

Political Stability and Absence of Violence and Terrorism

The *Political Stability and Absence of Violence and Terrorism* independent variable is taken from The World Bank's *Worldwide Governance Indicators* data set. This particular variable "measures perceptions of the likelihood of political instability and/or politically-motivated violence, including terrorism" (The World Bank, 2015). The Political Stability index is available for 215 countries during the period 1996-2014. It is measured on a scale from -2.5 to 2.5 with a more positive score correlating to a greater degree of political stability and lower levels of predicted violence and terrorism. While the purpose of this model is to test the likelihood of internal instability based on particular independent variables, including a measure of political stability allows the model to capture the significance of prior levels of instability on the future likelihood of instability. This model is better able to then model whether or not prior levels of instability are significant or if conflict occurs on a year by year or case by case basis regardless of prior events. To some degree, including this variable in the model is a check on whether or not the original prediction is accurate.

Rule of Law

As noted, the Rule of Law (taken from The World Bank's *Worldwide Governance Indicators* data set) is an estimate that "captures perceptions of the extent to which agents have confidence in and abide by the rules of society". Additionally, the Rule of Law estimate captures the quality of "contract enforcement, property rights, the police, and the courts" as well as the predicted level of violence and crime (The World Bank, 2015). This variable is included in order to measure the level of trust in the government as well as the strength of the institutions tasked with protecting the physical and material well-being of citizens. The lower the level of rule of law, the greater the potential for a higher level of internal conflict and regime instability.

Voice and Accountability

The voice and accountability variable is also taken from The World Bank and is an estimate of the level of citizen participation in government and the level of freedom of expression, freedom

of association, and freedom of the media. This factor is important to any study analyzing the level of internal instability and regime stability, as a greater level of citizen participation and freedom of expression, the higher the level of peaceful dissent. The likelihood of violent resistance against a government is far less likely if the regime is not repressive, and people are able to express their displeasure publicly, peacefully, and with no fear of violent retribution. Because this is the case, a variable that measures the openness and extent of government accountability is important to this study.

Mobile Cellular Subscriptions (per 100 people)

Another potentially significant variable is mobile cellular subscriptions per 100 people. In prior scholarship, the impact of technology has not been modeled, as it was not prevalent before the early 2000s. However, this study provides a foundation for future work on the importance of technology on internal instability. These data are provided by the World Bank, and are an estimate of the number of cellular subscriptions per 100 people in the entire country. This variable is important for several reasons. First, the Arab Spring began as a grass roots movement where information was sent regarding protests and the movements of the regime via cell phones and social media. In less developed and less free nations access to cell phones is more widespread than access to the internet and the censorship of its use if far more challenging. Second, access to, and the use of technology have not been modeled or tested in prior work on internal instability. Therefore, mobile cellular subscriptions per 100 people is used as a proxy variable to capture the potential impact of technology on the Arab Spring.

Internet Users (per 100 people)

In conjunction with Mobile Cellular Subscriptions, this study also includes the variable Internet Users (per 100 people). Many have speculated about the impact of social media, blog posts, and internet use in general on the Arab Spring. This study aims to quantify the speculation of many by including an independent variable that captures the use and prevalence of technology during the Arab Spring. By including internet users per 100 people as an independent variable, this study captures the potential impact of social media, blogging, and general internet use on the likelihood of internal instability. While this does not necessarily distinguish between the type of use, it does capture the accessibility and general use of the internet in each nation before, during,

and after the Arab Spring. This study provides a foundation for future work on the importance of technology on the Arab Spring and coming periods of internal instability.

Variables Not Included

Two variables that were found to be statistically significant and have an impact on the predictive probability of prior models – Male Secondary Education and Inequality – were not included in this model. This is largely due to the lack of complete data for the time period and countries used in this study. Furthermore, rather than looking at the education level of males, this study approaches the question of the importance of opportunities for males from a more economic perspective. This is evident in the fact that this study looks at the level of male unemployment rather than education. In terms of addressing inequality, this study uses GDP per Capita (purchasing power parity in USD) to capture economic opportunity, and the overall strength and health of a national economy.

Empirical Methodology

This study investigates the relationship between regime collapse and internal instability, and several independent variables. In particular, the impact of economic wellbeing indicators, and access to and the use of technology on the probability of regime collapse are studied. The study also analyzes the impact of the stability of the regime, the rule of law, and the level of freedom and accountability.

As previously mentioned, a logit regression is run, as it models a binary dependent variable, in this study, regime collapse. Using the statistical software program *Stata*, a regression is run for the probability of regime collapse (dependent variable) based on specific economic, political, social, and technological independent variables. Below is the general logit regression model:

$$\Pr(Y = 1|X1, X2, \dots X_K) = F(\beta_0 + \beta_1 X1 + \beta_2 X2 + \beta_K X_K)$$

$$\Pr(Y = 1|X1, X2, \dots X_K) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X1 + \beta_2 X2 + \beta_K X_K)}}$$

$$\Pr(Y = 1|X1, X2, \dots X_K) = \frac{1}{1 + \frac{1}{e^{(\beta_0 + \beta_1 X1 + \beta_2 X2 + \beta_K X_K)}}}$$

The general model above is then filled using the variables (dependent and independent) mentioned in the prior section. This results in the model outlined below:

$$\Pr\,(regimecollapse\ or\ instability) = 1|unemployment(\%male), population(total), politicalstability, ruleoflaw, voiceandaccountability, GDPpercapita, internetusers, mobilephonesubscriptions$$

$$= F(\beta_0 + \beta_1 unemployment(\%male) + \beta_2 population(total) + \beta_3\ politicalstability + \beta_4 ruleoflaw + \beta_5 voiceandaccountability + \beta_6 GDPpercapita + \beta_7 internetusers + \beta_8 mobilephonesubscriptions)$$

General Description of Data

The table below provides the descriptive statistics for the variables used to test the model.

Variable	**Observations**	**Mean**	**Standard Deviation**	**Min**	**Max**
Time (Year)	152	2010.5	2.298862	2007	2014
Country Name	152	10	5.495332	1	19
Regime Change or Instability	152	0.2434211	0.4305658	0	1
Unemployment (%male)	126	7.578571	4.175579	0.1	17.1
Population Total	152	1.99E+07	2.36E+07	406724	8.96E+07
Political Stability	152	-0.5293574	1.112623	-2.793988	1.271174
Rule of Law	152	-0.1771547	0.8066086	-1.923882	1.596532
Voice and Accountability	152	-0.9674259	0.6490644	-1.895699	1.237764
GDP per Capita (PPP-USD)	141	16788.37	20895.76	1060.815	97518.61
Internet Users (per 100)	151	36.6052	24.8092	0.93	91.49
Mobile Phone Subscriptions (per 100)	152	102.5032	45.63158	8.706632	218.4303

General Data Summary

The table above provides a general overview of the data. Some data points – *unemployment, population total, GDP per capita, Internet users* and *mobile phone subscriptions (per 100 people)* are all self-explanatory. However, understanding the data points of *Political Stability, Rule of Law,* and *Voice and Accountability* is vital to understanding the model. As previously noted, these three variables are the aggregation of numerous different variables from numerous studies. They range in value from -2.5 to 2.5. The higher the score (closer to 2.5) the more stable the country, the greater the rule of law, and the more responsive the government. As the table shows, the means for each of these variables is negative, indicating that the 19 countries as a whole are relatively unstable with limited rule of law and government accountability.

Results and Findings

Two separate models were run using Stata with the data entered as panel data and using the command to find a binary logit regression model of panel data.

The First Model

$$\Pr(regimecollapse\ or\ instability) = 1|unemployment(\%male), population(total), politicalstability, ruleoflaw, voiceandaccountability, GDPpercapita, internetusers, mobilephonesubscriptions$$

$$= F(\beta_0 + \beta_1 unemployment(\%male) + \beta_2 population(total) + \beta_3\ politicalstability + \beta_4 ruleoflaw + \beta_5 voiceandaccountability + \beta_6 GDPpercapita + \beta_7 internetusers + \beta_8 mobilephonesubscriptions)$$

Model One Summary

Number of Observations	119

Number of groups	18
Obs per group:	
min	1
avg	6.6
max	7
Integration points	12
Wald chi2(8)	19.05
Prob > chi2	0.0146
Log likelihood	-46.1347

Outcome

regimechangeinstability	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
mobilecellularsubscriptionsper10	0.0401979	0.012563	3.2	0.001	0.015576	0.06482
unemploymentmaleofmalelaborforce	0.0054299	0.121453	0.04	0.964	-0.23261	0.243473
populationtotalsppoptotl	4.41E-09	1.42E-08	0.31	0.756	-2.35E-08	3.23E-08
politicalstabilityandabsenceofvi	-2.230723	0.818593	-2.73	0.006	-3.83514	-0.62631
ruleoflawestimaterlest	0.3889231	1.070159	0.36	0.716	-1.70855	2.486396
voiceandaccountabilityestimateva	1.671666	0.68606	2.44	0.015	0.327014	3.016318
gdppercapitacurrentusnygdppcapcd	3.91E-06	3.87E-05	0.1	0.92	-7.2E-05	7.97E-05
internetusersper100peopleitnetus	-0.0261388	0.023875	-1.09	0.274	-0.07293	0.020655
_cons	-4.911351	1.852248	-2.65	0.008	-8.54169	-1.28101
/lnsig2u	-14.10668	43.83878			-100.029	71.81575
sigma_u	0.0008645	0.01895			1.90E-22	3.93E+15
rho	2.27E-07	9.96E-06			1.10E-44	1

Findings of Model One

The first model – which included all independent variables – had 119 observations (as the lack of unemployment data points decreased the number of observations – see Model 2). The log likelihood was -23.28. There were three independent variables that were statistically significant at the 10% level: (1) *Mobile Cellular Subscriptions* (z-score: of 3.2, p-value: 0.001, coef.: 0.04), (2) Pol*itical Stability and Absence of Violence and Terrorism* (z-score: -2.73, p-value: 0.006, coef.: -2.23), and (3) *Voice and Accountability* (z-score: 2.44, p-value: 0.015, coef.: 1.67). There

are no other statistically significant variables even if the level is increased to 20%. Internet Users (per 100 people) – a variable of focus in this paper – does not meet the threshold of statistical significance with a z-score of -1.09 and a p-value of 0.274. In addition to a lack of statistical significance, the coefficient is also very small (-0.026) which demonstrates its lack of impact on the predictive probability.

It is important to note that the *Unemployment Level* (% males), *Population* (total), and *GDP per capita* (PPP-USD) are all statistically insignificant. *Unemployment level* (% males) has a z-score of 0.04 and a p-value of 0.964. This is also the case with the *Population* (total), as the z-score is 0.31 and the p-value is 0.756. *GDP per capita* has a z-score of 0.1 and a p-value of 0.92. Furthermore, the coefficients on all of these variables are less than 0.001, indicating very limited impact on the predictive probability (not to mention the lack of statistical significance).

The variables that exhibited statistical significance at the 5% level – (1) *Mobile Cellular Subscriptions*, (2) *Political Stability and Absence of Violence and Terrorism*, and (3) *Voice and Accountability* – all provide interesting insights into the reasons internal instability occurs. Based on this model and the findings, both technology and *Voice and Accountability* have a positive correlation with the probability of internal instability. In terms of mobile phone subscriptions, this positive correlation indicates that the greater the information flowing between dissenters and the more easily accessible that information, the more likely there will be internal instability. However, it is interesting that a higher degree of freedom of speech and accountability would be positively correlated to regime change and internal instability. It is interesting that the data shows that a government that is more responsive to the demands of the people would be less stable and that greater accountability and freedom of speech would increase the likelihood of internal instability or regime change. However, perhaps this is due to the fact that a government that is more willing to allow dissenting opinions is also more likely to face internal instability in the form of protests and mass movements. However despite this possible explanation, the positive correlation between "voice and accountability" and increasing levels of regime change and internal instability found in this study warrant further study.

This model is also interesting, as the factors found by prior scholars to be statistically significant and impact the predictive probability of the model – *percent male Unemployment*, *Population*, and *GDP per capita* – were not statistically significant and had small coefficients

indicating limited impact on the predictive probability. It is interesting that this particular model did not concur with the vast majority of research and modeling in this area. However, much of the prior research and modeling focuses on regions and time periods that do not include the Arab Spring of 2010-2011, and perhaps do not capture the unique nature of the Arab Spring uprisings, instability, and regime change. It is interesting that this study did not find the economic variables (*Unemployment* and *GDP per capita*) to be statistically significant or impact the predictive probability of the model. This lack of impact can perhaps be attributed to the unique nature of the Arab Spring uprisings and the political focus of these uprisings. It is interesting that this model found that political factors such as the *Voice and Accountability* of the government and levels of prior internal instability as well as technology – *Mobile Phone Subscriptions* – were the most statistically significant and had the greatest impact on the predictive probability of the model. However this also calls into question whether this model could be applied to other datasets that capture different time periods, regions, and nations. Because of this discrepancy, further research on the Arab Spring, the significance of political vs. economic factors, and the role of technology warrant further research.

The Second Model

The second model does not include the *Unemployment* independent variable. This is because there is a lack of data points for *Unemployment* that limits the number of observations to 119. When the *Unemployment* independent variable is excluded, the number of observations increases to 140.

$$\Pr\,(regimecollapse\ or\ instability) = 1 | population(total), politicalstability, ruleoflaw, voiceandaccountability, GDPpercapita, internetusers, mobilephonesubscriptions$$

$$= F(\beta_0 + \beta_1 population(total) + \beta_2\ politicalstability + \beta_3 ruleoflaw + \beta_4 voiceandaccountability + \beta_5 GDPpercapita + \beta_6 internetusers + \beta_7 mobilephonesubscriptions)$$

Model Two Summary

Number of obs	140
Number of groups	19
Obs per group:	
min	1
avg	7.4
max	8
Integration points	12
Wald chi2(7)	21.79
Prob > chi2	0.0028

Outcome

regimechangeinstability	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
mobilecellularsubscriptionsper10	0.02982	0.009378	3.18	0.001	0.0114385	0.048201
populationtotalsppoptotl	1.62E-09	1.13E-08	0.14	0.886	-2.04E-08	2.37E-08
politicalstabilityandabsenceofvi	-1.4733	0.581081	-2.54	0.011	-2.612195	-0.3344
ruleoflawestimaterlest	-0.10423	0.794103	-0.13	0.896	-1.660643	1.452181
voiceandaccountabilityestimateva	1.255797	0.573653	2.19	0.029	0.1314582	2.380136
gdppercapitacurrentusnygdppcapcd	9.21E-07	2.91E-05	0.03	0.975	-0.0000561	5.79E-05
internetusersper100peopleitnetus	-0.02607	0.018743	-1.39	0.164	-0.062802	0.01067
_cons	-3.50988	1.042325	-3.37	0.001	-5.552795	-1.466958
/lnsig2u	-14.5468	646.7459			-1282.146	1253.052
sigma_u	0.000694	0.224343			3.90E-279	1.20E+272
rho	1.46E-07	9.46E-05			0	.

Findings of Model Two

The second model – which had 140 observations – did not include the unemployment variable as previously stated. As the table above demonstrates, there are three variables that are statistically significant at the five percent level. These variables are (1) *Mobile Cellular*

Subscriptions (z-score: 3.18, p-value: 0.001, coef.: 0.029), (2) *Political Stability* (z-score: -2.54, p-value: 0.011, coef.: -1.47), and (3) *Voice and Accountability* (z-score: 2.19, p-value: 0.029, coef.: 1.26). If the statistical significance level is increased to 20%, then Internet Users (per 100 people) is statistically significant (z-score: -1.39, p-value: 0.164, coef.: -0.026).Once again, this model does not find *Population* or *GDP per capita* to be statistically significant or have a large impact on the predictive probability of the model (refer to table above for z-scores, p-values, and coefficients). This confirms the findings of Model 1 which included the *Unemployment* variable and also found *Population* and *GDP per capita* to be statistically insignificant.

Dropping the *Unemployment* variable increases the number of observations which does have an impact on the statistical significance and predictive probability of the other independent variables. This is particular true in the case of *Internet Users*, which is statistically significant in the second model but not the first. However, its coefficient has a negative value which indicates that the greater the number of internet users, the less likely there will be internal instability. One possible explanation for this is the fact that nations that have greater access to the internet are also likely better off. This in turn means that people are materially satisfied and would potentially be less likely to participate in an uprising. Another possible explanation for this counter-intuitive finding is that the variable *Internet Users (per 100 people)* does not capture how those internet users use or used the internet. The level of government censorship and control over internet access is not measured, which limits the ability of this study to differentiate internet use for mundane tasks (shopping, talking to friends, etc.) and internet use that would fuel internal instability (dissenting blog posts, posting photos/videos of government violence, coordinating protests and gatherings, etc.). For this reason, it is necessary for further research to better differentiate between mundane and incendiary internet use.

The second model also confirms the importance of political factors and the lack of importance of economic factors (at least those used in this study), in this model and the Arab Spring more generally. As the statistical significance and impact on predictive probability indicates, political factors – *Voice and Accountability* and *Prior Internal Instability* – had a greater impact than economic factors – *Unemployment (% males)* and *GDP per capita* – on the likelihood of internal instability during the Arab Spring and the surrounding time period (2007-2014). Furthermore, we can see that technology did play during the Arab Spring. While *Mobile*

Cellular Subscriptions had a positive correlation with internal instability, its impact was limited as indicated by the small coefficient in both models. Interestingly, *Internet Users* (while only statistically significant in the second model) had a negative correlation to internal instability. This is odd, as it indicates that the greater the number of internet users, the less likely the probability of internal instability. Nonetheless, these findings indicate that increasing levels of technology could have a direct impact on the likelihood of conflict. As the spread and use of technology continues to grow, the importance of its use will only increase. This model demonstrates that technology does play a role in internal conflict and despite limited impact on predictive probability, it is a subject worth exploring further.

Predictive Accuracy of Model Two

Finally, in this section, Model Two is tested for its predictive accuracy. In order to do this, a threshold of when a conflict might occur must be determined. This paper follows the logic of Ward et al., who establish that a binary dependent variable with a value greater than or equal to 0.5 predicts internal conflict and a value less than 0.5 indicates no internal conflict (2010, p. 366). In order to check the predictive probability of the model, 140 observations were analyzed using the logit regression equation that calculates whether or not the dependent variable (Y) is equal to one (Y=1) for any value of X (Referred to as $\hat{p}$ in the equation below). Model Two has 12 incomplete data points, as the GDP per capita variable was unavailable for 11 countries during specific years while the Internet Users data was unavailable for a single year. Therefore, the predictive probability of the model was tested using 140 observations rather than the full 152. The logit regression equation is detailed below:

General Formula

$$\hat{p} = \frac{\exp\,(B_0 + \cdots + B_k X_k)}{1 + \exp\,(B_0 + \cdots + B_k X_k)} = \frac{e^{(B_0 + \cdots + B_k X_k)}}{1 + e^{(B_0 + \cdots + B_k X_k)}}$$

Specified Formula

$$\hat{p} = \frac{\exp(B_0 + \cdots + B_k X_k)}{1 + \exp(B_0 + \cdots + B_k X_k)}$$

$$= \frac{e^{(-3.51+0.0298X_1+1.62E-09X_2-1.473X_3-0.104X_4+1.256X_5+9.21E-07X_6-0.0261X_7)}}{1+e^{(-3.51+0.0298X_1+1.62E-09X_2-1.473X_3-0.104X_4+1.256X_5+9.21E-07X_6-0.0261X_7)}}$$

Variable	X_k Value	Coefficient Value
Mobile Cell Subscriptions	X_1	0.02982
Population	X_2	1.62E-09
Political Stability	X_3	-1.4733
Rule of Law	X_4	-0.10423
Voice and Accountability	X_5	1.255797
GDP per capita	X_6	9.21E-07
Internet Users	X_7	-0.02607
B_0 Value	NA	-3.50988

The accuracy of this model was tested using the formula above. Using the 0.5 threshold, the model correctly predicted nine periods of internal conflict. It did not predict 22 other cases of internal instability and had four false positives, where it predicted conflict but no conflict actually occurred. Furthermore, it did not predict conflict in 108 cases in which there was not conflict. If the predictive level is dropped to 0.45, the model becomes more effective at predicting conflict. The model correctly predicts 15 periods of internal conflict but the false positives increase to five. However, the number of conflicts that the model does not predict properly falls from 22 to 16. Using the 0.45 threshold, the model correctly predicts internal conflict one out of every two times (48.4%) compared to only 29 percent of the time with a 0.5 threshold. This indicates a relatively strong model compared to prior work. Fearon and Laitin's model correctly predicted 0 out of 107 periods of internal conflict at the 0.5 threshold while the model of Collier and Hoeffler predicted 3 out of 46 (7%) periods of internal conflict correctly with 5 false positives (Ward et al, 2010, p. 366). The model presented in this paper correctly predicts nine out of 31 periods of conflict correctly with four false positives at the 0.5 threshold and 15 out of 31 correctly with five false positives at the 0.45 threshold. This indicates that the model at both the 0.5 and 0.45 thresholds is better able to accurately predict conflict than some prior work. While this model does perform better than some prior research, there are limitations.

Limitations and Future Research

Several important limitations of this paper should be noted. One limitation of this paper is that it only uses one type of model (logit) to predict internal instability. Many of the more advanced systems, like the ICEWS of the US Department of Defense, combine numerous models and have thousands of data points and hundreds of case studies. The model used in this paper has, at most, 140 observations (Model Two, the more complete model, is missing 12 data points). This limits the accuracy of the model and the ability of the model to be used outside of the original data set. Another limitation of this data is that it focuses exclusively on the Middle East during one period of internal instability. With such limited data, it is hard to know how accurate this model is and how impactful technology truly is on internal instability. While this paper purposefully focuses on the impact of technology on internal conflict during the Arab Spring, this also severally limits the amount of data and case studies that are used. For this reason, the importance of technology must be further researched in the future using other case studies beyond the Arab Spring the Middle East more generally. Again, at this time, additional data sets or case studies are not readily available, as there have been only a limited number of serious cases of internal instability during the 21st century when technology truly became significant and widespread. As time goes on, and more periods of internal instability occur, future research will be better able to test whether or not technology plays a significant role in fostering internal instability.

Implications and Conclusion

Regime collapse and internal instability dramatically impact the ability of nations to protect their citizens and maintain stability. Furthermore, the repercussions of these conflicts and regime changes impact the international community and global economic markets. Recently, as technology has become more prevalent and easily accessed, governments, NGOs, and academics have all attempted to better understand the role of technology in fueling internal instability. This has largely taken the form of qualitative analysis of regional or country-specific experts who analyze the use of technology and the impact on internal instability. This was particularly true during the Arab Spring, when the use of social media, texting, and other forms of technology impacted the depth and breadth of uprisings throughout the Middle East. This study aimed to quantitatively measure the impact of technology on internal instability using proxy variables of *Mobile Cellular Subscriptions (per 100 people)* and *Internet Users (per 100 people)* to measure

the impact of technology on internal instability during the Arab Spring and surrounding time period (2007-2014). It is clear from the findings that technology did play a role. However, while both variables were statistically significant, neither had a major impact on the predictive probability (as indicated by their coefficients) and the impact of *Internet Users* was actually negatively correlated to internal instability which warrants further research.

The model did shed important light on the work of other scholars who found that (1) *Unemployment*, (2) *GDP per capita*, and (3) *Population* – were statistically significant and impacted the predictive probability of the model. However, this study did not find these three variables to be statistically significant nor did they have a major impact on the predictive probability of the model. These findings suggest that the economic indicators were not as important as political factors in instigating or preventing internal instability. Both *Political Stability and Absence of Violence and Terrorism* and *Voice and Accountability* were statistically significant and impacted the predictive probability of the model. This indicates that political factors were more significant to internal instability during the Arab Spring than were economic indicators. The unique nature of regimes in the region could play a role. The vast major were, and continue to be, authoritarian regimes or monarchies. These regimes limit political rights and personal freedoms. Economically, many nations in the Gulf are incredibly wealthy because of natural resource exploitation. However, the depth and duration of political oppression is perhaps more to blame for the uprisings during the Arab Spring than the desire for greater economic opportunities. However, the fact that better *Voice and Accountability* of a government had a negative correlation with regime stability indicates that further research must be done in order to better understand the impact of government responsiveness and freedom of expression on internal instability.

At both the 0.5 and 0.45 thresholds, the model was more effective at accurately predicting internal conflict than previous models have proven to be. At the 0.45 threshold, the model correctly predicted almost half of all periods of internal conflict. While this is not as accurate as governments, NGOs, and academia would like, it does provide a foundation for further research when there are greater data on periods of internal instability during this time of increasing access to and use of technology.

While this model is a preliminary study of the impact of technology on internal instability, it nonetheless sheds light on the changing nature of internal instability and the importance of changing models to fit the times. We have entered a period of incredible technological advancement, proliferation, and access. Nations are highly interconnected and news and information travels around the world in seconds. Future models must address the importance of technology on internal instability if they wish to remain relevant and provide new insights into this vital area of study.

References

Acemoglu, D., & Robinson, J. (2001). A theory of political transitions. *American Economic Association, 91*(4), 938.

Barton, F., von Hippel, K., Sequeria, S., & Irvine, M. (2008). *Early warning? A review of conflict prediction models and systems.* (PCR Project Special Briefing). Center for Strategic and International Studies.

Bell, S. R., Cingranelli, D., Murdie, A., & Caylayan, A. (2013). Coercion, capacity, and coordination: Predictors of political violence. *Conflict Management and Peace Science, 30*(3), 240-262.

Boucekkine, R., Prieur, F., & Puzon, K. (2014). On the timing of political regime changes: Theory and application to the arab spring. *Fondazione Eni Enrico Mattei: Economy and Society Series,* 9/21/2015.

Collier, P., & Hoeffler, A. (2004). Greed and grievance in civil war. *Oxford Economic Papers, 56*(4), 563-595.

Diamond, L. (2011). A fourth wave or false start? democracy after the Arab Spring. *Foreign Affairs*, 10/6/2015.

Fearon, J. D., & Laitin, D. D. (2003). Ethnicity, insurgency, and civil war. *American Political Science Review, 97*(1), 75-90.

Freedom House. (2015). *Nations in transit 2015*

Ginkel, J., & Smith, A. (1999). So you say you want a revolution: A game theoretic explanation of revolution in repressive regimes. *Journal of Conflict Resolution, 43*(3), 291.

Hoff, P. D., & Ward, M. D. (2004). Modeling dependencies in international relations networks. *Political Analysis, 12*(2)

Huntington, S. (1968). *Political order in changing societies*. New Haven and London: Yale University Press.

Huntington, S. (1991). *The third wave: Democratization in the late twentieth century*. London: University of Oklahoma Press.

International Monetary Fund. (2015). *Global financial stability report*

International Monetary Fund. (2015). *World economic outlook*

Keen, D. (2012). Greed and grievance in civil war. *International Affairs, 88*(4), 757-777.

Lockheed Martin Corporation. (2015). Integrated crisis early warning system. Retrieved from http://www.lockheedmartin.com/us/products/W-ICEWS.html

Lusitick, I. S., Miodownik, D., & Eidelson, R. J. (2004). Secessionism in multicultural states: Does sharing power prevent or encourage it? *American Political Science Review, 98*(2), 209.

Marshall, M. G. (2014). *Major episodes of political violence.* Center for Systemic Peace.

Marshall, M., & Cole, B. (2014). *Global report 2014: Conflict, governance and state fragility*. Center for Systemic Peace.

Moore, W. (2000). The repression of dissent: A substitution model of government coercion. *The Journal of Conflict Resolution, 44*(1)

O'Brien, S. (2010). Crisis early warning and decision support: Contemporary approaches and thoughts on future research. *International Studies Review, 12*(1), 87.

Pierskalla, J. H. (2010). Protest, deterrence, and escalation: The strategic calculus of government repression. *Journal of Conflict Resolution, 54*(1)

Przeworski, A., & Limongi, F. (1997). Modernization: Theories and facts. *World Politics, 49*(2), 155.

Shellman, S. M. (2008). Coding disaggregated intrastate conflict: Machine processing the behavior of substate actors over time and space. *Political Analysis, 16*, 464-477.

Silverman, B. G., Bharathy, G., Nye, B., & Smith, T. (2008). Modeling factions for 'effects based operations', part II: Behavioral game theory. *Computational and Mathematical Organization Theory, 14*(2), 120.

Smith, B. (2005). Life of the party: The origins of regime breakdown and persistence under single-party rule. *World Politics, 57*(3), 421.

The Economist. (2015). *Democracy index 2014: Democracy and its discontents*. The Economist.

The World Bank. (2015). *World development indicators* The World Bank.

United Nations. (2013). *UNData: A world of information*. United Nations.

United Nations Development Program. (2013). *Human development reports: Education index*. United Nations.

Ward, M. D., & Gleditsch, K. S. (2002). Location, location, location: An MCMC approach to modeling the spatial context of war and peace. *Political Analysis, 10*(3), 244.

Ward, M. D., Greenhill, B. D., & Bakke, K. M. (2010). The perils of policy by p-value: Predictin civil conflicts. *Journal of Peace Research, 47*(4)

Yadlin, A., & Golov, A. (2013). *Regime stability in the middle east: An analytical model to assess the possibility of regime change.* (No. 131). Institute for National Security Studies.